TACTICAL FORMATION MATCHUPS ASSOCIATED WITH THE OUTCOME OF SOCCER MATCHES

by

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ABSTRACT

PURPOSES: Though the link between statistics and outcome is well investigated in soccer, quantitative study of the interactions of differing formations via preferential occupation of space is underwhelming. This study aimed to provide statistical significance to long understood theories on formation favourability.

METHODS: Every match played in Europe's top five leagues from 17/18 to 19/20 was analysed including each team's value for a series of outcome variables. ANCOVAs were run to determine statistical significance in formation favourability, using Team Quality as a covariate.

RESULTS: Statistical significance was found in expected goals (xG), a measure of the quality of chances a team produces, ($p < 0.0001$) and xG Against ($p < 0.0001$) between the formations. 4-3-1-2 (1.42) ranked highest for xG whilst 4-2-2-2 (1.26) ranked lowest for xG against. Several formation matchups reported significant results. Most notably in xG for 4-1-4-1 (1.49) over 3-1-4-2 (1.23) ($p < 0.0001$).

CONCLUSIONS: Certain formations occupy space on a soccer pitch in a more favourable way to others. Those that generate overloads in midfield through pinning opposition defensive and attacking lines with as few players as possible tend to be more successful.

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List of Symbols, Nomenclature or Abbreviations

Antiphase - A stable state of coordination within two things that are acting exactly opposite. Defined mathematically as having a 180° phase difference. An example is two people taking turns in a conversation.

Backpass Rule - A rule within soccer, introduced in 1992, that prevents goalkeepers from using their hands after a teammate has passed the ball back to them.

Ball Possession - The time of which one team is in control of the ball. It's often expressed as a percentage with reference to how much time a team is in control of the ball over another.

Control of Space - A defined area on a pitch where one team has more players than the other.

Coupled Oscillators - A mathematical evaluation of two things that have distinct cycles that coordinate with each other.

Coupling Strength - The degree to which two things are coordinated which often decreases with distance.

Defensive Actions - Includes all tackle attempts (successful or not), interceptions, blocks, fouls and excludes aerial challenges.

Formations - The general notation of how a team sets up its players in space. Written as a series of numbers in the subgroups of Defenders-Midfielders-Attackers. The Midfielders subgroup may be split into two.

Game-State - The current score of a match.

Goal Difference - The goals scored minus the goals conceded by a team within a defined period.

Inphase - A stable state of coordination within two things where they are acting in exact synchrony. Defined mathematically as having 0° phase difference. An example is two people wagging their index finger in unison.

Interpersonal Coordination - The tendency for two or more people to coordinate their actions with or without intent.

Offside Law - A rule in soccer where a player cannot receive a pass from a teammate if he was nearer to his opponents' goal line than both the ball and the second last opponent when the pass was played.

Penalty Area - Known also as the 18-yard box, it is a rectangular area on a pitch that extends 18 yards from each goal post and 18 yards in front.

Pinning - The positioning of a player(s) on a pitch such that specific opponents can't leave their own position without leaving a simple progressive pass to the player in unguarded space.

Playing Style - The characteristic features of the way in which a team plays brought about through favouring certain on and off ball actions above others.

xG - The probability that a shot will result in a goal based on the characteristics of that shot and the events leading up to it. The value can be anything from 0-1. It's often reported cumulatively over a defined period.

Zone 14 - A rectangular area of space that extends centrally out of the penalty area. Shown in *Figure 13*.

Introduction

Two excerpts from 'Inverting the Pyramid' and 'Zonal Marking' articulate the sheer ambition driving an investigation into formation interaction effects in elite level soccer.

- "Egypt won the African Cup of Nations with a 3-4-1-2 in both 2006 and 2008 but that was probably largely because straight 4-4-2 still tends to dominate the thinking in Africa" (Wilson, 2008).
- "Mircea Lucescu's Inter arrived at Old Trafford in a 3-4-2-1 shape with Roberto Baggio and Youri Djorkaeff floating behind Ivan Zamorano. That's a tough system for a 4-4-2 to cope with: two players between the lines and often an overload in central positions" (Cox, 2017).

Clearly, formations (*Figure 1 and 2),* and in particular their matchups, in soccer affect the control of space on a pitch enough to influence the outcome of a match.

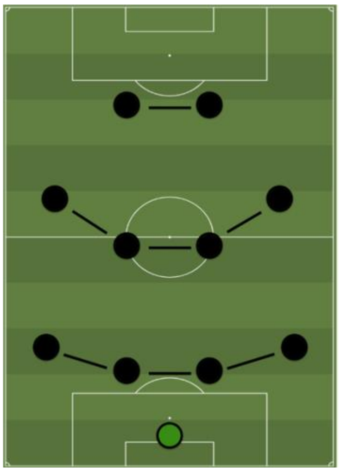

Figure 1 - A common soccer formation 4-4-2. Convention follows typically that the goalkeeper is dropped from the standard notation of the ten outfield players as Defenders-Midfielders-Attackers.

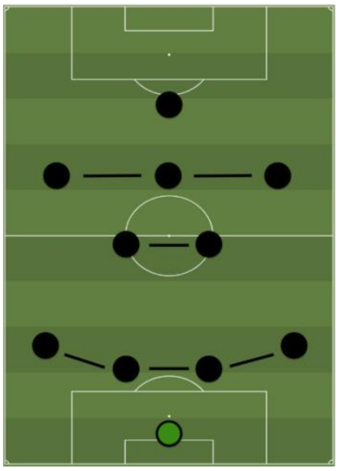

Figure 2 - An alternative formation 4-2-3-1. It is commonplace for the Midfielders' subgroup to be further split into two groups where necessary.

The first international soccer game between England and Scotland in 1872 featured an England formation of 1-2-7 and a Scotland formation of 2-2-6 (*Figure 3*).

Figure 3 - The first international soccer match, Scotland 0-0 England, 30th November 1872. England's formation was described as 1-2-7 whereas Scotland played in a 2-2-6 (Wilson, 2008).

Though viewed overwhelmingly as underdogs, Scotland were able to draw the game 0-0 through a combination of a more deliberate attempt to pass rather than dribble when receiving the ball and deploying an extra defender within their formation. A chronological evolution of formations to modern day follows a similar trend towards fielding more defenders and midfielders. For the most part, this was further enhanced due to alterations in the offside law and the outlawing of the back-pass rule in 1992 (Cox, 2017). As an example, it is not uncommon to see two teams play a match with formations as 4-3-3 vs 3-5-2. *Figure 4* shows how it is possible to evaluate a matchup of this kind from a control of space perspective.

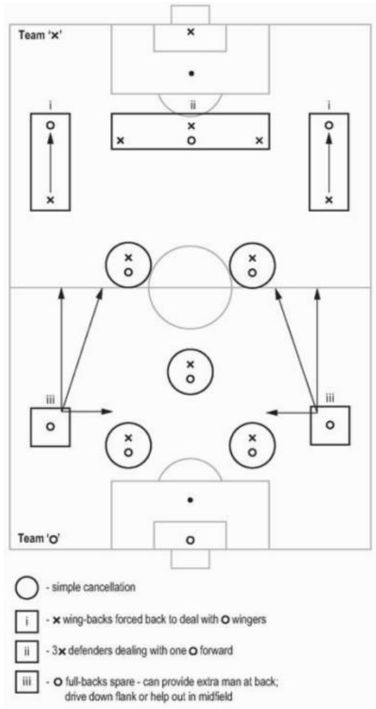

Figure 4 - A tactical breakdown of Team ‘o’s 4-3-3 vs Team ‘x’s 5-3-2. (Wilson, 2008)

Spatiotemporal tracking data evaluation is a growing trend of performance analysis in soccer. Its use has been mainly in looking for descriptions of how a team plays via their passing frequencies, directions and combinations. It’s possible to isolate frequent attacking patterns and centrality such that reporting a team's network, where nodes are indicative of position and touch frequency and edges of passing combinations, is now common practice (*Figure 5*).

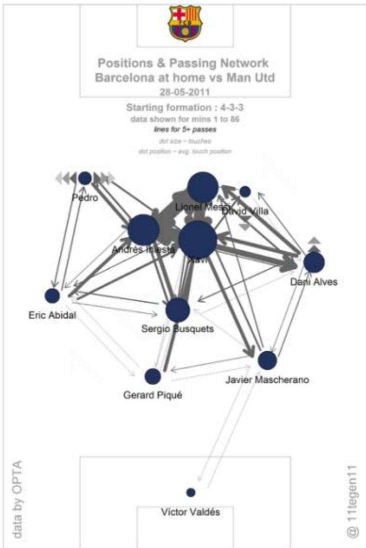

Figure 5 - A modern day pass network for Barcelona in their 2011 Champions League final against Manchester United (11tegen11, 2019).

Data of this kind can explain a team’s on-ball formation quantitatively with respect to actual in game actions. Since there are far more passes in elite level soccer matches than defensive actions, an analogous approach to defensive data is more challenging. The modern approach involves coding a player's individual defensive actions, tackles and interceptions and creating a convex hull to describe overall activity (*Figure 6*).

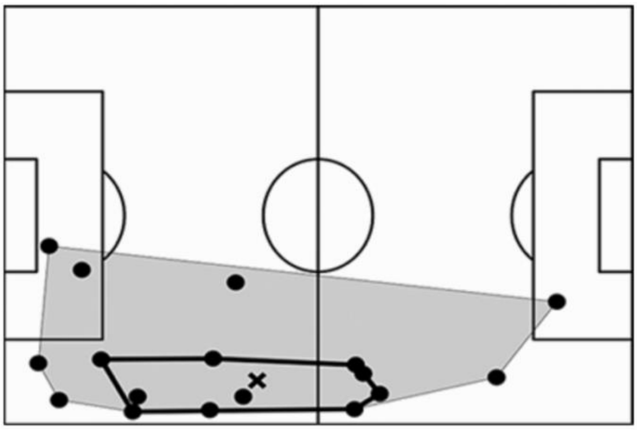

Figure 6 - Defensive actions of Juventus player Stephan Lichtsteiner in the first semi-final leg of the 2014/15 Champions League tie against Real Madrid. The dots indicate interceptions; the cross marks the average defensive action position and the solid line shows the convex hull for all actions close to this position (Sumpter, 2017).

The resulting shapes of the polygons reveal overall team defensive actions over the full pitch (*Figure 7*).

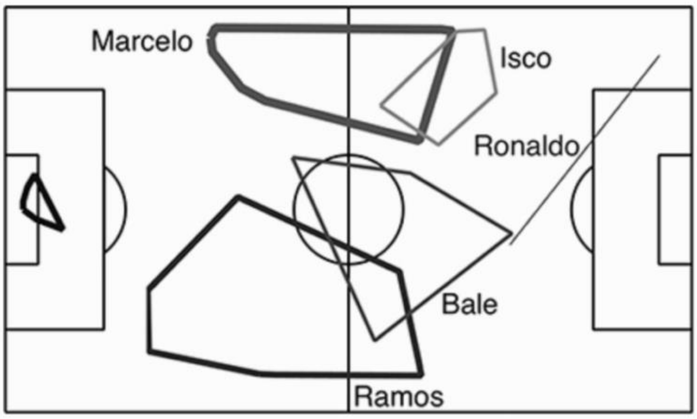

Figure 7 - Defensive convex hulls of five Real Madrid players in the same match as Figure 6.

The concept of formations as a deliberate setup to enhance performance is premised on the notion of greater interpersonal coordination. A set of players on a soccer team is an example of a complex system where individual agents are coupled to their nearest neighbours. In nature, these are found harmoniously, whether through a flock of birds or a school of fish. This interpersonal coordination emerges through these spontaneous self-organization processes to create overall order under specific task or field constraints.

Interpersonal coordination of two participants has frequently been modelled from the perspective of two coupled oscillators. Originating from the Haken-Kelso-Bunz model (Haken et al., 1985) for interlimb coordination, similar rationale allowed for its application to interpersonal coordination (*Figure 8*).

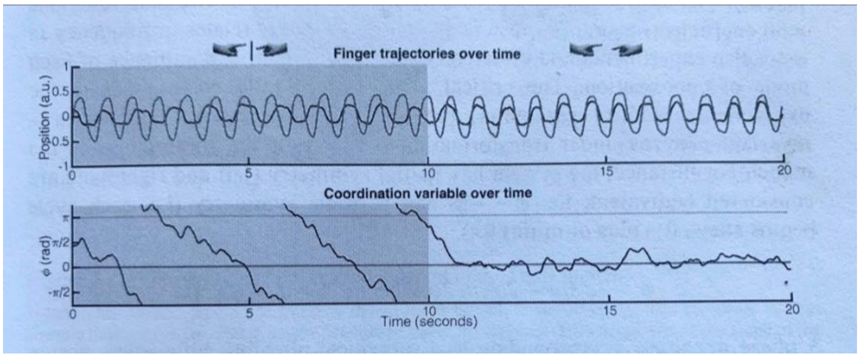

Figure 8 - The finger movement trajectories of two participants with time. Their initial movement is without sight of their partner (shaded region). At ten seconds an opaque screen becomes transparent, allowing partners to see each other. With no vision, no obvious coordination is observed. Upon vision, finger trajectories become ordered and the phase change is around zero, signifying coordination (Tognoli et al., 2007).

Analysis of the dominant mode of synchronisation between the oscillators, from in-phase (0 degree) to anti-phase (180 degrees) during a time period, yields valuable information on the coupling of two players in a sporting event. As an example, most racket sports studies show simple in phase or anti-phase coupling, both stable solutions of coupled oscillators. Interestingly it was reported that some squash contest behaviours showed tendencies towards quarter and three-quarter phase relations (McGarry, 2006) brought about through the juxtaposition of attacker-defender dynamics. It's theorised that this stable pattern is brought about through an attacker's desire for anti-phase coupling in contrast to a defender's preference for in-phase coupling.

Mathematical evaluation of interpersonal coordination using coupled oscillators in team sports becomes extremely challenging with changes in the number of players and coupling strength. Intrateam coordination is sustained through local interaction rules like interpersonal distance, maintained mostly through running at the same pace and direction as the ball carrier. These characteristics of multi-player systems allow for specific attacking and defensive subunits or more generally formations. Studies on attacking subunits in rugby union revealed that players adjusted their interpersonal distances when facing the first and second defensive lines, drawing closer initially before spreading out when facing the second line (Passos et al., 2011). Further studies suggested that intrateam coordination patterns may be crucial for successful performance when the opposition do not show such proficiencies within theirs (Rodrigues & Passos, 2013).

The relationship between in-game statistics and outcome in soccer is now well understood but it took up to the 1950's for meaningful statistics beyond goals to be recorded. Reep examined passing sequences leading to goals through first-hand notation and observed that 80% of goals came from passing sequences of three or fewer (Reep & Benjamin, 1968). *Figure 9* shows graphical representation of some of the data reported. Reep's work allowed for statistical interpretation and scrutiny of the performance-outcome relationship from passing data.

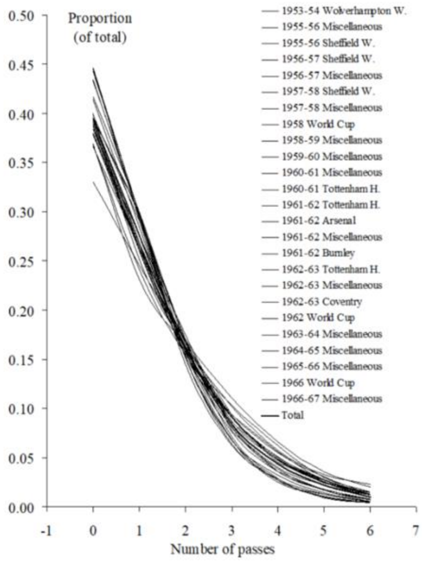

Figure 9 - Negative binomial distribution of the number of passing sequences in soccer for the teams and years listed. (McGarry and Franks, 2003). The original data was presented in tabular form by Reep and Benjamin (1968).

In an analogous study conducted on two World Cup Finals, passing data leading to goals was analysed showing more goals scored from longer passing sequences than shorter ones (Hughes & Franks, 2005). Additional findings demonstrated that longer possession spells resulted in more shots per possession, yet the ratio of goals from shots was better from shorter passing sequences than longer ones.

Another intuitive measure to study is ball possession. It seems logical that stronger teams may be better capable of retaining the ball than weaker teams. However, situational dependence prevents ball possession from being an effective single-game performance indicator (Lago-Penas & Dellal, 2010). It appears that game-state and quality of opponent, collectively and tactically, are both significant factors in single-game variance from general trends. Nonetheless, seasonal comparison shows a loosely positive connection between ball possession and goal difference in top European leagues as in *Figure 10*.

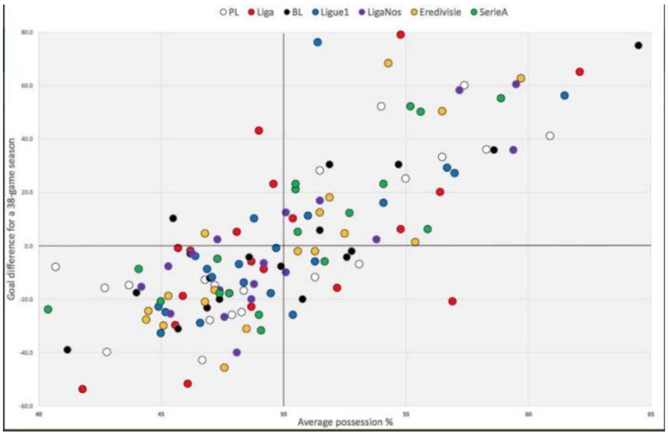

Figure 10 - Average ball possession % vs goal difference for a 38-game season. The data was taken from the major domestic European leagues listed by color for the 2016/17 season. Originally produced by Cox (2017).

These performance measures trace important, though not direct links, with the main outcome measure in soccer, goals. The precursor to goals is shots and whilst shot totals reveal somewhat useful information, there is a huge discrepancy in the quality of two different shots and how likely they are to result in a goal. This led to the development of expected goals (xG) as a quantitative measure used to describe this variation. In short, xG attempts to quantify the probability of a particular shot leading to a goal from an amalgamation of pre-shot information. Thus, cumulative xG values can yield information on single game and seasonal trends. The location of the ball before the shot (Armatas, 2010) seems to be the biggest factor, though other contributors include the type of shot (foot or head); the type of possession leading to the shot and the defensive pressure all affect the likelihood of a goal being scored. As in *Figure 11*, the quality of a shot deteriorates quite drastically with angle and distance. Studies have shown that xG does better at predicting future outcome measures than goals themselves (Caley, 2015).

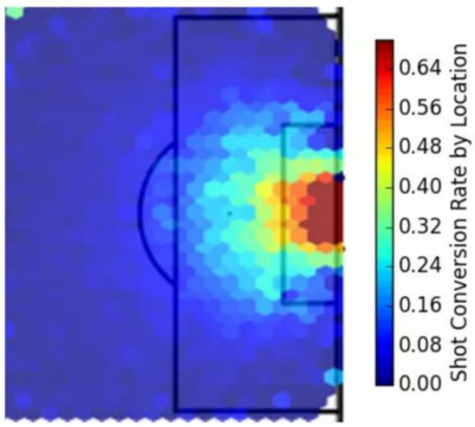

Figure 11 - The likelihood of a (non-headed, not assisted by a cross) shot being scored based on location (Caley, 2015).

Modern day analysis concerns adding quantitative value to in-game actions further back in possession sequences leading to shots. Distinct patterns in high value xG per shot values have been found to come from particular types of passes and crosses from the deep corners of the penalty box as in *Figure 12*.

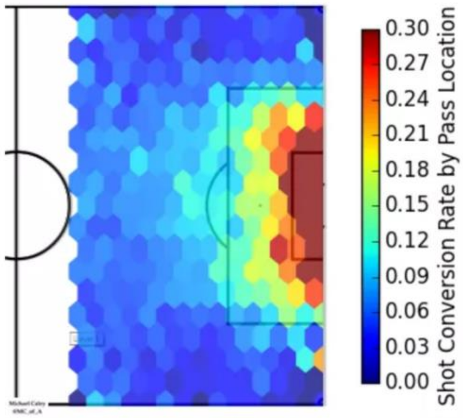

Figure 12 - The likelihood of a resulting shot being scored based on the location of a non-cross assist pass (Caley, 2015).

One can thus deduce that actions that result in moving the ball into the penalty area carry value for increasing the probability of scoring (Ruiz-Ruiz et al., 2013). Studies show that the central area of the pitch just outside the penalty area (zone 14) also shows proficiency in resulting goal scoring with ball-possession time and passing frequency (Horn et al., 2002; Smith, R. A. and Lyons, K. 2017). Visual representation is provided by *Figure 13*.

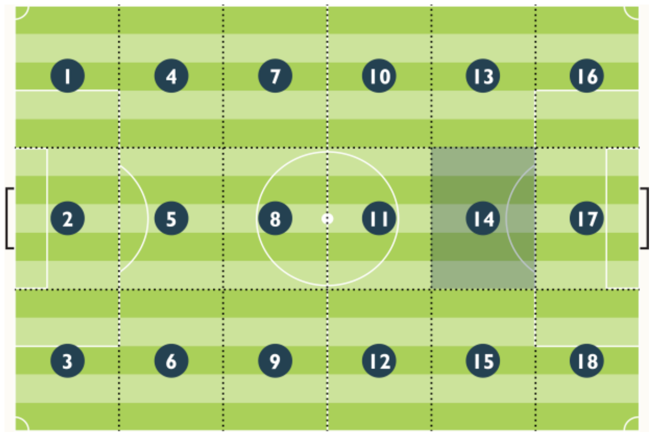

Figure 13 - A typical breakdown of a pitch into 18 characteristic zones. Zone 14 is highlighted because of the research associated with successful teams regularly accessing this area. Image provided by The Times UK (2019).

Quantifying the value of every action on a pitch remains the main focus of the current study. In particular, possessions have been evaluated with respect to their expected value in scoring/conceding a goal at any point in the sequence (Fernandez et al., 2019). This sort of work became a catalyst for study on using continuous tracking data to build a model with constantly evolving temporal changes in team's likelihood of scoring/conceding (Lawrence, 2019).

Conducting the Research and Boundaries

The aim of this research is to attach quantitatively significant findings to long understood theories on preferential formation matchups established from a control of space perspective. The continuous nature of soccer games and variance in player by player profiles renders exact formation grouping difficult though not impossible (Shaw & Glickman, 2019). Moreover, it is not uncommon for teams to change formation in game or failing that, adjust specific patterns of play to suit a particular opposition. Though these are legitimate boundaries to specific formation matchup evaluation, they should not be seen as barriers to research as formations can differ greatly in their occupation of space. Some of these boundaries can be overcome by sheer sample size and deliberate measures to use team quality as a covariate within the study. This research seeks to build on previous work of xG by applying it within an experimental framework to scrutinize the effect of formation matchups.

Literature Review

Soccer Tactics and Strategy

Naturally the aim of a competitive soccer game is to win. Tactics, defined as "an action or strategy carefully planned to achieve a specific end" are therefore crucial (Carling, 2005; Kannekens et al., 2011; Sampaio and Macas 2012; Yiannakos and Armatas 2006). In particular, the tactic encompasses a team's control of space, time and individual actions to win a game (Fradua et al., 2013; Garganta 2009). The overarching term of tactics is well understood to be split into the components of individual, group, team and match tactics (Bisanz and Gerisch 1980; Carling et al., 2005). Individual tactics are self-intuitive, i.e. that they concern individual player matchups, but group tactics refer to the cooperation of subgroups in deliberate ways. Team tactics describe a team's preferred offensive and defensive formations and the positioning of the formation on the pitch (Grunz et al., 2012). Game tactics provide information on a team's playing philosophy.

Successfully implementing tactics at all the levels described requires the coach to take into account the team, the opposition and external factors like home-away bias and the weather (Gréhaigne and Godbout 1995; Lago 2009; Mackenzie and Cushion 2013; Sarmento et al. 2014). Therefore, tactics themselves are influenced by decisions made both before and during a game. Hence gaining knowledge through in-game interactions between two teams should lead to adjustments (Balagué and Torrents 2005; Garganta 2009; Grehaigne et al. 1997; Gréhaigne and Godbout 2014).

As knowledge of the game has increased, so too has tactical complexity, placing greater scrutiny on coaches' tactical ability. Interestingly, this has been in contrast to scientific investigations of tactical decisions in elite soccer (Carling et al. 2005c; Garganta 2009; Sampaio and Macas 2012; Sarmento et al. 2014). This could simply be down to a lack of accessible and reliable data required for high level tactical analysis (Rampinini et al., 2007). It's still commonplace to assess tactics and performance by individual game observations (Dutt-Mazumder et al. 2011; Mackenzie and Cushion 2013) leading to bias and an inaccurate overall assessment. In addition, observational approaches are highly time-consuming and limit their application (Carling et al. 2008; James 2006). A quantitative approach to analyze team behaviour is desirable (Beetz et al. 2005; Carling et al. 2014; Lucey et al. 2013a, b; Wang et al. 2015) to couple together the recent evolution of tactics in elite soccer with science.

Formations Emerging from Dynamic Self-Organization

Formations encompass a certain aspect of soccer tactics referred to as team tactics (Grunz et al. 2012). Broadly, formations emerge from the notion of interpersonal coordination, a term that helps define how we as humans interact (Passos et al., 2016). A formation within soccer, or indeed other sports, is an example of a dynamic self-organizing system. Biologically this is a common trend. Herring form characteristic shapes (Partridge et al., 1980) when swimming together in response to predator intrusion (Nottestad & Axelsen, 1999). This large-scale order from simple animals is described as "a process in which the pattern at the global level of a system emerges solely from numerous interactions among the lower-level components of a system. Moreover, the rules specifying interactions among the system's components are executed using only local information, without reference to the global pattern" (Camazine et al., 2001). In this example, the fish are perceptually coupled to neighbours where distinctive swimming coordination gives rise to global patterns of collective locomotion.

Human research on interpersonal coordination was inspired after findings from intrapersonal analysis of rhythmic coordination in limbs. In particular, it was postulated that the same dynamical process of oscillatory entrainment seen with one person could occur across two people (Newtson et al., 1987). It was noted that limbs could be modelled as oscillators with their coordination understood via characteristic self-organization processes (Kelso, Holt, Rubin, & Kugler, 1981). Building on this, Haken, Kelso, and Bunz (1985) generated a mathematical model (the HKB model) to help understand stable phases of coordination. The model demonstrates the stability of in-phase coordination, as if two people were acting jointly, as well as anti-phase coordination, as if two people were acting opposite. Fascinatingly it also shows an anti to in-phase transition as the frequency of oscillation is increased, a finding that can be demonstrated using index finger wagging.

Sports provide a unique platform for practical application of the HKB model. The changes in interpersonal distance between two players in the Japanese martial art Kendo have been evaluated as a linear mass spring pendulum (Dietrich et al., 2010). The coupling of the two players' movements showed how each stepped forward and backward from one another in conjunction with a linear coupled harmonic oscillator. Racket sports provide further movement kinematics where displacement to and from the T-position is indicative of an oscillatory cycle. Research into squash rallies initially showed anti-phase coordination (McGarry et al., 1999). Similarly, tennis rallies showed mutual tuning of players' movements to stable periods approximating in-phase and anti-phase coordination (Lames, 2006; Palut & Zanone 2005; Walter, Lames & McGarry, 2007).

The stability of in-phase and anti-phase coordination within the HKB model's solutions is derived from coupling functions formulated such that oscillators are attracted towards each other's behaviour. Interestingly, upon inverted oscillatory coupling, numerical solutions to the HKB model revealed stable coordination to quarter-phase (90°) (Kelso et al., 2009). It is theorized that this inverse coupling better explains the attacker-defender coupling in sports where a defender seeks in-phase coordination with the attacker whilst the attacker desires the exact opposite. Further analysis of tennis rallies indicated more frequently stable three-quarter and quarter phase relations (De Poel, Van de Laarschot & Noorbergen, 2014) to coincide with stable in-phase patterns. It's possible that scrutinization of these phases could reveal information as to who is the more dominant player within exchanges.

The most archetypical coordination dynamics for multi-player sports is in crew rowing. In this instance, due to the resulting net torques around the centre of the boat from poor synchronization (Baudouin & Hawkins, 2002), ideal coordination is paramount. It follows that stable coordinative patterns such as in-phase rowing yields the most optimal forward velocity (Hill & Fahrig, 2009).

The presence of interpersonal coordination between players in team sports emerges through spontaneous self-organization processes which often change, examples of which include field boundaries, location of goal and players' relative position to each other (Passos & Chow, 2016). The interactive behaviour of each player to co-adapt their actions to teammates and opposing players is a crucial feature for success (Passos et al., 2013). Interpersonal coordination within team sports thus needs to be analysed from an intra and interteam perspective.

The interteam model is most commonly evaluated from attacker-defender behaviours. As is the case with other dyadic sports, identifying coordinative variables that are created by the cooperation of the individual parts of a system is the first step (Kelso, 2009). An example of such is the interpersonal angle, calculated using a vector spanning upwards from a horizontal line parallel to the goal line from defender to attacker (Passos et al., 2009). Angles below 0° would indicate the attacker had successfully passed the defender. It's found that fluctuations within this angle signifies that the dyadic system is poised for a transition where examples would include the attacker dribbling past the defender or the defender stealing the ball. These moments of criticality provide interesting feedback mechanisms into the overall system as they have a large influence on the actions of nearby players. Hence, attacker-defender systems in team sports alternate between periods of stability and variability and can be known as self-organized criticality (Passos et al., 2009; Passos et al., 2013).

The intrateam level of analysis refers to a team's ability for their players to coordinate their actions with teammates. Players are temporarily coupled to fit different task goals that may shift in intensity and priority within game scenarios (Eiler, Kallen, Harrison & Richardson, 2013). As such the coupling strength between the system components tends to change significantly in continuous time-dependent sports. Collective behaviour places a demand on the adherence to functional local interaction rules like interpersonal distance and common velocities and directions on the pitch. Such rules allow for complex and specific collective structures to form (e.g a diamond-shaped structure). An attacking subunit in a competitive Rugby Union context showed interpersonal distances to be smaller when facing the first line of opposition pressure before spreading out to attack the second (Passos et al., 2011). Another study showed that intrateam coordination patterns may be crucial for success when facing opposition teams that fail to achieve such coordination. Nonetheless, when similar levels of intrateam coordination was observed, other factors impacted performance (Rodrigues & Passos, 2013).

The complex and ever-evolving nature of interpersonal coordination within competitive team sports results in challenges to mathematical evaluation. In order to use a similar dynamical self-organisation approach as was seen with dyadic sports, a single coordinative variable must be isolated that can help describe the behaviour of the system of players.

Several attempts have been made to provide this variable in the context of soccer using spatial-temporal analysis. A common approach is the team centroid method (Folgado et al. 2014; Frencken et al. 2011, 2012; Yue et al. 2008) which uses the geometric centre of the positions of all players from a team to analyze overall behaviour. Results have shown strong in-game between centroid coupling (Frencken et al., 2011); changes in inter-centroid distance due to pitch size (Duarte et al. 2012a, b; Frencken et al. 2013) and greater inter-team coupling variability upon shot taking (Frencken et al., 2012). Other studies concluded a greater centroid behaviour regularity in novice players after tactical training (Duarte et al. 2012a, b; Sampaio and Macas 2012) and a greater regularity in players movements relative to their own subgroup centroids than others, as in defenders, midfielders and attackers (Goncalves et al., 2014). Research into team centroids has been rife in recent years but it is not clear exactly what team centroids inform about team behaviour.

Further ideas have followed studying the control of space. Merand (1976) introduced a concept of effective space as “the polygonal area that one obtains by drawing a line that links all involved players [of both teams] at the periphery of the play at a given instant”. This idea was built on with the use of convex hulls as the smallest polygon that encloses all the points within a set (Frencken et al. 2011; Moura et al. 2012, 2013). Interesting analysis reported a greater surface area from attacking teams over defending teams (Frencken et al. 2011; Moura et al. 2012) and that more experienced players covered a greater area than those less so (Duarte et al. 2012a, b; Olthof et al. 2015). Space control can also be investigated by voronoi-diagrams, where dominated space is calculated using the location and distances between individual players. These methods reported similar findings to convex hulls (Fonseca et al. 2012; Fujimura and Sugihara 2005; Gudmundsson and Wolle 2014; Kim 2004; Taki and Hasegawa 2000). Results from these studies highlight space control as an important feature in understanding team tactics and the interactive nature of soccer games (Duarte et al. 2013; Garganta 2009; Grehaigne et al. 1997; Tenga et al. 2010a, b).

A more emerging analysis technique includes team passing networks (Watts and Strogatz, 1998) where players and their average position indicate nodes and the passes, including the number of them, denote the weighted vertices between players (Duarte et al. 2012a, b; Passos et al. 2011). This approach begins to allow links from common outcome variables and available statistics to infer about team tactics. As an example, it is possible to pinpoint key players and common passing links that inform how a team attacks (Gama et al. 2014; Passos et al. 2011, Wang et al. 2015). Passing networks form a large part of modern-day analysis because of their simplicity to create a graphical representation of team tactics above and beyond traditional notational analysis.

The use of spatio-temporal positional data is a great weapon for analysing team behaviour. It is common to use machine based learning algorithms to identify and model specific data patterns (Bialkowski et al. 2014a, b; Fernando et al. 2015; Xinyu et al. 2013). Interestingly this approach was taken to identify team formations from an entire season in the English Premier League (Bialkowski et al. 2014a, b; Lucey et al. 2013a, b) by using a two-step algorithm where the formation could only be identified after each player was assigned a specific role. Other uses of tracking data include to predict the location of the ball on the pitch and calculating flow-fields from the players movements (Kihwan et al., 2010); using cluster analysis of game sequences to identify attacking plays (Xinyu et al., 2013; Fernando et al., 2015) and neural network modelling to study tactical patterns (Barton et al. 2006;

Bauer and Schöllhorn 1997; Dutt-Mazumder et al. 2011; Kohonen 1990, 2001; Lees and Barton 2003).

It is important to note that although a plethora of compelling techniques for studying team tactics and formations have been reported, there is little conceptual connection between them. As alluded to, the main challenge is the lack of a theoretical model (Garganta 2009; Glazier 2015; Mackenzie and Cushion 2013) which has consistently been proposed in the literature stemming from a dynamical system theoretic framework (Duarte et al. 2012a, b; Duarte et al. 2013; Garganta 2009; McGarry et al. 2002; Reed and Hughes 2006; Ric et al. 2016). As of yet, the question of whether team sports can be modelled under the same mathematical oscillatory assumption with phase space informing a great deal about the system, has yet to be resolved. Such an explanatory model may need to integrate information from several domains including tactics, physiology and motor skills (Garganta 2009; Sarmento et al. 2014).

Speculation on the exact effect that team formations have on each other with relation to outcome has largely been understood for many years (Zauli, 2003; Wilson 2008; Cox 2017). Descriptions of these effects are mostly explained from a control of space perspective and are primarily explained through observation. There are few quantitative direct studies that have looked into the influence of team formations in 11v11 matches and outcome measures with elite players (Dellal et al., 2012; Gonçalves et al., 2017) though research on physiological demands is well publicised.

Research into 4-3-3 and 4-4-2 formations from Brazilian national league matches showed that players covered greater distance, at higher speeds and with increased high intensity during 4-3-3 formations over 4-4-2 (Aquino et al., 2017). A study on 70 matches in the English Premier League found defenders playing in a 4-4-2 to cover greater distances than those in a 4-3-3 or 4-5-1 formation and in addition teams using a 4-4-2 or 4-3-3 played more passes than in a 4-5-1 (Carling et al., 2011). Using GPS data from five common formations (4-4-2; 4-3-3; 3-5-2; 3-4-3; 4-2-3-1) in U19 and U21 squads showed interesting findings. Covered distances were shorter in a 4-4-2 compared to 4-2-3-1, whereas high speed running distances were greater for 4-2-3-1 and 3-5-2 than 4-4-2. The author noted that 3-5-2 posed the greatest physiological challenges (Clarke, Duncan Tierney & Young, 2016). To conclude, a study using tracking data from 45 French Ligue 1 matches on a reference team that used a 4-3-3 or 4-5-1 formation showed some interesting physical and skill-related performance effects when facing other formations. The reference team performed more passes and touches per play when playing against a 4-4-2 compared to the other formations. When facing a 4-2-3-1, more tackles and aerial duels were observed. Physiologically, the reference team covered greater distances when facing a 4-2-3-1 compared to 4-4-2 and there were high intensity running discrepancies between the two (Carling, 2011).

A recent controlled experimental study observed tactical key performance indicators (KPI's) in a 4-2-3-1 vs 3-5-2 scenario where the KPI's were measured using dynamical positioning variables such as effective playing space and space control gain. Though neither team showed differences in some measures, a 3-5-2 exceeded a 4-2-3-1 formation for the Player Length per Width ratio and Pressure Passing Efficiency KPI's (Memmert, Raabe, Schwab & Rein 2019).

The Relationship between Soccer Statistics and Outcome Variables

Though soccer dates back to the 19th century, it was not until the 1950's that anything other than goals were recorded as in-game statistics. In a study that was conducted via pen and paper notation on a dataset of English Division 1 matches and World Cup matches from 1957-1966, it was found that 80% of goals came from passing sequences of three or fewer (Reep & Benjamin, 1968). Further analysis showed that in excess of 90% of passing moves consisted of three passes or fewer (Reep & Benjamin, 1971). These findings were to have a profound effect on English soccer as Reep argued the case for the "long-ball" strategy, one which favoured direct attacks to reach the opposition's penalty box, rather than long-chain passing sequences that are more common today.

In an analogous study to that conducted by Reep and Benjamin years earlier, passing data leading to goals were analysed from two FIFA World Cup Finals. The key finding was that, after normalizing the data with respect to the frequency of the respective passing sequences, there were more goals from longer passing sequences than shorter ones. It was also found that there were more shots per possession for longer passing sequences but the ratio of goals per shot was greater from shorter sequences (Hughes & Franks, 2005).

Though it is well reported that there appears to be a positive correlation between average ball possession and goal difference over an entire season dataset (Cox, 2017), it is noted that ball-possession is too situational dependent to be an effective single game performance indicator (Lago-Penas & Dellal, 2010). However, adding extra parameters to ball possession measures has reported some interesting findings. Scoring teams tend to have less possession in the attacking and middle thirds after scoring, where the converse was true for the team that just conceded (Ridgewell, 2011) and unsuccessful teams were found to play more passes in their own defensive third (Scoulding et al., 2004).

When analysing soccer matches in outcome terms, it seems logical to start with goals and interpret their first derivative, shots. A number of studies show that shooting more at goal than your opponent tends to be a characteristic of winning teams (Bosca et al., 2009; Lago-Peñas et al., 2010; Lago-Peñas et al., 2011; Perin et al., 2013), though further scrutiny has shown important distinctions in the perceived quality of each shot taken. The location of the ball before the shot (Armatas, 2010; Bekris et al., 2013 and Pollard & Reep, 1997) appears to be the greatest contributor, though the type of possession leading to the shot (Carmichael et al., 2001 & Lago-Peñas et al., 2011); the type of shot and the defensive pressure around the ball when the shot was taken are other important factors. Modern day elite soccer outcome measures encompass all of these influencers in formulation of expected goals (xG) models.

xG models assign a probability of any shot leading to a goal based on a predetermined algorithm of many similar shots beforehand (Bertin, 2015a; Caley, 2015; Caley, 2014a; Pleuler, 2014; Trainor & Chappas, 2013 and 11tegen11, 2014). Put together cumulatively, xG can yield information about how successful a team has been over a defined time period.

In fact, xG, in particular a team’s xG in contrast to the xG they allow, has been shown to be a better predictor of goals scored and allowed than actual goal difference (Caley, 2014). With the addition of spatiotemporal tracking data to model defensive pressure and understand goalkeeper location, it's been possible to reduce the error in xG calculations further (Goodman, 2018).

The introduction of xG has been hugely important in greater understanding performance but it is still largely descriptive. By tracing a passing sequence back further from shots, it’s been shown that winning teams make more passes into the opposition’s penalty box and receive much fewer than losing teams (Ruiz-Ruiz et al., 2013). Tracking further, it's been found that over 80% of entries into a central zone of space outside the penalty area (zone 14) resulted in a shot on target within the penalty area (Horn et al., 2002). Finally, teams that have a higher number of passes in the final third of the pitch are more likely to create goal scoring opportunities (Partridge et al., 1993).

Despite these studies revealing information on successful teams, often they are analysing the terminal states of possession sequences and neglecting some important aspects of build-up play that got the ball into these dangerous zones (Cervone et al., 2014). In attempts to understand the value of every action made in a soccer game, a recent expected possession value (EPV) model has been formulated. EPV, defined as “the expected outcome of a soccer possession based on the full resolution spatiotemporal data”, expresses the likelihood of a possession leading to a goal for the attacking or defending team as probabilities from 1 to -1 (Fernandez, Bornn and Cervone, 2019). Analogous but subtly different models to EPV exist today (Singh, 2019; Lawrence, 2019).

Summary of Holes in Literature

The major hole in the literature is the link between formations, and in particular formation matchups, and outcome variables using a quantitative study approach. The emergence of spatiotemporal tracking data in recent years has allowed for easier explanation of team tactics and playing style (Fernandez-Navarro et al., 2016). Findings of this approach has allowed playing styles to be categorised due to distinctive patterns observed within data (Fernandez-Navarro, 2018). A large-scale experimental approach designed specifically to evaluate formation matchups and their effect on direct performance measures indicative of successful teams like xG, shots, passes into opposition penalty area and passes into the opposition's final third, has yet to be conducted.

Whilst links between a team's formation and its players physiological demands has been found (Carling et al., 2011; Clarke, Duncan Tierney & Young, 2016), there are much fewer examples of formations and correlations to even the most basic notational descriptive statistics over a large dataset. Also, studies of this mould have looked at a narrow set of formations, mostly due to validity and sample size, rather than explore the huge range of those played by teams in elite soccer (Bielsa, 2017).

The last gap in literature to be addressed is how team quality and playing style influence the choice of formation and formation matchup. The contradictory nature of the previous studies on physiological demands of players within different formations could be explained by the lack of control for how successful a team is overall. Clearly the skill of the players making up the team has a large bearing on the resulting outcome variables regardless of team formation. It’s also possible to imagine how different playing styles may be conducive towards different formations and in-game formation matchups. With these gaps in the literature in mind, three hypotheses have been proposed to address these limitations.

Hypotheses

The first hypothesis under investigation is that the formations with a greater number of players in central positions (4-3-1-2, 3-3-3-1, 3-4-1-2, etc) will show higher values for xG, Progressive Passes, Passes into the Penalty Area and Ball Possession per match than formations favouring players on the wings (4-4-2, 4-5-1, etc), on average. More players in central areas should allow for greater interpersonal coordination because of reductions in interpersonal distance, leading to more success (Rodrigues & Passos, 2013). It is also noted that more players in the centre may make zone 14 more attainable, thus creating more success (Horn et al., 2002).

The second hypothesis of interest is that formations with a greater number of players in central positions will show lower values for xG, Progressive Passes and Passes into the Penalty Area per match, all against, than formations favouring players on the wings, on average. It's postulated that not only should the central focused formations produce higher values in the descriptive and outcome variables created within a game, but they should also afford the opposition lower values within these metrics than wider formations. It's believed that the notion of interpersonal coordination is as important for zonal occupation of space when defending as it is when attacking.

The third hypothesis addressed is that there will be significant differences found in the descriptive and outcome variables for specific formation matchups. It is postulated that certain formations may occupy space in a more beneficial manner to others. That is to say that a certain formation may utilise the space it naturally occupies in a dangerous way and negate the danger of the space it affords to a specific other. Formations that have an extra player in defence and midfield may be more successful in accordance to mechanisms proposed in *Figure 4* (i.e 3-5-2 vs 4-4-2, 4-3-1-2 vs 4-3-3 etc).

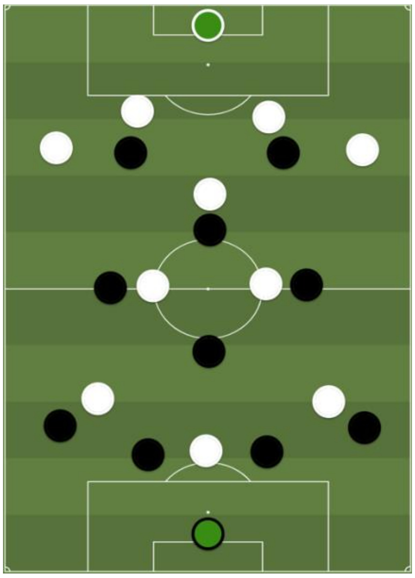

Figure 14 - A 4-3-1-2 (Black) vs 4-3-3 (White) matchup. The central four players that make up the diamond of 4-3-1-2 overload the three central midfield players in 4-3-3.

Dataset

The dataset for all three hypotheses includes all matches played within the following domestic league competitions over the specified time period:

- English Premier League (2017-18 to 2019-20)
- French Ligue 1 (2017-18 to 2019-20)
- German Bundesliga (2017-18 to 2019-20)
- Italian Serie A (2017-18 to 2019-20)
- Spanish La Liga (2017-18 to 2019-20)

The shorter format cup competitions cease to provide enough match samples to make comparative statements about team quality across the competition and thus will not be used as data within the testing of the hypotheses. The competitions listed are believed to be the pinnacle for elite level soccer with the smallest deviations in team quality throughout. The five national domestic leagues are acknowledged by the independent governing body UEFA as the strongest. (UEFA, 2020).

The data will be acquired from www.fbref.com, which releases publicly available data through partnership with the software company Statsbomb. Themselves, a leader within the soccer analytics community, have built and run a brand-new proprietary dataset coding elite level soccer games with positional and event data. Their work expands within teams in leagues across the globe (Statsbomb, 2020).

The congregation of all matches played within the sample listed sums to 5377. Each team within each season typically plays 38 matches each with the exception of the German Bundesliga, where teams play 34 matches each. A notable exception includes the 2019/20 French Ligue 1 competition where the impact of the global pandemic resulted in a premature ending - teams within this season played either 28 or 27 matches.

From the full dataset, a breakdown of the number of matches played by each formation is indicated below.

Formation	**Number of matches played in the dataset**
4-1-4-1	2775
4-2-3-1	2721
4-3-1-2	513
4-2-2-2	1855
3-4-1-2	463
3-1-4-2	1159
3-4-2-1	1109
3-3-3-1	159

Table 1 - The frequency of each formation within the dataset

Descriptive Statistics

An example of the non-adjusted descriptive statistics by formation relating to the xG created is provided below for context on the overall distribution of the data.

Formation	Mean	Median	Standard Deviation	Variance
4-1-4-1	1.39	1.30	0.799	0.639
4-2-3-1	1.34	1.20	0.755	0.571
4-3-1-2	1.34	1.20	0.772	0.597
4-2-2-2	1.30	1.20	0.749	0.562
3-4-1-2	1.40	1.30	0.791	0.626
3-1-4-2	1.21	1.10	0.710	0.504
3-4-2-1	1.25	1.10	0.741	0.550
3-3-3-1	1.19	1.10	0.796	0.634

Table 2 - Descriptive Statistics by formation in xG created across the full dataset.

Metrics and Data Transformations

Formations

Within the dataset, each match includes both teams' listed formations. The formations themselves are not listed by each team professionally and are determined from Statsbomb through in-game data. It's typical for some formations to be reported as different to others when in reality, they differ only in the positioning of one or two players in vertical or lateral directions. Examples of which include 5-3-2 and 3-5-2 as well as 4-4-1-1 and 4-2-3-1. Whilst the aim within the third hypothesis is to test for significant differences in formation matchups from a control of space perspective, it makes sense to congregate similar formations and study matchups only with distinctively different makeup's within the typical defenders-midfielders-attackers notation. A full list of which will be published within the methods section.

Expected Goals (xG)

As discussed, a brief explanation of xG is the probability that a shot will result in a goal based on the characteristics of that shot and the events leading up to it (FBref, 2020). Typically, the greatest stumbling block within the accuracy of xG has been modelling the defensive pressure around the ball to which the shot is affected (Caley, 2015). In most models, this is estimated from secondary markers, though Statsbomb uses freeze frames with positional data at the point of pre-shot to overcome this problem and produces much more accurate results in instances such as open goals. For each match played within the sample, each team is given a cumulative xG value, taken as the sum of xG from every shot taken by a player within their team.

Progressive Passes

This is defined by Statsbomb as a completed pass that moves the ball towards the opponent's goal at least 10 yards from its furthest point in the last six passes. It excludes passes from the defending 40% of the pitch. Its definition, though subjective, seeks to attach value to passes that either directly move the ball towards the opponent's goal or lead to on-ball actions that do, in effect, driving an attacking move forward. The parameters are put forward to isolate passes that are deemed to be significant in bypassing opposition players, hence excluding the defending 40% of the pitch. It's postulated that completing lots of these passes will lead to more entries into the final third and penalty area.

Passes into the Penalty Area

This is defined by Statsbomb as the number of completed passes into the 18-yard box excluding set pieces. Data from the 2006 World Cup revealed winning teams received significantly fewer entries into their own penalty area than drawing and losing teams. Also, teams that received more entries into their own penalty area than the opponent were significantly more likely to concede a goal (Ruiz-Ruiz et al., 2011). Studies as such, as well as general observation, highlight the importance of a team receiving passes in the opposition penalty area and reducing the amount on their own.

Ball Possession

Each match designates each team with a percentage of time with which they have possession of the ball. Due to its simplicity, ball possession is the most commonly investigated soccer performance indicator (Mackenzie & Cushion 2013) and though it's too situational dependent to be effective for single matches (Lago-Penas & Dellal, 2010),

Figure 10 shows how more successful teams tend to report greater values. It's also innately descriptive and allows for a simple perspective on the pattern of a match.

Team Quality

A measurement for team quality will be provided, for use within all hypotheses, for each team taken over an entire season subset. The resulting metric can be described as the expected goal difference per 90 minutes (xGDiff/90). The value will be adjusted such as to remove the contribution of the xG by the match in question, leaving the team quality as an average of the xGDiff/90 of all other games the team played within that season. As such, stronger teams will show high positive values and weaker teams, highly negative.

Methods

Dataset Generation

The dataset was generated using the aforesaid www.fbref.com website that provided all the data subsequently used for analysis within the study. Access to the data from within the website required navigation to the appropriate competition, season and team web pages. An example is provided below for the team RB Leipzig within the German Bundesliga in 2018/19.

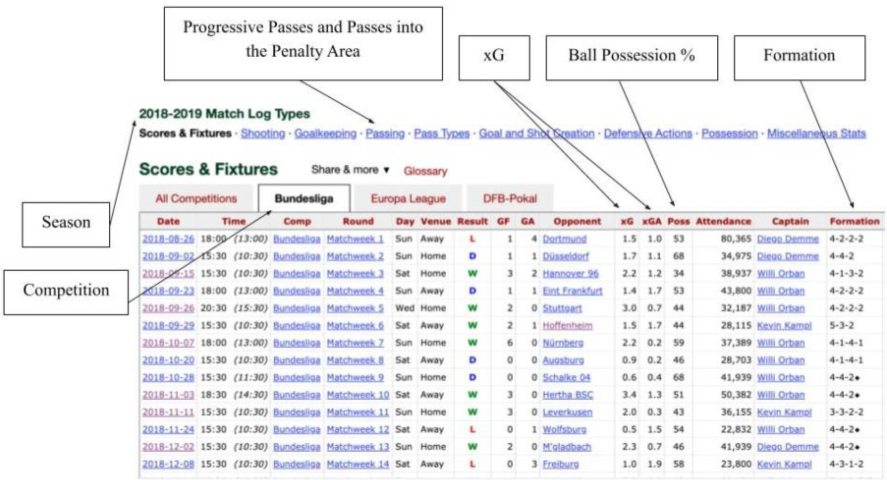

Figure 15 - RB Leipzig 2018/19 example dataset collection.

Accessing the tabs indicated by the ‘Passing’ link provided the Progressive Passes and Passes into the Penalty Area values for each game. This tab also allows access to the opposition’s values for these metrics. The covariate team quality was accessed on the league overview page as the xGDiff/90 for each team within a competition and season subset. A full overview of the step by step process in formulating the dataset from the source of the data is detailed in the flowchart below.

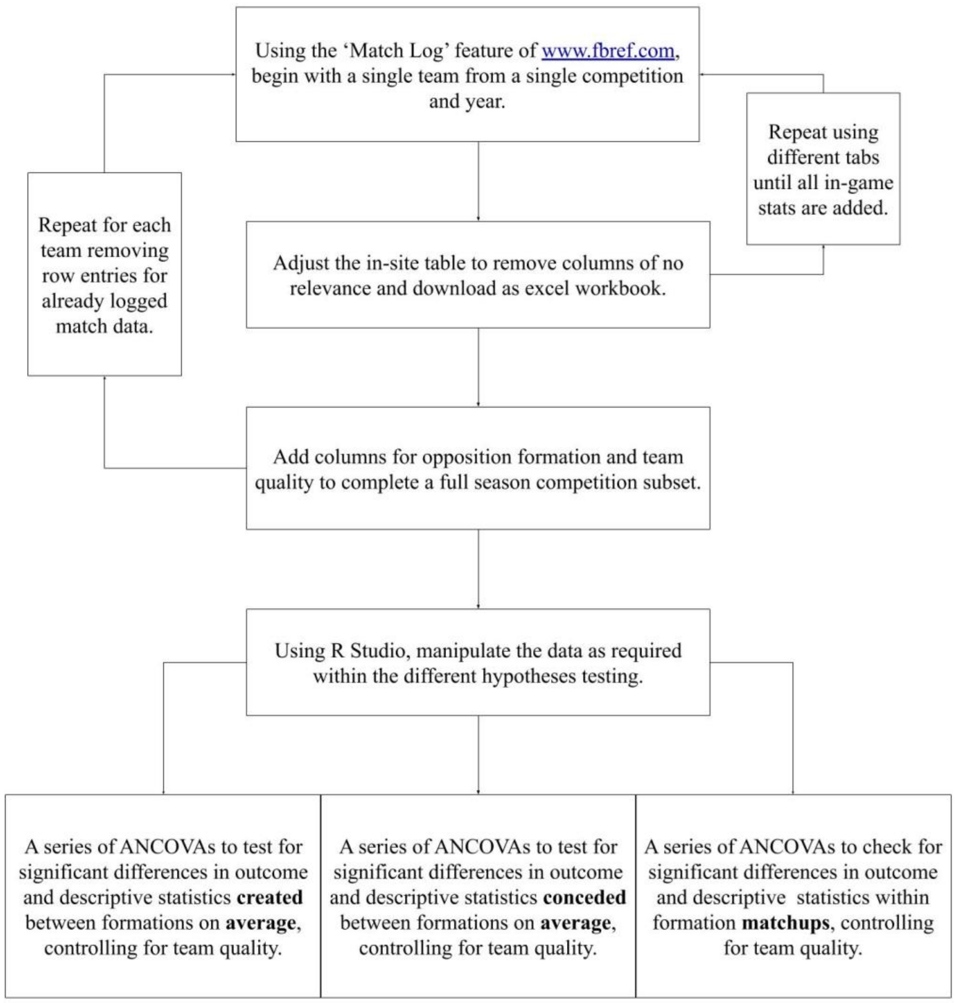

Figure 16 - A flowchart mapping the path from data collection to output and results.

Dataset Manipulation

Values for the xG, Progressive Passes, Passes into the Penalty area, and Ball Possession percentages all for and against were used within the dataset in their raw form. The formations were categorised into eight distinctively different setups. The brackets indicate formations that have been congregated due to similarity:

- 4-1-4-1 (4-3-3, 4-3-2-1, 4-1-2-3)
- 4-2-3-1 (4-4-1-1, 4-2-1-3)
- 4-3-1-2 (4-1-3-2, 4-4-2 Diamond, 4-1-2-1-2)
- 4-2-2-2 (4-4-2, 4-2-4)
- 3-4-1-2 (5-2-1-2, 3-2-3-2)
- 3-1-4-2 (3-5-2, 5-3-2, 5-1-2-2, 3-3-2-2)
- 3-4-2-1 (3-4-3, 5-4-1, 3-2-4-1, 3-2-2-3)
- 3-3-3-1 (3-3-1-3, 3-4-3 Diamond, 5-3-1-1, 3-1-3-3)

For measurements of team quality, as mentioned, the xGDiff/90 values provided were altered such as to remove the effect of the match under investigation. A formula for this adjustment is provided below:

$$\text{Team Quality} = (X(xGDiff/90) - (xG - xGA)) / (X-1)$$

In this instance, the team quality attached to a team for a single match is calculated from the xG and xGA for that team within a match, along with the number of matches played by that team within a season, X, and the xGDiff/90 for that team within a season.

Quality Control

In checking the accuracy of the dataset entry, matches from the 2018/19 German Bundesliga and 2019/20 English Premier League were re-entered into a separate dataset and compared to the equivalent values within the original dataset. These matches made up

13% of the entire population. Using the all.equal function within R generated the following mean relative differences between the variables:

Variable	Mean Significant Difference
Formation Home	2 string mismatches
Formation Away	2 string mismatches
Progressive Passes (Home)	0.248
Progressive Passes (Away)	0.294
Passes into the Penalty Area (Home)	0.377
Passes into the Penalty Area (Away)	0.490
Ball Possession % (Home)	0.205
Ball Possession % (Away)	0.155

Table 3 - The original dataset compared to a re-entered new dataset with a smaller sample.

The variables that denote team quality and xG for both home and away teams are not shown as there were no differences in the two datasets. The lack of differences is mostly due to the way these variables are retrieved from the source - requiring much less manual insertion and manipulation before they're tabulated into the dataset. The biggest mean significant difference corresponds to the Passes into the Penalty Area variables for away teams. Calculation of the average value for Passes into the Penalty Area for away teams across the two datasets combined relates to 7.91. Hence the mean significant difference between the datasets in *Table* 3 relates to a maximum 6.2% error in reporting the values. This is not seen as a significant enough barrier to prevent carrying through with the large-scale analysis of the original full dataset.

Statistical Analysis

For the first two hypotheses, the full dataset was used in observing changes in the descriptive and outcome variables between formations on average. In these two hypotheses, only the most significant results are reported within the body of the text. The other significant results are provided in full, in the appendix.

Within the first hypothesis, four ANCOVAs were run to isolate significant findings in the variables xG, Progressive Passes, Passes into the Penalty Area and Ball Possession percentage per match all created by a team, using team quality as a covariate. As such, for each ANCOVA, the independent variable was the categorized eight formations and the covariate was the Team Quality. The dependent variable was changed for each of the four ANCOVAs relating to the four variables mentioned.

The second hypothesis followed a similar line of statistical analysis but used the xG, Progressive Passes and Passes into the Penalty area that a team gave up within a match. There was no requirement to use the Ball Possession percentage given up by a team because the nature of a percentage allows one to infer about how much a team gave up ball possession based entirely from how much ball possession they had themselves. Therefore, in testing the second hypothesis, three ANCOVAs were run to isolate significant findings in the variables xG, Progressive Passes, Passes into the Penalty Area per match all conceded by a team, using Team Quality as a covariate. For each ANCOVA, the independent variable was the categorized eight formations and the covariate was the Team

Quality. The dependent variable was changed for each of the three ANCOVAs relating to the three variables mentioned.

The third hypothesis used subset data to isolate only matches involving the formation matchup under investigation. Because there were eight categorized formations, this led to 28 formation matchups. For each of the 28 formation matchups, four ANCOVAs were run, leading to a total of 112 ANCOVAs in evaluating the third hypothesis. Each matchup followed the same analysis and, in all cases, the two formations that made up the matchup were the independent variable for the ANCOVAs, and the Team Quality was used as a covariate throughout. Hence for each formation matchup, the difference in the ANCOVAs run was the use of either xG, Progressive Passes, Passes into the Penalty Area or Ball Possession percentage per match as the dependent variable.

For every ANCOVA within the study, the emmeans_test function was used in R with a bonferroni correction. Such a function is used to estimate the marginal mean of the dependent variables after an adjustment is made to them from their raw form in accordance with the impact of Team Quality as a covariate. In addition to performing the ANCOVAs, a series of assumptions were checked. Violations to these assumptions are provided within the appendix, though in these eventualities, no statistical techniques were used to reanalyse the data upon an assumption violation. This is due to the extremely large dataset. A full list of assumptions that were checked for each ANCOVA within the study, along with a note on how each was checked is listed below:

- **Linearity between the covariate and the outcome variable** - For every formation within each ANCOVA, the assumption is that there is a linear relationship between the team quality and the dependent variable. This was checked in R by creating a grouped scatter plot of the team quality and dependent variable of the ANCOVA under investigation. This was further checked using the cor.test function with a pearson method in observing significance for non-linear relationships.
- **Homogeneity of regression slopes** - The slopes of the regression lines, formed by the team quality and dependent variable are assumed to be the same for each formation within the ANCOVA in question. This assumption evaluates that there is no interaction between the team quality and the dependent variable. This was checked by the grouped scatter plot in observing if the regression slopes of the formations were parallel. This was further checked using an ANOVA to evaluate for a significant difference in the team quality and formation interaction. In this study, significant covariate interactions are reported in the body of the text for each result.
- **The outcome variable should be approximately normally distributed** - This assumption was checked using the Shapiro-Wilk test of normality and noting significance.
- **Homoscedasticity** - This assumption relates to the homogeneity of variance for all formations within an ANCOVA. The assumption was checked by using Levene's test and noting significance.

Another assumption commonly used is that of no significant outliers within the groups of the categorical variable. In this study, outliers were not removed from the dataset. This is due to the complex nature of soccer matches and some of the limitations already discussed within this study. Because of the large dataset, it's impossible to know exactly the root of any outlier reported and hence discarding it could undermine the validity of the results. It may well be the case that the value of an outlier is explained still within the effects of the formation interactions of primary investigation within this study. In addition, there may be matches that fall within the residual range and hence are not flagged as outliers but may have values affected by variables not considered within this study. Examples include the impact of a red card or significant formation change by one team after a short time period.

Results

Hypothesis 1

xG vs Formation

There was a statistically significant difference in xG between the formations, $F(7, 10745) = 5.21$, $p < 0.0001$. The xG was significantly greater on average for teams that played 4-3-1-2 (1.42 +/- 0.0317) than those that played 3-3-3-1 (1.18 +/- 0.0568), p = 0.00524; 3-1-4-2 (1.25 +/- 0.0211), p = 0.000261 and 3-4-2-1 (1.28 +/- 0.0215), p = 0.00586. There was a non-significant formation-team quality interaction $F(7, 10738) = 1.580$, $p = 0.136$.

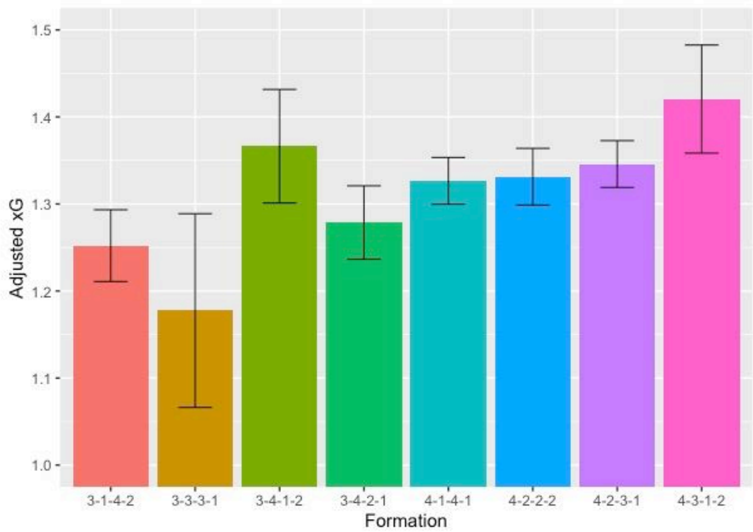

Figure 17 - The Adjusted xG per game for each formation on average. The height of the bars shows the estimated mean, adjusted with the use of Team Quality as a covariate. The error bars refer to the 95% confidence interval of the true estimated marginal mean.

Progressive Passes vs Formation

There was a significant difference in the number of Progressive Passes between the formations, F(7, 10745) = 12.56, p <0.0001. The number of Progressive Passes was significantly greater on average for teams that played 4-3-1-2 (46.7 +/- 0.557) than those that played 3-1-4-2 (41.2 +/- 0.370), p <0.0001; 3-3-3-1 (42.0 +/- 0.998), p = 0.00103; 3-4-1-2 (43.6 +/- 0.585), p = 0.00364; 3-4-2-1 (42.0 +/- 0.378), p <0.0001; 4-1-4-1 (43.6 +/- 0.24), p <0.0001; 4-2-2-2 (42.5 +/- 0.292), p <0.0001 and 4-2-3-1 (43.3 +/- 0.241), p <0.0001. There was a significant formation-team quality interaction F(7, 10738) = 4.48, p <0.0001.

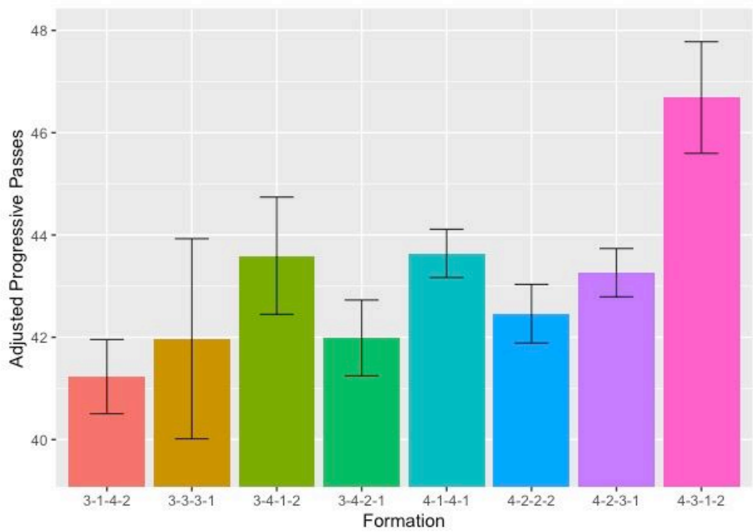

Figure 18 - The Adjusted Progressive Passes per game for each formation on average.

Passes into the Penalty Area vs Formation

There was a significant difference in the number of Passes into the Penalty Area between the formations, $F(7, 10745) = 10.82$, $p < 0.0001$. The number of Passes into the Penalty Area was significantly greater for teams that played a 4-3-1-2 (9.10 +/- 0.180) than those that played 3-1-4-2 (7.68 +/- 0.119), $p < 0.0001$; 3-3-3-1 (7.64 +/- 0.322), $p = 0.000195$; 3-4-1-2 (8.19 +/- 0.189), $p = 0.0134$; 3-4-2-1 (7.73 +/- 0.122) $p < 0.0001$; 4-1-4-1 (8.27 +/- 0.0776), $p = 0.000540$; 4-2-2-2 (7.84 +/- 0.0944), $p < 0.0001$ and 4-2-3-1 (7.76 +/- 0.0778), $p < 0.0001$. There was a significant formation-team quality interaction $F(7, 10738) = 7.02$, $p < 0.0001$.

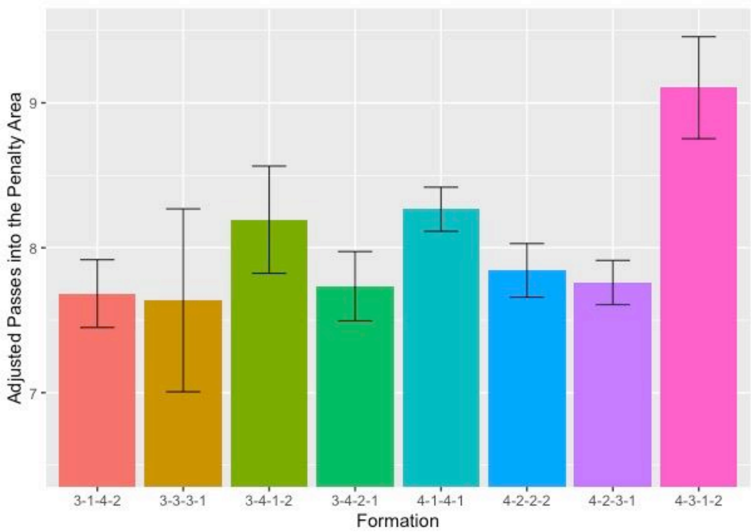

Figure 19 - The Adjusted Passes into the Penalty Area per game for each formation on average.

Ball Possession vs Formation

There was a significant difference in the percentage of Ball Possession between the formations, F(7, 10745) = 30.31, p <0.0001. The percentage of Ball Possession was significantly greater on average for teams that played 4-3-1-2 (52.4 +/- 0.442) than those that played 3-1-4-2 (47.5 +/- 0.294), p <0.0001; 3-3-3-1 (48.5 +/- 0.792), p = 0.000503; 3-4-1-2 (49.3 +/- 0.464), p <0.0001; 3-4-2-1 (49.4 +/- 0.300), p <0.0001 and 4-2-2-2 (48.5 +/- 0.232), p <0.0001. There was a significant formation-team quality interaction F(7, 10738) = 10.53, p <0.0001.

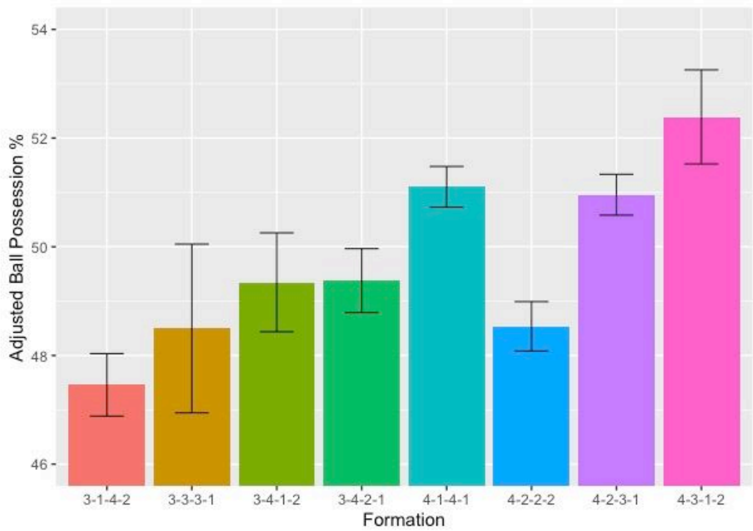

Figure 20 - The Adjusted Ball Possession percentage per game for each formation on average.

Hypothesis 2

xG Against vs Formation

There was a significant difference in the xG against between the formations, $F(7, 10745) = 4.55$, $p < 0.0001$. The xG Against was significantly smaller on average for teams that played 4-2-2-2 (1.26 +/- 0.0172) than those that played 3-1-4-2 (1.38 +/- 0.0218), $p = 0.00109$; 3-4-1-2 (1.39 +/- 0.0345), $p = 0.0214$; 3-4-2-1 (1.36 +/- 0.0223), $p = 0.0237$ and 4-3-1-2 (1.39 +/- 0.0328). There was a significant formation-team quality interaction $F(7, 10738) = 3.515$, $p < 0.0001$.

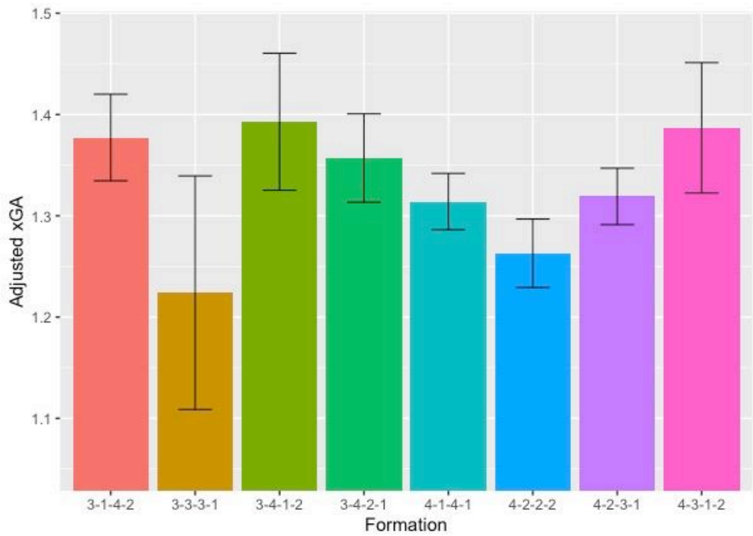

Figure 21 - The Adjusted xG Against per game for each formation on average.

Progressive Passes Against vs Formation

There was a significant difference in the number of Progressive Passes against between the formations, $F(7, 10745) = 4.83$, $p < 0.0001$. The number of Progressive Passes against was significantly greater on average for teams that played 3-3-3-1 (46.3 +/- 1.01) than those that played 4-1-4-1 (43.0 +/- 0.243), p = 0.0424; 4-2-2-2 (42.7 +/- 0.295), p = 0.0170; 4-3-1-2 (42.4 +/- 0.562), p = 0.0204 and 4-2-3-1 (42.4 +/- 0.244), p = 0.00443. There was a significant formation-team quality interaction $F(7, 10738) = 7.633$, $p < 0.0001$.

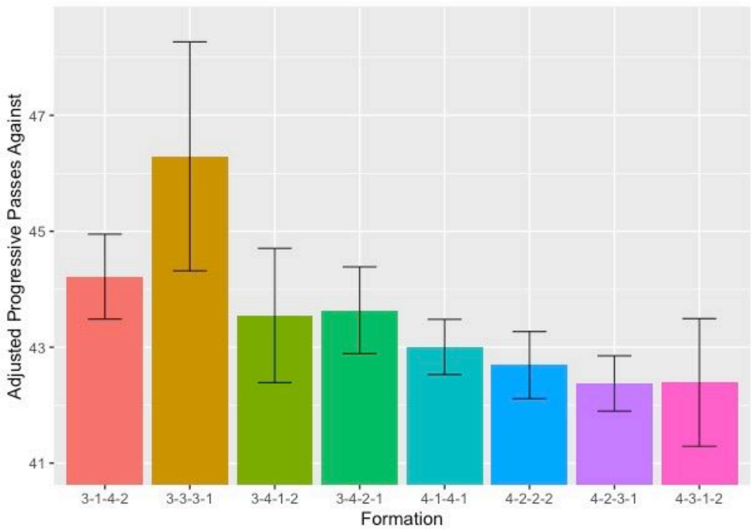

Figure 22 - The Adjusted Progressive Passes Against per game for each formation on average.

Passes into the Penalty Area Against vs Formation

There was a significant difference in the number of Passes into the Penalty Area Against between the formations, F(7, 10745) = 6.3, p <0.0001. The number of Passes into the Penalty Area against was significantly greater for teams that played 4-3-1-2 (8.73 +/- 0.189) than teams that played 4-2-3-1 (7.63 +/- 0.0820), p <0.0001; 4-2-2-2 (8.06 +/- 0.0994), p = 0.0434; 4-1-4-1 (8.00 +/- 0.0817), p = 0.0103 and 3-4-2-1 (7.86 +/- 0.128), p = 0.00402. There was a significant formation-team quality interaction F(7, 10738) = 3.215, p = 0.002.

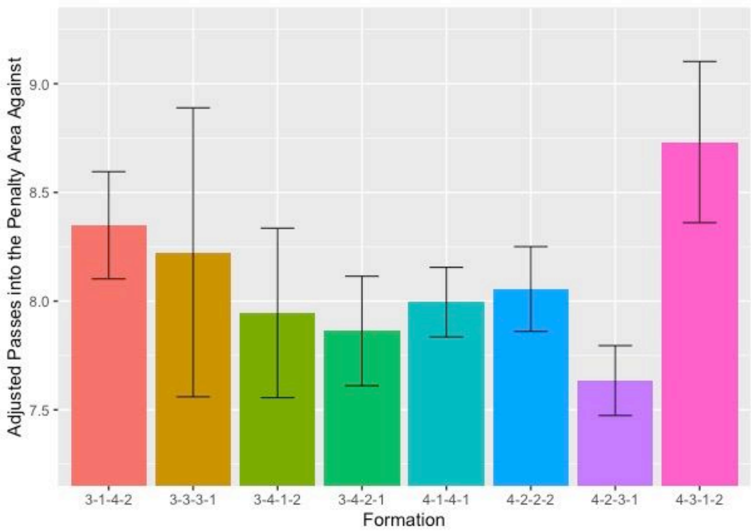

Figure 23 - The Adjusted Passes into the Penalty Area against per game for each formation on average.

Hypothesis 3

4-1-4-1 vs 4-2-3-1

ANCOVAs were run to determine the effect of formation matchup on the outcome variables xG; Progressive Passes; Passes into the Penalty Area and Ball Possession after controlling for the Team Quality. After adjustment for the Team Quality, there was no significance in the outcome variables between 4-1-4-1 and 4-2-3-1.

		4-1-4-1			
	p-values	**xG** (1.33 +/- 0.0259)	**Progressive Passes** (43.2 +/- 0.462)	**Passes into the Penalty Area** (7.94 +/- 0.142)	**Ball Possession %** (50.4 +/- 0.368)
4-2-3-1	**xG** (1.32 +/- 0.0259)	0.84			
	Progressive Passes (43.0 +/- 0.462)		0.76		
	Passes into the Penalty Area (7.63 +/- 0.142)			0.12	
	Ball Possession % (49.6 +/- 0.368)				0.097

Table 4 - The p-values associated with the ANCOVA tests between the formation matchup 4-1-4-1 vs 4-2-3-1 with the listed metrics (per match) as the dependent variables. Also shown is the adjusted estimated marginal means and standard error from the use of team quality as a covariate.

4-1-4-1 vs 4-3-1-2

There was a significant difference in Ball Possession percentage between the formations, F(1, 257) = 8.72, p = 0.003. The Ball Possession percentage was significantly greater for 4-3-1-2 (51.8 +/- 0.880) than 4-1-4-1 (48.2 +/- 0.880). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	**4-1-4-1** **xG** (1.49 +/- 0.0682)	**4-1-4-1** **Progressive Passes** (43.6 +/- 1.24)	**4-1-4-1** **Passes into the Penalty Area** (9.25 +/- 0.394)	**4-1-4-1** **Ball Possession %** (48.2 +/- 0.880)
4-3-1-2	**xG** (1.36 +/- 0.0682)	0.18			
4-3-1-2	**Progressive Passes** (46.1 +/- 1.24)		0.17		
4-3-1-2	**Passes into the Penalty Area** (8.93 +/- 0.394)			0.56	
4-3-1-2	**Ball Possession %** (51.8 +/- 0.880)				0.003

Table 5 - 4-1-4-1 vs 4-3-1-2 and associated p-values, estimated marginal means and standard error.

4-1-4-1 vs 4-2-2-2

There was a significant difference in xG, F(1, 937) = 6.53, p = 0.011; Progressive Passes, F(1, 937) = 38.49, p <0.0001; Passes into the Penalty Area, F(1, 937) = 53.67, p <0.0001 and Ball Possession percentage, F(1, 937) = 225.4, p <0.0001 between the formations. All the outcome variables were significantly greater for 4-1-4-1 than 4-2-2-2.

	p-values	***4-1-4-1*** **xG** (1.39 +/- 0.0327)	**Progressive Passes** (45.9 +/- 0.593)	**Passes into the Penalty Area** (9.30 +/- 0.191)	**Ball Possession %** (54.8 +/- 0.452)
4-2-2-2	**xG** (1.27 +/- 0.0327)	0.011			
	Progressive Passes (40.7 +/- 0.593)		<0.0001		
	Passes into the Penalty Area (7.32 +/- 0.191)			<0.0001	
	Ball Possession % (45.2 +/- 0.452)				<0.0001

Table 6 - 4-1-4-1 vs 4-2-2-2 and associated p-values, estimated marginal means and standard error.

4-1-4-1 vs 3-4-1-2

There was a significant difference in Ball Possession percentage between the formations, $F(1, 227) = 13.74$, $p = 0.00026$. The Ball Possession percentage was significantly greater for 4-1-4-1 (52.2 +/- 0.838) than 3-4-1-2 (47.8 +/- 0.838). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	**4-1-4-1** **xG** (1.37 +/- 0.0729)	**4-1-4-1** **Progressive Passes** (43.4 +/- 1.18)	**4-1-4-1** **Passes into the Penalty Area** (8.01 +/- 0.364)	**4-1-4-1** **Ball Possession %** (52.2 +/- 0.838)
3-4-1-2	**xG** (1.34 +/- 0.0729)	0.80			
3-4-1-2	**Progressive Passes** (43.2 +/- 1.18)		0.91		
3-4-1-2	**Passes into the Penalty Area** (8.01 +/- 0.364)			1	
3-4-1-2	**Ball Possession %** (47.8 +/- 0.838				0.00026

Table 7 - 4-1-4-1 vs 3-4-1-2 and associated p-values, estimated marginal means and standard error.

4-1-4-1 vs 3-1-4-2

There was a significant difference in xG, $F(1, 545) = 18.25$, $p < 0.0001$; Progressive Passes, $F(1, 545) = 32.76$, $p < 0.0001$; Passes into the Penalty Area, $F(1, 545) = 12.76$, $p = 0.000385$ and Ball Possession percentage, $F(1, 545) = 108.3$, $p < 0.0001$ between the formations. All the outcome variables were significantly greater for 4-1-4-1 than 3-1-4-2.

	p-values	**4-1-4-1** **xG** (1.49 +/- 0.0432)	**4-1-4-1** **Progressive Passes** (46.4 +/- 0.809	**4-1-4-1** **Passes into the Penalty Area** (8.95 +/- 0.269)	**4-1-4-1** **Ball Possession %** (54.7 +/- 0.626)
3-1-4-2	**xG** (1.23 +/- 0.0432)	<0.0001			
3-1-4-2	**Progressive Passes** (39.7 +/- 0.809)		<0.0001		
3-1-4-2	**Passes into the Penalty Area** (7.57 +/- 0.269			0.000385	
3-1-4-2	**Ball Possession %** (45.3 +/- 0.626)				<0.0001

Table 8 - 4-1-4-1 vs 3-1-4-2 and associated p-values, estimated marginal means and standard error.

4-1-4-1 vs 3-4-2-1

There was a significant difference in the number of Progressive Passes, $F(1, 485) = 9$, $p = 0.003$ and Ball Possession percentage, $F(1, 485) = 35.89$, $p < 0.0001$ between the formations. In both cases, the variables were significantly greater for 4-1-4-1 than 3-4-2-1. There was no significance in the xG and Passes into the Penalty Area variables between the formations.

		4-1-4-1			
	p-values	**xG** (1.36 +/- 0.0466)	**Progressive Passes** (45.2 +/- 0.851)	**Passes into the Penalty Area** (8.05 +/- 0.268)	**Ball Possession %** (52.9 +/- 0.679)
3-4-2-1	**xG** (1.30 +/- 0.0466)	0.42			
	Progressive Passes (41.6 +/- 0.851)		0.003		
	Passes into the Penalty Area (8.13 +/- 0.268)			0.84	
	Ball Possession % (47.1 +/- 0.679)				<0.0001

Table 9 - 4-1-4-1 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

4-1-4-1 vs 3-3-3-1

There was a significant difference in Ball Possession percentage between the formations, F(1, 87) = 3.99, p = 0.049. The Ball Possession percentage was significantly greater for 4-1-4-1 (51.8 +/- 1.29) than 3-3-3-1 (48.2 +/- 1.29). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

		4-1-4-1			
	p-values	**xG** (1.20 +/- 0.100)	**Progressive Passes** (46.4 +/- 1.76)	**Passes into the Penalty Area** (7.95 +/- 0.522)	**Ball Possession %** (51.8 +/- 1.29)
3-3-3-1	**xG** (1.12 +/- 0.100)	0.61			
	Progressive Passes (41.7 +/- 1.76)		0.063		
	Passes into the Penalty Area (7.50 +/- 0.522)			0.55	
	Ball Possession % (48.2 +/- 1.29)				0.049

Table 10 - 4-1-4-1 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 4-3-1-2

There was no significance in the outcome variables between 4-2-3-1 and 4-3-1-2.

		4-2-3-1			
	p-values	**xG** (1.50 +/- 0.0818)	**Progressive Passes** (43.4 +/- 1.31)	**Passes into the Penalty Area** (8.75 +/- 0.413)	**Ball Possession %** (50.1 +/- 0.914)
4-3-1-2	**xG** (1.34 +/- 0.0818)	0.16			
	Progressive Passes (44.2 +/- 1.31)		0.65		
	Passes into the Penalty Area (8.12 +/- 0.413)			0.29	
	Ball Possession % (49.9 +/- 0.914)				0.94

Table 11 - 4-2-3-1 vs 4-3-1-2 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 4-2-2-2

There was a significant difference in the xG , $F(1, 1015) = 4.54$, $p = 0.033$ and Ball Possession percentage, $F(1, 1015) = 55.51$, $p < 0.0001$ between the formations. The xG was significantly greater for 4-2-2-2 (1.34 +/- 0.0297) than 4-2-3-1 (1.25 +/- 0.0297), though the Ball Possession percentage was significantly greater for 4-2-3-1 (52.2 +/- 0.410) than 4-2-2-2 (47.8 +/- 0.410). There was no significance in the number of Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	***4-2-3-1*** **xG** (1.25 +/- 0.0297)	**Progressive Passes** (42.4 +/- 0.517)	**Passes into the Penalty Area** (7.71 +/- 0.169)	**Ball Possession %** (52.2 +/- 0.410)
4-2-2-2	**xG** (1.34 +/- 0.0297)	0.033			
	Progressive Passes (42.2 +/- 0.517)		0.85		
	Passes into the Penalty Area (7.88 +/- 0.169)			0.48	
	Ball Possession % (47.8 +/- 0.410)				<0.0001

Table 12 - 4-2-3-1 vs 4-2-2-2 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 3-4-1-2

There was a significant difference in Ball Possession percentage between the formations, F(1, 141) = 10, p = 0.0019. The Ball Possession percentage was significantly greater for 4-2-3-1 (52.4 +/- 1.05) than 3-4-1-2 (47.6 +/- 1.05). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	**4-2-3-1** **xG** (1.59 +/- 0.0926)	**Progressive Passes** (45.3 +/- 1.45)	**Passes into the Penalty Area** (8.63 +/- 0.432)	**Ball Possession %** (52.4 +/- 1.05)
3-4-1-2	**xG** (1.37 +/- 0.0926)	0.1			
	Progressive Passes (44.9 +/- 1.45)		0.84		
	Passes into the Penalty Area (7.89 +/- 0.432)			0.23	
	Ball Possession % (47.6 +/- 1.05)				0.0019

Table 13 - 4-2-3-1 vs 3-4-1-2 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 3-1-4-2

There was a significant difference in Progressive Passes, $F(1, 457) = 7.98$, $p = 0.005$; Passes into the Penalty Area, $F(1, 457) = 4.41$, $p = 0.036$ and Ball Possession percentage, $F(1, 457) = 70.94$, $p < 0.0001$ between the formations. All three outcome variables were significantly greater for 4-2-3-1 than 3-1-4-2. There was no statistical significance in the xG variables between the formations.

	p-values	4-2-3-1 **xG** (1.36 +/- 0.0846)	4-2-3-1 **Progressive Passes** (44.3 +/- 0.876)	4-2-3-1 **Passes into the Penalty Area** (8.06 +/- 0.267)	4-2-3-1 **Ball Possession %** (54.0 +/- 0.662)
3-1-4-2	**xG** (1.26 +/- 0.0846)	0.16			
	Progressive Passes (40.8 +/- 0.876)		0.005		
	Passes into the Penalty Area (7.26 +/- 0.267)			0.036	
	Ball Possession % (46.0 +/- 0.662)				<0.0001

Table 14 - 4-2-3-1 vs 3-1-4-2 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 3-4-2-1

There was a significant difference in the number of Progressive Passes , $F(1, 413) = 6.14$, $p = 0.014$ and Ball Possession percentage, $F(1, 413) = 10.47$, $p = 0.001$ between the formations. In both cases, the variables were significantly greater for 4-2-3-1 than 3-4-2-1. There was no significance in the xG and Passes into the Penalty Area variables between the formations.

		4-2-3-1			
	p-values	**xG** (1.40 +/- 0.0509)	**Progressive Passes** (44.1 +/- 0.864)	**Passes into the Penalty Area** (7.86 +/- 0.266)	**Ball Possession %** (51.6 +/- 0.710)
3-4-2-1	**xG** (1.27 +/- 0.0509)	0.066			
	Progressive Passes (41.1 +/- 0.864)		0.014		
	Passes into the Penalty Area (7.43 +/- 0.266)			0.25	
	Ball Possession % (48.4 +/- 0.710)				0.001

Table 15 - 4-2-3-1 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

4-2-3-1 vs 3-3-3-1

There was no significance in the outcome variables between 4-2-3-1 and 3-3-3-1.

	p-values	**4-2-3-1** **xG** (1.24 +/- 0.152)	**Progressive Passes** (45.1 +/- 2.72)	**Passes into the Penalty Area** (7.60 +/- 0.699)	**Ball Possession %** (50.1 +/- 2.26)
3-3-3-1	**xG** (1.14 +/- 0.152)	0.64			
	Progressive Passes (40.0 +/- 2.72)		0.2		
	Passes into the Penalty Area (7.45 +/- 0.699)			0.88	
	Ball Possession % (49.9 +/- 2.26)				0.91

Table 16 - 4-2-3-1 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

4-3-1-2 vs 4-2-2-2

There was a significant difference in Ball Possession percentage between the formations, F(1, 103) = 8.5, p = 0.004. The Ball Possession percentage was significantly greater for 4-3-1-2 (52.5 +/- 1.23) than 4-2-2-2 (47.5 +/- 1.23). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

		4-3-1-2			
	p-values	**xG** (1.56 +/- 0.105)	**Progressive Passes** (46.7 +/- 1.71)	**Passes into the Penalty Area** (9.22 +/- 0.561)	**Ball Possession %** (52.5 +/- 1.23)
4-2-2-2	**xG** (1.31 +/- 0.105)	0.097			
	Progressive Passes (43.1 +/- 1.71)		0.14		
	Passes into the Penalty Area (8.39 +/- 0.561)			0.30	
	Ball Possession % (47.5 +/- 1.23)				0.004

Table 17 - 4-3-1-2 vs 4-2-2-2 and associated p-values, estimated marginal means and standard error.

4-3-1-2 vs 3-4-1-2

There was a significant difference in the number of Progressive Passes between the formations, $F(1, 85) = 4.2$, $p = 0.044$. The number of Progressive Passes was significantly greater for 4-3-1-2 (47.7 +/- 1.82) than 3-4-1-2 (42.3 +/- 1.82). There was no significance in the xG; Passes into the Penalty Area and Ball Possession percentage variables between the formations.

	p-values	**4-3-1-2** xG (1.49 +/- 0.114)	**4-3-1-2** Progressive Passes (47.7 +/- 1.82)	**4-3-1-2** Passes into the Penalty Area (8.99 +/- 0.633)	**4-3-1-2** Ball Possession % (50.2 +/- 1.23)
3-4-1-2	**xG** (1.43 +/- 0.114)	0.72			
3-4-1-2	**Progressive Passes** (42.3 +/- 1.82)		0.044		
3-4-1-2	**Passes into the Penalty Area** (9.01 +/- 0.633)			0.98	
3-4-1-2	**Ball Possession %** (49.8 +/- 1.23)				0.85

Table 18 - 4-3-1-2 vs 3-4-1-2 and associated p-values, estimated marginal means and standard error.

4-3-1-2 vs 3-1-4-2

There was a significant difference in the number of Progressive Passes , $F(1, 177) = 4.97$, $p = 0.027$ and Ball Possession percentage, $F(1, 177) = 34.99$, $p < 0.0001$ between the formations. In both cases, the variables were significantly greater for 4-2-3-1 than 3-4-2-1. There was no significance in the xG and Passes into the Penalty Area variables between the formations.

		4-3-1-2			
	p-values	**xG** (1.34 +/- 0.0735)	**Progressive Passes** (45.6 +/- 1.27)	**Passes into the Penalty Area** (8.84 +/- 0.442)	**Ball Possession %** (53.6 +/- 0.858)
3-1-4-2	**xG** (1.30 +/- 0.0735)	0.75			
	Progressive Passes (41.5 +/- 1.27)		0.027		
	Passes into the Penalty Area (8.26 +/- 0.442)			0.28	
	Ball Possession % (46.4 +/- 0.858)				<0.0001

Table 19 - 4-3-1-2 vs 3-1-4-2 and associated p-values, estimated marginal means and standard error.

4-3-1-2 vs 3-4-2-1

There was no significance in the outcome variables between 4-3-1-2 and 3-4-2-1.

		4-3-1-2			
	p-values	**xG** (1.27 +/- 0.0998)	**Progressive Passes** (44.9 +/- 2.00)	**Passes into the Penalty Area** (7.69 +/- 0.588)	**Ball Possession %** (51.4 +/- 1.55)
3-4-2-1	**xG** (1.40 +/- 0.0998)	0.35			
	Progressive Passes (44.2 +/- 2.00)		0.83		
	Passes into the Penalty Area (8.49 +/- 0.588)			0.34	
	Ball Possession % (48.6 +/- 1.55)				0.21

Table 20 - 4-3-1-2 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

4-3-1-2 vs 3-3-3-1

There was a significant difference in the number of Progressive Passes , $F(1, 25) = 7.51$, $p = 0.011$ and Ball Possession percentage, $F(1, 25) = 30.73$, $p < 0.0001$ between the formations. In both cases, the variables were significantly greater for 4-3-1-2 than 3-3-3-1. There was no significance in the xG and Passes into the Penalty Area variables between the formations.

		4-3-1-2			
	p-values	**xG** (1.19 +/- 0.176)	**Progressive Passes** (49.2 +/- 2.75)	**Passes into the Penalty Area** (9.47 +/- 1.01)	**Ball Possession %** (54.4 +/- 1.12)
3-3-3-1	**xG** (1.03 +/- 0.176)	0.53			
	Progressive Passes (38.5 +/- 2.75)		0.011		
	Passes into the Penalty Area (9.46 +/- 1.01)			0.9	
	Ball Possession % (45.6 +/- 1.12)				<0.0001

Table 21 - 4-3-1-2 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

4-2-2-2 vs 3-4-1-2

There was a significant difference in Ball Possession percentage between the formations, F(1, 79) = 13.6, p = 0.00041. The Ball Possession percentage was significantly greater for 3-4-1-2 (53.8 +/- 1.47) than 4-2-2-2 (46.2 +/- 1.47). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	**4-2-2-2** **xG** (1.40 +/- 0.110)	**4-2-2-2** **Progressive Passes** (40.6 +/- 1.72)	**4-2-2-2** **Passes into the Penalty Area** (7.46 +/- 0.567)	**4-2-2-2** **Ball Possession %** (46.2 +/- 1.47)
3-4-1-2	**xG** (1.34 +/- 0.110)	0.67			
3-4-1-2	**Progressive Passes** (42.4 +/- 1.72)		0.47		
3-4-1-2	**Passes into the Penalty Area** (8.45 +/- 0.567)			0.22	
3-4-1-2	**Ball Possession %** (53.8 +/- 1.47)				0.00041

Table 22 - 4-2-2-2 vs 3-4-1-2 and associated p-values, estimated marginal means and standard error.

4-2-2-2 vs 3-1-4-2

There was no significance in the outcome variables between 4-2-2-2 and 3-1-4-2.

	p-values	**xG** (1.35 +/- 0.0587)	**Progressive Passes** (42.5 +/- 1.04)	**Passes into the Penalty Area** (7.83 +/- 0.346)	**Ball Possession %** (51.1 +/- 0.829)
		4-2-2-2			
3-1-4-2	**xG** (1.22 +/- 0.0587)	0.11			
	Progressive Passes (42.2 +/- 1.04)		0.484		
	Passes into the Penalty Area (7.88 +/- 0.346)			0.91	
	Ball Possession % (48.9 +/- 0.829)				0.066

Table 23 - 4-2-2-2 vs 3-1-4-2 and associated p-values, estimated marginal means and standard error.

4-2-2-2 vs 3-4-2-1

There was a significant difference in the xG between the formations, $F(1, 387) = 8.7$, $p = 0.003$. The xG was significantly greater for 4-2-2-2 (1.36 +/- 0.0517) than 3-4-2-1 (1.14 +/- 0.0517). There was no significance in the number of Progressive Passes; Passes into the Penalty Area and Ball Possession percentage variables between the formations.

	p-values	***4-2-2-2*** **xG** (1.36 +/- 0.0517)	**Progressive Passes** (43.0 +/- 0.821)	**Passes into the Penalty Area** (7.60 +/- 0.264)	**Ball Possession %** (49.2 +/- 0.629)
3-4-2-1	**xG** (1.14 +/- 0.0517)	0.003			
	Progressive Passes (41.2 +/- 0.821)		0.12		
	Passes into the Penalty Area (7.44 +/- 0.264)			0.68	
	Ball Possession % (50.8 +/- 0.629)				0.078

Table 24 -4-2-2-2 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

4-2-2-2 vs 3-3-3-1

There was a significant difference in the xG, $F(1, 23) = 8.31$, $p = 0.008$; Progressive Passes, $F(1, 23) = 7.42$, $p = 0.012$ and Ball Possession percentage, $F(1, 23) = 8.46$, $p = 0.008$ between the formations. All three outcome variables were significantly greater for 4-2-2-2 than 3-3-3-1. There was no significance in the xG variables between the formations.

	p-values	**4-2-2-2** **xG** (1.51 +/- 0.140)	**4-2-2-2** **Progressive Passes** (47.6 +/- 3.17)	**4-2-2-2** **Passes into the Penalty Area** (8.58 +/- 0.970)	**4-2-2-2** **Ball Possession %** (55.2 +/- 2.51)
3-3-3-1	**xG** (0.94 +/- 0.140)	0.008			
3-3-3-1	**Progressive Passes** (35.4 +/- 3.17)		0.012		
3-3-3-1	**Passes into the Penalty Area** (6.19 +/- 0.970)			0.094	
3-3-3-1	**Ball Possession %** (44.8 +/- 2.51)				0.008

Table 25 - 4-2-2-2 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

3-4-1-2 vs 3-1-4-2

There was no significance in the outcome variables between 3-4-1-2 and 3-1-4-2.

	p-values	**3-4-1-2** xG (1.46 +/- 0.0810)	**3-4-1-2** Progressive Passes (45.5 +/- 1.26)	**3-4-1-2** Passes into the Penalty Area (8.48 +/- 0.454)	**3-4-1-2** Ball Possession % (51.2 +/- 0.920)
3-1-4-2	**xG** (1.31 +/- 0.0810)	0.20			
3-1-4-2	**Progressive Passes** (42.6 +/- 1.26)		0.12		
3-1-4-2	**Passes into the Penalty Area** (7.68 +/- 0.454)			0.20	
3-1-4-2	**Ball Possession %** (48.8 +/- 0.920)				0.064

Table 26 - 3-4-1-2 vs 3-1-4-2 and associated p-values, estimated marginal means and standard error.

3-4-1-2 vs 3-4-2-1

There was no significance in the outcome variables between 3-4-1-2 and 3-4-2-1.

		3-4-1-2			
	p-values	**xG** (1.53 +/- 0.104)	**Progressive Passes** (44.9 +/- 1.50)	**Passes into the Penalty Area** (8.91 +/- 0.479)	**Ball Possession %** (50.1 +/- 1.20)
3-4-2-1	**xG** (1.38 +/- 0.104)	0.31			
	Progressive Passes (41.0 +/- 1.50)		0.069		
	Passes into the Penalty Area (7.63 +/- 0.479)			0.062	
	Ball Possession % (49.9 +/- 1.20)				0.92

Table 27 - 3-4-1-2 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

3-4-1-2 vs 3-3-3-1

There was a significant difference in Progressive Passes, F(1, 9) = 6.45, p = 0.032; Passes into the Penalty Area, F(1, 9) = 12.04, p = 0.007 and Ball Possession percentage, F(1, 9) = 6.42, p = 0.032 between the formations. All three outcome variables were significantly greater for 3-4-1-2 than 3-3-3-1. There was no significance in the xG variables between the formations.

		3-4-1-2			
	p-values	**xG** (0.0986+/- 0.257)	**Progressive Passes** (52.1 +/- 5.16)	**Passes into the Penalty Area** (10.4 +/- 1.38)	**Ball Possession %** (57.4 +/- 3.86)
3-3-3-1	**xG** (1.13 +/- 0.257)	0.72			
	Progressive Passes (32.4 +/- 5.16)		0.032		
	Passes into the Penalty Area (3.14 +/- 1.38)			0.007	
	Ball Possession % (42.6 +/- 3.86)				0.032

Table 28 - 3-4-1-2 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

3-1-4-2 vs 3-4-2-1

There was a significant difference in Ball Possession percentage between the formations, $F(1, 267) = 4.21$, $p = 0.041$. The Ball Possession percentage was significantly greater for 3-4-2-1 (51.2 +/- 0.827) than 3-1-4-2 (48.8 +/- 0.827). There was no significance in the xG; Progressive Passes and Passes into the Penalty Area variables between the formations.

	p-values	***3-1-4-2*** **xG** (1.29 +/- 0.0533)	**Progressive Passes** (41.6 +/- 0.978)	**Passes into the Penalty Area** (7.73 +/- 0.350)	**Ball Possession %** (48.8 +/- 0.827)
3-4-2-1	**xG** (1.36 +/- 0.0533)	0.33			
	Progressive Passes (42.6 +/- 0.978)		0.47		
	Passes into the Penalty Area (7.56 +/- 0.350)			0.73	
	Ball Possession % (51.2 +/- 0.827)				0.041

Table 29 - 3-1-4-2 vs 3-4-2-1 and associated p-values, estimated marginal means and standard error.

3-1-4-2 vs 3-3-3-1

There was a significant difference in Progressive Passes, $F(1, 45) = 10.14$, $p = 0.003$; Passes into the Penalty Area, $F(1, 45) = 4.41$, $p = 0.041$ and Ball Possession percentage, $F(1, 45) = 12.36$, $p = 0.001$ between the formations. All three outcome variables were significantly greater for 3-3-3-1 than 3-1-4-2. There was no significance in the xG variables between the formations.

		3-1-4-2			
	p-values	**xG** (1.03 +/- 0.153)	**Progressive Passes** (37.3 +/- 2.47)	**Passes into the Penalty Area** (6.05 +/- 0.823)	**Ball Possession %** (45.4 +/- 1.80)
3-3-3-1	**xG** (1.35 +/- 0.153)	0.16			
	Progressive Passes (48.8 +/- 1.47)		0.003		
	Passes into the Penalty Area (8.58 +/- 0.823)			0.041	
	Ball Possession % (54.6 +/- 1.80)				0.001

Table 30 - 3-1-4-2 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

3-4-2-1 vs 3-3-3-1

There was no significance in the outcome variables between 3-4-2-1 and 3-3-3-1.

	p-values (3-4-2-1)	**xG** (1.31 +/- 0.155)	**Progressive Passes** (48.3 +/- 3.20)	**Passes into the Penalty Area** (9.11 +/- 1.11)	**Ball Possession %** (51.6 +/- 1.79)
3-3-3-1	**xG** (1.46 +/- 0.155)	0.52			
	Progressive Passes (45.5 +/- 3.20)		0.53		
	Passes into the Penalty Area (8.56 +/- 1.11)			0.73	
	Ball Possession % (48.4 +/- 1.79)				0.20

Table 31 - 3-4-2-1 vs 3-3-3-1 and associated p-values, estimated marginal means and standard error.

Discussion

This study aimed to identify formations and formation matchups in elite level soccer that were favourable in their occupation of space, resulting in statistical significance of the outcome variables xG; Progressive Passes; Passes into the Penalty Area and Ball Possession percentage. The results highlight more general trends in performance for certain formations over others whilst also signalling key matchups that favour one formation over another.

General Trends

It was hypothesised that formations with a greater central presence may lead to more success. Indeed, teams that played 4-3-1-2 and its close cousin 3-4-1-2 displayed the highest xG and Progressive Passes per match. Together, they share the same attacking setup of two attackers operating ahead and to either side of an advanced central attacking midfielder. Such a setup allows for runs into depth behind the opposition's defence by the attackers, coupled with an obvious provider. The number of players in central positions allows for more options to move the ball forwards vertically.

On the other hand, the formations 3-1-4-2, 3-3-3-1 and 3-4-2-1 represent the lowest values of xG, Progressive Passes and Passes into the Penalty Area. Whilst nominally using one less defender in the setup, it's common for teams that use three central defenders to field full-backs in the wide midfielder/wing-back roles. Because of the difficulty in covering the full lateral areas of the pitch with three players, most teams that play three central defenders often drop into a back five when defending, nullifying its effect and often making the setup more defensive. This dropping into a back five makes ball progression and circulation easier for an opposition team. All back three setups receive more Progressive Passes against them than any of the back four setups. 3-3-3-1, whilst showing huge variance due to the rarity of its use, was most commonly played in the dataset by teams using five defenders with a midfield diamond and one lone striker. Such a setup provides obvious challenges in generating movement that would danger an opposing team's defensive line, hence showing the lowest value for xG for all formations.

4-3-1-2 also flags highest for Ball Possession percentage and lowest for Progressive Passes against. Clearly, its structure prevents opposition teams from consistently moving the ball up the pitch. Though effective in high pressing and chance creation, 4-3-1-2 does seem susceptible when opposition teams are able to beat the press - it’s highest for xG and Passes into the Penalty Area against. The extreme nature to which the 4-3-1-2 looks to control central and vertical areas of the pitch leads to a cat and mouse game with the opposition where if they are able to move the ball into wide areas consistently, it should yield success. *Figure 24* provides a visual of this by demonstrating the area of space best controlled by 4-3-1-2 in red, leaving the space vulnerable to exploitation in blue. 3-4-1-2 shares the mantle of being the formation with the highest xG against and its analogous structure also cedes control of areas of space in wide areas.

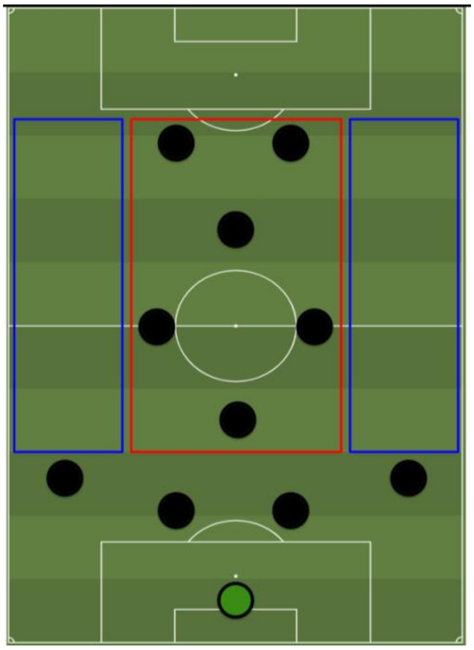

Figure 24 - A typical 4-3-1-2 formation. The highlighted red shows the area of strength with six players, leaving the area of weakness in wider areas in blue, vulnerable to exploitation.

In contrast, 4-2-2-2 and 4-2-3-1 report the lowest xG against and Passes into the Penalty Area against respectively. Very similar formations, both share two lines of four when defending, enabling space to be covered effectively laterally without compromising vertically by fielding two players ahead to provide pressure (*Figure 25*). This balance of effective lateral and vertical coverage of the pitch seems to be an important one for success when defending. Formations that focus too heavily on lateral coverage, as is the case with 3-4-2-1 and 4-1-4-1 tend to allow more space for opposition teams to progress the ball vertically against them. Conversely, we have already seen how a too drastic approach to stopping ball progression can lead to a weak structure when defending the penalty area and ultimately the goal, as in 4-3-1-2 and 3-4-1-2.

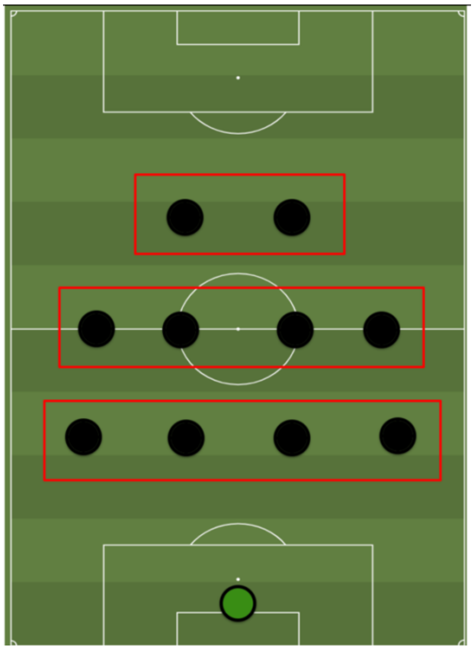

Figure 25 - A 4-2-2-2 (4-4-2) formation in its defensive setup. The lines of four are compact as they cover the pitch well laterally. The two attackers provide balance in covering the pitch vertically.

4-2-3-1 in particular seems to offer this perfect balance. The dropping of an attacker into an attacking midfield role from the 4-2-2-2 adds an element of extra vertical coverage to reduce the number of progressive passes it receives to least of all formations - doing so without much, if any, sacrifice in defending its penalty area.

After subtracting the average xG against per match from the average xG created, 4-3-1-2 and 4-2-2-2 show the two highest values. 4-3-1-2 achieves this through a strong attack, whilst 4-2-2-2 compromises and achieves success through a strong defence. The combination of a four-man defence with four midfielders and two attackers appears most effective on average in net chance creation in soccer.

Formation Matchups

Of the 28 matchups studied, two showed significant results in all four outcome variables for one formation over the other. 4-1-4-1 appears effective against 4-2-2-2 and 3-1-4-2, where both formations share the two-striker setup without a central attacking midfielder. Such a setup allows the two centre-backs and holding deep midfielder of the 4-1-4-1 to form a 3v2 overload against the opposition's two attackers, turning into 4v2 when the goalkeeper takes an active role in the build-up. The positioning of the holding midfielder is perhaps most significant in pinning the attackers.

A player is able to pin opposition players with their positioning if there is an easy progressive pass into them in space when the opposition players they are pinning vacate their own position. This is most commonly seen when players naturally occupy positions between and behind two opposing players. In a way similar to the holding midfielder, the wide midfielders of the 4-1-4-1 can act as pinning players by standing between opposition full or wing backs and centre backs (*Figure 26*), making constant runs into depth throughout. This effect reduces the possibility of these pinned players engaging in pressure elsewhere as the danger of receiving an easy progressive pass into the pinning player is rarely worth the trade off, hence allowing for numerical overloads. In the case of 4-1-4-1 vs 3-1-4-2 as in *Figure 26*, the pinning of the defensive and attacking line by 4-1-4-1 generates a 4v3 overload in midfield - the area of space it is hypothesised to be most important to control.

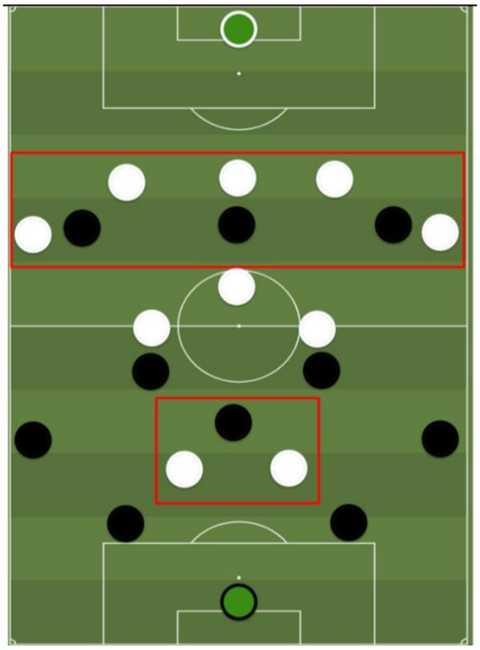

Figure 26 - 4-1-4-1 (Black) vs 3-1-4-2 (White). The highlighted areas represent positions the players in a 4-1-4-1 can take up to pin players in a 3-1-4-2.

Infact, the concept of pinning opposition defensive and attacking lines with as few attacking players as possible seems to be a recurring theme for success. As well as the success of 4-1-4-1 against 3-1-4-2 and 4-2-2-2, 4-2-3-1 shows significant success against 3-4-2-1 in Progressive Passes and Ball Possession percentage. In this instance, the three attackers of the 4-2-3-1 can pin back five defenders in 3-4-2-1 whilst also pinning the three attackers of the 3-4-2-1 with four defenders. The net effect is a 3v2 overload in the middle.

A net overload in the centre may also explain the significant success in xG for 4-2-2-2 over 4-2-3-1 and in Ball Possession percentage for 4-3-1-2 over 4-2-2-2. Examples of the pinning of a back five with three players has been shown in *Figure 4 and 26* though the equivalent pinning of four defenders with two attackers is dependent on their positioning. By standing in the channel between the opposition full and centre backs and making runs into depth behind the defensive line, the two attackers force all four of the opposition defenders to stay back or risk leaving easy space to exploit (*Figure 27*).

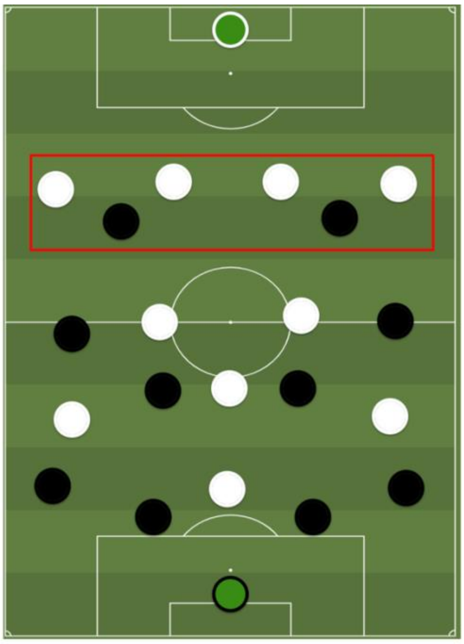

Figure 27 - 4-2-2-2 (Black) vs 4-2-3-1 (White). By standing between opposition full and centre backs, the two attackers of 4-2-2-2 can pin four defenders, creating a 4v3 advantage in midfield.

Interestingly, with the 4-2-2-2 and 4-2-3-1 matchup, 4-2-3-1 seems to produce significantly higher Ball Possession percentages than 4-2-2-2. This may just be a manifestation of the full backs of 4-2-3-1 advancing with their positioning despite the fact they are pinned by the two strikers, hence leaving its structure vulnerable to conceding high quality chances when the ball is lost.

A buck to the trend arises through the significant success of 4-3-1-2 over 3-1-4-2 and 3-4-1-2 over 3-3-3-1. In the case of the latter, the expectation, in accordance with the proposed theories as above, would be for 3-3-3-1 to be a successful formation to use against 3-4-1-2. This is due to the striker and two wide midfielders pinning back the central defenders and wing backs of the 3-4-1-2. Furthermore, the three central defenders could effectively deal with the two attackers - creating in effect a 4v3 overload in the centre.

An alternative mechanism is put forward where the attackers of the 3-4-1-2 are positioned wide of the central defenders of the 3-3-3-1. An advanced central attacking midfielder allows for this without jeopardizing the structure of the overall team. The reluctance of the middle centre back of the 3-3-3-1 to step out may lead to two attackers effectively pinning five opposition defenders (*Figure 28*), thus in actual effect creating a 3v2 central overload for 3-4-1-2 over 3-3-3-1. This mechanism where two strikers effectively pin five defenders could also explain the significant success of 4-3-1-2 over 3-1-4-2.

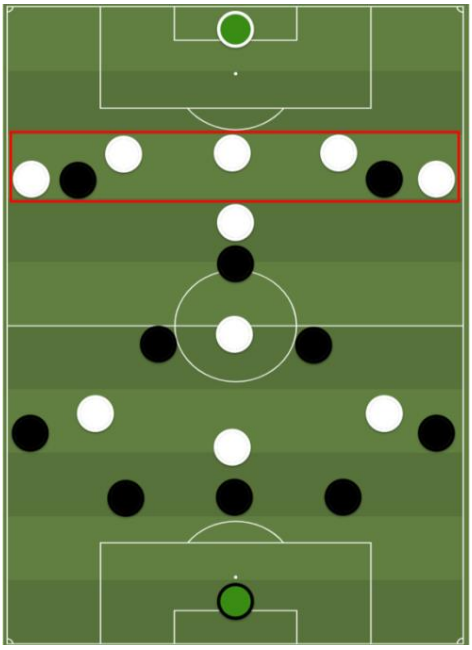

Figure 28 - 3-4-1-2 (Black) vs 3-3-3-1 (White). The split positioning of the attackers of the 3-4-1-2 to pin five defenders creating a 3v2 advantage in midfield.

It seems as though the ability to generate an overload in midfield, through effective pinning, is a significant barometer for success. However just having extra players available in midfield does not directly correlate with the outcome variables like xG and Passes into the Penalty Area.

To comprehend this link, an overload must occur frequently within zone 14, an area well studied in its connection to creating goal-scoring opportunities (Horn et al, 2002). In two of the significant results for xG favourability of one formation over another, there are distinctive and obvious ways in which a zone 14 overload can be created by the more successful formation. In the case of 4-1-4-1 vs 4-2-2-2, effective pinning can allow the three forwards of 4-1-4-1 to be isolated 3v2 in zone 14 against the two centre backs of the 4-2-2-2. Similarly, 4-2-2-2 itself can generate a 4v3 overload in zone 14 against the three centre backs of the 3-4-2-1. From this position, it is possible to imagine how the ball can regularly enter the ideal assist zone, followed by the ideal shooting zone (*Figure 11 and 12*). Possible player movement pathways have been provided within *Figure 29 and 30* to help explain this overload generation out of the original formation in possession. In both cases, zone 14 (red) and the ideal assist (green) and shooting zone (blue) have been highlighted to better convey their connections. Note also within the 4-1-4-1 vs 4-2-2-2 matchup as in *Figure 29*, the centre backs and holding midfielder overload their own zone 14 area 3v2, stifling lots of possibly dangerous attacks.

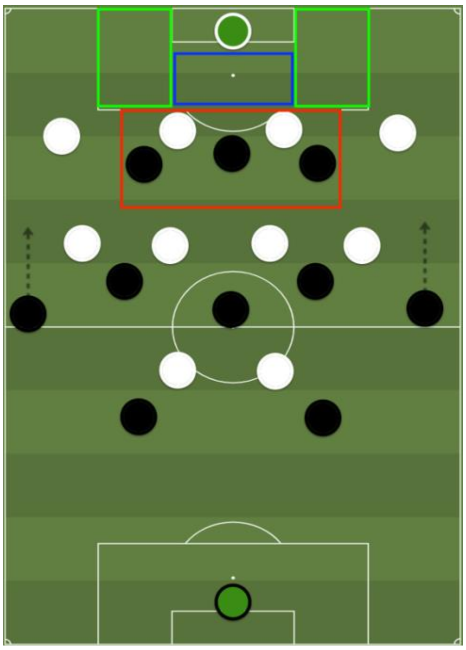

Figure 29 - 4-1-4-1 (Black) vs 4-2-2-2 (White). The movement player pathways using effective pinning to generate an overload in zone 14 for when 4-1-4-1 has possession.

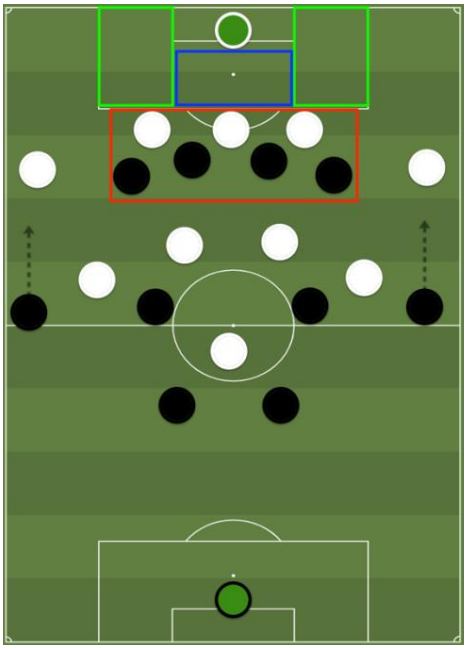

Figure 30 - 4-2-2-2 (Black) vs 3-4-2-1 (White). The movement player pathways using effective pinning to generate an overload in zone 14 for when 4-2-2-2 has possession.

The closest opposition players that could help negate the possibility of being overloaded in zone 14 are the full or wingbacks, doing so by shifting in-field laterally. Hence for attacking teams, it's a high priority to ensure they are pinned wide by threatening the space between the sideline and their position. Within *Figure 29 and 30*, the attacking team's own full backs could fulfil this task, provided the midfielders are conservative in their own positioning such as to be appropriately organized to defend a transition if the ball is lost. The net effect on the attacking structure is to form an inverted triangle with the point coinciding with the attacking team's centre-backs and the base spanning across the opposition's defensive line. This opens up zone 14 access for overload creation (*Figure 31*).

Figure 31 - An example of an attacking structure for 4-3-1-2 out of their baseline positions (listed). The inverted triangle geometry opens up access to zone 14.

Though these effects are somewhat trivial, due to the freedom of movement and continuous nature of soccer matches, they bring to the front some important principles for managing and controlling space. In other cases where effective pinning has occurred to create a central overload, there may be less obvious movement patterns in accessing zone 14. Nonetheless, good ball retention should allow the free player within the central overload to be accessed within this zone. It may be the case that constant interchange of positions leads to that free player being different depending on the pattern of play, including the direction and type of pass received - still the overload principle remains.

There is an interesting pattern observed through the interactions of the formations 4-3-1-2, 4-2-2-2 and 3-4-2-1. The estimated marginal means in xG provide a fascinating analogy to the globally played game 'rock, paper, scissors'. 4-3-1-2 outperforms 4-2-2-2, which outperforms 3-4-2-1. In full circle, interestingly 3-4-2-1 outperforms 4-3-1-2. Explanations to these findings can be understood through the aforementioned net pinning techniques but more importantly, these results neatly highlight how formation interactions clearly impact outcome.

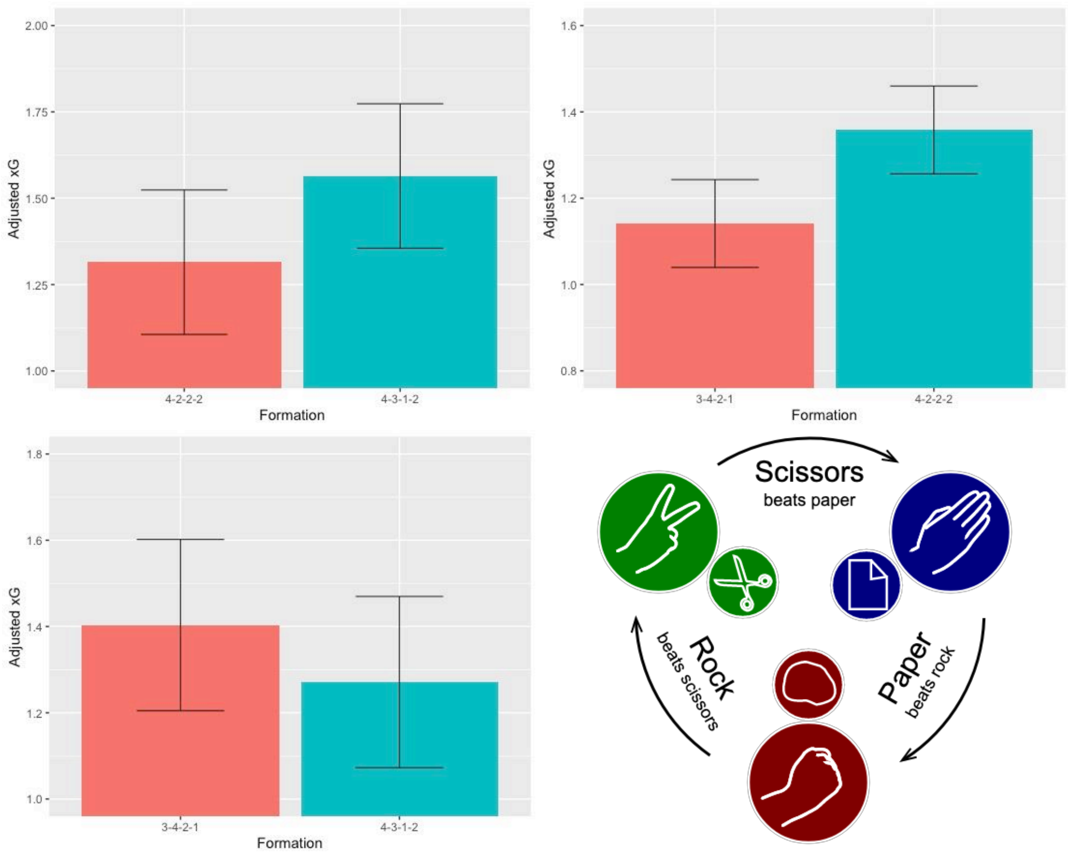

Figure 32 - The rock, paper, scissors analogy observed through the interactions of 4-3-1-2, 4-2-2-2 and 3-4-2-1.

It was postulated that formations with a greater number of players in central positions may lead to greater success. As a general trend, 4-3-1-2 performs well in most of the outcome variables, attack especially. However, 3-3-3-1 tends to struggle - most likely due to inefficiencies in pinning opposition defences and fielding too many defenders than are required to deal with opposition attackers. It seems to be the case that a greater number of players in midfield leads to more success with the caveat that the opposition's defensive and attacking lines are pinned with the fewest possible players. Four defenders and two attackers seem the best way to achieve this net effect.

Limitations

The results of this research provide valuable insight into the dynamics of interacting formations based on preferential occupation of space, but they are not without limitations. Firstly, the congregation of formations to provide enough data for analysis negates some of the nuances of exact player positioning. As an example, when evaluating 4-2-2-2, both combinations of a flat midfield four and slightly raised attacking midfielders ahead of the central midfielders are congregated as being the same within the dataset. Though subtle, this difference changes the emphasis on vertical and lateral coverage of the pitch.

Secondly, whilst the data is adjusted for the quality of teams, there is no factor included that describes the personality and profile of the teams or players that make up the positions. The pinning of four defenders with two attackers as in *Figure 27* is dependent on the two attackers having the attributes to constantly make runs into depth regardless of their actual quality. In addition, the spaces afforded by each team's formation can only be accessed if the ball is continuously able to be in those spaces - each team's style of building out from the back and pressing from the front influences this.

Finally, the dataset assumes the formation to be consistent throughout all phases within each game. Therefore, a tactical change in formation from one coach at any point in the game is not accounted for within the analysis. Also, the assumption that a formation remains the same within the attacking and defensive phase isn't accurate. Due to the amount of time teams are able to keep possession at an elite level, there can be different structural changes in how teams adapt their general formation when attacking and defending - pushing men forwards or backwards to generate distinctive patterns of play characterised by the type of players involved.

It's also important to note that there were violations to some of the assumptions that presupposed the ANCOVA analysis - in particular for formations that had significantly fewer points in the dataset, as was the case with 3-3-3-1. There were no direct measures taken in cases, specifically within the smaller subset of formation matchups, to negate the impact of these violations. This was mostly to ensure a consistent statistical method throughout all tests. Within most of the tests, the sample size was large enough for the central limit theorem to hold true, even for cases of non-normal data. A list of violations to these tests have been provided in the appendix.

Conclusion

As a general trend, the results indicate that the formations 4-3-1-2 and 4-2-2-2 are most successful in xG difference after adjustment for team quality. 4-3-1-2 appears to be the most dangerous formation in attack by showing the highest values for xG; Progressive Passes; Passes into the Penalty Area and Ball Possession percentage amongst all formations. 4-2-2-2 and 4-2-3-1 seem most resistant to attack by ranking lowest in xG against and Passes into the Penalty Area against respectively. When analysing formation matchups, the results suggest the key to success involves generating an overload of players in midfield areas through pinning opposition defensive and attacking lines with as few players as possible. The link between this effect and the outcome variables can be explained through zone 14 access. Because of the structural differences in the formations, the mechanisms for which this pinning is achieved varies in ways explained.

Further Studies

It would be insightful to dissect further into the outcome variables to help understand just what type of action is causing the quantitative values. As an example, for teams who more regularly counterattack, it would be useful to understand what formations and formation matchups tend to lead to xG values attributed to counter attacks. Furthermore, the use of positional tracking data in identifying the exact moments one team is attacking and the other is defending would allow for a similar analysis on the effect of more specific attacking and defensive sub-structures on the outcome variables. This would provide valuable solutions to attacking-defending dynamics and optimal structural changes to general formation when in or out of possession. Attacking and Defending substructures could be congregated in a similar way to this study.

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Appendix

Hypothesis 1

<u>xG vs Formation</u>

- No assumption violations

Formation	Adjusted xG Estimated Mean +/- Standard Error
4-1-4-1	1.33 +/- 0.0137
4-2-3-1	1.35 +/- 0.0137
4-3-1-2	1.42 +/- 0.0317
4-2-2-2	1.33 +/- 0.0166
3-4-1-2	1.37 +/- 0.0333
3-1-4-2	1.25 +/- 0.0211
3-4-2-1	1.28 +/- 0.0215
3-3-3-1	1.18 +/- 0.0568

Table 32 - xG per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		1	0.185	1	1	0.0868	1	0.300
4-2-3-1			0.854	1	1	0.00536	0.237	0.111
4-3-1-2				0.350	1	0.00026	0.00586	0.00524
4-2-2-2					1	0.0881	1	0.262
3-4-1-2						0.105	0.757	0.115
3-1-4-2							1	1
3-4-2-1								1
3-3-3-1								

Table 33 - p values for xG per match formation differences on average.

Progressive Passes vs Formation

- Violation of Homogeneity of Regression Slopes: F(7, 10738) = 4.48, p <0.0001.
- Violation of Levene's test: p <0.0001

Formation	Adjusted Progressive Passes Estimated Mean +/- Standard Error
4-1-4-1	43.6 +/- 0.240
4-2-3-1	43.3 +/- 0.241
4-3-1-2	46.7 +/- 0.557
4-2-2-2	42.5 +/- 0.292
3-4-1-2	43.6 +/- 0.585
3-1-4-2	41.2 +/- 0.370
3-4-2-1	42.0 +/- 0.378
3-3-3-1	42.0 +/- 0.998

Table 34 - Progressive Passes per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		1	<0.0001	0.0530	1	<0.0001	0.00653	1
4-2-3-1			<0.0001	0.957	1	0.00012	0.125	1
4-3-1-2				<0.0001	0.00364	<0.0001	<0.0001	0.00103
4-2-2-2					1	0.255	1	1
3-4-1-2						0.0181	0.590	1
3-1-4-2							1	1
3-4-2-1								1
3-3-3-1								

Table 35 - p values for Progressive Passes per match formation differences on average.

Passes into the Penalty Area vs Formation

- Violation of Homogeneity of Regression Slopes: $F(7, 10738) = 7.02$, $p < 0.0001$.
- Violation of Levene's test: $p < 0.0001$

Formation	Adjusted Passes into the Penalty Area Estimated Mean +/- Standard Error
4-1-4-1	8.27 +/- 0.0776
4-2-3-1	7.76 +/- 0.0778
4-3-1-2	9.10 +/- 0.180
4-2-2-2	7.84 +/- 0.0944
3-4-1-2	8.19 +/- 0.189
3-1-4-2	7.68 +/- 0.119
3-4-2-1	7.73 +/- 0.122
3-3-3-1	7.64 +/- 0.322

Table 36 - Passes into the Penalty Area per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		0.00012	0.00054	0.016	1	0.0013	0.0069	1
4-2-3-1			<0.0001	1	0.94	1	1	1
4-3-1-2				<0.0001	0.013	<0.0001	<0.0001	0.0019
4-2-2-2					1	1	1	1
3-4-1-2						0.63	1	1
3-1-4-2							1	1
3-4-2-1								1
3-3-3-1								

Table 37 - p values for Passes into the Penalty Area per match formation differences on average.

Ball Possession vs Formation

- Violation of Homogeneity of Regression Slopes: $F(7, 10738) = 10.5$, $p < 0.0001$.
- Violation of Levene's test: $p < 0.0001$

Formation	Adjusted Ball Possession (%) Estimated Mean +/- Standard Error
4-1-4-1	51.1 +/- 0.191
4-2-3-1	51.0 +/- 0.191
4-3-1-2	52.4 +/- 0.442
4-2-2-2	48.5 +/- 0.232
3-4-1-2	49.3 +/- 0.464
3-1-4-2	47.5 +/- 0.294
3-4-2-1	49.4 +/- 0.300
3-3-3-1	48.5 +/- 0.792

Table 38 – Ball Possession % per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		1	0.22	<0.0001	0.013	<0.0001	<0.0001	0.039
4-2-3-1			0.082	<0.0001	0.037	<0.0001	0.00026	0.071
4-3-1-2				<0.0001	<0.0001	<0.0001	<0.0001	0.0005
4-2-2-2					1	0.11	0.74	1
3-4-1-2						0.017	1	1
3-1-4-2							0.00013	1
3-4-2-1								1
3-3-3-1								

Table 39 - p values for Ball Possession % per match formation differences on average.

Hypothesis 2

xG Against vs Formation

- Violation of Homogeneity of Regression Slopes: $F(7, 10738) = 3.515$, $p = 0.0009$

Formation	Adjusted xG Against Estimated Mean +/- Standard Error
4-1-4-1	1.31 +/- 0.0142
4-2-3-1	1.32 +/- 0.0142
4-3-1-2	1.39 +/- 0.0328
4-2-2-2	1.26 +/- 0.0172
3-4-1-2	1.39 +/- 0.0345
3-1-4-2	1.38 +/- 0.0218
3-4-2-1	1.36 +/- 0.0223
3-3-3-1	1.22 +/- 0.0588

Table 40 - xG Against per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		1	1	0.632	0.963	0.429	1	1
4-2-3-1			1	0.336	1	0.713	1	1
4-3-1-2				0.0231	1	1	1	0.440
4-2-2-2					0.0214	0.00110	0.0237	1
3-4-1-2						1	1	0.373
3-1-4-2							1	0.409
3-4-2-1								0.970
3-3-3-1								

Table 41 - p values for xG Against per match formation differences on average.

Progressive Passes Against vs Formation

- Violation of Homogeneity of Regression Slopes: $F(7, 10738) = 7.63$, $p < 0.0001$

Formation	Adjusted Progressive Passes Against Estimated Mean +/- Standard Error
4-1-4-1	43.0 +/- 0.243
4-2-3-1	42.4 +/- 0.244
4-3-1-2	42.4 +/- 0.562
4-2-2-2	42.7 +/- 0.295
3-4-1-2	43.5 +/- 0.591
3-1-4-2	44.2 +/- 0.374
3-4-2-1	43.6 +/- 0.382
3-3-3-1	46.3 +/- 1.01

Table 42 – Progressive Passes Against per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	4-2-3-1	4-3-1-2	4-2-2-2	3-4-1-2	3-1-4-2	3-4-2-1	3-3-3-1
4-1-4-1		1	1	1	1	0.19	1	0.042
4-2-3-1			1	1	1	0.0010	0.15	0.0044
4-3-1-2				1	1	0.19	1	0.020
4-2-2-2					1	0.037	1	0.017
3-4-1-2						1	1	0.52
3-1-4-2							1	1
3-4-2-1								0.39
3-3-3-1								

Table 43 - p values for Progressive Passes Against per match formation differences on average.

Passes into the Penalty Area Against vs Formation

- Violation of Homogeneity of Regression Slopes: $F(7, 10738) = 3.22$, $p = 0.002$
- Violation of Levene's test: $p = 0.00026$

Formation	Adjusted Passes into the Penalty Area Against Estimated Mean +/- Standard Error
4-1-4-1	8.00 +/- 0.0817
4-2-3-1	7.63 +/- 0.0820
4-3-1-2	8.73 +/- 0.189
4-2-2-2	8.06 +/- 0.0994
3-4-1-2	7.95 +/- 0.199
3-1-4-2	8.35 +/- 0.126
3-4-2-1	7.86 +/- 0.128
3-3-3-1	8.22 +/- 0.339

Table 44 – Passes into the Penalty Area Against per match estimated marginal mean and standard error for each formation.

	p-values							
	4-1-4-1	**4-2-3-1**	**4-3-1-2**	**4-2-2-2**	**3-4-1-2**	**3-1-4-2**	**3-4-2-1**	**3-3-3-1**
4-1-4-1		0.52	0.010	1	1	0.52	1	1
4-2-3-1			<0.0001	0.030	1	<0.0001	1	1
4-3-1-2				0.043	0.12	1	0.0040	1
4-2-2-2					1	1	1	1
3-4-1-2						1	1	1
3-1-4-2							0.19	1
3-4-2-1								1
3-3-3-1								

Table 45 - p values for Passes into the Penalty Area Against per match formation differences on average.

Hypothesis 3

4-1-4-1 vs 4-2-3-1

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1559) = 0.042$, $p = 0.84$

Progressive Passes:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1559) = 0.093$, $p = 0.76$

Passes into the Penalty Area:

- Violation of Homogeneity of Regression Slopes: $F(1, 1558) = 6.939$, $p = 0.009$
- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1559) = 2.374$, $p = 0.12$

Ball Possession %:

- Violation of Homogeneity of Regression Slopes: $F(1, 1558) = 5.130$, $p = 0.024$
- Violation of Levene's test: $p = 0.0099$
- ANCOVA: $F(1, 1559) = 2.758$, $p = 0.097$

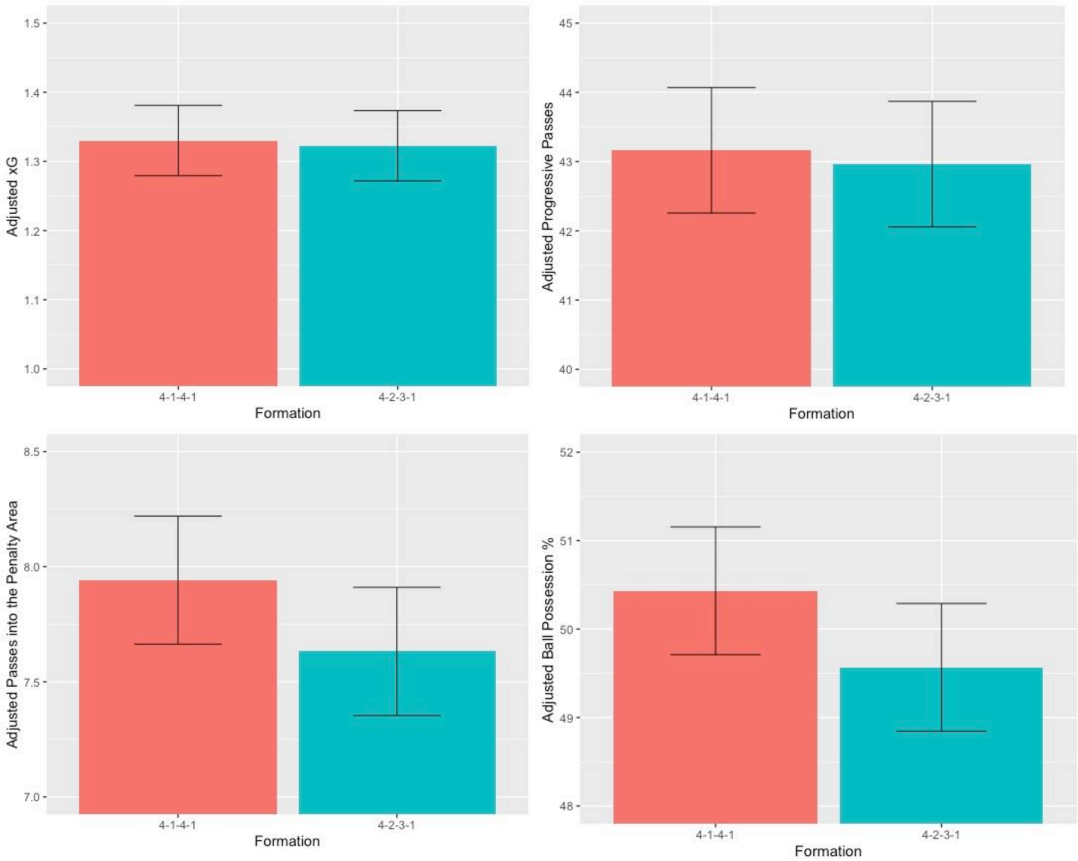

Figure 33 - 4-1-4-1 vs 4-2-3-1 adjusted outcome metrics and error bars.

4-1-4-1 vs 4-3-1-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 257) = 1.848$, $p = 0.18$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.012$
- ANCOVA: $F(1, 257) = 1.885$, $p = 0.17$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 257) = 0.333$, $p = 0.57$

Ball Possession %:

- ANCOVA: $F(1, 1257) = 8.719$, $p = 0.003$

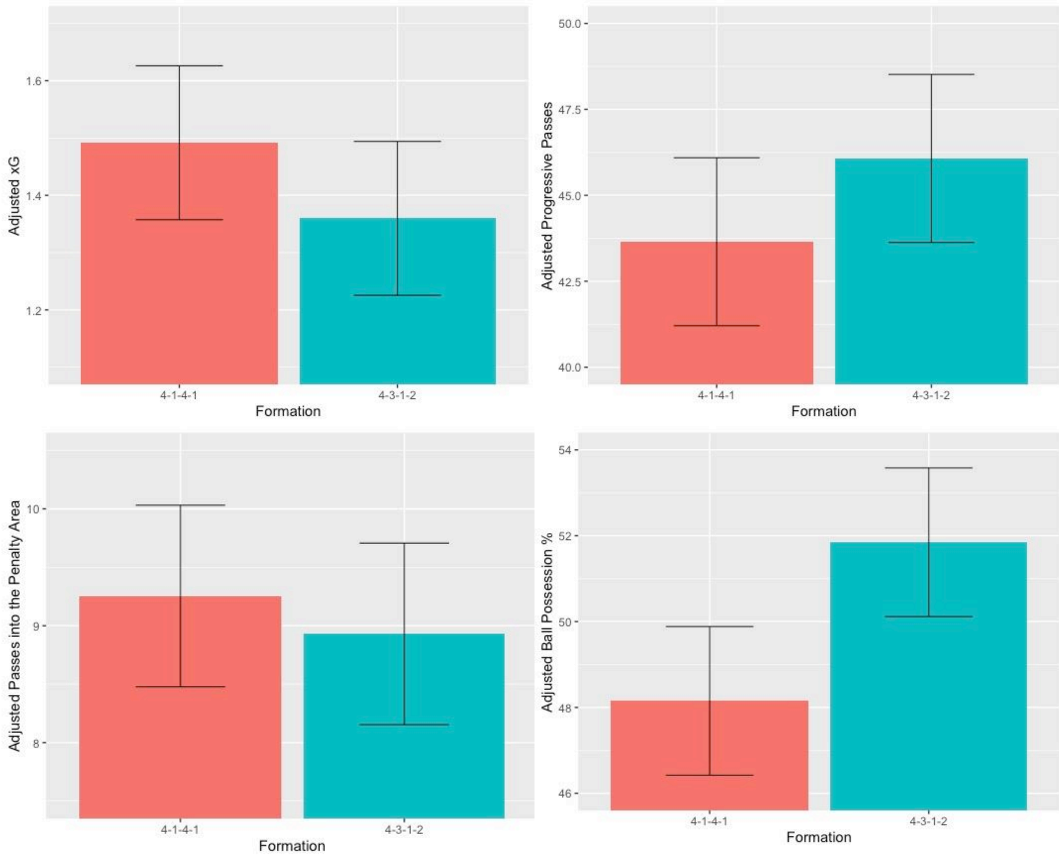

Figure 34 - 4-1-4-1 vs 4-3-1-2 adjusted outcome metrics and error bars.

4-1-4-1 vs 4-2-2-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 937) = 6.534$, $p = 0.011$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.00037$
- Violation of Levene's test: $p = 0.0012$
- ANCOVA: $F(1, 937) = 38.493$, $p <0.0001$

Passes into the Penalty Area:

- Violation of Homogeneity of Regression Slopes: $F(1, 936) = 5.392$, $p = 0.02$
- Violation of Shapiro Wilk test: $p < 0.0001$
- Violation of Levene's test: $p = 0.00016$
- ANCOVA: $F(1, 937) = 53.668$, $p <0.0001$

Ball Possession %:

- Violation of Levene's test: $p = 0.02$
- ANCOVA: $F(1, 937) = 225.4$, $p < 0.0001$

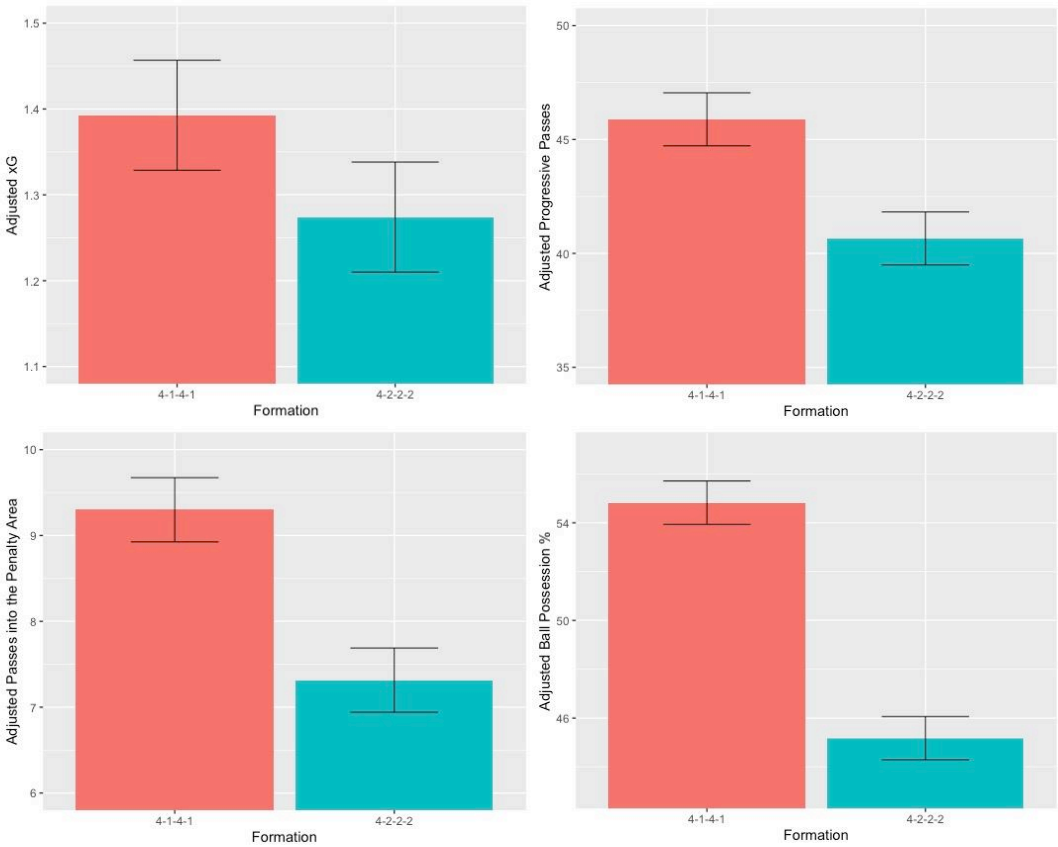

Figure 35 - 4-1-4-1 vs 4-2-2-2 adjusted outcome metrics and error bars.

<u>4-1-4-1 vs 3-4-1-2</u>

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 227) = 0.062$, $p = 0.80$

Progressive Passes:

- ANCOVA: $F(1, 227) = 0.013$, $p = 0.91$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 227) = 0.000027$, $p = 1$

Ball Possession %:

- ANCOVA: $F(1, 227) = 13.745$, $p = 0.00026$

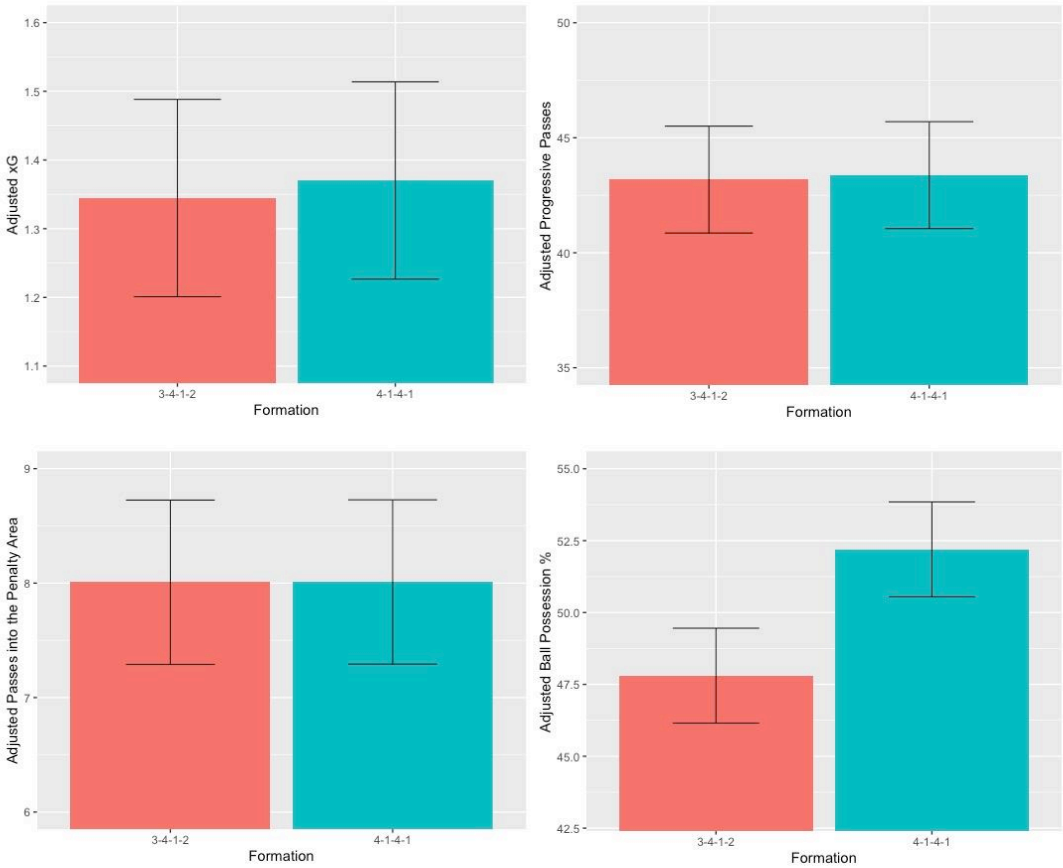

Figure 36 - 4-1-4-1 vs 3-4-1-2 adjusted outcome metrics and error bars.

4-1-4-1 vs 3-1-4-2

xG:
- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 545) = 18.249$, $p < 0.0001$

Progressive Passes:
- Violation of Shapiro Wilk test: $p < 0.0001$
- Violation of Levene's test: $p = 0.0096$
- ANCOVA: $F(1, 545) = 32.765$, $p < 0.0001$

Passes into the Penalty Area:
- Violation of Homogeneity of Regression Slopes: $F(1, 544) = 4.865$, $p = 0.028$
- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 545) = 12.762$, $p = 0.00039$

Ball Possession %:
- Violation of Homogeneity of Regression Slopes: $F(1, 544) = 12.326$, $p = 0.00048$
- Violation of Shapiro Wilk test: $p = 0.0022$
- Violation of Levene's test: $p < 0.0001$
- ANCOVA: $F(1, 545) = 108.304$, $p < 0.0001$

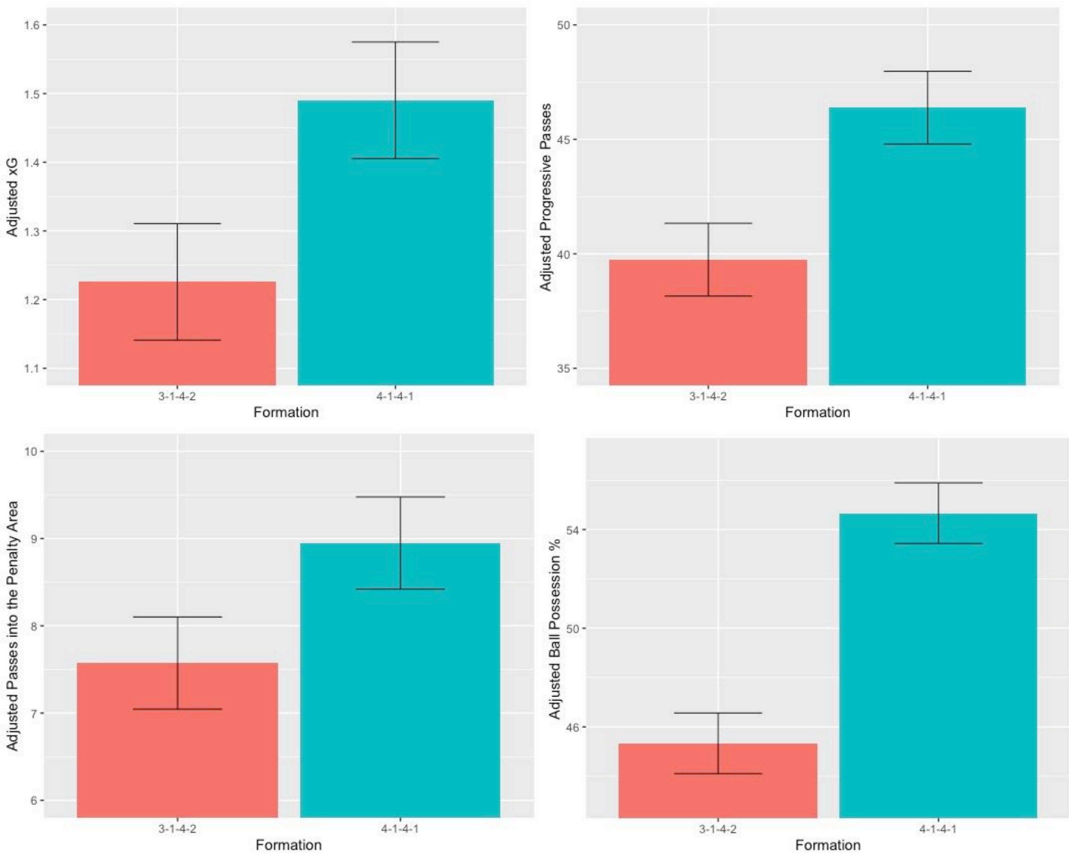

Figure 37 - 4-1-4-1 vs 3-1-4-2 adjusted outcome metrics and error bars.

4-1-4-1 vs 3-4-2-1

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 485) = 0.648$, $p = 0.42$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.0068$
- ANCOVA: $F(1, 485) = 9.001$, $p = 0.003$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 485) = 0.040$, $p = 0.84$

Ball Possession %:

- Violation of Homogeneity of Regression Slopes: $F(1, 484) = 4.239$, $p = 0.04$
- Violation of Levene's test: $p <0.0001$
- ANCOVA: $F(1, 485) = 35.892$, $p <0.0001$

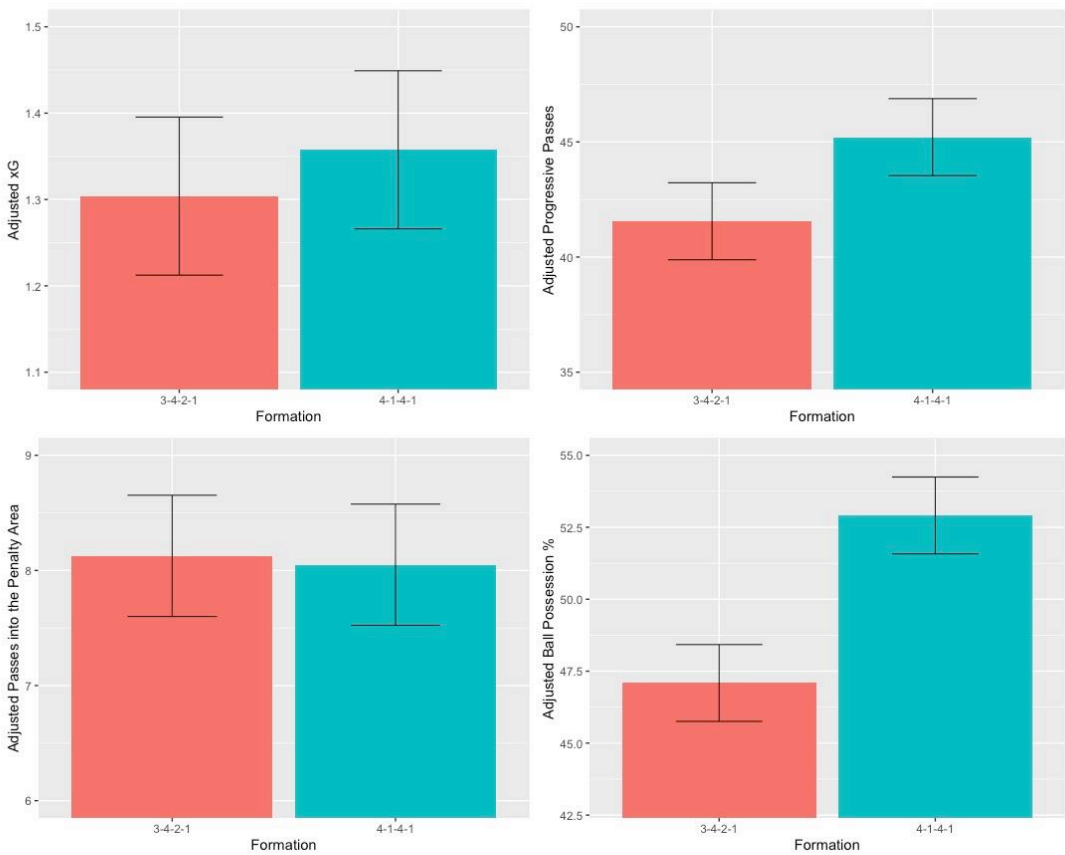

Figure 38 - 4-1-4-1 vs 3-4-2-1 adjusted outcome metrics and error bars.

<u>4-1-4-1 vs 3-3-3-1</u>

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 87) = 0.255$, $p = 0.62$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.034$
- ANCOVA: $F(1, 87) = 3.549$, $p = 0.06$

Passes into the Penalty Area:

- ANCOVA: $F(1, 87) = 0.370$, $p = 0.55$

Ball Possession %:

- ANCOVA: $F(1, 87) = 3.992$, $p = 0.049$

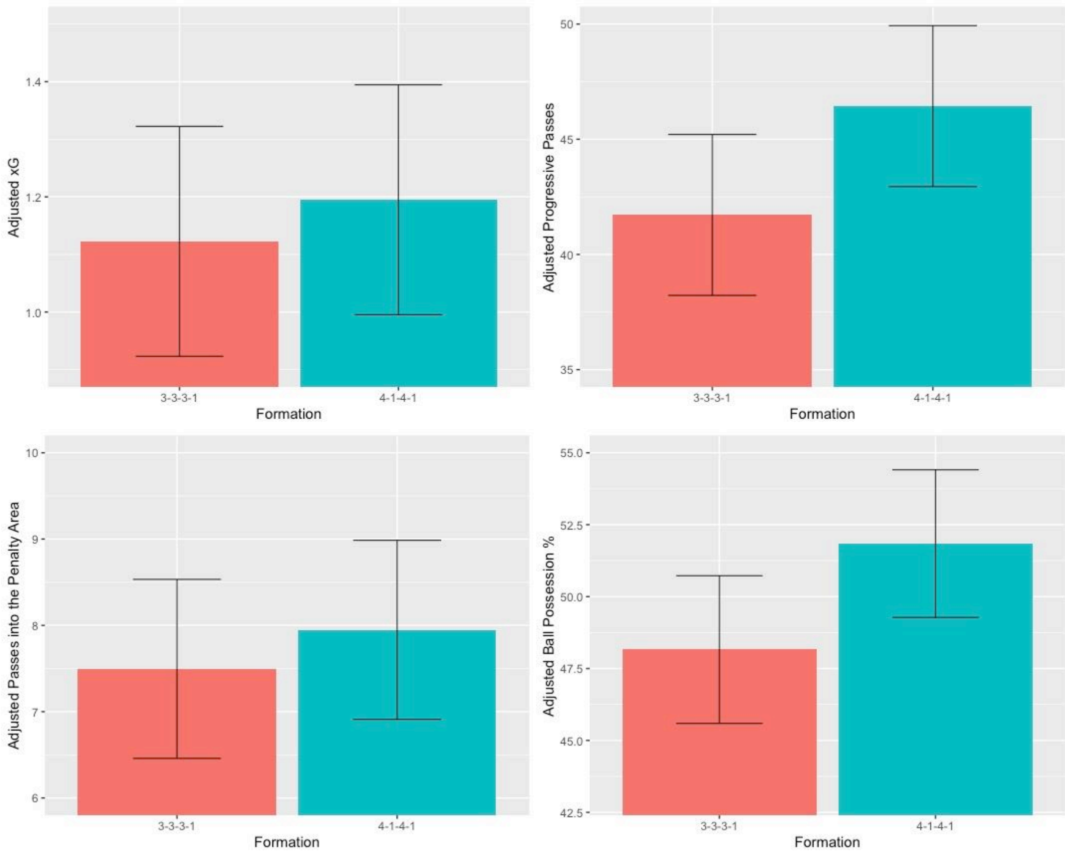

Figure 39 - 4-1-4-1 vs 3-3-3-1 adjusted outcome metrics and error bars.

4-2-3-1 vs 4-3-1-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 175) = 1.999$, $p = 0.16$

Progressive Passes:

- ANCOVA: $F(1,175) = 0.208$, $p = 0.65$

Passes into the Penalty Area:

- Violation of Homogeneity of Regression Slopes: $F(1, 174) = 4.623$, $p = 0.033$
- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 175) = 1.120$, $p = 0.29$

Ball Possession %:

- ANCOVA: $F(1, 175) = 0.006$, $p = 0.94$

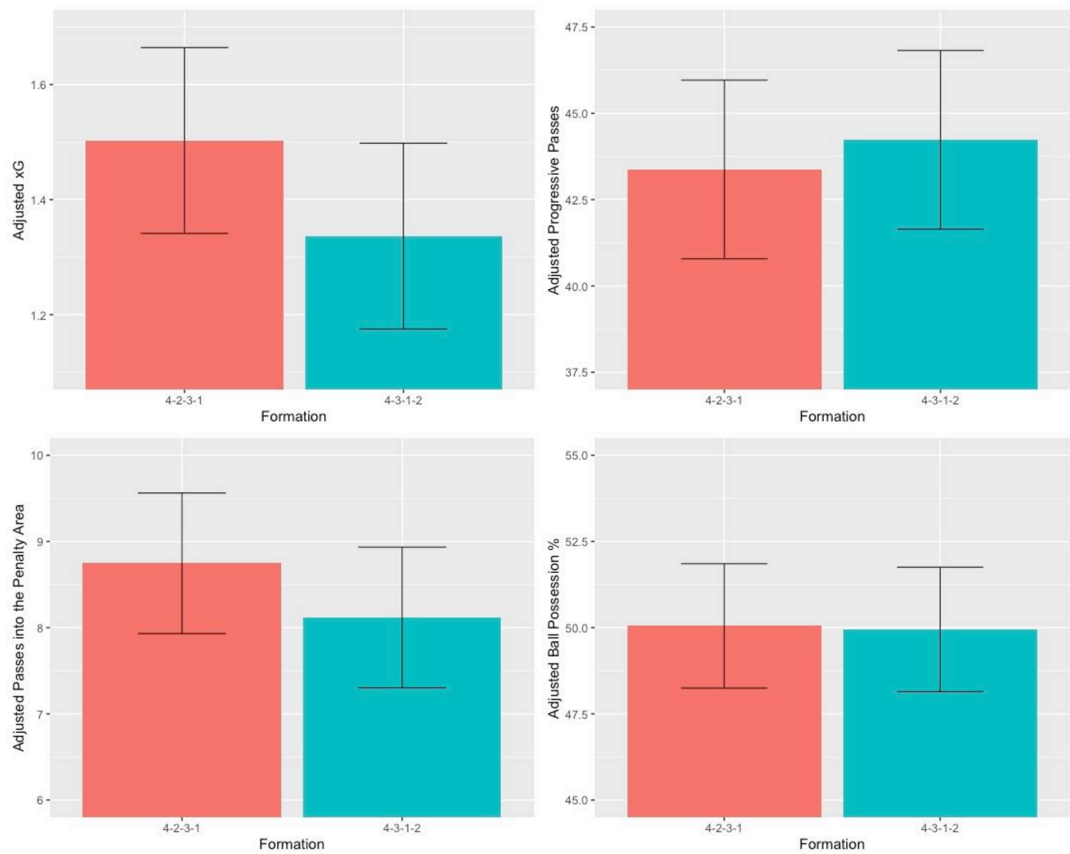

Figure 40 - 4-2-3-1 vs 4-3-1-2 adjusted outcome metrics and error bars.

<u>4-2-3-1 vs 4-2-2-2</u>

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1015) = 4.535$, $p = 0.033$

Progressive Passes:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1015) = 0.035$, $p = 0.85$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 1015) = 0.505$, $p = 0.48$

Ball Possession %:

- ANCOVA: $F(1, 1015) = 55.509$, $p < 0.0001$

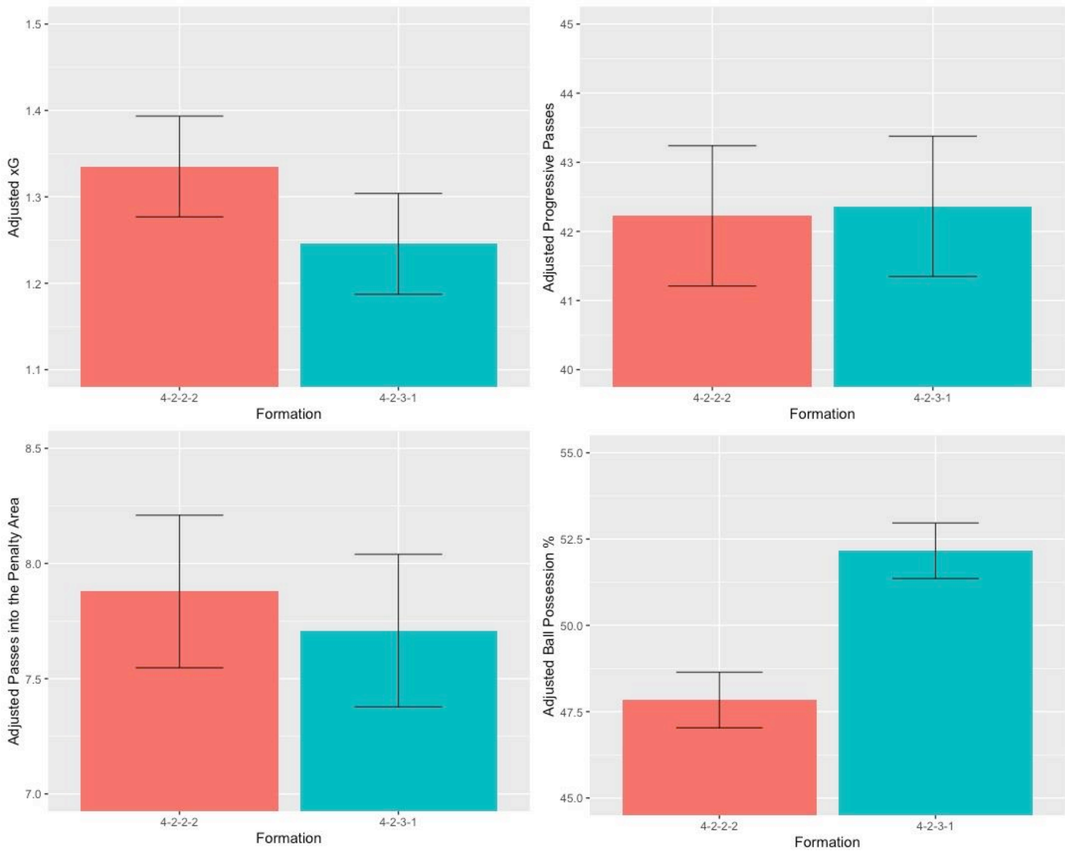

Figure 41 - 4-2-3-1 vs 4-2-2-2 adjusted outcome metrics and error bars.

4-2-3-1 vs 3-4-1-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- Violation of Levene's test: $p = 0.0068$
- ANCOVA: $F(1, 141) = 2.673$, $p = 0.10$

Progressive Passes:

- ANCOVA: $F(1, 141) = 0.039$, $p = 0.84$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p = 0.0042$
- ANCOVA: $F(1, 141) = 1.465$, $p = 0.23$

Ball Possession %:

- ANCOVA: $F(1, 141) = 9.999$, $p = 0.002$

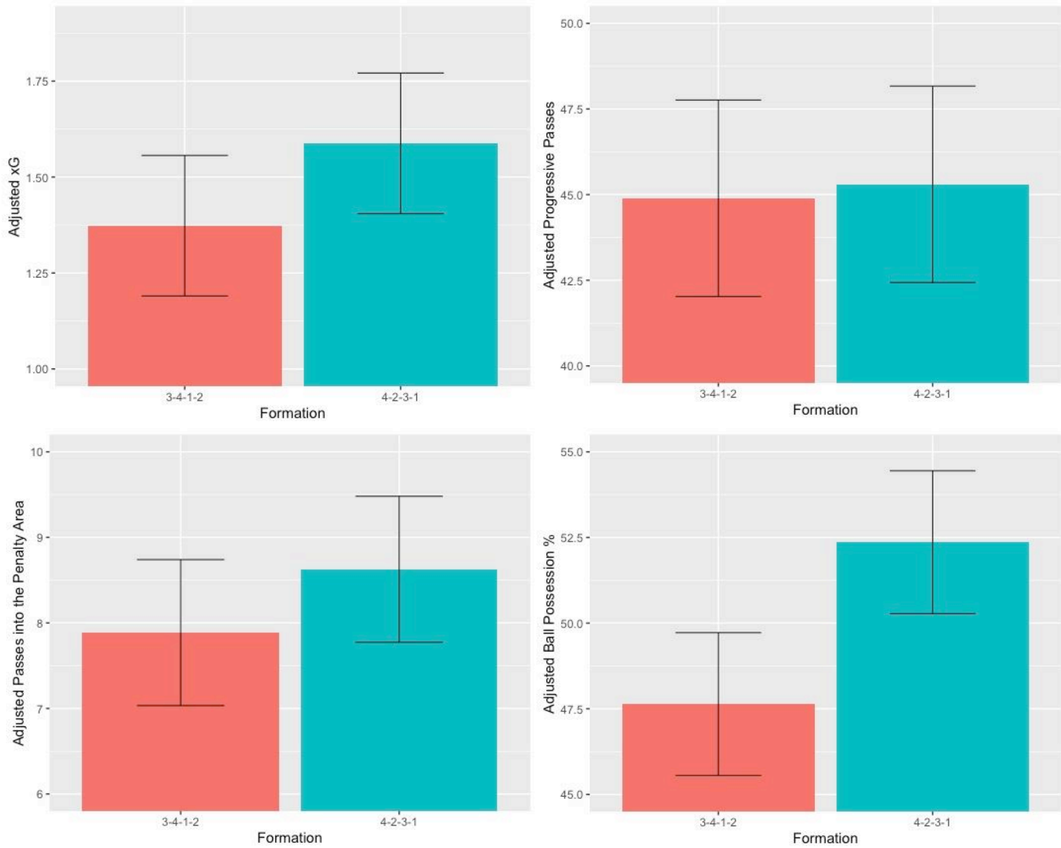

Figure 42 - 4-2-3-1 vs 3-4-1-2 adjusted outcome metrics and error bars.

4-2-3-1 vs 3-1-4-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 457) = 1.939$, $p = 0.16$

Progressive Passes:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 457) = 7.977$, $p = 0.005$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 457) = 4.411$, $p = 0.036$

Ball Possession %:

- ANCOVA: $F(1, 457) = 70.943$, $p < 0.0001$

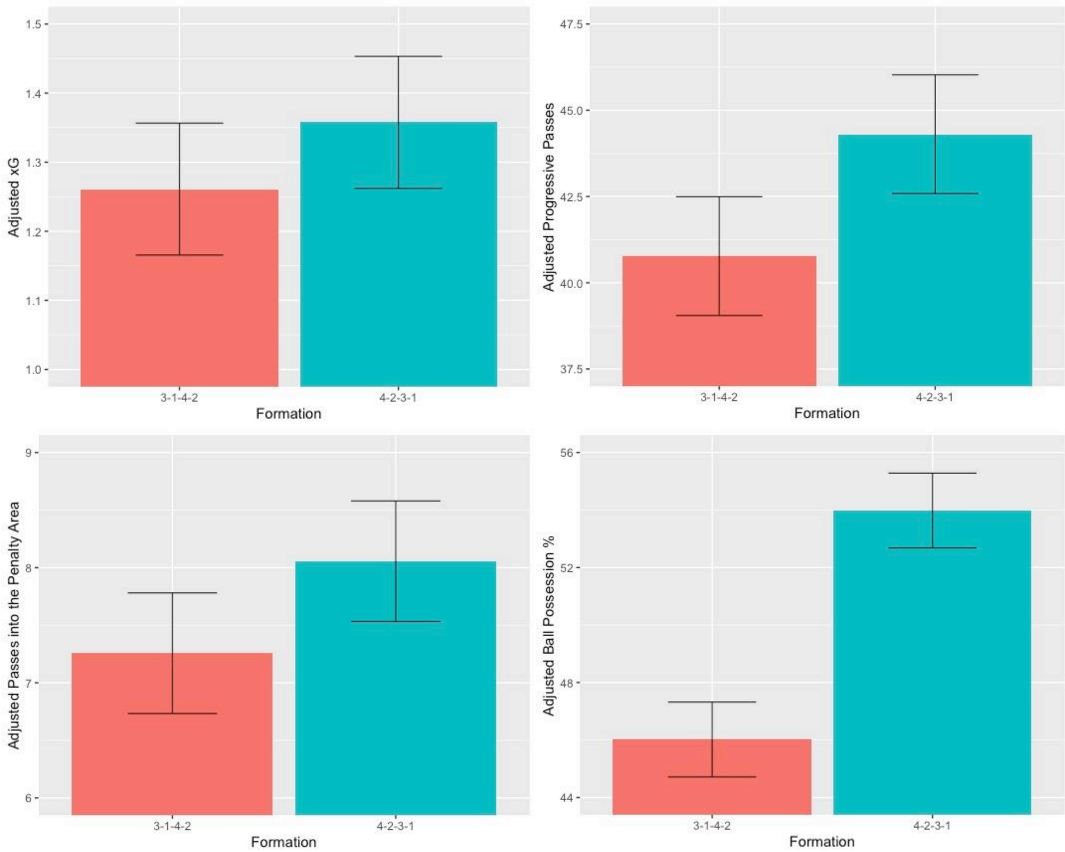

Figure 43 - 4-2-3-1 vs 3-1-4-2 adjusted outcome metrics and error bars.

4-2-3-1 vs 3-4-2-1

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 413) = 3.396$, $p = 0.066$

Progressive Passes:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 413) = 6.142$, $p = 0.014$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 413) = 1.31$, $p = 0.25$

Ball Possession %:

- ANCOVA: $F(1, 413) = 10.468$, $p = 0.001$

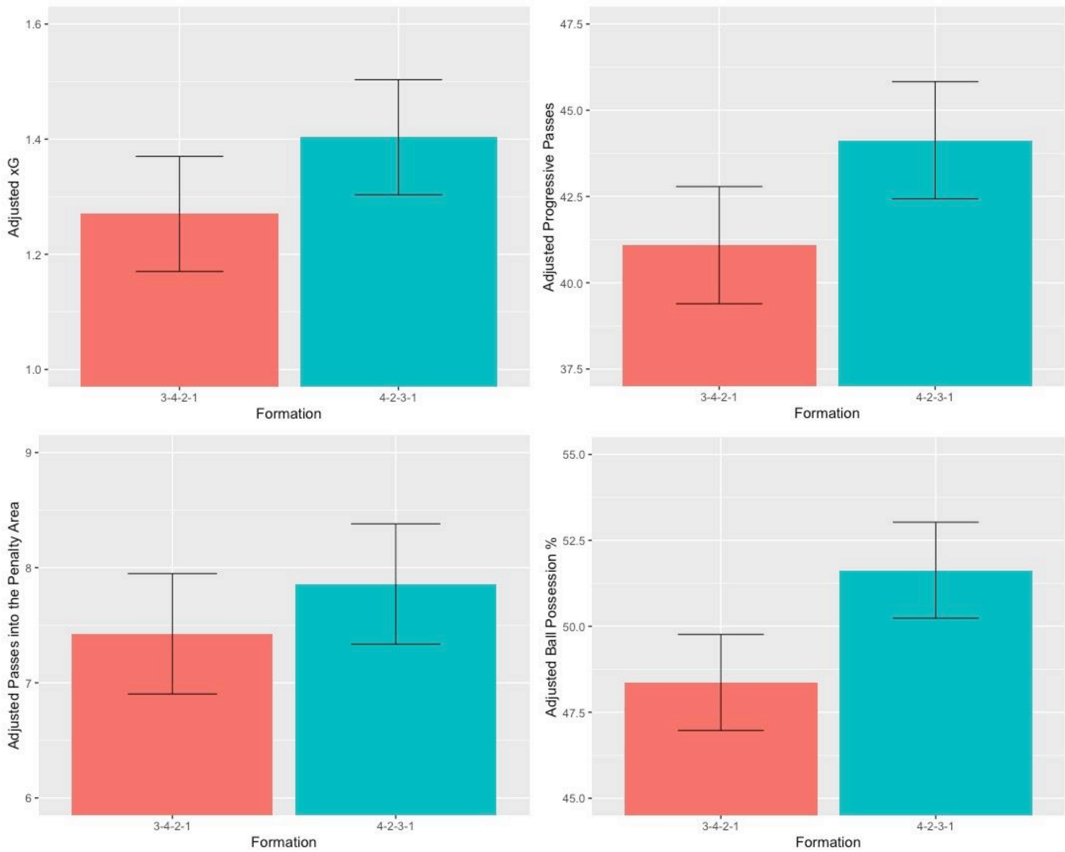

Figure 44 - 4-2-3-1 vs 3-4-2-1 adjusted outcome metrics and error bars.

4-2-3-1 vs 3-3-3-1

xG:

- Violation of Pearson's product-moment correlation: $p = 0.26$
- Violation of Shapiro Wilk test: $p = 0.0052$
- ANCOVA: $F(1, 37) = 0.222$, $p = 0.64$

Progressive Passes:

- Violation of Pearson's product-moment correlation: $p = 0.26$
- ANCOVA: $F(1, 37) = 1.691$, $p = 0.20$

Passes into the Penalty Area:

- ANCOVA: $F(1, 37) = 0.024$, $p = 0.88$

Ball Possession %:

- Violation of Pearson's product-moment correlation: $p = 0.91$
- ANCOVA: $F(1, 37) = 0.006$, $p = 0.94$

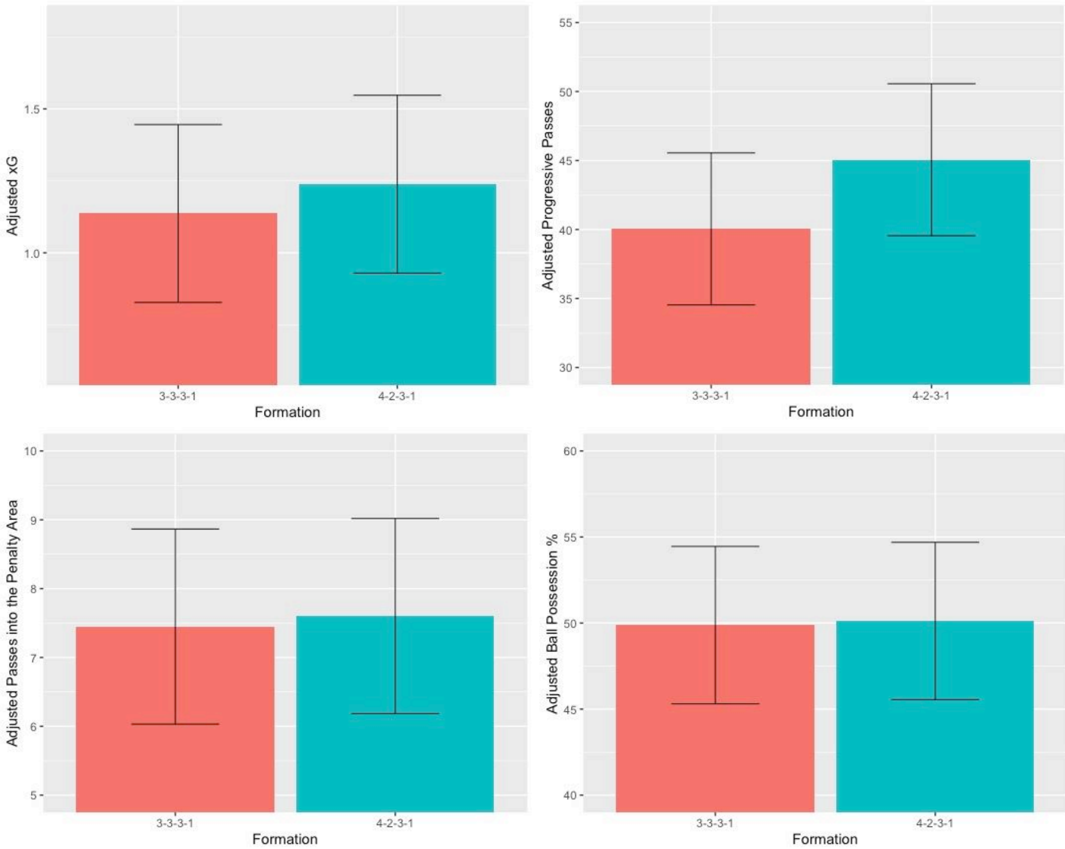

Figure 45 - 4-2-3-1 vs 3-3-3-1 adjusted outcome metrics and error bars.

4-3-1-2 vs 4-2-2-2

xG:

- Violation of Shapiro Wilk test: $p = 0.0052$
- Violation of Levene's test: $p = 0.021$
- ANCOVA: $F(1, 103) = 2.800$, $p = 0.097$

Progressive Passes:

- ANCOVA: $F(1, 103) = 2.176$, $p = 0.14$

Passes into the Penalty Area:

- Violation of Levene's test: $p = 0.035$
- ANCOVA: $F(1, 103) = 1.095$, $p = 0.30$

Ball Possession %:

- ANCOVA: $F(1, 103) = 8.503$, $p = 0.004$

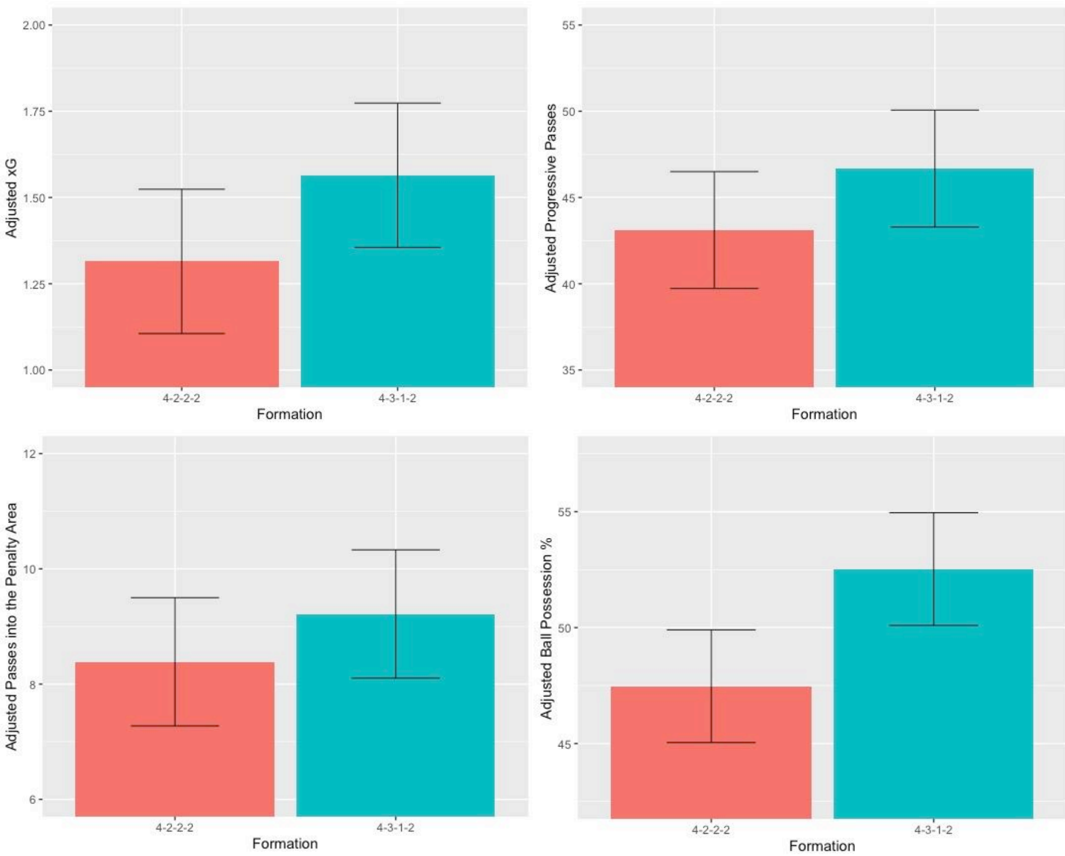

Figure 46 - 4-3-1-2 vs 4-2-2-2 adjusted outcome metrics and error bars.

4-3-1-2 vs 3-4-1-2

xG:

- ANCOVA: $F(1, 85) = 0.127$, $p = 0.72$

Progressive Passes:

- Violation of Homogeneity of Regression Slopes: $F(1, 84) = 8.505$, $p = 0.005$
- ANCOVA: $F(1, 85) = 4.196$, $p = 0.044$

Passes into the Penalty Area:

- Violation of Homogeneity of Regression Slopes: $F(1, 84) = 6.205$, $p = 0.015$
- Violation of Shapiro Wilk test: $p = 0.0026$
- Violation of Levene's test: $p = 0.035$
- ANCOVA: $F(1, 85) = 0.000674$, $p = 0.98$

Ball Possession %:

- ANCOVA: $F(1, 85) = 0.036$, $p = 0.85$

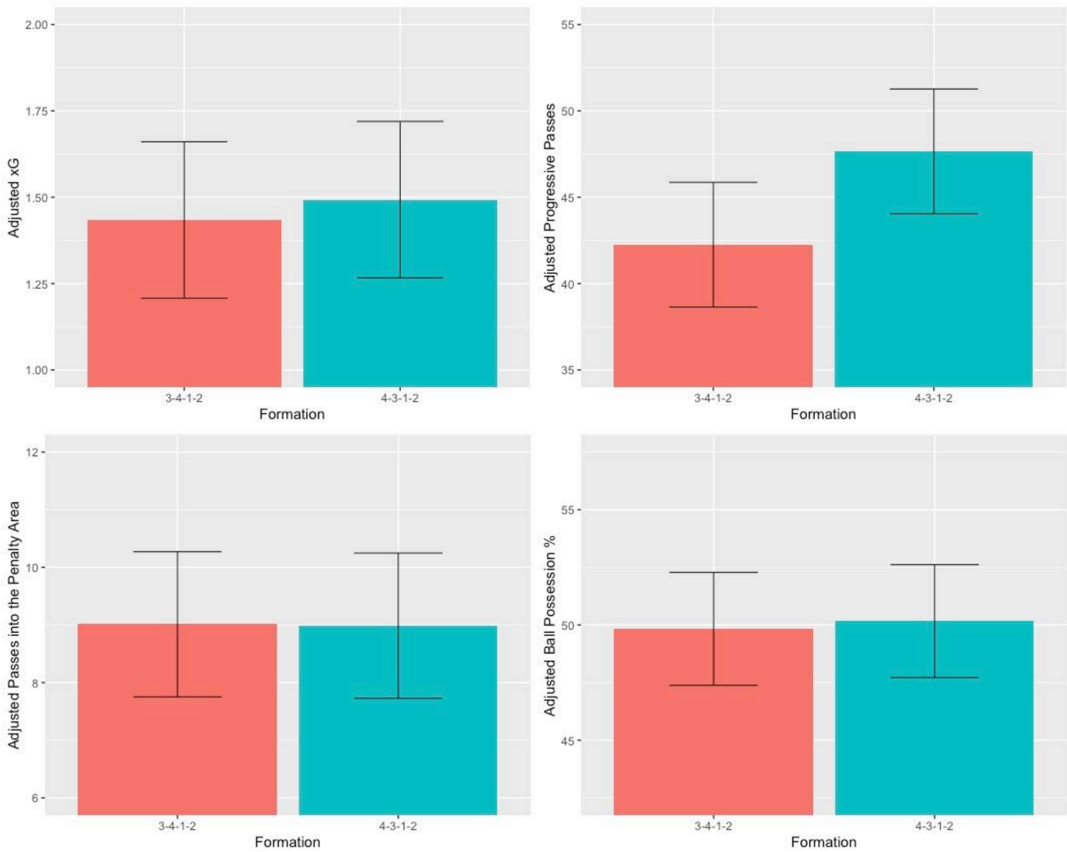

Figure 47 - 4-3-1-2 vs 3-4-1-2 adjusted outcome metrics and error bars.

4-3-1-2 vs 3-1-4-2

xG:

- Violation of Homogeneity of Regression Slopes: $F(1, 176) = 4.486$, $p = 0.036$
- Violation of Shapiro Wilk test: $p = 0.0026$
- ANCOVA: $F(1, 177) = 0.099$, $p = 0.75$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.009$
- ANCOVA: $F(1, 177) = 4.966$, $p = 0.027$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p <0.0001$
- Violation of Levene's test: $p = 0.035$
- ANCOVA: $F(1, 177) = 1.160$, $p = 0.28$

Ball Possession %:

- ANCOVA: $F(1, 177) = 34.989$, $p <0.0001$

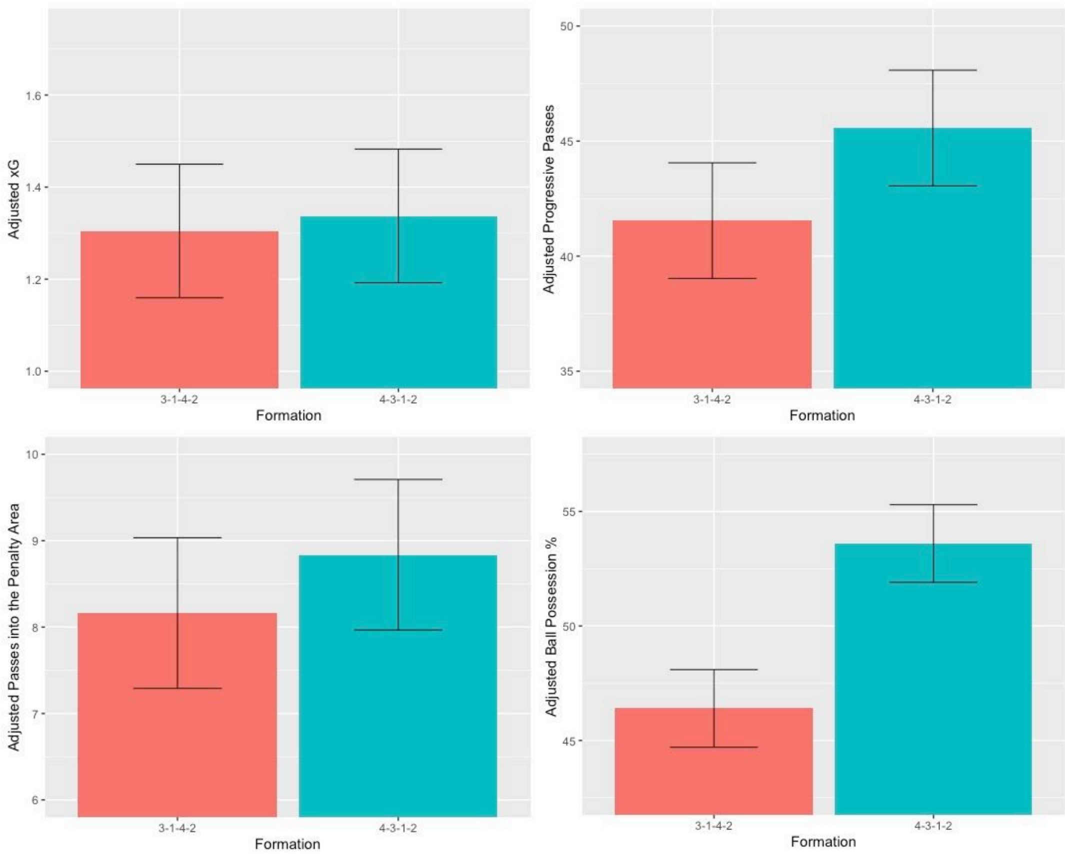

Figure 48 - 4-3-1-2 vs 3-1-4-2 adjusted outcome metrics and error bars.

4-3-1-2 vs 3-4-2-1

xG:

- Violation of Shapiro Wilk test: $p = 0.0067$
- ANCOVA: $F(1, 83) = 0.876$, $p = 0.35$

Progressive Passes:

- ANCOVA: $F(1, 83) = 0.047$, $p = 0.83$

Passes into the Penalty Area:

- ANCOVA: $F(1, 83) = 0.932$, $p = 0.34$

Ball Possession %:

- ANCOVA: $F(1, 83) = 1.575$, $p = 0.21$

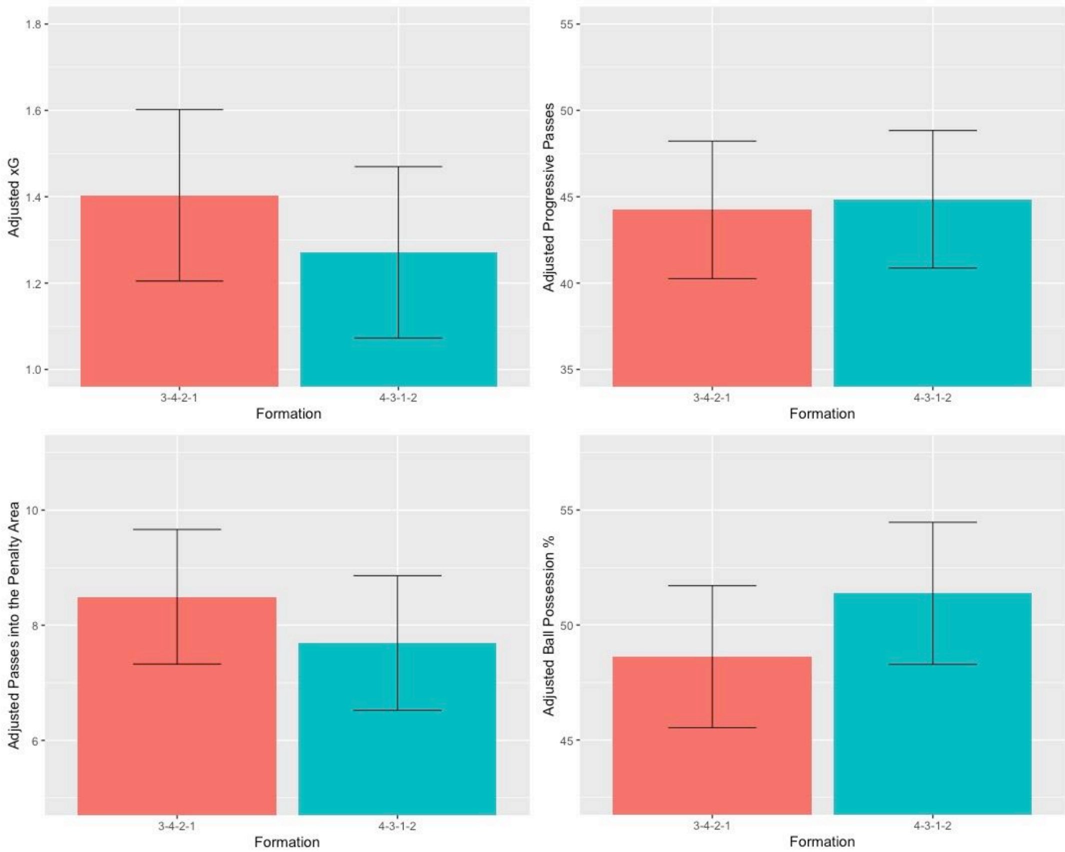

Figure 49 - 4-3-1-2 vs 3-4-2-1 adjusted outcome metrics and error bars.

4-3-1-2 vs 3-3-3-1

xG:

- Violation of Shapiro Wilk test: p = 0.045
- ANCOVA: F(1, 25) = 0.415, p = 0.53

Progressive Passes:

- Violation of Pearson's product-moment correlation: p = 0.80
- ANCOVA: F(1, 25) = 7.509, p = 0.011

Passes into the Penalty Area:

- Violation of Pearson's product-moment correlation: p = 0.45
- ANCOVA: F(1, 25) = 0.000149, p = 0.99

Ball Possession %:

- Violation of Pearson's product-moment correlation: p = 0.31
- ANCOVA: F(1, 25) = 30.727, p <0.0001

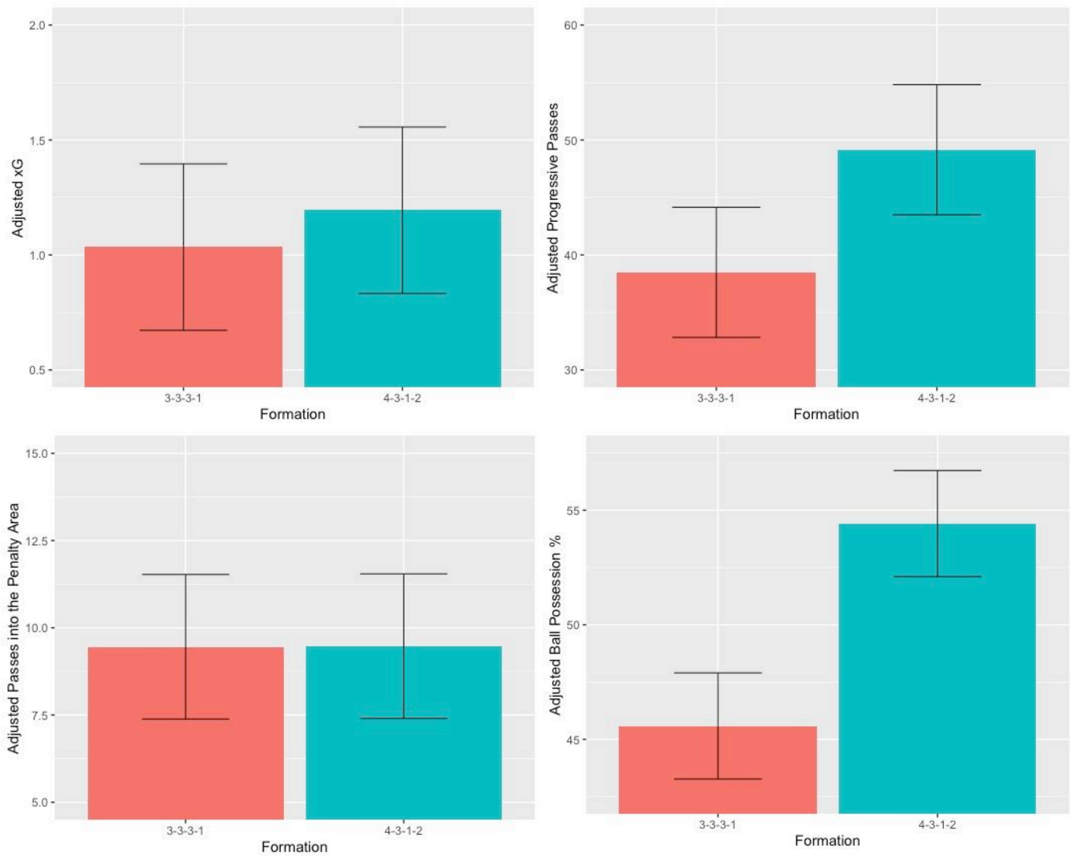

Figure 50 - 4-3-1-2 vs 3-3-3-1 adjusted outcome metrics and error bars.

4-2-2-2 vs 3-4-1-2

xG:

- Violation of Pearson's product-moment correlation: $p = 0.14$
- Violation of Shapiro Wilk test: $p = 0.034$
- ANCOVA: $F(1, 79) = 0.185$, $p = 0.67$

Progressive Passes:

- ANCOVA: $F(1, 79) = 0.526$, $p = 0.47$

Passes into the Penalty Area:

- ANCOVA: $F(1, 79) = 1.522$, $p = 0.22$

Ball Possession %:

- ANCOVA: $F(1, 79) = 13.599$, $p = 0.00041$

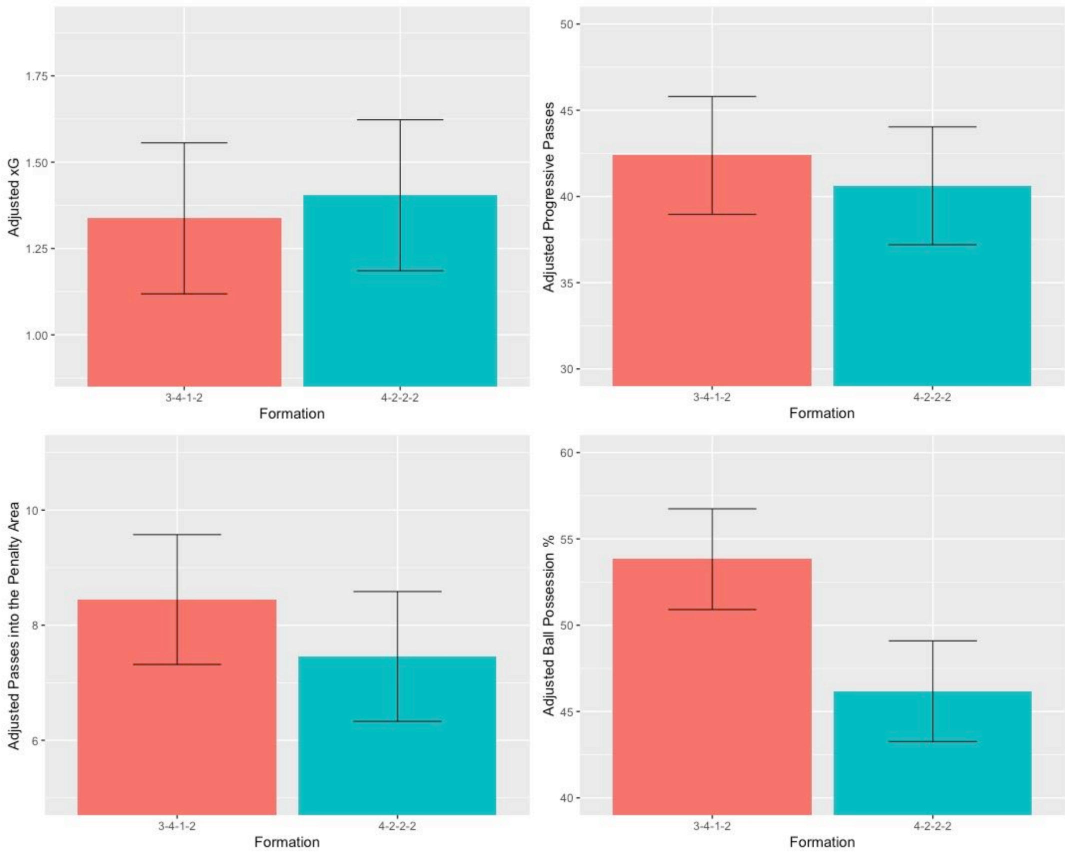

Figure 51 - 4-2-2-2 vs 3-4-1-2 adjusted outcome metrics and error bars.

4-2-2-2 vs 3-1-4-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 297) = 2.521$, $p = 0.11$

Progressive Passes:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 297) = 0.040$, $p = 0.84$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 297) = 0.013$, $p = 0.91$

Ball Possession %:

- ANCOVA: $F(1, 297) = 3.406$, $p = 0.066$

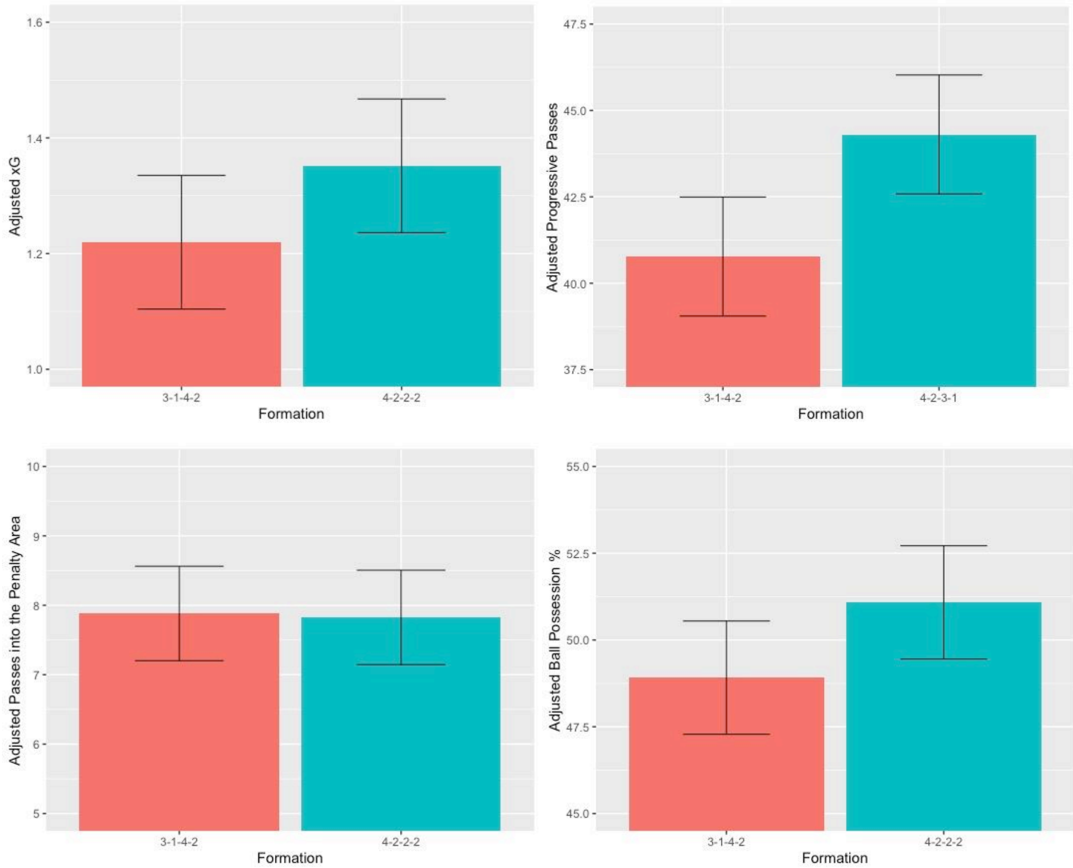

Figure 52 - 4-2-2-2 vs 3-1-4-2 adjusted outcome metrics and error bars.

4-2-2-2 vs 3-4-2-1

xG:

- Violation of Homogeneity of Regression Slopes: $F(1, 386) = 10.376$, $p = 0.001$
- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 387) = 8.699$, $p = 0.003$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.019$
- ANCOVA: $F(1, 387) = 2.404$, $p = 0.12$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 387) = 0.169$, $p = 0.68$

Ball Possession %:

- ANCOVA: $F(1, 387) = 3.116$, $p = 0.078$

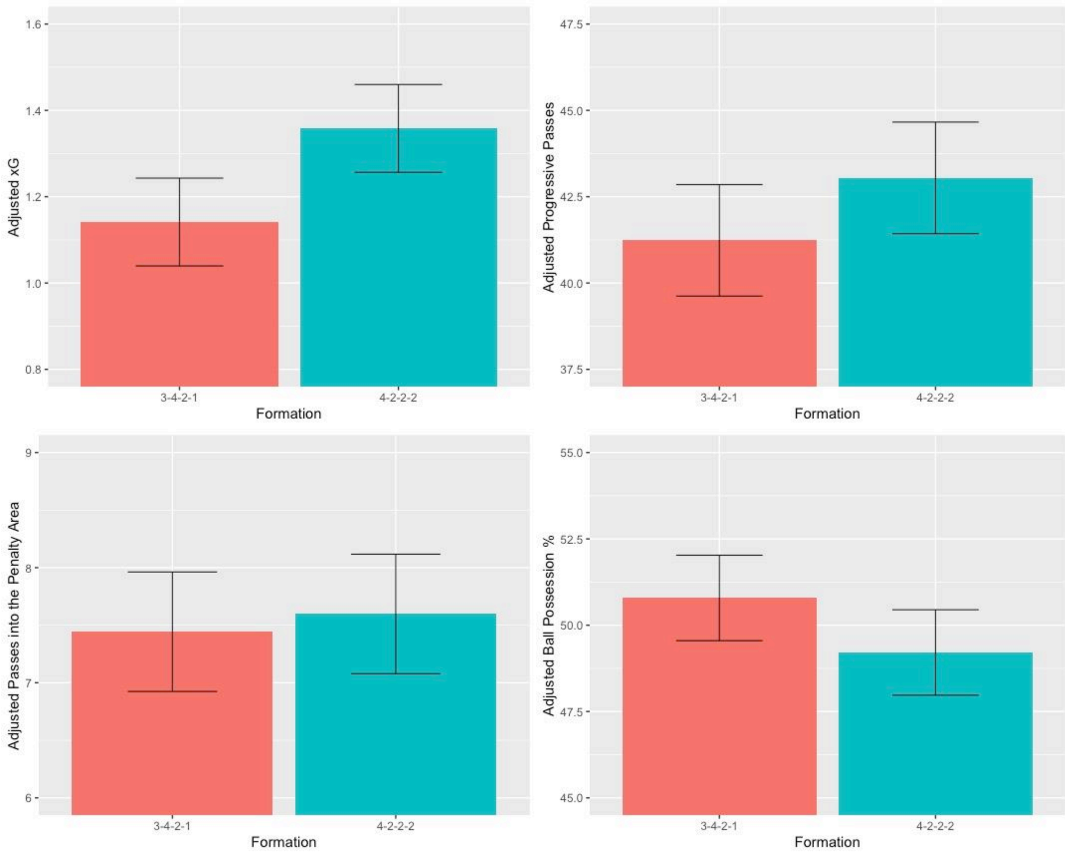

Figure 53 - 4-2-2-2 vs 3-4-2-1 adjusted outcome metrics and error bars.

<u>4-2-2-2 vs 3-3-3-1</u>

xG:

- ANCOVA: $F(1, 23) = 8.311$, $p = 0.008$

Progressive Passes:

- ANCOVA: $F(1, 23) = 7.418$, $p = 0.012$

Passes into the Penalty Area:

- ANCOVA: $F(1, 23) = 3.048$, $p = 0.094$

Ball Possession %:

- ANCOVA: $F(1, 23) = 8.461$, $p = 0.008$

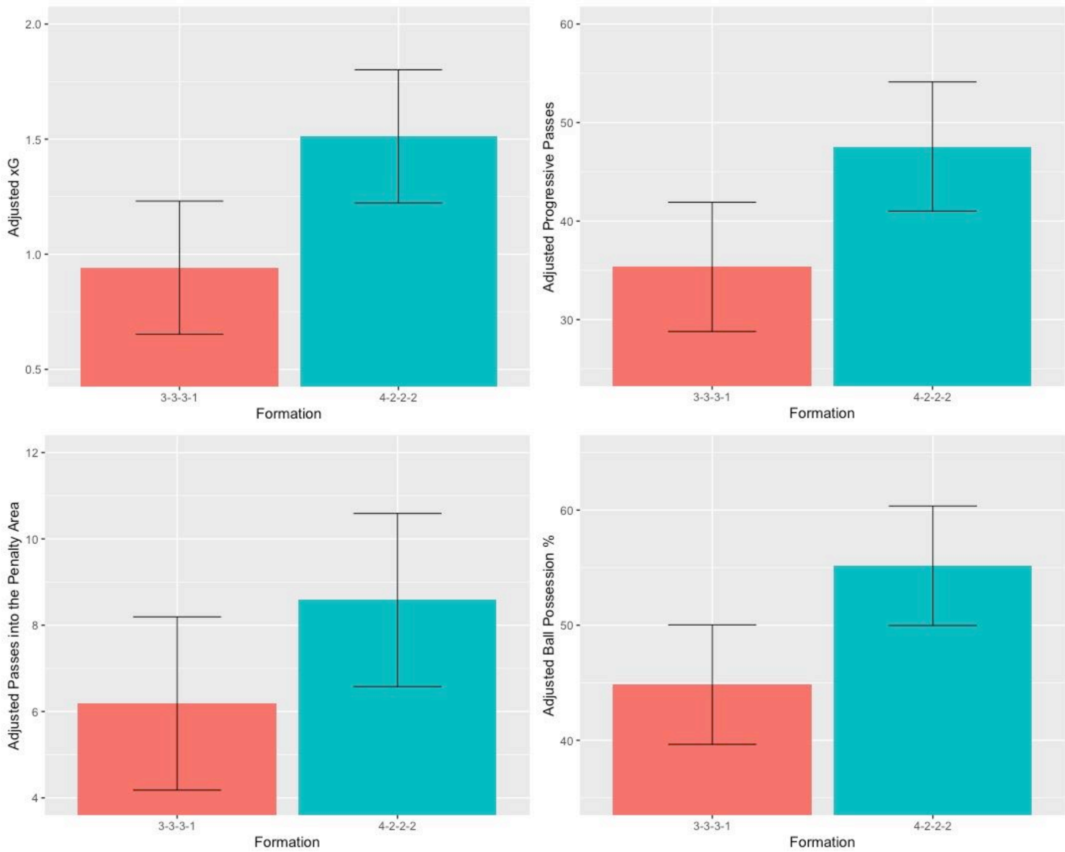

Figure 54 - 4-2-2-2 vs 3-3-3-1 adjusted outcome metrics and error bars.

3-4-1-2 vs 3-1-4-2

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 181) = 1.683$, $p = 0.20$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.019$
- ANCOVA: $F(1, 181) = 2.449$, $p = 0.12$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 181) = 1.673$, $p = 0.20$

Ball Possession %:

- Violation of Shapiro Wilk test: $p = 0.034$
- ANCOVA: $F(1, 181) = 3.480$, $p = 0.064$

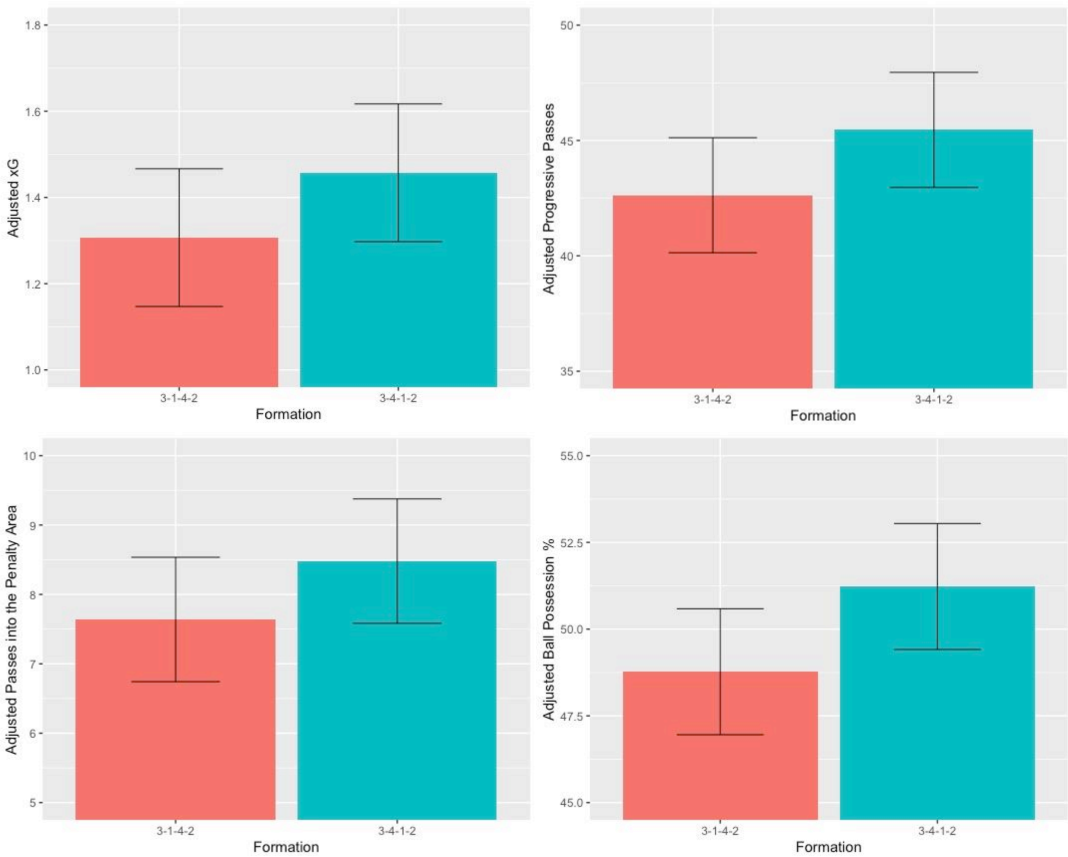

Figure 55 - 3-4-1-2 vs 3-1-4-2 adjusted outcome metrics and error bars.

3-4-1-2 vs 3-4-2-1

xG:

- Violation of Shapiro Wilk test: $p < 0.0001$
- ANCOVA: $F(1, 111) = 1.028$, $p = 0.31$

Progressive Passes:

- ANCOVA: $F(1, 111) = 3.381$, $p = 0.069$

Passes into the Penalty Area:

- ANCOVA: $F(1, 111) = 3.567$, $p = 0.062$

Ball Possession %:

- ANCOVA: $F(1, 111) = 0.009$, $p = 0.92$

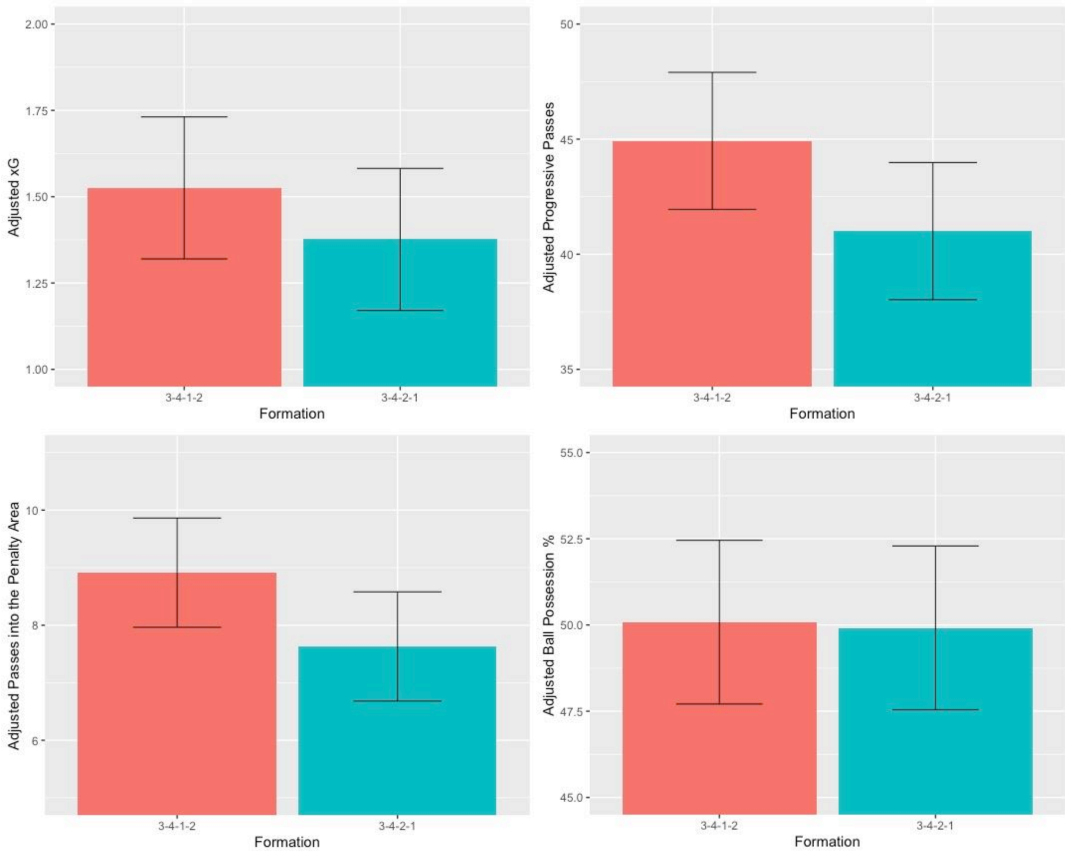

Figure 56 - 3-4-1-2 vs 3-4-2-1 adjusted outcome metrics and error bars.

3-4-1-2 vs 3-3-3-1

xG:

- Violation of Pearson's product-moment correlation: $p = 0.30$
- ANCOVA: $F(1, 9) = 0.14$, $p = 0.72$

Progressive Passes:

- Violation of Pearson's product-moment correlation: $p = 0.46$
- Violation of Shapiro Wilk test: $p = 0.03$
- ANCOVA: $F(1, 9) = 6.453$, $p = 0.032$

Passes into the Penalty Area:

- Violation of Pearson's product-moment correlation: $p = 0.46$
- ANCOVA: $F(1, 9) = 12.038$, $p = 0.007$

Ball Possession %:

- Violation of Pearson's product-moment correlation: $p = 0.10$
- Violation of Homogeneity of Regression Slopes: $F(1, 8) = 7.609$, $p = 0.025$
- ANCOVA: $F(1, 9) = 6.416$, $p = 0.032$

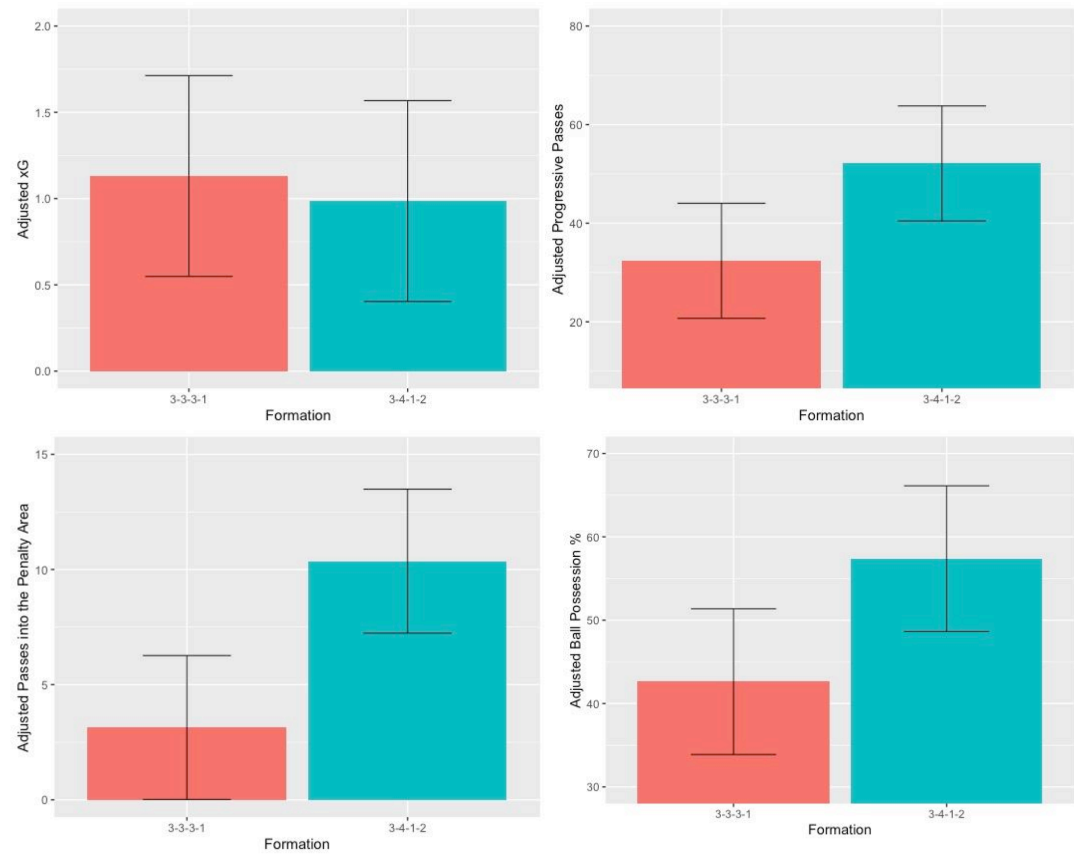

Figure 57 - 3-4-1-2 vs 3-3-3-1 adjusted outcome metrics and error bars.

3-1-4-2 vs 3-4-2-1

xG:

- Violation of Shapiro Wilk test: $p = 0.00031$
- ANCOVA: $F(1, 267) = 0.957$, $p = 0.33$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.012$
- ANCOVA: $F(1, 267) = 0.515$, $p = 0.47$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p <0.0001$
- ANCOVA: $F(1, 267) = 0.117$, $p = 0.73$

Ball Possession %:

- ANCOVA: $F(1, 267) = 4.214$, $p = 0.041$

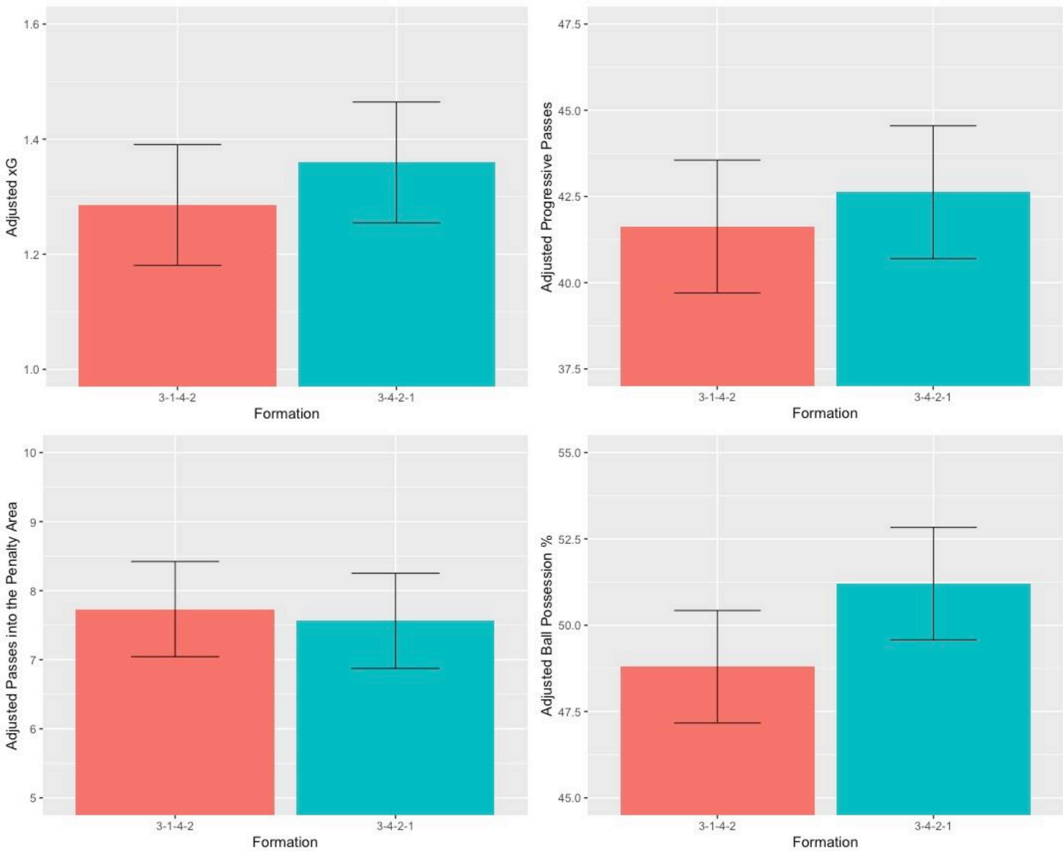

Figure 58 - 3-1-4-2 vs 3-4-2-1 adjusted outcome metrics and error bars.

3-1-4-2 vs 3-3-3-1

xG:

- Violation of Pearson's product-moment correlation: $p = 0.071$
- ANCOVA: $F(1, 45) = 2.072$, $p = 0.16$

Progressive Passes:

- ANCOVA: $F(1, 45) = 10.142$, $p = 0.003$

Passes into the Penalty Area:

- Violation of Pearson's product-moment correlation: $p = 0.050$
- ANCOVA: $F(1, 45) = 4.407$, $p = 0.041$

Ball Possession %:

- ANCOVA: $F(1, 45) = 12.355$, $p = 0.001$

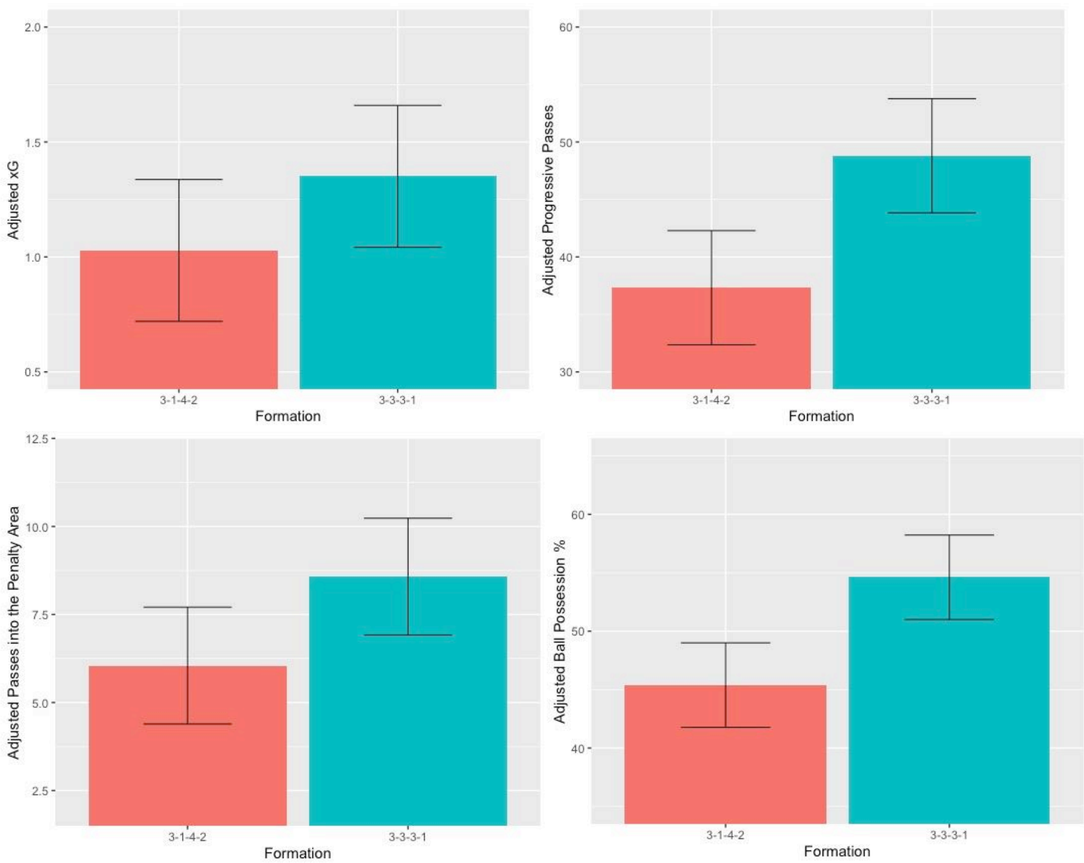

Figure 59 - 3-1-4-2 vs 3-3-3-1 adjusted outcome metrics and error bars.

3-4-2-1 vs 3-3-3-1

xG:

- ANCOVA: $F(1, 51) = 0.427$, $p = 0.52$

Progressive Passes:

- Violation of Shapiro Wilk test: $p = 0.013$
- ANCOVA: $F(1, 51) = 0.395$, $p = 0.53$

Passes into the Penalty Area:

- Violation of Shapiro Wilk test: $p = 0.00035$
- ANCOVA: $F(1, 51) = 0.121$, $p = 0.73$

Ball Possession %:

- ANCOVA: $F(1, 51) = 1.665$, $p = 0.20$

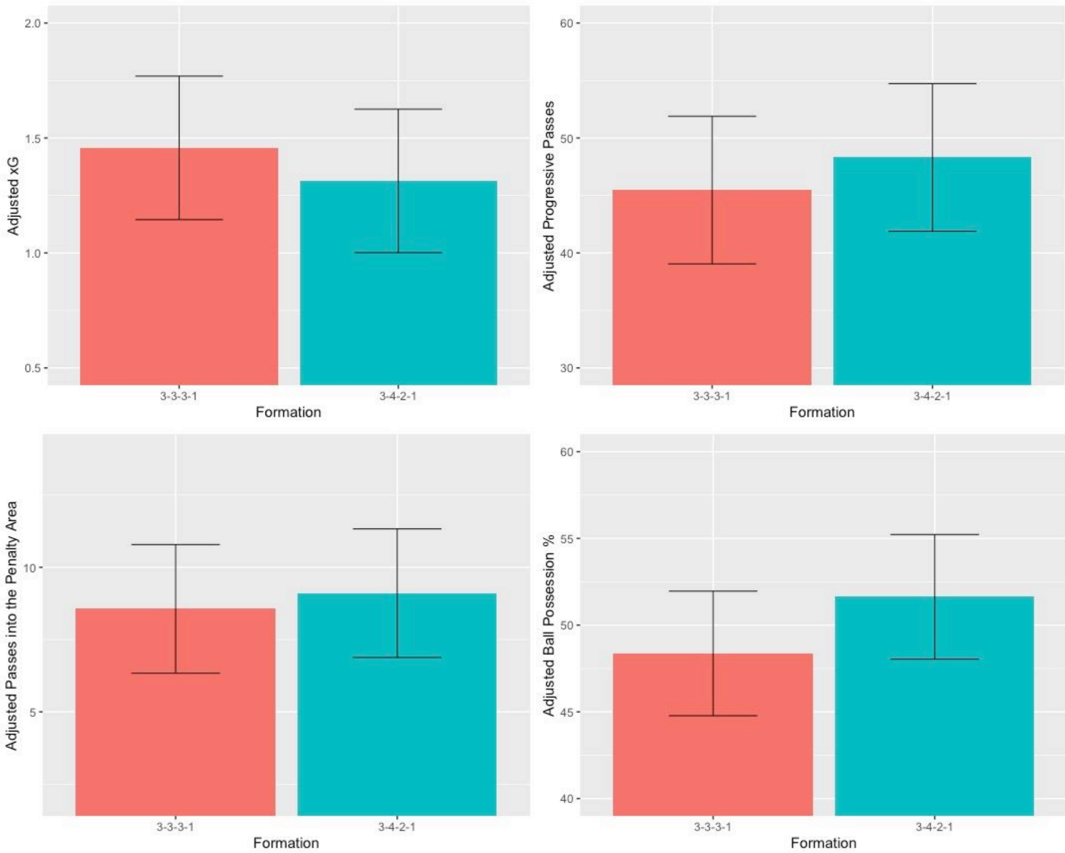

Figure 60 - 3-4-2-1 vs 3-3-3-1 adjusted outcome metrics and error bars.

Sample R code

```
df4312h <- subset(Dataset, Dataset$`Formation Home` == '4-3-1-2' &
              Dataset$`Formation Away` == '4-1-4-1', select =
              c("Formation Home","xG(Home)","Poss Home","PP(Home)",
                "PPA(Home)","TQH"))

df4141a <- subset(Dataset, Dataset$`Formation Home` == '4-3-1-2' &
              Dataset$`Formation Away` == '4-1-4-1', select =
              c("Formation Away","xG(Away)","Poss Away","PP(Away)",
                "PPA(Away)","TQA"))

df4141h <- subset(Dataset, Dataset$`Formation Home` == '4-1-4-1' &
              Dataset$`Formation Away` == '4-3-1-2', select =
              c("Formation Home","xG(Home)","Poss Home","PP(Home)",
                "PPA(Home)","TQH"))

df4312a <- subset(Dataset, Dataset$`Formation Home` == '4-1-4-1' &
              Dataset$`Formation Away` == '4-3-1-2', select =
              c("Formation Away","xG(Away)","Poss Away","PP(Away)",
                "PPA(Away)","TQA"))


names(df4312h) <- c("Formation","xG","Possession","PP","PPA","TQ")
names(df4312a) <- c("Formation","xG","Possession","PP","PPA","TQ")
names(df4141h) <- c("Formation","xG","Possession","PP","PPA","TQ")
names(df4141a) <- c("Formation","xG","Possession","PP","PPA","TQ")


df4312v4141 <- data.frame(rbind(df4312h,df4312a,df4141h,df4141a))
```

```
## Assumption: Linearity between the covariate and outcome variable for each
Formation

library(ggpubr)

ggscatter(df4312v4141, x = "TQ", y = "xG",
        color = "Formation", add = "reg.line")+
  stat_regline_equation(aes(label =
                          paste(..eq.label.., ..rr.label.., sep = "~~~~"),
                        color = Formation))
cor.test( ~ TQ + xG, data=df4312v4141, method = "pearson")

## Assumption: Homogeneity of Regression Slopes (No Cov:Group) interaction
df4312v4141 %>% anova_test(xG ~ Formation*TQ)

## Assumption: Normality of Residuals
library(broom)
# Fit the model, the covariate goes first
modelxG <- lm(xG ~ TQ + Formation, data = df4312v4141)
# Inspect the model diagnostic metrics
model.metricsxG <- augment(modelxG)
head(model.metricsxG, 3)

# Assess normality of residuals using shapiro wilk test
shapiro_test(model.metricsxG$.resid)

## Assumption: Homogeneity of Variances
model.metricsxG %>% levene_test(.resid ~ Formation)
```

```
## Computation
res.aovxG <- df4312v4141 %>% anova_test(xG ~ TQ + Formation)
get_anova_table(res.aovxG)

## Post-hoc
library(emmeans)
PostHocxG <- df4312v4141 %>%
  emmeans_test(xG ~ Formation, covariate = TQ,p.adjust.method = "bonferroni")
PostHocxG
# Display the adjusted means of each group
# Also called as the estimated marginal means (emmeans)
get_emmeans(PostHocxG)

## Visualization: bar plots with p-values

barchart <- ggplot(get_emmeans(PostHocxG)) +
  geom_bar(aes(Formation, emmean, fill = Formation), stat = "identity") +
  ylab("Adjusted xG") +
  geom_errorbar(aes(x=Formation, ymin=conf.low, ymax=conf.high),
              width=0.4, alpha=0.9, size=0.4)

barchart + coord_cartesian(ylim = c(1.1,1.7)) + theme(legend.position = "none")
```

Curriculum Vitae

Candidate's full name: Alex Dodgshon

Universities attended: University of St Andrews, 2013-2018, Master of Chemistry

Publications: *"Probability Analysis of Sports Contests"*- Essentials of Performance Analysis 3rd Ed