THE ROAD TO VICTORY IN THE UEFA WOMEN'S CHAMPIONS LEAGUE:

PROFILE OF SUCCESSFUL COACHES, TEAMS, AND COUNTRIES

EDSON FILHO

FINAL REPORT

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ABSTRACT

To advance scholarly understanding of the expert mechanisms underpinning top performance in women's football, a census-like study of the past five seasons (2011-12 to 2015-16) of the UEFA Women's Champions League was conducted. Official data records were provided by UEFA and supplementary data was gathered from FIFA.com and other reliable sporting websites. Descriptive analysis was used to profile the characteristics of coaches, teams, and countries participating in the UEFA Women's Champions League. Furthermore, exploratory hierarchical linear modeling was used to predict performance in the UEFA Women's Champions League. Specifically, coaches' characteristics (level-1 variables; e.g., sport experience), team factors (level-2 variables; e.g., number of international players on roster), and country information (level-3 variables; e.g., budget for women's football) were tested as predictors of performance (final rank, ranging from 1 to 32) in the UEFA Women's Champions League. The descriptive analysis revealed that coaches are mostly males in their early forties. Hence, extensive experience is likely needed before an individual becomes a head coach of an elite women's professional team in Europe. Moreover, it is paramount to discuss gender rights policies to promote an increase in the number of female coaches in women's high-performance football. Descriptive analysis also indicated that former midfielders were more likely to be coaches at the UEFA Women's Champions League than players from other positions. Former midfielders might have a better understanding of the game in both its defensive and offensive requirements. At the team-level, descriptive statistics revealed that the majority of international players in the UEFA Women's Champions League come from North America, particularly the United States. Wide variability in country-level factors was observed, likely because the member countries of UEFA differ greatly in size, economic power, culture, and football organization. The hierarchical linear modeling yielded a two- and three-level solution. The two-level solution was deemed more realistic and applied, and thereby was chosen as the omnibus final model. Within the two-level solution, *Years coaching experience in Champions League* at level-1 (γ_{10} = -2.90), and *Number of times team has won Champions League* (γ_{01} = -7.13) as well as *Number of international players on roster* (γ_{02} = -1.08) at level-2, predict final performance at the UEFA Women's Champions League (i.e., a negative coefficient is indicative of a performance improvement). Accordingly, hiring coaches with previous experience in the competition increases the chance of winning the title. Furthermore, hiring players from traditionally successful teams as well as international players will likely increase the chance of victory. Former winners and international players bring the experience and confidence that propels performance in high-stake competitions. Overall, these findings suggest that the quality of the team, positive cross-cultural effects from an international roster, and the experience of the coach are paramount for success in the UEFA Women's Champions League. Further applied implications, the strengths and limitations of the study, as well as avenues for future research are discussed throughout.

LITERATURE REVIEW

It is important to examine the profile of successful coaches as previous research has suggested that coach behaviors influence team outcomes across domains of human performance (Côté & Gilbert, 2009; Gershgoren, Filho, Tenenbaum, & Schinke, 2013). It is also imperative to consider the role of team factors, as in-group characteristics (e.g., number of national team players; number of international players) have been shown to influence performance in sports (Filho, Gershgoren, Basevitch, & Tenenbaum, 2014c). Given the paucity of research on the unique mechanisms of expert performance in women's football, this study aimed to comprehensively and systematically examine what factors differentiate successful coaches and teams from unsuccessful coaches and teams in the UEFA Women's Champions League, while controlling for country-level factors.

Characteristics of Successful Coaches

The role of coaches in sport is multifaceted. First, there is general agreement that coaches act as role models, influencing how players think, feel, and act (i.e., the cognitive-affective-behavioral link; see Hanin, 2007; Tenenbaum, Basevitch, Gershgoren, & Filho, 2013). Coaches also model key pro-active social behaviors that are positively associated with learning, performance, and resilience in sports (Frick & Simmons, 2008). Second, coaches are responsible for developing positive group dynamics by fostering cohesion, shared mental models, and a collective sense of confidence (Filho, Tenenbaum, & Yang, 2014d). Third, coaches are in charge of designing training sessions that develop athletes' technical, tactical, and mental skills (Becker, 2009).

To this extent, Bandura's social learning theory (1997) has generated numerous studies on how coaching actions influence performance outcomes by instilling achievement motivation beliefs and behaviors, and developing myriad social skills in applied contexts, including organizational skills in sport settings. With respect to the former, there is extant evidence suggesting that athletes live up to their coaches' expectations across domains of human performance, including sports (see Solomon et al., 1996). Overall, Bandura's social learning theory reflects the notion that coaches model positive behaviors, which in turn influence the development of athletes' confidence and psychological well-being (for a review see Bandura, 1997; Eklund & Tenenbaum, 2014).

Furthermore, coaches are essential in developing group processes, including cohesion, shared mental models, and collective efficacy beliefs. These three factors are inter-related group processes that influence team performance in sports. Cohesion is the tendency of a group to remain united in the pursuit of social goals or instrumental objectives (see Filho, Dobersek, Gershgoren, Becker, & Tenenbaum, 2014a). Cohesion influences the development of shared mental models, which consists of shared knowledge on team tasks, strategies, and teammates' traits (Eccles & Tenenbaum, 2007). In turn, shared knowledge leads to the development of collective efficacy beliefs (Filho, Gershgoren, Basevitch, Schinke, & Tenenbaum, 2014b). Altogether, successful performance in team sports depends in part on how well coaches are able to develop cohesion, shared mental models, and collective efficacy within their team.

In addition to modeling successful behaviors and promoting the development of team processes, coaches are also fundamental in organizing training and competition in such a way that promotes rather than hinders talent development in sports. To this extent, Côté and his colleagues (1995) proposed that expert performance development in sports depends primarily on the interaction of coach-level characteristics (e.g., demographics, sport experience), team-level characteristics (e.g., size of team, hours of practice per week), and contextual characteristics (e.g., training resources) (Figure 1). Coach-level characteristics consider any variable related to the coach that may influence the team, positively or negatively. Team-level characteristics include aspects of the team, such as personal abilities, that may affect the coaching process. Contextual characteristics involve factors outside the athletes and coach, such as playing conditions, which could affect the coaching process. Coaches ultimately integrate these three components in order to maximize the development of athletes and the performance of the team as a whole. Overall, the Coaching Model provides a conceptual framework on which to assess the factors that are most significant in the coaching process.

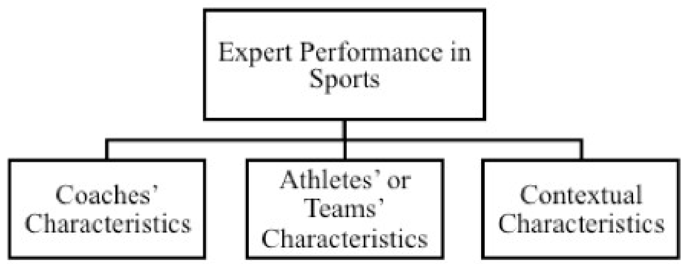


Figure 1. *The Coaching Model.* Adapted from Côté et al., 1995, p. 10.

Expert coaching in sports. Extant research indicates that expert coaches have previous athletic experience, participate in formal and informal educational programs, and have extensive coaching experience, which collectively allow them to perform at the highest level (Starkes & Ericsson, 2003).

The role of previous playing experience in general, and elite-level athletic involvement in particular, has been examined in relation to expert coaching in sport. Nash and Sproule (2009) asked nine expert coaches from different sports (i.e., football, hockey, and swimming) in the United Kingdom how they had learned to become an expert coach. The coaches all reported being introduced to sport at an early age and the majority reached an elite level as athletes. Similarly, Cregan, Bloom, and Reid (2007) interviewed male coaches of elite swimmers with a physical disability and found they were all successful athletes, including one who was a world-ranked Paralympian swimmer. In another study, Gilbert, Côté, & Mallett (2006) found that successful coaches (e.g., softball, American football, and volleyball), many of who competed at the highest level of their sport, viewed themselves as having been "above average" athletes during their playing careers. Likewise, many successful basketball and cross-country coaches rated themselves as "better than average" athletes during their competitive career (Gilbert, Lichtenwaldt, Gilbert, Zelezny, & Côté, 2009). Schinke, Bloom, and Salmela (1995) looked at athletic experience in the evolution of national or international elite Canadian basketball coaches. The coaches noted that competing in elite sport was an important factor in their coaching development. Altogether, research examining the developmental pathways of expert coaches has highlighted the importance of previous playing experience.

Formal education, such as coaching courses and degrees in a sport-related domain (e.g., Exercise Physiology, Physical Education, Sport Biomechanics, Sport Psychology), as well as informal education opportunities, such as mentorship programs and networking with other coaches, are important elements of successful coaches. Structured interviews with high-performance Canadian coaches, across a range of team and individual sports, revealed the importance of participation in formal coaching education courses (Erickson, Côté, & Fraser-Thomas, 2007). Carter and Bloom (2009) conducted interviews with male Canadian University coaches in basketball, volleyball, and ice hockey. Despite never competing competitively beyond high school, the coaches noted that studying Physical Education or Kinesiology and learning from other coaches all contributed to their development as elite coaches. Similarly, Anderson and Gill (1983) found that many expert coaches acquired their initial coaching knowledge while enrolled in an undergraduate Physical Education degree. Noteworthy, the importance of coaching courses and sport-related degrees on coaching expertise is increasingly apparent around the world. Most major football associations (i.e., English Football Association, United States Soccer Federation) offer coaching education courses, and certifications are often required to coach at different levels. Furthermore, unique coaching-specific undergraduate degree programs are becoming available. For example, within the United Kingdom, there are several universities that currently offer football-related undergraduate degrees. While formal and informal education appears to play a role in coach expertise, prior coaching experience is also a critical component of coach development.

Coaching experience, ranging from serving as a head coach of a youth team to an assistant coach at the university level, plays an important role in coaching development and expertise (Cregan et al., 2007; Schinke et al., 1995). In interviews with United States National team, Pan American, and Olympic coaches, coaching experience at the national and international level was the most frequently cited variable in preparation to become an elite coach (Gould, Giannini, Krane, & Hodge, 1990; Gould, Hodge, Peterson, & Giannini, 1989). Expert Canadian basketball coaches outlined several developmental stages that led to their current position, including novice coaching, developmental coaching, national elite coaching, and international elite coaching (Schinke et al., 1995). Despite commonalities across disciplines, expertise in coaching should also depend on sport modality. The focus of the present study was on uncovering factors linked to expert coaching in football.

Expert coaching in football. Within the sport literature, only a few studies have examined characteristics of expert coaches in football. Of these studies, several have involved qualitative examinations of coaching behaviors (e.g., instruction, modeling, praise) used by men's coaches in professional English football during practice sessions. Potrac and his colleagues (2002) examined the pedagogical strategies used by an expert football coach in the practice environment. The coach, who had achieved the highest level of coaching certification from the English Football Association and competed professionally in the sport, was found to rely heavily on pre-instruction (providing initial information to a player prior to a desired action being executed), concurrent instruction (delivering cues or reminders during the execution of a skill), and post-instruction (offering correction or instructional feedback after the execution of a skill). The emphasis on instruction was related to the coach's desire to clearly identify the role of each player in order to maximize the likelihood of a positive outcome for the team. The coach also noted that his primary role as an expert coach was to develop successful teams. A similar study, conducted by Potrac, Jones, and Cushion (2007), examined the coaching behaviors of head coaches of professional English football clubs over the course of a season. Each coach was observed in the practice environment three times during the early, middle, and late part of the season. Over half of the recorded behaviors related to instruction, specifically concurrent and post-instruction feedback. The heavy reliance on instruction suggests that coaches believe it to be an effective means to elicit the desired performance from players and the team as a whole. Coaches were also considerably more likely to engage in praise than scold. In addition to coaching behaviors, the stability of a coach within an organization also has the potential to positively or negatively impact performance. The present study advances research on expert coaching in football by relying on a quantitative predictive model of coaches' characteristics and performance, rather than on a descriptive qualitative approach.

Quantifying coaching factors may help to advance knowledge on the linkage between coaching turnover and performance in football. Given the important role that coaches play, it could be expected that long-term coaches establish a rapport with players and develop team-related knowledge that leads to positive outcomes. A new coach, on the other hand, may enhance motivation for players and provide beneficial changes in tactics and playing styles (Höffler & Sliwka, 2003). Other research suggests that coach turnover may have no significant relationship with team performance. De Paola and Scoppa (2008) looked at the impact of coach dismissal on team performance in the men's Italian Serie A football league over a period of five seasons. After controlling for variables related to the dismissal, such as number of matches already played in the season and whether it was a forced or voluntary resignation, they found that changing the coach had no significant effect on team performance. The present study examines whether time as a coach of a given team significantly predicts performance in the UEFA Women's Champions League, thus advancing knowledge of whether coach turnover is a factor in performance in women's football.

Expert coaching in women's football. The literature on expert coaching in women's football is even more scant than in football in general. Vangucci, Potrac, and Jones (1998) examined the behaviors of coaches at three different levels of women's football in England (e.g., National Women's Football League, Greater London Region Football League Premier Division, and Division One). The coaches at the highest level were found to engage in different coaching behaviors than those at lower levels. More specifically, coaches in the top-level National League engaged in more post-instruction (e.g., feedback provided after the execution of a skill), while coaches at the lower-level Division One were more likely to use concurrent instruction (e.g., cues given during the actual execution of a skill). Noteworthy, the present study will advance understanding of women's football by shedding light on significant characteristics of successful coaches in the UEFA Women's Champions League, while statistically controlling for a number of team-level factors.

Characteristics of Successful Teams

Successful sport teams tend to share certain characteristics. Research suggests that the quality of players on the team, rather than the quality of coaches, determines sport success (Szymanski & Kuypers, 1999). For instance, comparing a coach of an amateur team to a coach of a professional team would not take into consideration the differences in the quality of the players on each team.

Most studies examining football performance have focused on the differences between top and bottom teams in terms of game strategies, styles of play, and goals scored and conceded (Hirotsu & Wright, 2003; Tenga, Holme, Ronglan, & Bahr, 2010; Yates, North, Ford, & Williams, 2006). To date, there is general agreement that expert performance in football can be reached through different approaches to the game, or what has been named the "equifinality principle" in human movement sciences (Schmidt, McGown, Quinn, & Hawkins, 1986). For instance, one team may succeed by playing offensive style football (e.g., Brazil), whereas other teams may succeed by playing defensive football (e.g., Italy; see Filho, Basevitch, Yang, & Tenenbaum, 2013). Moreover, one team may succeed by playing long passes and fast breaks (e.g., Italian National

Team), whereas other teams may favor ball possession and short passing (e.g., Barcelona). Although different playing styles can lead to success in football, previous research suggests that teams' characteristics (e.g., number of international players on the team; number of years the team has played together) influence team performance in football irrespective of the playing style adopted by a given team (Filho et al., 2013). As such, the present study involved testing the predictive power of myriad team-level factors (e.g., number of international players on the roster; number of players with national team experience) on performance in the UEFA Women's Champions League.

Financial factors are also likely to influence performance in football. To this extent, previous research has established a positive correlation between spending on team payrolls and team performance in European football (Szymanski, 2000; Szymanski & Kuypers, 1999; Szymanski & Smith, 1997). Teams that have the financial resources to hire better coaches may ultimately achieve greater performance, partly because better coaches can reduce the technical inefficiencies of the players. Frick and Simmons (2008) examined the German premier football league, Bundesliga, over 22 seasons, and found that teams that hire better head coaches achieve higher league points by decreasing the team's technical inefficiencies. Moreover, Frick and Simmons (2008) noted that wealthier teams are also able to hire better players, while providing optimal material and human resources to assist in the development of expert performance in football.

Expert women's football teams. There is extensive research on expert performance in men's football (see Haugaasen & Jordet, 2012). However, despite the growth in the number of women playing football (number of female players has grown five times from 1985 to 2014; Women's Football across National Associations Report: 2014-2015), the literature on characteristics of expert women's football teams is limited. To this extent, there is general consensus that additional research on women sports is needed (Hallal et al., 2012; Telford, Telford, Olive, Cochrane, & Davey, 2016). Promoting knowledge of women sports is essential to encourage young girls to engage in physical activity at an early age, thus fostering consistent, healthy physical activity habits in adulthood (Azzarito, Solmon, & Harrison, 2006). It follows that the uniqueness of the present study rests on examining excellence in women's football. To date, most of the research in sports is based on a stereotypical sample of white, male, college athletes (for a review see Ryba, Schinke, & Tenenbaum, 2010). Gender-specific models are paramount, as men's and women's football game styles and socio-cognitive dynamics are likely to differ (Filho et al., 2014c). Overall, several studies have assessed variables that differentiate successful from unsuccessful teams. However, to my knowledge, no other study has systematically examined coach, team, and country-level variables related to performance in the UEFA Women's Champions League.

Characteristics of Successful Countries

While coach- and team-level characteristics are important factors in overall team performance, the country in which the team hails from may also play a role in success. Certain countries have reputations for excellence in football in general, and women's football in particular. In fact, since the inception of the men's FIFA World Cup in 1930, winners of the tournament have come from only eight countries: Argentina, Brazil, England, France, Germany, Italy, Spain, and Uruguay (Filho et al., 2013). This is particularly striking given that there are more countries affiliated with FIFA than with the United Nations (Pollard & Reep, 1997). The picture is similar for the women's game. In fact, since the women's FIFA World Cup began in 1991 only four different teams (i.e., Germany, Japan, Norway, and United States) have won the tournament. Importantly, the countries that dominate men's football differ from those that traditionally succeed in the women's game, thereby suggesting within-country gender idiosyncrasies in football. At the club level, in both major European (UEFA Champions League) and South American Championships (Libertadores Cup), winning teams have also been concentrated from few countries (see Hoffmann, Ging, & Ramasamy, 2002).

The history of football varies substantially by country and therefore the tradition and culture of football play also likely differs by country, as do player and coach developmental practices (Salmela & Moraes, 2003). The economics of a country may also impact the success of teams from that nation (Noll, 2002; Torgler, 2004). Specifically, teams from small countries or small cities may have a competitive disadvantage compared to those teams that hail from large countries and cities. For instance, Dejonghe and Vandeweghe (2006) have noted the challenges faced by professional men's teams in Belgium, a small country with a population of only 10 million residents, and the difficulty competing against teams from larger countries with different league structures.

Overall, myriad country-level variables may influence how teams play and coaches develop and instruct, ultimately influencing the performance of club and national teams in important international tournaments. From a multi-level statistical standpoint, players are nested within teams, which in turn are nested within countries. As such, several country-level variables were considered in the multi-level profiling of potential predictors of success in the UEFA Women's Champions League.

AIMS & HYPOTHESES

The overarching research question for this research project was: "*What does it take to win the UEFA Women's Champions League?*" This question was proposed as a broad exploratory question stemming from the notion that coach and team characteristics are linked to excellence in sports, and constrained to a given social context. The more specific research questions were:

(1) What coaches' characteristics are linked to successful performance in the UEFA Women's Champions League?
(2) What teams' characteristics are linked to successful performance in the UEFA Women's Champions League?
(3) What country characteristics are linked to successful performance in the UEFA Women's Champions League?

Congruent with the three research questions, the following three hypotheses were proposed:

(H1) Coaches' characteristics (level-1) will predict objective performance in the UEFA Women's Champions League, thus allowing for the identification of differences among successful and unsuccessful coaches.

(H2) At least one team-level characteristic (level-2) will add explanatory power to the final hierarchical linear model.

(H3) At least one country-level characteristic (level-3) will add explanatory power to the final hierarchical linear model.

H1 is congruent with the Expert-Novice paradigm assumptions and the Coaching Model tenets. H2 and H3 are aligned with the Coaching Model tenets, and consistent with current methodological guidelines on parsimonious hierarchical linear model estimation in which level-2 and level-3 variables must be added "one by one" (see Raudenbush & Bryk, 2002).

METHODS

Design

This project involved archival analysis of factual data on teams and coaches participating in the UEFA Women's Champions League (2011-12 until 2015-16). Country-level variables for the same period were also taken into account. The final UEFA Women's Champions League rank was the dependent variable, coaches' characteristics represented level-1 data, teams' characteristics represented level-2 data, and country characteristics accounted for level-3 data.

Data Collection

Data was obtained from the official UEFA website, as well as other reliable, publically available, online sources (e.g., professional sporting websites), in agreement with previous exploratory research on the predictors of performance in professional football (Filho et al., 2013; Hirotsu & Wright, 2003). Furthermore, official team rosters and result sheets were obtained from UEFA representatives. Altogether, a total of 46 Excel spreadsheet files were provided by UEFA, under the auspices of former Education Programme Intern at the National Associations Department, Mr. Matthias Kraetschmer, and Mr. Jean-Baptiste Alliot. The documents gathered from UEFA confer a high level of reliability to the study, as they consist of official archived data for the UEFA Women's Champions League. Importantly, feedback and peer debriefing meetings with UEFA representatives positively influenced the data set gathered for this study.

Peer debriefing meetings with UEFA representative. In August, I received an email from Mr. Kraetschmer with specific and constructive feedback regarding the choice of variables to be examined in the project. We exchanged several subsequent emails discussing the project as well as Skype and phone conversations. Overall, many of the variables that were suggested in the original email (dated August 10, 2016) have been incorporated into the study. I discussed at length the variables with the Research Assistant (Dr. Jean Rettig) who assisted with the data collection and input.

Originally, the plan was to examine the UEFA women's tournament every year since its inception as the UEFA Women's Cup in 2001-02. However, after conversing with Mr. Kraetschmer, we realized that information from the earlier years of the tournament (2001-02 to 2008-09, when it was referred to as the UEFA Women's Cup) was not reliably and freely available. In particular, the number of teams and stages in the tournament varied and, perhaps most importantly, the information for each team and coach was not available in the UEFA database. Therefore, at this point, it was decided to focus on the 2009-10 to 2015-16 seasons when the tournament was branded the UEFA Women's Champions League.

Mr. Kraetschmer provided numerous Excel spreadsheets of information for each team from the 2009-10 season until the 2015-16 season. After reviewing the qualifying procedures for the tournament, and noting the number of teams that attempted to qualify each season (i.e., over 50 teams competed for a spot in the Round of 32 in 2015-16), it was decided that the data input and analysis would measure only the knockout stage of the tournament (Round of 32). In this way, the dependent variable for the regression model (i.e., UEFA Women's Champions League final rank) would have the same range (i.e., 1-32) for all seasons. Furthermore, it is important to note that the structure of the UEFA Women's Champions League allows teams to submit different rosters for each part of the tournament (e.g., Qualifying Round, Round of 32, Round of 16, Quarter-finals, Semi-finals and Final). Therefore, to be consistent across all teams, regardless of how far the team advanced in the tournament, the coach- and team-level data was based on information for the Round of 32.

In terms of data collection, a yearly report (Women's Football across National Associations Report), compiled by UEFA, was located online for the 2013-14, 2014-15, and 2015-16 seasons. The report, which included detailed information for each UEFA member association, provided valuable country-level data such as the budget for women's football and the league structure. Mr. Kraetschmer was able to provide the report for the 2011-12 and 2012-13 seasons, and noted that the report did not appear to exist for the previous years. Given that the yearly reports were published starting in 2011-12, and after assessing the value of the information contained in these documents, it was further determined that the project would include only the 2011-12 to 2015-16 seasons. In all, the data gathered in collaboration with UEFA helped to further delineate the coach, team, and country factors that may predict successful performance in the UEFA Women's Champions League.

Data Input – Variables Included in the Analysis

One dependent variable was included in the analysis as well as independent variables related to the coach (level-1), team (level-2), and country (level-3). The variables included in the analysis are described in detail next.

Dependent variable. Final rank for the UEFA Women's Champions League was determined based on several criteria. The winner of the final match was ranked 1 and the finalist was ranked 2. All remaining teams were ranked based on the following criteria: (1) Greatest combined goal difference in all matches; (2) Greatest combined number of goals scored in all matches; and (3) If more than one team remained level after applying the above criteria, their final ranking was determined based on how far the team that they were eliminated by advanced in the tournament. If the teams that were tied were beaten by teams that advanced to the same round of the tournament, then the greatest combined goal difference in all matches for the advanced team was used to separate the tie.

Independent coach-level variables. Coach-level variables included *age*, *gender*, *nationality status*, *former professional player*, *full national team playing experience*, *international playing experience*, *position as a player*, *coaching experience of a national team*, *years coaching experience in Champions League*, and *time at current position* (Table 1, page 11).

Before data for the coach-level variables was gathered, the head coach of each team was identified. Across all years, there were 11 instances where two individuals were listed as the coach of a team. For data analysis purposes, each team could only have one coach. Each case was examined independently to determine which coach to include in the analysis. Once this issue was resolved, every coach was assigned a unique identification number to ensure anonymity in the data pool.

Age. Age, in years, was included in the data set and calculated based on the date of birth for each coach listed on the official UEFA roster.

Gender. Gender was included to examine whether differences exist between male and female coaches. To this extent, gender has been found to influence performance as well as group dynamics in sports (Carron, Colman, Wheeler, & Stevens, 2002).

Nationality status. The coach's nationality status was coded according to whether they coached a team from their native country or a team from outside their native country. Previous research has suggested that nationality influences performance in team sports (Filho et al., 2014d). Of note, a study examining coaches in the men's Bundesliga in Germany found that in 2006 only two of 18 coaches were non-German (Frink & Simmons, 2008), suggesting that teams may be hesitant to hire coaches from outside the country. Information regarding each coach's nationality status was obtained from the official UEFA roster.

Former professional player. As discussed in the literature review, playing experience has been shown to be an important element in the developmental pathways of successful coaches. Whether the coach was a former professional football player was included as a measure of playing experience. The publicly available online biographies of many coaches indicated their level of playing experience. However, others only listed the teams on which they played. In that case, the team was reviewed to determine whether it played in an amateur or professional league. Of note, this variable represents the highest level of playing experience the coach achieved during his/her career.

Full national team playing experience. The coach's involvement as a player in his/her full national team was recorded based on information from national team rosters available online. This variable was another attempt to control for the quality of playing experience of the coach.

International playing experience. It was noted whether the coach competed at the international level for his/her full national team (e.g., FIFA World Cup, Olympics, UEFA Champions League).

Position as a player. It was also considered whether successful football coaches were more likely to have played a certain position. Specifically, players in centralized positions have more access to information, and thus are thought to be better decision makers. Furthermore, performance expectations differ between goalkeepers, defenders, midfielders, and forwards (Di Salvo et al., 2007). Therefore, the position in which the coach played during his/her career (e.g., goalkeeper, defender, midfielder, forward) was coded for in the data.

Coaching experience of a national team. This variable took into consideration whether the coach had experience as the head coach of a national team, including a youth or full national team from any country.

Years coaching experience in Champions League. The number of previous times each coach was involved in the UEFA Women's Champions League was recorded as a measure of previous coaching experience.

Time at current position. Time at current position, measured in years, was calculated for each coach. As mentioned previously, team performance may be impacted by the length of time the coach has been in the position (De Paola & Scoppa, 2008; Höffler & Sliwka, 2003). Several coaches were assistant coaches at the club prior to assuming the head position. However, this variable only considered the time spent as head coach of the current team.

Table 1

Coding and Description for Coach-Level Variables

Variable	**Coding Description**
Age	Continuous
Gender	Dummy coded; 0 = male, 1 = female
Nationality status	Dummy coded; 0 = coaches team from outside native country; 1 = coaches team from native country
Former professional player	Dummy coded; 0 = did not play as a professional; 1 = played as a professional
Full national team playing experience	Dummy coded; 0 = did not play on full national team; 1 = played on full national
International playing experience	Dummy coded; 0 = did not play internationally; 1 = played in World Cup, Olympics, or Champions League
Position as a player Goalkeeper; Defender; Midfielder; Forward	Dummy coded; 0 = no, 1 = yes
Coaching experience of a national team	Dummy coded; 0 = did not coach a youth or full national team; 1 = coached a youth or full national team
Years coaching experience in Champions League	Continuous
Time at current position	Continuous

Independent team-level variables. Team-level variables included *number of times team has qualified for Champions League*, *number of times team has won Champions League*, *number of international players on roster*, and *number of players with national team experience* (Table 2, page 12).

Prior to gathering data for the team-level variables, the 32 teams in the Round of 32 (knockout stage) of the tournament for each year (2011-12 to 2015-16) were identified. This information was available on the UEFA website and confirmed through the official team rosters provided by UEFA. Every team was assigned a unique identification number for analysis purposes.

Number of times team has qualified for Champions League. The number of times the team has qualified for the UEFA Women's Champions League reflects the experience of the team and success in previous years. This information was based on documents provided by UEFA and confirmed by online records on the official UEFA website.

Number of times team has won Champions League. The number of times the team has won the UEFA Women's Champions League title provides information about the past quality of the team. This information was gathered from the UEFA website.

Number of international players on roster. The number of international players on the roster might be related to the financial capacity of the team (Dejonghe & Vandeweghe, 2006). This data was amassed from the official UEFA team rosters, which indicate the country of origin of each player.

Number of players with national team experience. The total number of players with national team experience was included as an indicator of the football quality of the club team. Playing for your country's national team is associated with expertise in international football and thus the number of national team players is likely indicative of the overall quality of the club team. During the data collection process, it was noted that some teams have national team players all from one country, while other teams have players who represent various countries. For instance, Brescia Calcio Femminile (2015-16) had 12 players with national team experience, all with Italy. On the other hand, FC Bayern München AG (2015-16) had 16 players with national team experience across several countries (four with Austria, three with Germany, two with Switzerland, and one with Spain, Italy, Scotland, Norway, Finland, United States, and the Netherlands). This information was collected from national association websites and individual player profiles.

Table 2

Coding and Description for Team-Level Variables

Variable	**Coding Description**
Number of times team has qualified for Champions League	Continuous
Number of times team has won Champions League	Continuous
Number of international players on roster	Continuous
Number of players with national team experience	Continuous

Independent country-level variables. Country-level variables included *FIFA world ranking*, *total number of divisions*, *number of teams in top division*, *number of registered female players (18+ years)*, *number one favorite team sport*, and *budget for women's football* (Table 3, page 13). For data analysis purposes, each country was assigned a unique identification number.

FIFA world ranking. The FIFA world ranking for the country of which the team is from was included in order to account for the strength of women's football in the given country. It was deemed important to consider the ranking for each country at the point closest to the start of the UEFA Women's Champions League, as it was expected that this most accurately reflects the quality of football in the country at the given time. The ranking used for the analysis was the one issued most immediately preceding the start of the UEFA Women's Champions League knockout round. For instance, for the 2015-16 competition, the rankings were from September 25, 2015 and the knockout stage started on October 7, 2015. The same procedure was applied to all other seasons (i.e., 2011-12 to 2014-15). All rankings were amassed from the FIFA website.

Total number of divisions. To control for differences in league structures across countries, the total number of divisions in the domestic women's football league was included in the model.

Number of teams in top division. Given that the size of divisions also differs across countries, the total number of teams in the top national division was used to control for the league structure.

Number of registered female players (18+ years). The total number of registered female players, above 18 years of age, for the current year was used to measure the popularity of women's football in each country.

Number one favorite team sport. Data gathered by UEFA also indicated whether football was the number one favorite team sport in each country, based on media, exposure, marketing and spectators. This was included in the model to further control for the overall popularity of women's football in each country. Several countries reported two top sports, and if football was listed as one of them then it was coded as the number one favorite team sport.

Budget for women's football. The budget (in Euros) for women's football for each country was included in the data set to assess the general financial status of the sport in the country. Extant research suggests a positive relationship between the amount of money spent on team payrolls and team performance in football (Szymanski, 2000; Szymanski & Kuypers, 1999; Szymanski & Smith, 1997).

With the exception of FIFA world ranking, data for the country-level variables was based on information included in the annual Women's Football across National Associations Reports.

Table 3

Coding and Description for Country-Level Variables

Variable	**Coding Description**
FIFA world ranking	Continuous
Total number of divisions	Continuous
Number of teams in top division	Continuous
Number of registered female players (18+ years)	Continuous
Number one favorite team sport	Continuous
Budget for women's football	Continuous

Data Treatment – Variables Excluded from the Analysis

Several coach, team, and country-level variables were gathered for the project but ultimately not included in the analysis for a variety of reasons. Each variable is described next and justification for why it was excluded from the analysis is provided.

Coach-level variables. Coach-level variables that were collected but not used in the analysis include: *years as a professional player*, *playing experience* (highest league, lowest league, youth national team player), *previous coaching experience other than in the Women's Champions League* (club high level, club low level, other, none), *coaching experience by gender* (women's game, men's game, both), and *coaching qualifications* (UEFA PRO, UEFA A, UEFA B, UEFA C).

Years as a professional player. The data for this variable was questionable. Specifically, for coaches who played on numerous different teams throughout their career, both professionally and as amateurs, it was difficult to determine which years counted as professional experience versus amateur experience. Furthermore, the playing experience of older coaches was generally not as well documented as younger coaches, and the teams in which they competed on often changed status from amateur to professional at some point during their tenure, and the exact time of this change was not always clear.

Playing experience. Playing experience, in terms of highest league and lowest league, was difficult to determine for most coaches. Many coaches had extensive playing careers, in many different leagues and countries, and it became difficult to code this variable consistently across all coaches. While full national team experience was included in the final model, whether or not a coach competed on his/her youth national team was dropped from the analysis. While the records for this variable appeared accurate for younger coaches, the biographies of older coaches did not often reference such information.

Previous coaching experience other than in the Women's Champions League. This variable was excluded from the analysis, as it was difficult to ensure accuracy in coding. Given that many coaches had diverse and lengthy coaching experience, sometimes decades long, it was difficult to determine the level of the teams at the time the particular coach was in charge.

Coaching experience by gender. Determining each coach's previous experience in training males only, females only, or both males and females, was also problematic, as it was impossible to know if online biographies contained a complete history of all coaching experience for the individual.

Coaching qualifications. After an extensive online search, and contacting the UEFA representative regarding a possible list of the UEFA license holders, the missing data for the variable was too substantial to be included in the final analysis. Furthermore, a major challenge with this variable was verifying in what year the coach received a certain license. For instance, a coach may currently have a UEFA PRO license, the highest awarded coaching qualification, but it was unclear, based on information available online, when s/he achieved the qualification. In addition, several coaches had "pending" qualifications, which made accurate coding difficult.

Team-level variables. For team-level variables information for *seed* and *average number of appearances for national team players* was gathered but not included in the analysis.

Seed. Whether or not the team was seeded was dropped from the analysis because conceptually and statistically (r = .71, p < .001; see Appendix A) it overlapped greatly with the dependent variable. In line with general recommendations for multi-level inferential analysis (see Raudenbush & Bryk, 2002), regression models should only include variables with unique possible contributions to the model.

Average number of appearances for national team players. This variable was intended to control for the quality of the team. However, determining the average number of appearances for national teams players for challenging, primarily because online sporting websites list the total number of caps for each player, but do not break down the appearances by year. For instance, a player may be listed as having earned 115 caps at the present moment, but the number of appearances relative to each year of analysis was not clear. Furthermore, for several countries, the number of national team appearances for the players was not available online. For example, Brescia Femminile (2015-16) had 12 players on the Italian national team but there were no records of the number of appearances each player has made for the national team. Some club teams had a complete record of national team players but an incomplete record for their number of appearances. For instance, for Bayern München, there are 14 players with national team experience. Information on the number of appearances for 11 of the 14 players was available, but the information for the remaining three players was not available. Together, these inconsistences made the values and related variances for this variable unreliable.

Country-level variables. Country-level variables that were collected but not used in the analysis include: *number of professional players*, *number of teams with professional players*, *years of existence*, and *FAP budget for women's football*. In addition, although the desire was to control for the strength of women's football in each country, several variables suggested by the UEFA representative (percent of women's footballers who are playing professionally, number of women's teams and leagues) were unable to be collected in an accurate manner.

Number of professional players. After closely examining this variable across the years, it appeared that different countries reported the data differently, and thus the inclusion of the variable would be flawed.

Number of teams with professional players. The observed values for this variable were deemed unreliable, as it appeared that countries used different criteria to classify players as professionals. It is possible that some countries consider a player a professional if she receives any form or financial compensation for her performance, whereas other countries apply different standards to define an athlete as being a professional.

Years of existence. Data on program existence, based on the year women's football began in each country, was computed but was not included in the final model.

FAP budget for women's football. During initial exploration of possible variables, the Financial Assistance Programme (FAP) budget for women's football, which is financial support provided by FIFA to member associations, was identified as a possible variable of interest. However, this information only became available in 2012 and thus could not be included in the analysis.

Data Analysis

The first step in data analysis involved dealing with missing data. Subsequently, descriptive and hierarchical linear modeling analyses were applied to the data set.

Missing data. Variables with over 5% of missing data point were not included in the hierarchical linear modeling analysis (i.e., former professional player; position as a player). Variables with up to 5% missing data points were treated, in line with recommendations for quantitative research analysis (see Creswell, 2008). Specifically, missing data was treated in three ways: (1) for dummy variables, missing data was coded as "0" ("no" or the absence of the attribute); (2) for continuous variables, the median was computed to avoid inflation due to high standard deviations and variability; and (3) for *budget for women's football* interpolation was used to determine the values for the missing data.

Descriptive analysis. Descriptive analysis is particularly informative in census-like inquiries, such as in the case of the present study (Creswell, 2008). Accordingly, measures of central tendency, namely mean, median, and standard deviation, as well as natural frequency counts, were performed.

Hierarchical linear modeling. A three-level hierarchical linear model was tested with coach variables representing level-1, team variables representing level-2, and country variables representing level-3 data. Figure 2 (page 16) is a schematic descriptive summary as well as a graphic representation of all variables considered in the hierarchal linear modeling analysis. The dependent variable was the final rank for the UEFA Women's Champions League. For the null unconditional model, all dummy coded variables were treated as fixed effects, whereas continuous variables were initially conceptualized as random effects in the tested model. Furthermore, across the three levels of analysis, all variables were treated as raw, non-centered scores, given that there was (1) an interest in estimating the unique contribution of each predictor, and (2) no occasion in which a value of zero represented either an undesirable or an unreasonable score.

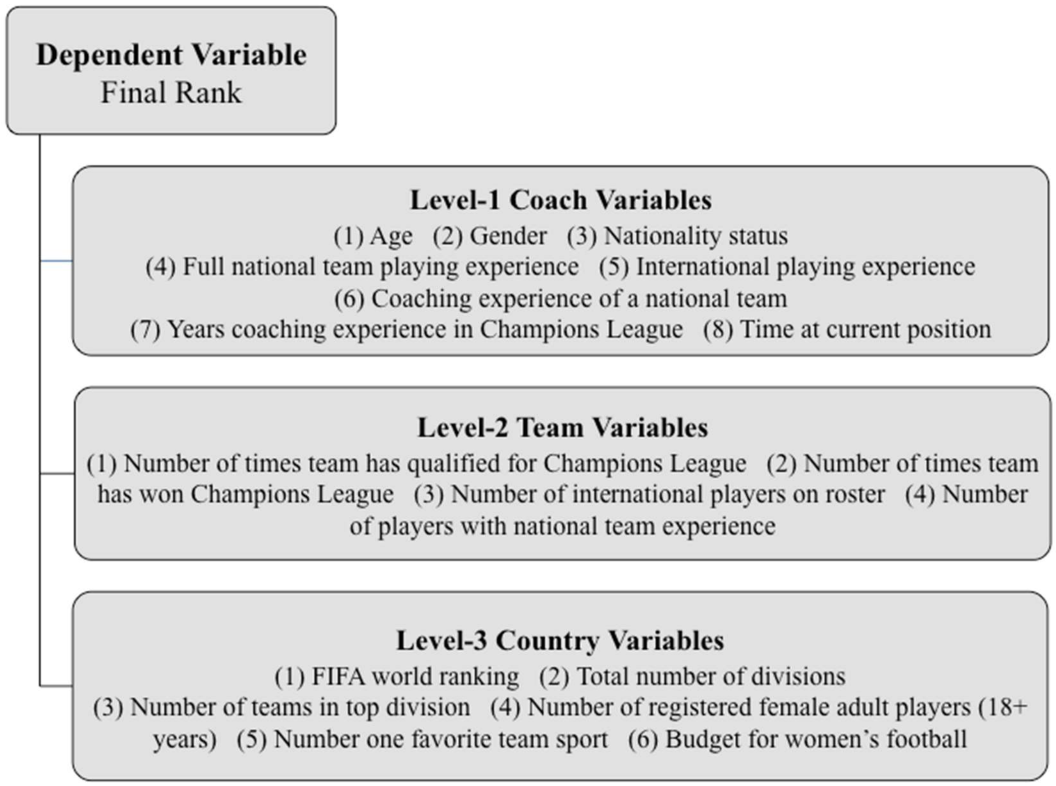


Figure 2. *Summary of variables included in the hierarchical linear modeling analysis.*

RESULTS

With respect to expertise in sports, scholars speak of descriptors and predictors (Williams & Ericsson, 2005). Descriptors might be essential to perform at a given level, namely coach at the UEFA Women's Champions League. Predictors explain why some sport actors (e.g., coaches, athletes) reach higher levels in an outcome variable, such as final ranking in the UEFA Women's Champions League, in comparison to their less successful counterparts. Accordingly, I first present the descriptive analysis applied to the final data set. Subsequently, I present the multi-level analysis in a step-by-step mode, from the null unconditional model until the final parsimonious model.

Descriptive Analysis for Coaches

For demographic factors (Table 4, page 17), the descriptive analysis revealed that the coaches are in their early forties, are mostly male, and primarily coach a team in their native country rather than a foreign country. A post-hoc chi-square analysis (see Garcia-Pérez & Núñez-Antón, 2003) confirmed that the proportion of male coaches is statistically greater than the proportion of female coaches ($\chi 2$ (5) = 186.39, $p < .001$), and that the magnitude of this difference is large (Cohen's $d = 2.03$).

Table 4

Descriptive Statistics for Coach-Level Variables

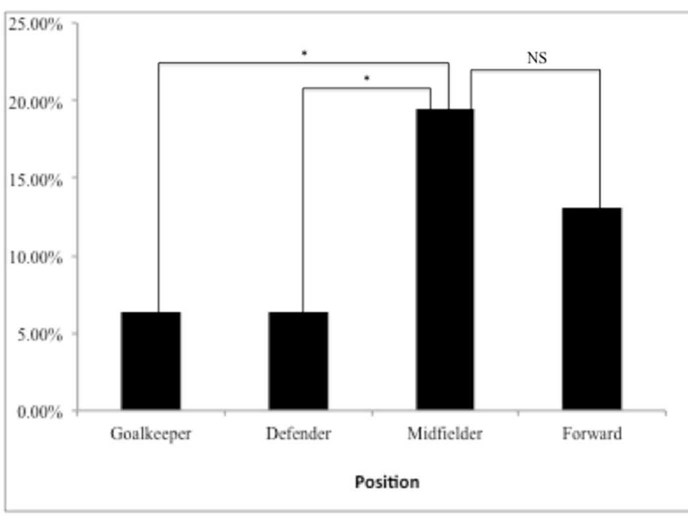
Variables	Code or Range	Median	Mean (SD)	Valid % (n)	Missing % (n)	Included in HLM Model
Age	27–71	43.00	43.51 (9.95)	99.40 (159)	.60 (1)	Yes
Gender	0/1			100 (160)	0 (0)	Yes
Male	0			85.60 (137)	-	
Female	1			14.40 (23)	-	
Nationality status	0/1			100 (160)	0 (0)	Yes
Coaches team from outside native country	0			8.10 (13)	-	
Coaches team from native country	1			91.90 (147)	-	
Former professional player	0/1			68.10 (109)	31.90 (51)	No
Did not play as a professional	0			54.10 (59)	-	
Played as a professional	1			45.90 (50)	-	
Full national team playing experience	0/1			100 (160)	0 (0)	Yes
Did not play on full national team	0			86.90 (139)	-	
Played on full national team	1			13.10 (21)	-	
International playing experience	0/1			95.60 (153)	4.40 (7)	Yes
Did not play internationally	0			88.90 (136)	-	
Played in World Cup, Olympics, or Champions League	1			11.10 (17)	-	
Position as a player				45.00 (72)	55.00 (88)	No
Goalkeeper	0/1			13.90 (10)	-	
Defender	1			13.90 (10)	-	
Midfielder	1			43.10 (31)	-	
Forward	1			29.10 (21)	-	

Table #4 – continued

Variables	Code or Range	Median	Mean (SD)	Valid % (n)	Missing % (n)	Included in HLM Model
Coaching experience of a national team	0/1			94.40 (151)	5.60 (9)	Yes
Did not coach a youth/full national team	0			62.90 (95)	-	
Coached a youth/full national team	1			37.10 (56)	-	
Years coaching experience in Champions League	0–4	0.00	0.81 (1.00)	100 (160)	0 (0)	Yes
Time at current position	0–24	2.00	3.36 (4.51)	98.80 (158)	1.20 (2)	Yes

With respect to coaches' previous experience as football players, the majority of the coaches were not former professional footballers (Table 4). A post-hoc chi-square test revealed that the proportion of coaches with no professional playing experience was greater than that of coaches with professional playing experience, $\chi 2$ (1) = .74, p = .39. Noteworthy, for the most part (> 85%), coaches with professional playing experience did not play at premiere international level competitions, such as the FIFA World Cup, Olympics, or UEFA Champions League. Coaches with previous playing experience at any level were mostly midfielders (Figure 3). The proportion of midfielders was found to be greater than the proportion of former goalkeepers and defenders $\chi 2$ (2) = 10.90, p < .01, but did not differ significantly from the proportion of forwards, $\chi 2$ (1) = 1.13, p = .29.

With respect with the coaches' coaching experience (Table 4), the descriptive analysis revealed that most of them were at their current club in a head coach capacity for about three years (M = 3.36; SD = 4.51), and coaching for the first time in the UEFA Women's Champions League. Over a third of the coaches (37.10%, n = 56) had previously led a youth or full national team.



*p < .01

Figure 3. *Playing position of coaches.*

Descriptive Analysis for Teams

Central tendency estimates and frequency counts for all level-2 variables are presented in Table 5. On average, teams had qualified for the UEFA Women's Champions League two times within the five-year interval considered in the present study. Thus, to reach the knockout stage of the UEFA Women's Champions League, previous experience in the competition likely matters. Furthermore, the teams had a median of 13 players with national team experience, and the average team size was approximately 23 players (M = 22.71; SD = 2.19).

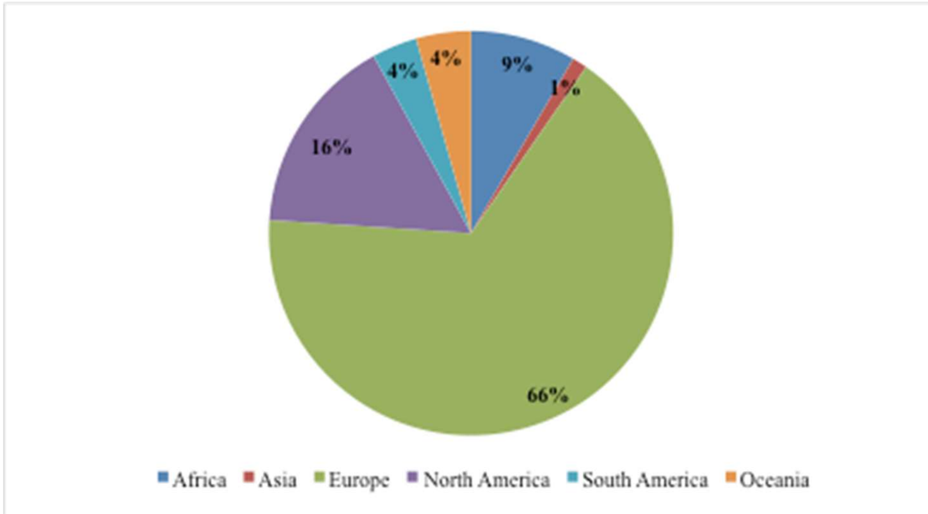
Table 5

Descriptive Statistics for Team-Level Variables

Variables	Range	Median	Mean (SD)	Valid % (n)	Missing % (n)	Included in HLM Model
Number of times team has qualified for Champions League	0 – 6	2.00	1.79 (1.56)	100 (160)	0 (0)	Yes
Number of times team has won Champions League	0 – 2	0.00	0.11 (.42)	100 (160)	0 (0)	Yes
Number of international players on roster	0 – 15	4.00	4.40 (3.43)	99.40 (159)	.60 (1)	Yes
Number of players with national team experience	2 – 20	13.00	12.46 (3.85)	99.40 (159)	.60 (1)	Yes

On average, the teams had four international players on their rosters. Of note, the majority of international players were from European countries, followed by North American and Africa countries (Figure 4, Panel A, page 20). South American and Oceania countries accounted for 4% of the international trade each, with Asian nations accounting for the remaining 1% of foreign players. This trend was found to be consistent across all five years analyzed (Figure 4, Panel B, page 20). The proportion of European players was found to be greater than all other continents, $\chi2$ (5) = 186.39, $p < .001$. The number of players from North America was found to differ significantly from the proportion of players coming from Africa, South America, Oceania, and Asia, $\chi2$ (4) = 20.48, $p < .001$. No other statistically significant differences were observed when comparing the proportion of international players across continents.

Panel A



Panel B

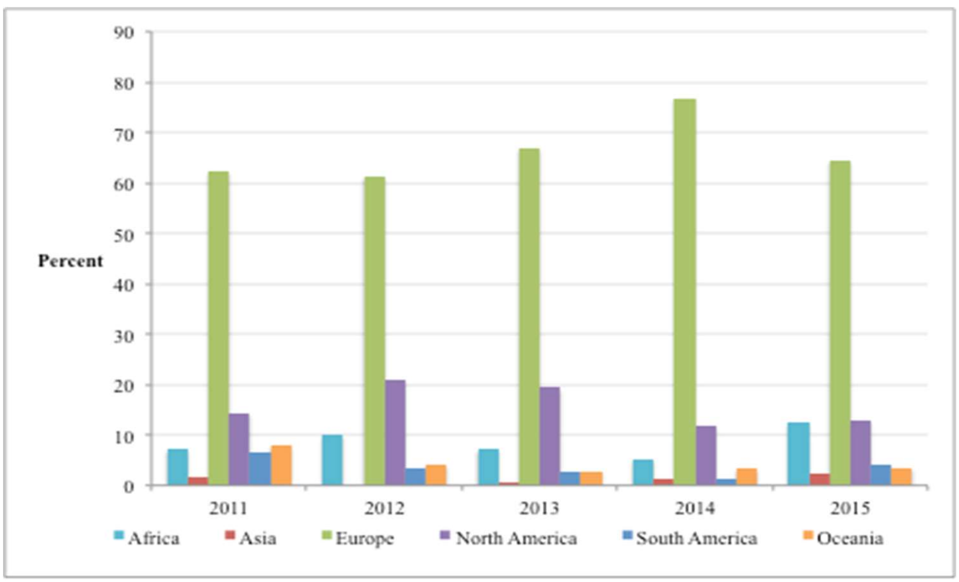


Figure 4. *Overall proportion of international players per continent competing in the UEFA Women's Champions League from 2011-12 to 2015-16 (Panel A). Proportion of international players per continent by year (Panel B).*

Descriptive Analysis for Countries

Central tendency estimates and frequency counts for all level-3 variables are presented in Table 6 (page 21). Teams were from countries with a large range of FIFA world rankings. Across countries, the average number of football divisions was approximately four (SD = 2.06), with the average number of teams in the top division being about 10 (SD = 2.60). The number of registered female football players, over age 18, varied greatly among countries and was roughly 21,000 (M = 21,287; SD = 24,216). However, this value is not particularly informative as the variance was large. These values are likely wide-ranging because member countries of UEFA differ in size as well as in their formal and informal procedures to account for football players. Also noteworthy. football was the favorite sport in approximately 60% of the countries, with the budget allotted to women's football being, on average, close to four million Euros per year (M = 3,953,011; SD = 4,152,050; Median = 2,500,000). Altogether, the country-level data was marked by wide variability, thereby corroborating the importance of controlling for country specificity in line with multi-level analysis guidelines in general, and with feedback from the UEFA panel in particular.

Table 6

Descriptive Statistics for Country-Level Variables

Variables	Code or Range	Median	Mean (SD)	Valid % (n)	Missing % (n)	Included in HLM Model
FIFA world ranking	2 – 111	17.50	22.72	98.80 (158)	1.20 (2)	Yes
Total number of divisions	1 – 18	4.00	4.21 (2.06)	93.10 (149)	6.90 (11)	Yes
Number of teams in top division	5– 20	10.00	10.55 (2.60)	96.90 (155)	3.10 (5)	Yes
Number of registered female players (18+ years)[*]	100 – 117,100	14,140	21,287 (24,216)	93.80 (150)	6.20 (10)	Yes
Number one favorite team sport	0/1	-	-	96.20 (154)	3.80 (6)	Yes
Any sport other than football	0			40.30 (62)		
2 Football	1			59.70 (92)		
Budget for women's football[*]	51,600 – 18,370,000	2,500,000	3,953,011 (4,152,050)	95.60 (153)	4.40 (7)	Yes

Note. [*]Values for median, mean and standard deviation are rounded to the nearest whole number.

Hierarchical Linear Modeling

First, correlation analyses were performed among the independent variables included in the analysis and the dependent variable (see Appendix A). Overall, a linear relationship was observed, thus attesting for the application of hierarchical linear modeling analysis to the data set (see Raudenbush & Bryk, 2002). For clarity and brevity, only the null unconditional model and omnibus final model are defined in the text. The statistical definitions and coefficients for all models, including the intermediate models not detailed in the text, are presented in Appendix B in the order in which they were ran.

Null unconditional model. Initially, the null unconditional model with two levels and no independent variables was tested:

Level-1 Model

$$Final\ rank_j = \beta_{0j} + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

where

β_{0j} : The intercept

r_{ij} : The residual

γ_{00} : The grand mean for the dependent variable final rank in the population

u_{0j} : A random effect for football team j

Fixed and random effect statistics for the null unconditional model are presented in Table 7. The reliability estimate for this model indicated that 19% of the variance of final rank for the UEFA Women's Champions League was due to between-group variables. The grand mean estimate was significant at 17.75 (CI = 19.72, 15.77), and thus near the median value (final ranking = 16, as there are 32 teams) for the final ranking across all teams. There was no significant effect for the variance components, thus suggesting the adoption of a fixed effect model for the subsequent models. Specifically, robust standard errors estimation was used, as the data set involved collecting data over a time-series (2011-12 to 2015-16), in which a conservative estimation of effects is advisable (Cohen, Cohen, West, & Aiken, 2002). This result is likely due to the fact that most variables were dummy coded in order to account for their specific effects on the dependent variable. Moreover, the adoption of a fixed effect model likely reflects the fact that this study was based on census-like data rather than a random cross-sectional analysis. Thus, these findings cannot be generalized beyond high-performance women's football. Notwithstanding, random effect results are still reported throughout to allow for replication and reproducibility comparisons.

Table 7

Multilevel Regression Estimates for the Null Unconditional Model

Fixed Effect	Coefficient	SE	*t*-Ratio	*p*-value
Intercept, γ_{00}	17.75	1.01	17.61	< .001
Random Effect	Variance	*df*	x^2	*p*-value
Intercept, u_0	3.69	68	84.12	.090
Level-1 effect, r_{ij}	57.53			

Reliability estimate for level-1= .19
Deviance 487.23; Number of estimated parameters = 2

Level-1 Modeling. Model A included all level-1 coach variables. The coefficients, standard errors, t-ratios and respective *p*-values for all tested variables are presented in Table 8. A negative coefficient is indicative of a performance improvement. All significant predictors of final rank, as well as variables with marginal significance, $.05 \leq p \geq .15$, were kept in the subsequent intermediate analysis (see Appendix B), akin to previous research in the sport literature (Filho et al., 2014c; Umbach, Palmer, Kuh, & Hannah, 2006).

Table 8

Multilevel Regression Estimates for Two-Level Model A

Fixed Effect	Coefficient	SE	*t*-Ratio	*p*-value
Intercept, γ_{00}	14.25	6.63	2.15	.04
Age, γ_{10}	-0.01	0.10	-0.14	.90
Gender, γ_{20}	0.95	4.85	0.20	.85
Nationality status, γ_{30}	6.10	5.33	1.15	.26
Full national team playing experience, γ_{40}	1.50	5.11	0.29	.77
Coaching experience of a national team, γ_{50}	4.38	2.48	1.77	.08
International playing experience, γ_{60}	-4.30	3.91	-1.10	.28
Years coaching experience in Champions League, γ_{70}	-4.29	1.58	-2.71	.01
Time at current position, γ_{80}	-0.04	.37	-0.11	.91
Random Effect	Variance	*df*	x^2	*p*-value
Intercept, u_0	3.43	68	72.35	.34
Level-1 effect, r_{ij}	57.35			

Reliability estimate for level-1= .17
Deviance = 453.24; Number of estimated parameters = 2

Based on the results of Model A (Table 8), the next step involved advancing a more parsimonious model. Specifically, congruent with guidelines on parsimonious statistical modeling (Cohen et al., 2002), Model B contained only the level-1 significant predictor of final rank: *Years coaching experience in Champions League* (Table 9, page 24). Specifically, for every one year of experience coaching in the UEFA Women's Champion's League, final rank was found to improve by 4.29 positions (γ_{70} = -4.29, p = .009). The intercept for the model was estimated at 14.25 (CI = 11.66, 16.84) with the confidence interval encompassing the expected average value for final ranking across all teams. The reliability estimated between groups decreased slightly to 17% after adding coaching experience to the model. Moreover, computation of Pseudo R^2 (for the equation, see Raudenbush & Bryk, 2002) indicated that Model B explained 6.84% more variance of final ranking than the null unconditional model (Table 7) with no predictors.

Table 9

Multilevel Regression Estimates for Two-Level Model B

Fixed Effect	Coefficient	SE	*t*-Ratio	*p*-value
Intercept, γ_{00}	20.02	1.32	15.16	< .001
Years coaching experience in Champions League, γ_{10}	-3.63	1.46	-2.49	.015
Random Effect	Variance	*df*	x^2	*p*-value
Intercept, u_0	3.53	68	82.62	.109
Level-1 effect, r_{ij}	53.59			
Reliability estimate for level-1 = .19 Deviance = 476.77; Number of estimated parameters = 2				

Level-2 Modeling. This step involved the consideration of team-level variables. Congruent with guidelines on parsimonious hierarchical linear modeling (Raudenbush & Bryk, 2002), an a priori exploratory analysis was conducted to determine which level-2 variables should be included in the model (Table 10) in order to advance the simplest, most parsimonious, two-level model as possible.

Table 10

Exploratory Analysis for Potential Level-2 Significant Predictors

Level-1 Coefficient	Potential Level-2 Predictors*			
	1	2	3	4
Coefficient	-0.21	-1.50	-0.22	-0.14
Standard error	0.15	0.62	0.05	0.05
t-value	-1.37	-2.41	-4.43	-3.09

Note. *1-Number of times team has qualified for Champions League. 2-Number of times team has won Champions League. 3-Number of international players on roster. 4-Number of players with national team experience.

Level-2 variables were included on a “one to one basis” in the analysis, depending on their putative coefficient impact as per the exploratory estimated *t*-values given in Table 10, until a final solution wherein all predictors were statistically significant was reached. Results for this model, namely Model C (Table 11, page 25), suggested that *Years coaching experience in Champions League* at level-1, and *Number of times team has won Champions League* and *Number of international players on roster* at level-2, were significant predictors of final rank. Specifically, for every additional year of experience coaching in the Champions League, final rank improved by approximately three positions (γ_{10} = -2.90, p = .038). Moreover, for every time a team raised the Champions League trophy, final rank was estimated to improve by seven positions (γ_{01} = -7.13, p < .001). Finally, every international player on the roster represented an improvement in final rank by about one position (γ_{02} = -1.08, p < .001). The intercept for the model was significant at 24.56 (CI = 21.76, 27.36).

Table 11

Multilevel Regression Estimates for Two-Level Model C

Fixed Effect	Coefficient	SE	*t*-Ratio	*p*-value
Intercept, γ_{00}	24.56	1.43	17.23	< .001
Number of times team has won Champions League, γ_{01}	-7.13	1.83	-3.89	< .001
Number of international players on roster, γ_{02}	-1.08	0.25	-4.26	< .001
Years coaching experience in Champions League, γ_{10}	-2.90	1.37	-2.12	.038
Random Effect	Variance	*df*	x^2	*p*-value
Intercept, r_0	9.24	66	80.15	.113
Level-1 effect r_{ij}	39.64			

Reliability estimate for level-1= .19
Deviance = 451.28; Number of estimated parameters = 2

Level-3 Modeling. To test whether a three-level model was required or whether a two-level model would suffice, variance was fixed at ".19" (see Raudenbush & Bryk, 2002), which was the reliability estimate for Model C (Table 11), and an exploratory analysis of all level-3 predictors was conducted (Table 12).

Table 12

Exploratory Analysis for Potential Level-3 Significant Predictors

Level-1 Coefficient	Potential Level-3 Predictors*					
	1	2	3	4	5	6
Coefficient	0.02	-0.29	-0.17	0.00	-0.93	0.00
Standard error	0.01	0.15	0.12	0.00	0.62	0.00
t-value	2.37	-1.98	-1.50	-1.80	-1.51	-1.24

Note. *1- FIFA world ranking. 2-Total number of divisions. 3-Number of teams in top division. 4-Number of registered female players (18+ years). 5-Number one favorite team sport. 6-Budget for women's football.

The variables found to be statistically significant at level-1 (i.e., *Years coaching experience in Champions League*) and level-2 (i.e., *Number of times team has won Champions League*;

Number of international players on roster) were then added to the regression analysis, as well as *FIFA world ranking* at level-3, which was found to significantly predict final rank (Table 13). The intercept for the model was estimated at 21.85 (CI = 18.86, 24.84), with the reliability estimate for level-2 suggesting that 12% of the variation in the means of final rank was due to true variation between countries. Importantly, in this three-level solution, *Years coaching experience in Champions League* was no longer found to be a significant predictor of final rank.

Table 13

Multilevel Regression Estimates for Three-Level Model D

Fixed Effect	Coefficient	SE	*t*-Ratio	*p*-value
Intercept, γ_{000}	21.85	1.53	14.25	< .001
FIFA world ranking, γ_{001}	0.09	0.03	3.03	.005
Number of times team has won Champions League, γ_{010}	-5.79	1.87	-3.10	.004
Number of international players on roster, γ_{020}	-1.25	0.25	-4.99	< .001
Years coaching experience in Champions League,	-0.81	1.49	-0.54	*p* >.05
<u>Random Effect Level-3</u>	Variance	*df*	x^2	*p*-value
Intercept 1/Intercept 2, u_{00}	1.80	32	37.52	.23
Reliability estimate for level-1 = .99				
Reliability estimate for level-2 = .12				
Deviance = 215.20; Number of estimated parameters = 7				

Final Model. Both the three-level solution given in Table 13 and the two-level solution presented in Table 11 are suitable omnibus models to explain final rank for the UEFA Women's Champions League. As is often the case with evidence-based research, reliance on statistical guidelines for model estimation does not provide a straightforward answer for deciding between two alternative non-equivalent models (Raudenbush & Bryk, 2002). On the one hand, arguments can be developed in favor of choosing better-fit indices (see Stapleton, 2006), in which case the three-level solution given in Table 13 would be preferable as Pseudo R^2 computation indicates that this model accounted for an additional 55.23% of the variance of final ranking scores. On the other hand, arguments can be developed in favor of the more parsimonious two-level solution given in Table 11 (Gigerenzer, 2010; Tenenbaum & Filho, 2015). Specifically, every time you add factors to a model, the complexity of the model increases (over parametrization) and its applicability tends to decrease.

To reach a decision between the two alternative solutions, the estimated impact of the level-3 and level-1 predictors on the criterion final rank were analyzed in detail. In regards to a three-level solution (Table 13), the estimated beta for the variable *FIFA world ranking* would have no meaningful impact for teams with the best *FIFA world ranking* (γ_{001} = .09 * 2 = .18), but would result in a ten-position downgrade effect for the teams with the worst *FIFA world ranking* (γ_{001} =

.09 * 111 = 9.99), given the observed ranges for this variable (Table 6, page 21). Apart from these extremes, numerous effects in between are possible (Figure 5), with the median effect of *FIFA world ranking* on final ranking being close to a two-position downgrade (γ_{001} = 0.09 * 17.5 = 1.58).

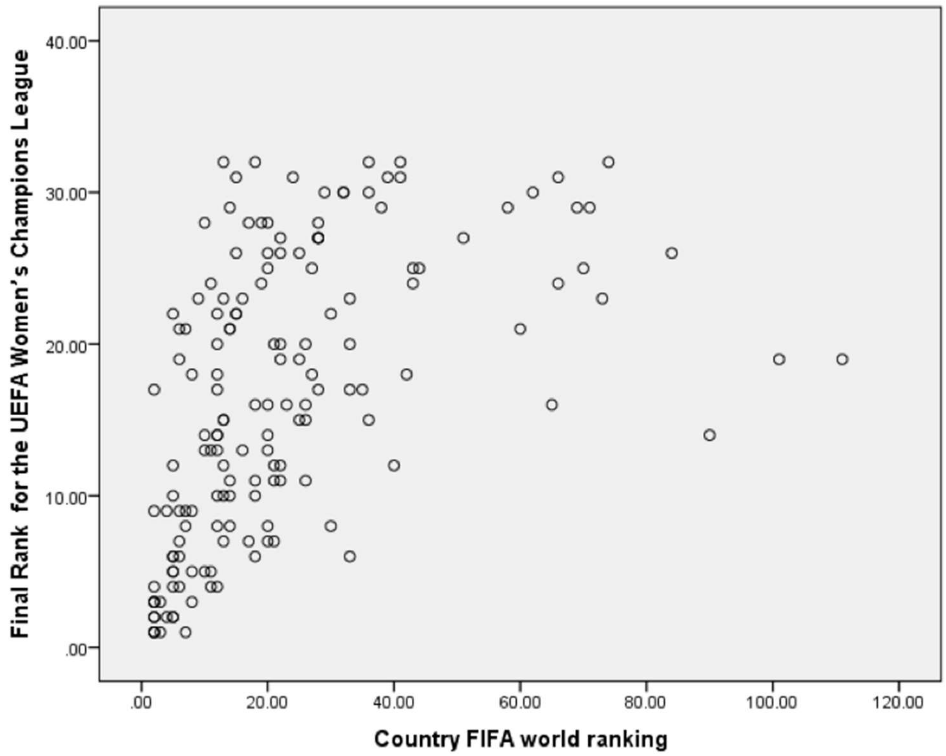


Figure 5. *Relationship between country FIFA world ranking and final rank for the UEFA Women's Champions League.*

Regarding a two-level solution (Table 11, page 25), there would be no effect for coaches without any previous experience in the UEFA Women's Champions League (γ_{10} = -2.90 * 0), with this effect increasingly linearly over time (Figure 6, page 28) and influencing final ranking by a maximum of approximately twelve positions for coaches with four years of experience in the league (γ_{10} = -2.90 * 4 = 11.60), as per the observed range for this variable (Table 4). The estimated average effect of *years coaching experience in Champions League* on final ranking is about a two-position upgrade (γ_{10} = -2.90 * .81 = -2.35).

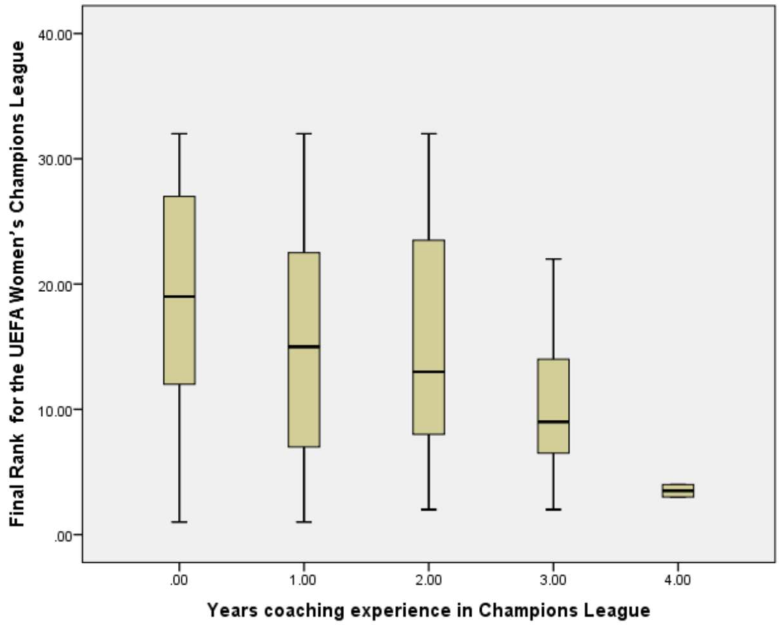


Figure 6. *Relationship between years coaching experience in Champions League and final rank for the UEFA Women's Champions League.*

Altogether, the impact of *years coaching experience in Champions League* on final rank is more substantial as it can reach up to 12 positions based on the estimated beta and the range of the variable. Moreover, the importance of the significant level-2 predictors (i.e., *Number of times team has won Champions League*; *Number of international players on roster*) remains similar in either a two- or three-level solution. Furthermore, added explained variance for the level-3 solution does not yield greater generalizability, as the random effect was not significant. On this final note, and perhaps most importantly, a two-level solution has implications on the immediate coach-team linkage, rather than on the broader country context, which in turn is nested within the European continent. Thus, on the basis of the aforementioned arguments, a final choice for a two-level solution is proposed herein:

Level-1 Model

$$\textit{Final rank}_{ij} = \beta_{0j} + \beta_{1j}*(\textit{Years coaching experience in Champions League}) + r_{ij}$$

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(\textit{Number of times team has won Champions League}) + \gamma_{02}*(\textit{Number of international players on roster}) + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

β_{0j} : The predicted final rank mean controlling for the number of previous Champions League wins and the number of international players on a given team j

β_{1j} : The predicted change in final rank for every year of coaching experience in the Champions League for a given coach i in a given team j

γ_{00} : The grand mean for the dependent variable final rank across teams

γ_{01} : The average change in final rank for every time a given team j has won the Champions League

γ_{02} : The average change in final rank for every international player on a given team j

r_{ij} : The deviation of final rank from its predicted value for a given coach i in a given team j

u_{0j}: A random effect for team j

The above-specified model, therefore, supports H1 and H2 but does not corroborate H3. Had a three-level solution been selected, H3 and H2 would have been supported but not H1. Importantly, as is the case for every regression model, the final model needs to be considered with respect to the intercept and the range for each variable. Therefore, considering the final coefficients estimated for this study (Table 11, page 25), the lowest "error free" hypothetical final rank value represents the intercept itself and would consist of a coach with no previous experience in the UEFA Women's Champions League, coaching a team with no previous UEFA Women's Champions League title, and without any international players on the roster according to the equation:

$$\textit{Final rank} = 24.56 + (-2.90) * (0) + -7.13 * (0) + -1.08\ (0)$$

Variations in the final rank value would depend on the number of previous years of experience in the UEFA Women's Champions League by a given coach, a team with up to two overall UEFA Women's Champions League titles within the past five years, and with a maximum number of 15 international players on the roster. Within these parameters, all realistic values for the studied sample should apply. Again, the reported coefficients are fixed rather than random, and thus apply primarily to the studied sample.

DISCUSSION

The purpose of this study was to explore coach, team, and country factors linked to performance in the UEFA Women's Champions League. To this end, descriptive statistics and hierarchical linear modeling was applied to a data set spanning five seasons, for the three-aforementioned levels of analysis. The main observed findings are discussed next.

Descriptive Analysis for Coaches

Our analysis revealed that the coaches were in their early forties. To coach at a high level of performance, previous experience in the sport seems compulsory. To illustrate, over a third of the coaches reported previous coaching experience of a full or youth national team. Hence, it is unlikely that early professionals will be managing a women's team in the premier football tournament in Europe. This is often the case in other domains of human performance as well, as individuals tend to peak in certain careers at very specific age intervals, or "sensitive windows" (see Bloom, 1985; Munakata, Casey, & Diamond, 2004). Particular to coaching and management, in a classic study profiling characteristics of over 1,000 executives, Bantel and Jackson (1989) observed that CEOs from large corporations were in their forties on average.

Whereas previous experience seems to be essential to lead premier football clubs in Europe, the type of experience might differ across individuals. In particular, the statistical analysis revealed that former professional players were not more likely to coach in the league than those with no previous professional experience as a player. Thus, the pathways to become a coach in the UEFA Women's Champions League seem to vary, akin to the equifinality principle (see Von Bertalanffy, 1968), which purports that expert performance can be reached through different routes. This finding bears implications for the on-going global debate on coaching education (see Vargas-Tonsing, 2007), as it suggests that different types of experience (e.g., former professional player, explicit academic training, or formal coaching education) can lead individuals to coaching at the highest competitive level.

It is noteworthy, however, that the majority of coaches with playing experience at any level used to play as midfielders. Coaches who played as a midfielder might have a greater chance of leading an elite women's football club in Europe. Midfielders have been found to perceive performance requirements differently than players from other positions (i.e., goalkeepers, defenders, and forwards) likely because midfielders are, in a sense, a hybrid position that shares both defensive and offensive responsibilities (Filho et al., 2014c). As such, former midfielders might have developed a better understanding of the game in both its defensive and offensive requirements. Moreover, previous research has shown that athletes that play in centralized positions have more access to information, and thus are more likely to facilitate team coordination and performance by communicating shared and complementary information to their teammates (Filho et al., 2014b).

The likelihood of coaching a top women's football team in Europe also depends on gender. Male coaches were found to be much more prevalent in the league than female coaches. At least two explanations, and its compound interaction effects, are viable to explain this result. First, the number of female coaches in the population is smaller than the number of male coaches, and the observed effect is a true reflection of this population trend. Second, there is job inequality at the highest level of football in Europe, similar to the empirical evidence that women are less likely to hold top positions in business, science, and politics. If the latter explanation is true, then initiatives to incentivize girls and women to play and coach sports in general, and football in particular, should be put in place. In terms of playing sports, girls and women are less physically active than men, and part of this is bounded to gender stereotypes (Azzarito et al., 2006). Suggestions that women are less prone to sport play because they are "fragile" should continue to be challenged (Telford et al., 2016). In terms of coaching sports, policies should be designed to encourage former female players to seek the necessary licenses and qualifications to pursue a career in coaching. If the former thesis is true, then policies to equalize power and job opportunities in football should be discussed as a matter of urgency.

Economic dynamics might explain the fact that only about 10% of the coaches were from international countries. There is less money in women's football than in men's football and this might explain the relatively low frequency of international coaches at the knockout round of the UEFA Women's Champions League. Economics may also explain job stability in the analysed sample. Coaches were found to serve in their current position for over three years on average, thus signalizing a smaller coaching turnover than those observed in the men's game (see De Paola & Scoppa, 2008). Taken together, these findings reinforce the notion that economics impact job migration and stability in various domains (see Greenwood, 2014), including women's club football in Europe. These effects are not only sensible at the individual level of analysis but also at the team level of analysis.

Descriptive Analysis for Teams

Frequency counts revealed that only three teams had won the UEFA Women's Champions League within the five-year span analysed. Accordingly, there is evidence that "hubs of expertise" occur and are dominant within the European league network. As per the Pareto law, 80% of outcomes tend to come from 20% of the inputs. It follows that qualitative analysis of these highly successful cases is warranted as previous research suggests that studying the modus operandi of a few expert teams can yield important insights to inform the development of less successful teams (Gershgoren et al., 2013).

Although few squads had earned the overall title, the teams had on average two years of experience participating in the UEFA Women's Champions League. This suggests that the quality of the squad is paramount, as teams are likely to have repeated participation in the league within a five-year interval. Skill matters in the quest for success, which is why companies from all domains seek to hire and retain highly qualified employees (Lockwood & Ansari, 1999).

In fact, the team-level data suggests that teams in the UEFA Women's Champions League have top quality players, with an average of over 12 players with national team experience per team. This finding opens another question pertaining to the direction of this putative relationship: Do footballers that play for their national teams join the best club teams in Europe or does playing on a strong team in the UEFA Women's Champions League increase a player's chance of being invited to join her national team? It is likely that a reciprocal relationship occurs, wherein playing on a top club team increases the players' visibility to join her respective national squad and vice-versa: playing on a national team increases the chance of being hired by a leading football club in Europe. This reciprocal dynamic may also be linked to the hiring of international players from different continents to join European clubs.

On average, teams had four international players on their squad. This figure is likely constrained by the fact that European countries control the number of players outside Europe that can play in their leagues (see Flores, Forrest, & Tena, 2010). While the number of players is a constrained factor, the origin of the players is a "free parameter", mainly shaped by the unique dynamics of women's football. Specifically, the majority of international players at the UEFA Women's Champions League come from North America, particularly the United States, who has been the major force in women's football for the past decade. As is the case with many job markets, local protective measures along with the strength of the marketplace in other countries, establishes the migration flow of workers around the globe (Greenwood, 2014). The strength of other country-level factors on team dynamics and coaching factors is discussed next.

Descriptive Analysis for Countries

Across the 35 countries represented in the UEFA Women's Champions League over the five-year span, football was found to be the *number one favourite sport* among women. In the past, football has been stereotypically associated with male rather than female socially desirable traits (Azzarito et al., 2006). However, a positive shift has been noticed more recently, with an increasing number of girls and women playing football around the globe (Lunz, 2007). It is important that researchers and practitioners continue to observe how societal and cultural changes (e.g., gender rights movement) influence sport play and choice for women in different countries.

All other country-level variables were characterized by wide variability. In fact, from the *FIFA world ranking* to *total number of divisions* and *number of teams in the top division*, great dispersion in the data pool was the major trend observed. Scattered data patterns were also noticed for *number of registered female players* and *budget for women's football* among the 35 countries that were analysed. Together, these findings suggest, not surprisingly, that heteroscedasticity in the organization of national leagues as well as the economics of football is part of the women's game in Europe. Hence, the recommendation derived from these findings is that scholars and practitioners should continue to account for country-level factors when studying expertise among individual sport actors, such as coaches in the present study, and teams at large.

Cross-Level Effects: Coaches within Teams within Countries

Agents at one level are systems in another (Von Bertalanffy, 1968). For this reason, mapping cross-level effects allows for a deeper understanding of optimal performance across domains of human interest, including football (Filho et al., 2014c). In the multi-level analysis applied herein, the results support the hypotheses that coach- and team-level variables are related to performance in the UEFA Women's Champions League for a two-level solution, and that team-level factors and country-level factors are paramount within a three-level solution. From a three-level perspective, countries with higher FIFA world rankings have better teams that are more likely to be successful regardless of their coaches, in comparison to weaker teams from less traditional football countries. From a two-level view, coaches with more experience increase the chances of victory in the UEFA Women's Champions League. Experienced and successful coaches are also more likely to be recruited and retained by better teams. Altogether, *reciprocal determinism* (see Bandura, 1997) from a socio-cognitive standpoint or *affordances* (see Fajen, Riley, & Turvey, 2009) from a naturalistic account might be at play here. In a nutshell, reciprocal determinism pertains to the notion that individual, group, and contextual processes are intertwined and mutually influence one another. Within an affordance view, changes to input throughout and output relations in a given system are more or less likely depending on a set of constraints and initial values. For instance, it has been shown that success in sports and other areas of human performance depends, in part, on place of birth (Côté, Macdonald, Baker, & Abernethy, 2006). In all, countries influence the development of teams and coaches. Likewise, hiring experienced coaches may influence the development of strong teams, which in turn may influence the development of football over time in a given country.

Regardless of which view is adopted (the two-level solution proposed herein or the aforementioned three-level alternative solution), the quality of the teams was found to matter the most in predicting performance at the UEFA Women's Champions League. In other words, the strongest predictive effects originate from the team-level of analysis. A team that has won the UEFA Women's Champions League before is more likely to succeed again. In fact, previous performance accomplishments are a major predictor of efficacy beliefs, which in turn are major predictors of performance in team sports in general (Feltz, Short, & Sullivan, 2008), and football in particular (Filho et al., 2014d; Leo, Sánchez-Miguel, Sánchez-Oliva, Amado, & García-Calvo, 2013). To Bandura (1997), success boosts confidence, which in turn increases the chance of further success.

The number of international players on the team was also found to predict final rank at the UEFA Women's Champions League after controlling for several level-1 coach, and level-3 country relevant variables. International players aggregate value to the team, as they perceive performance differently, and thus apply different defensive and offensive tactics to football play

(Filho, 2014c). Moreover, international players are usually top-level athletes that have left their native countries to take on more prosperous job opportunities in foreign nations. Similar to top-level engineers from around the world who are hired by multinational corporations in Silicon Valley for instance, world-class foreign footballers are hired by European clubs to aggregate value to their squads. To illustrate further, at the moment, Marta Da Silva (Brazil) and Carli Lloyd (United States), two the most successful women footballers of all times, are playing away from their homes for football clubs in Europe.

With respect to level-1 data, previous experience coaching in the UEFA Women's Champions League was also found to predict final rank. Coaches that have competed in the league before are likely more aware of the challenges that the competition imposes, such as strategies to counter-act home field advantage and the away goals rule (i.e., goals scored at away venues count more than goals scored at home). In effect, experience at the highest level of competition is important in the development of expertise (Bloom, 1985; Cote et al., 1995; Williams & Ericsson, 2005). Previous experience allows one to develop mental representations that can be applied before, during, and after decisive moments in the game (Filho & Tenenbaum, 2015; Tenenbaum et al., 2013). Put differently, once exposed to high-pressure situations, individuals develop mental skills that allow them to self-regulate and perform better the next time around.

With respect to level-3 data, expressive variability was observed across countries in all measured variables. Hence, controlling for country factors is important in research on women's football. However, the size and financial power of a country is not the major factor predicting performance of teams at the UEFA Women's Champions League. Importantly, previous research has shown that the size and financial power of a country does not necessarily explain performance in football (Hoffmann et al., 2002). Countries of smaller size and budget may also succeed in sports if the culture around that sport is strong enough (e.g., Jamaica in track events). From the present analysis, the only factor that might play a role in performance at the UEFA Women's Champions League was the FIFA world ranking for a given country. More traditional countries may perform slightly better than less traditional ones. Thus, it is important to control for country-level factors when studying performance in women's football. However, it is important to reiterate that, for the present study, the quality of the team and the experience of the coach are paramount for success in the UEFA Women's Champions League. That is, teams from less traditional countries that have a winning story and an experienced coach may triumph in the end. The scope of these findings, limitations, applied implications, and avenues for future research are discussed next.

Limitations, Strengths, Applied Implications, and Future Research

There are at least three limitations that need elaborating to orient future research in women's football. In terms of scope, these findings are not generalizable beyond high-performance women's football in Europe. As previously mentioned, the iterative model was fixed rather than random and thus generalizability is limited to the variables tested within their respective ranges. Moreover, this study was correlational in nature and, as such, inferences of causality are not appropriate. Finally, missing data prevented an even broader census analysis of the UEFA Women's Champions League. To circumvent the missing data issue, it is recommended that teams, leagues, and federations keep detailed records of information related to coaches, players, teams, and countries. Developing and maintaining comprehensive logs of sport actors, teams, and contextual variables will yield reliable information to advance research and practice in football.

Despite these limitations, this study advances the literature on many counts. For instance, findings of this study contrasted many common notions in men's football, thus making it clear that gender effects exist in the “beautiful game” and that guidelines derived from men’s football do not necessarily apply to high-performance women’s football. Moreover, although the findings do not predict performance at lower levels of competitive play, the results are pertinent for professional clubs wanting to develop excellence in football. Researchers in performance and sport psychology aim to study experts, and use the insights gained to help other individuals, groups, and countries to reach higher levels of functioning. Also, notwithstanding the cross-sectional nature of the study, the comprehensive census-like analysis presented herein provides more than a “snap shot profile” of high-performance women’s football in Europe. Natural frequency counts revealed the current status of coaches, teams, and countries participating in the league. This information should be used to inform the development of best practice guidelines for coaches, teams, and countries.

Based on the findings of this study, teams seeking to win the UEFA Women’s Champions League should hire coaches that have previous experience in the competition. As discussed, previous high-stake experience fosters the development of mental representations, which are the basis for effective cognitive, affective, and behavioural patterns differentiating expert individuals and teams from their less-successful counterparts. Furthermore, hiring players from traditionally successful teams as well as international players will likely increase the chance of victory at the UEFA Women’s Champions League. Former winners and international players bring the experience and confidence that propels performance in high-stake competitions. Beyond recruitment guidelines, that might be limited by financial resources, sport actors (e.g., coaches, club managers and directors, referees, scholars, sport professionals) wanting to understand peak performance in women’s football should interact with expert coaches and winning teams, and study the positive cross-cultural effects of having international players on a roster.

Future research could focus on studying expert coaches through qualitative lenses. As the results have shown, the proportion of female coaches in the league is much smaller than the proportion of male coaches. What are the backgrounds, developmental pathways, motivations, challenges, and mental skills of these female coaches? More studies on the migration flow of international athletes are also warranted. As the findings illustrate, the immigration flow of footballers at the UEFA Women’s Champions League contrasts with what is known about the male player migration (Elliott & Harris, 2014). Also, the effect of the team’s budget on performance variables should be examined. In the present study, budget for women’s football was modelled at the country-level of analysis, not the team-level. It is likely that the quality and number of international players on the team, factors that have been found significant in the present study, co-vary with the team’s annual operating budget. However, it might be challenging to obtain this information, as teams might not be willing to disclose financial data.

To conclude, I echo the call for comprehensive studies in sports, particularly in minority populations such as women’s football, using multi-levels of analysis. By examining cross-level effects it is possible to advance knowledge on how to foster talent at the individual level of analysis, while promoting the development of expert teams, and advancing country-level policies to promote quality sport play around the world.

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APPENDIX A – CORRELATION MATRIX AMONG DEPENDENT VARIABLE AND INDEPENDENT VARIABLES

Abbreviated names	Variables
<u>Dependent Variable</u>	
finalrank	Final rank
<u>Level-1 Coach Variables</u>	
Coach_age	Age
Coach_gender	Gender
Coach_national	Nationality status
Coach_FNT	Full national team playing experience
Coach_Interlevel	International playing experience
Coach_nationalteam	Coaching experience of a national team
Coach_ChampsExpYears	Years coaching experience in Champions League
Coach_Time	Time at current position
<u>Level-2 Team Variables</u>	
Team_Seeded	Seed
Team_Qualify	Number of times team has qualified for Champions League
Team_Wins	Number of times team has won Champions League
Team_International	Number of international players on roster
Team_National	Number of players with national team experience
<u>Level-3 Country Variables</u>	
Country_FIFA	FIFA world ranking
Country_TotDiv	Total number of divisions
Country_TmsTop	Number of teams in the top division
Country_RegPlayers	Number of registered female players (18+ years)
Country_Rank	Number one favorite team sport
Country_Bdgt	Budget for women's football

CORRELATION MATRIX BETWEEN THE DEPENDENT VARIABLE AND COACH-LEVEL VARIABLES

Correlations

		finalrank	Coach_age	Coach_gender	Coach_national	Coach_FNT	Coach_Interlevel	Coach_nationalteam	Coach_ChampsExpYears	Coach_Time
finalrank	Pearson Correlation	1	-.052	.078	.061	.043	.019	.063	-.284**	-.143
	Sig. (2-tailed)		.519	.326	.446	.588	.813	.443	.000	.073
	N	160	159	160	160	160	153	151	160	158
Coach_age	Pearson Correlation	-.052	1	-.107	-.002	-.017	-.021	.342**	.242**	.344**
	Sig. (2-tailed)	.519		.181	.977	.830	.801	.000	.002	.000
	N	159	159	159	159	159	152	151	159	157
Coach_gender	Pearson Correlation	.078	-.107	1	-.074	.474**	.418**	.048	-.066	-.049
	Sig. (2-tailed)	.326	.181		.354	.000	.000	.558	.410	.540
	N	160	159	160	160	160	153	151	160	158
Coach_national	Pearson Correlation	.061	-.002	-.074	1	.048	.033	.040	.104	.128
	Sig. (2-tailed)	.446	.977	.354		.548	.684	.625	.190	.110
	N	160	159	160	160	160	153	151	160	158
Coach_FNT	Pearson Correlation	.043	-.017	.474**	.048	1	.968**	.127	-.149	-.090
	Sig. (2-tailed)	.588	.830	.000	.548		.000	.119	.060	.263
	N	160	159	160	160	160	153	151	160	158
Coach_Interlevel	Pearson Correlation	.019	-.021	.418**	.033	.968**	1	.203*	-.130	-.077
	Sig. (2-tailed)	.813	.801	.000	.684	.000		.014	.108	.345
	N	153	152	153	153	153	153	146	153	153
Coach_nationalteam	Pearson Correlation	.063	.342**	.048	.040	.127	.203*	1	.180*	.190*
	Sig. (2-tailed)	.443	.000	.558	.625	.119	.014		.027	.020
	N	151	151	151	151	151	146	151	151	150
Coach_ChampsExpYears	Pearson Correlation	-.284**	.242**	-.066	.104	-.149	-.130	.180*	1	.569**
	Sig. (2-tailed)	.000	.002	.410	.190	.060	.108	.027		.000
	N	160	159	160	160	160	153	151	160	158
Coach_Time	Pearson Correlation	-.143	.344**	-.049	.128	-.090	-.077	.190*	.569**	1
	Sig. (2-tailed)	.073	.000	.540	.110	.263	.345	.020	.000	
	N	158	157	158	158	158	153	150	158	158

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

CORRELATION MATRIX BETWEEN THE DEPENDENT VARIABLE AND TEAM-LEVEL VARIABLES

Correlations

		finalrank	Team_Seeded	Team_Qualify	Teams_Wins	Team_International	Team_National
finalrank	Pearson Correlation	1	-.709**	-.304**	-.363**	-.355**	-.393**
	Sig. (2-tailed)		.000	.000	.000	.000	.000
	N	160	160	160	160	159	159
Team_Seeded	Pearson Correlation	-.709**	1	.513**	.269**	.273**	.332**
	Sig. (2-tailed)	.000		.000	.001	.001	.000
	N	160	160	160	160	159	159
Team_Qualify	Pearson Correlation	-.304**	.513**	1	.267**	.115	.210**
	Sig. (2-tailed)	.000	.000		.001	.149	.008
	N	160	160	160	160	159	159
Teams_Wins	Pearson Correlation	-.363**	.269**	.267**	1	.129	.316**
	Sig. (2-tailed)	.000	.001	.001		.106	.000
	N	160	160	160	160	159	159
Team_International	Pearson Correlation	-.355**	.273**	.115	.129	1	.206**
	Sig. (2-tailed)	.000	.001	.149	.106		.009
	N	159	159	159	159	159	159
Team_National	Pearson Correlation	-.393**	.332**	.210**	.316**	.206**	1
	Sig. (2-tailed)	.000	.000	.008	.000	.009	
	N	159	159	159	159	159	159

**. Correlation is significant at the 0.01 level (2-tailed).

CORRELATION MATRIX BETWEEN THE DEPENDENT VARIABLE AND COUNTRY-LEVEL VARIABLES

Correlations

		finalrank	Country_FIFA	Country_TotDiv	Country_TmsTop	Country_RegPlayers	Country_Rank	Country_Bdgt
finalrank	Pearson Correlation	1	.510**	-.268**	-.219**	-.505**	-.322**	-.444**
	Sig. (2-tailed)		.000	.001	.006	.000	.000	.000
	N	160	158	149	155	150	154	153
Country_FIFA	Pearson Correlation	.510**	1	-.413**	-.279**	-.510**	-.451**	-.529**
	Sig. (2-tailed)	.000		.000	.000	.000	.000	.000
	N	158	158	148	153	148	152	151
Country_TotDiv	Pearson Correlation	-.268**	-.413**	1	.115	.439**	.381**	.146
	Sig. (2-tailed)	.001	.000		.170	.000	.000	.083
	N	149	148	149	145	143	143	143
Country_TmsTop	Pearson Correlation	-.219**	-.279**	.115	1	.068	.070	.011
	Sig. (2-tailed)	.006	.000	.170		.414	.392	.897
	N	155	153	145	155	145	150	149
Country_RegPlayers	Pearson Correlation	-.505**	-.510**	.439**	.068	1	.326**	.505**
	Sig. (2-tailed)	.000	.000	.000	.414		.000	.000
	N	150	148	143	145	150	144	145
Country_Rank	Pearson Correlation	-.322**	-.451**	.381**	.070	.326**	1	.350**
	Sig. (2-tailed)	.000	.000	.000	.392	.000		.000
	N	154	152	143	150	144	154	148
Country_Bdgt	Pearson Correlation	-.444**	-.529**	.146	.011	.505**	.350**	1
	Sig. (2-tailed)	.000	.000	.083	.897	.000	.000	
	N	153	151	143	149	145	148	153

**. Correlation is significant at the 0.01 level (2-tailed).

APPENDIX B – HIERARCHICAL LINEAR MODELS

The statistical software program does not allow for names longer than a certain number of characters and therefore abbreviates the names for the variables included in the analysis. Below is a summary of the abbreviated names and the respective variables.

Abbreviated names	Variables
Level-1 Coach Variables	
(COACH_AG)	Age
(COACH_GE)	Gender
(COACH_NA)	Nationality status
(COACH _FN)	Full national team playing experience
(COACH_IN)	International playing experience
(V13_A)	Coaching experience of a national team
(COACH_CH)	Years coaching experience in Champions League
(COACH_TI)	Time at current position
Level-2 Team Variables	
(TEAM_QUA)	Number of times team has qualified for Champions League
(TEAM_WI)	Number of times team has won Champions League
(TEAM_INT)	Number of international players on roster
(TEAM_NAT)	Number of players with national team experience
Level-3 Country Variables	
(COUNTRY)	FIFA world ranking
(V3_A)	Total number of divisions
(V4_A)	Number of teams in the top division
(V6_A)	Number of registered female players (18+ years)
(V7_A)	Number one favorite team sport
(BUDGETRE)	Budget for women's football

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	27 February 2017, Monday
Time:	10:10:11

Specifications for this HLM2 run

Problem Title: no title

The data source for this run = Feb21_Level2
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = \\lha-034\pers-H\000738BA\My
Documents\Edson_2015\UEFA_HLM_Analysis\SPSS\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00} + u_{0j} + r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 57.52728$

τ

INTRCPT1,β_0 13.64104

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.192

The value of the log-likelihood function at iteration 6 = -2.436165E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	17.752899	1.015591	17.480	68	<0.001

Final estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	17.752899	1.008205	17.608	68	<0.001

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	3.69338	13.64104	68	84.12438	0.090
level-1, r	7.58467	57.52728			

Statistics for current covariance components model

Deviance = 487.233008
Number of estimated parameters = 2

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	23 March 2017, Thursday
Time:	9:12:12

Specifications for this HLM2 run

Problem Title: no title

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The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\EFilho\Desktop\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + \beta_{1j}*(COACH\_AG_{ij}) + \beta_{2j}*(COACH\_GE_{ij}) + \beta_{3j}*(COACH\_NA_{ij})$
$+ \beta_{4j}*(COACH\_FN_{ij}) + \beta_{5j}*(V13\_A_{ij}) + \beta_{6j}*(COACH\_IN_{ij}) + \beta_{7j}*(COACH\_CH_{ij})$
$+ \beta_{8j}*(COACH\_TI_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$
$\beta_{3j} = \gamma_{30}$
$\beta_{4j} = \gamma_{40}$
$\beta_{5j} = \gamma_{50}$
$\beta_{6j} = \gamma_{60}$
$\beta_{7j} = \gamma_{70}$
$\beta_{8j} = \gamma_{80}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00}$
$+ \gamma_{10}*COACH\_AG_{ij}$
$+ \gamma_{20}*COACH\_GE_{ij}$
$+ \gamma_{30}*COACH\_NA_{ij}$
$+ \gamma_{40}*COACH\_FN_{ij}$
$+ \gamma_{50}*V13\_A_{ij}$
$+ \gamma_{60}*COACH\_IN_{ij}$
$+ \gamma_{70}*COACH\_CH_{ij}$
$+ \gamma_{80}*COACH\_TI_{ij}$
$+ u_{0j} + r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 57.35082$

τ
INTRCPT1,β_0 11.80353

Random level-1 coefficient	Reliability estimate

INTRCPT1, β_0	0.171

The value of the log-likelihood function at iteration 6 = -2.266189E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	14.250575	6.861981	2.077	68	0.042
For COACH_AG slope, β_1					
INTRCPT2, γ_{10}	-0.014258	0.127763	-0.112	61	0.912#
For COACH_GE slope, β_2					
INTRCPT2, γ_{20}	0.952919	3.743686	0.255	61	0.800#
For COACH_NA slope, β_3					
INTRCPT2, γ_{30}	6.102938	4.822950	1.265	61	0.211#
For COACH_FN slope, β_4					
INTRCPT2, γ_{40}	1.499127	8.328180	0.180	61	0.858#
For V13_A slope, β_5					
INTRCPT2, γ_{50}	4.384012	2.749192	1.595	61	0.116#
For COACH_IN slope, β_6					
INTRCPT2, γ_{60}	-4.298304	8.452062	-0.509	61	0.613#
For COACH_CH slope, β_7					
INTRCPT2, γ_{70}	-4.286651	1.886412	-2.272	61	0.027#
For COACH_TI slope, β_8					
INTRCPT2, γ_{80}	-0.041585	0.451405	-0.092	61	0.927#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	14.250575	6.629756	2.149	68	0.035
For COACH_AG slope, β_1					
INTRCPT2, γ_{10}	-0.014258	0.103422	-0.138	61	0.891#
For COACH_GE slope, β_2					
INTRCPT2, γ_{20}	0.952919	4.853668	0.196	61	0.845#
For COACH_NA slope, β_3					
INTRCPT2, γ_{30}	6.102938	5.331175	1.145	61	0.257#
For COACH_FN slope, β_4					
INTRCPT2, γ_{40}	1.499127	5.106866	0.294	61	0.770#

For V13_A slope, β_5					
INTRCPT2, γ_{50}	4.384012	2.480292	1.768	61	0.082#
For COACH_IN slope, β_6					
INTRCPT2, γ_{60}	-4.298304	3.910090	-1.099	61	0.276#
For COACH_CH slope, β_7					
INTRCPT2, γ_{70}	-4.286651	1.582401	-2.709	61	0.009#
For COACH_TI slope, β_8					
INTRCPT2, γ_{80}	-0.041585	0.374618	-0.111	61	0.912#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	3.43563	11.80353	68	72.34893	0.336
level-1, r	7.57303	57.35082			

Statistics for current covariance components model

Deviance = 453.237778
Number of estimated parameters = 2

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	27 February 2017, Monday
Time:	10:13:30

Specifications for this HLM2 run

Problem Title: no title

The data source for this run = Feb21_Level2
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = \\lha-034\pers-H\000738BA\My
Documents\Edson_2015\UEFA_HLM_Analysis\SPSS\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + \beta_{1j}*(V13\_A_{ij}) + \beta_{2j}*(COACH\_CH_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10}$
$\beta_{2j} = \gamma_{20}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00}$
$+ \gamma_{10}*V13\_A_{ij}$
$+ \gamma_{20}*COACH\_CH_{ij} + u_{0j} + r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 52.87261$

τ
INTRCPT1,β_0 12.11967

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.186

The value of the log-likelihood function at iteration 6 = -2.364508E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	19.334214	1.406088	13.750	68	<0.001
For V13_A slope, β_1					
INTRCPT2, γ_{10}	3.498798	2.399468	1.458	67	0.149#
For COACH_CH slope, β_2					
INTRCPT2, γ_{20}	-4.212770	1.496482	-2.815	67	0.006#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	19.334214	1.404832	13.763	68	<0.001
For V13_A slope, β_1					
INTRCPT2, γ_{10}	3.498798	2.458834	1.423	67	0.159#
For COACH_CH slope, β_2					
INTRCPT2, γ_{20}	-4.212770	1.426672	-2.953	67	0.004#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	3.48133	12.11967	68	81.12881	0.132
level-1, r	7.27136	52.87261			

Statistics for current covariance components model

Deviance = 472.901573
Number of estimated parameters = 2

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	27 February 2017, Monday
Time:	10:18:56

Specifications for this HLM2 run

Problem Title: no title

The data source for this run = Feb21_Level2
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = \\lha-034\pers-H\000738BA\My
Documents\Edson_2015\UEFA_HLM_Analysis\SPSS\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + \beta_{1j}*(COACH\_CH_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + u_{0j}$
$\beta_{1j} = \gamma_{10}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00}$
$+ \gamma_{10}*COACH\_CH_{ij} + u_{0j} + r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 53.58943$

τ
INTRCPT1,β_0 12.49532

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.189

The value of the log-likelihood function at iteration 6 = -2.383845E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	20.022004	1.335698	14.990	68	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-3.629867	1.454171	-2.496	68	0.015#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	20.022004	1.320954	15.157	68	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-3.629867	1.460348	-2.486	68	0.015#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	$d.f.$	χ^2	p-value
INTRCPT1, u_0	3.53487	12.49532	68	82.62225	0.109
level-1, r	7.32048	53.58943			

Statistics for current covariance components model

Deviance = 476.768924
Number of estimated parameters = 2

Exploratory Analysis: estimated level-2 coefficients and their standard errors obtained by regressing EB residuals on level-2 predictors selected for possible inclusion in subsequent HLM runs

Level-1 Coefficient	Potential Level-2 Predictors			
INTRCPT1, β_0				
	TEAM_QUA	TEAMS_WI	TEAM_INT	TEAM_NAT
Coefficient	-0.206	-1.498	-0.220	-0.142
Standard Error	0.151	0.621	0.050	0.046
t-value	-1.365	-2.411	-4.426	-3.093

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	27 February 2017, Monday
Time:	10:20:12

Specifications for this HLM2 run

Problem Title: no title

The data source for this run = Feb21_Level2
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = \\lha-034\pers-H\000738BA\My
Documents\Edson_2015\UEFA_HLM_Analysis\SPSS\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + \beta_{1j}*(COACH\_CH_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(TEAM\_INT_j) + u_{0j}$
$\beta_{1j} = \gamma_{10}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00} + \gamma_{01}*TEAM\_INT_j$
$+ \gamma_{10}*COACH\_CH_{ij} + u_{0j} + r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 42.03917$

τ
INTRCPT1,β_0 9.79874

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.189

The value of the log-likelihood function at iteration 6 = -2.310766E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	25.162834	1.661556	15.144	67	<0.001
TEAM_INT, γ_{01}	-1.169415	0.265407	-4.406	67	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-4.012474	1.290843	-3.108	68	0.003#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	25.162834	1.355998	18.557	67	<0.001
TEAM_INT, γ_{01}	-1.169415	0.254496	-4.595	67	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-4.012474	1.269528	-3.161	68	0.002#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	$d.f.$	χ^2	p-value
INTRCPT1, u_0	3.13029	9.79874	67	81.38370	0.111
level-1, r	6.48376	42.03917			

Statistics for current covariance components model

Deviance = 462.153221
Number of estimated parameters = 2

Exploratory Analysis: estimated level-2 coefficients and their standard errors obtained by regressing EB residuals on level-2 predictors selected for possible inclusion in subsequent HLM runs

Level-1 Coefficient	Potential Level-2 Predictors		
INTRCPT1, β_0			
	TEAM_QUA	TEAMS_WI	TEAM_NAT
Coefficient	-0.122	-1.149	-0.072
Standard Error	0.134	0.551	0.042
t-value	-0.909	-2.083	-1.718

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM2.EXE (7.01.21202.1001)
Date:	27 February 2017, Monday
Time:	10:24:32

Specifications for this HLM2 run

Problem Title: no title

The data source for this run = Feb21_Level2
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = \\lha-034\pers-H\000738BA\My
Documents\Edson_2015\UEFA_HLM_Analysis\SPSS\hlm2.html
The maximum number of level-1 units = 69
The maximum number of level-2 units = 69
The maximum number of iterations = 100

Method of estimation: restricted maximum likelihood

The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$FINALRAN_{ij} = \beta_{0j} + \beta_{1j}*(COACH\_CH_{ij}) + r_{ij}$

Level-2 Model

$\beta_{0j} = \gamma_{00} + \gamma_{01}*(TEAMS\_WI_j) + \gamma_{02}*(TEAM\_INT_j) + u_{0j}$
$\beta_{1j} = \gamma_{10}$

Mixed Model

$FINALRAN_{ij} = \gamma_{00} + \gamma_{01}*TEAMS\_WI_j + \gamma_{02}*TEAM\_INT_j$
$+ \gamma_{10}*COACH\_CH_{ij}$
$+ u_{0j}+ r_{ij}$

Final Results - Iteration 6

Iterations stopped due to small change in likelihood function

$\sigma^2 = 39.64194$

τ
INTRCPT1,β_0 9.23668

Random level-1 coefficient	Reliability estimate
INTRCPT1,β_0	0.189

The value of the log-likelihood function at iteration 6 = -2.256387E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.557404	1.636011	15.011	66	<0.001
TEAMS_WI, γ_{01}	-7.131790	3.190754	-2.235	66	0.029
TEAM_INT, γ_{02}	-1.083295	0.260584	-4.157	66	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-2.896665	1.349209	-2.147	68	0.035#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of fixed effects
(with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, β_0					
INTRCPT2, γ_{00}	24.557404	1.425006	17.233	66	<0.001
TEAMS_WI, γ_{01}	-7.131790	1.833326	-3.890	66	<0.001
TEAM_INT, γ_{02}	-1.083295	0.254522	-4.256	66	<0.001
For COACH_CH slope, β_1					
INTRCPT2, γ_{10}	-2.896665	1.369256	-2.116	68	0.038#

The p-vals above marked with a "#" should regarded as a rough approximation.

Final estimation of variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, u_0	3.03919	9.23668	66	80.14523	0.113
level-1, r	6.29618	39.64194			

Statistics for current covariance components model

Deviance = 451.277382
Number of estimated parameters = 2

Exploratory Analysis: estimated level-2 coefficients and their standard errors obtained by regressing EB residuals on level-2 predictors selected for possible inclusion in subsequent HLM runs

Level-1 Coefficient	Potential Level-2 Predictors	
INTRCPT1, β_0		
	TEAM_QUA	TEAM_NAT
Coefficient	-0.114	-0.059
Standard Error	0.129	0.041
t-value	-0.887	-1.435

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM3.EXE (7.01.21202.1001)
Date:	22 March 2017, Wednesday
Time:	17:11: 9

Specifications for this HLM3 run

Problem Title: no title

The data source for this run = finaltest
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\EFilho\Desktop\hlm3.html
The maximum number of level-1 units = 35
The maximum number of level-2 units = 35
The maximum number of level-3 units = 34
The maximum number of iterations = 100
Method of estimation: full maximum likelihood
The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$$\text{FINALRAN}_{ijk} = \pi_{0jk} + e_{ijk}$$

Level-2 Model

$\pi_{0jk} = \beta_{00k} + r_{0jk}$

Level-3 Model

$\beta_{00k} = \gamma_{000} + u_{00k}$

Mixed Model

$FINALRAN_{ijk} = \gamma_{000} + r_{0jk} + u_{00k}$

For starting values, data from 35 level-1 and 35 level-2 records were used

Final Results - Iteration 13

Iterations stopped due to small change in likelihood function

$\sigma^2 = 0.19000$

τ_π
INTRCPT1,π_0 36.53504
Standard error of τ_π
INTRCPT1,π_0 48.24770

Random level-1 coefficient	Reliability estimate
INTRCPT1,π_0	0.995

τ_β
INTRCPT1
INTRCPT2,β_{00}
26.39068
Standard error of τ_β
INTRCPT1
INTRCPT2,β_{00}
49.24530

Random level-2 coefficient	Reliability estimate

INTRCPT1/INTRCPT2,β_{00}	0.423

The value of the log-likelihood function at iteration 13 = -1.221032E+002

Final estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	20.314544	1.354330	15.000	33	<0.001

Final estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	20.314544	1.354109	15.002	33	<0.001

Final estimation of level-1 and level-2 variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1,r_0	6.04442	36.53504	1	182.74864	<0.001

Final estimation of level-3 variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1/INTRCPT2,u_{00}	5.13719	26.39068	33	59.14234	0.004

Statistics for the current model

Deviance = 244.206375
Number of estimated parameters = 3

Exploratory Analysis: estimated level-3 coefficients and their standard errors obtained by regressing EB residuals on level-3 predictors selected for possible inclusion in subsequent HLM runs

Level-1 Coefficient	Potential Level-3 Predictors					
INTRCPT1/INTRCPT2, β_{00}						
	COUNTRY	V3_A	V4_A	V6_A	V7_A	BUDGETRE
Coefficient	0.055	-0.698	-0.303	-0.000	-2.910	-0.001
Standard Error	0.021	0.309	0.242	0.000	1.295	0.000
t-value	2.543	-2.259	-1.253	-3.376	-2.248	-3.158

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM3.EXE (7.01.21202.1001)
Date:	22 March 2017, Wednesday
Time:	17:16:43

Specifications for this HLM3 run

Problem Title: no title

The data source for this run = finaltest
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\EFilho\Desktop\hlm3.html
The maximum number of level-1 units = 35
The maximum number of level-2 units = 35
The maximum number of level-3 units = 34
The maximum number of iterations = 100
Method of estimation: full maximum likelihood
The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$\mathrm{FINALRAN}_{ijk} = \pi_{0jk} + \pi_{1jk}*(COACH\_CH_{ijk}) + e_{ijk}$

Level-2 Model

$\pi_{0jk} = \beta_{00k} + \beta_{01k}*(TEAMS\_WI_{jk}) + \beta_{02k}*(TEAM\_INT_{jk}) + r_{0jk}$
$\pi_{1jk} = \beta_{10k}$

Level-3 Model

$\beta_{00k} = \gamma_{000} + \gamma_{001}(COUNTRY_{k}) + u_{00k}$
$\beta_{01k} = \gamma_{010}$

$\beta_{02k} = \gamma_{020}$
$\beta_{10k} = \gamma_{100}$

Mxed Model

$FINALRAN_{ijk} = \gamma_{000} + \gamma_{001}*\mathrm{COUNTRY}_k + \gamma_{010}*\mathrm{TEAMS\_WI}_{jk} + \gamma_{020}*\mathrm{TEAM\_INT}_{jk}$
$+ \gamma_{100}*COACH\_CH_{ijk}$
$+ r_{0jk} + u_{00k}$

For starting values, data from 35 level-1 and 35 level-2 records were used

Final Results - Iteration 493

Iterations stopped due to small change in likelihood function

$\sigma^2 = 0.19000$

τ_π
INTRCPT1,π_0 23.98579
Standard error of τ_π
INTRCPT1,π_0 27.31703

Random level-1 coefficient	Reliability estimate
INTRCPT1,π_0	0.992

τ_β
INTRCPT1
INTRCPT2,β_{00}
3.24677
Standard error of τ_β
INTRCPT1
INTRCPT2,β_{00}
26.89424

Random level-2 coefficient	Reliability estimate
INTRCPT1/INTRCPT2,β_{00}	0.121

The value of the log-likelihood function at iteration 493 = -1.076011E+002

F inal estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	21.847253	2.093381	10.436	32	<0.001
COUNTRY, γ_{001}	0.094559	0.034222	2.763	32	0.009
For TEAMS_WI, β_{01}					
INTRCPT3, γ_{010}	-5.794310	2.949856	-1.964	33	0.058#
For TEAM_INT, β_{02}					
INTRCPT3, γ_{020}	-1.251432	0.291807	-4.289	33	<0.001#
For COACH_CH slope, π_1					
For INTRCPT2, β_{10}					
INTRCPT3, γ_{100}	-0.806408	1.307200	-0.617	colspan=2>Unable to compute	

The p-vals above marked with a "#" should regarded as a rough approximation.

F inal estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	*t*-ratio	Approx. *d.f.*	*p*-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	21.847253	1.533395	14.248	32	<0.001
COUNTRY, γ_{001}	0.094559	0.031213	3.029	32	0.005
For TEAMS_WI, β_{01}					
INTRCPT3, γ_{010}	-5.794310	1.866847	-3.104	33	0.004#
For TEAM_INT, β_{02}					
INTRCPT3, γ_{020}	-1.251432	0.251035	-4.985	33	<0.001#
For COACH_CH slope, π_1					
For INTRCPT2, β_{10}					
INTRCPT3, γ_{100}	-0.806408	1.484853	-0.543	colspan=2>Unable to compute	

The p-vals above marked with a "#" should regarded as a rough approximation.

F inal estimation of level-1 and level-2 variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1, r_0	4.89753	23.98579	too few df to compute		

F inal estimation of level-3 variance components

Random Effect	Standard Deviation	Variance Component	*d.f.*	χ^2	*p*-value
INTRCPT1/INTRCPT2,u_{00}	1.80188	3.24677	32	37.52179	0.230

Statistics for the current model

Deviance = 215.202104

Number of estimated parameters = 7

Exploratory Analysis: estimated level-3 coefficients and their standard errors obtained by regressing EB residuals on level-3 predictors selected for possible inclusion in subsequent HLMruns

Level-1 Coefficient	Potential Level-3 Predictors				
INTRCPT1/INTRCPT2,β_{00}					
	V3_A	V4_A	V6_A	V7_A	BUDGETRE
Coefficient	-0.029	-0.028	-0.000	-0.061	-0.000
Standard Error	0.058	0.045	0.000	0.243	0.000
t-value	-0.503	-0.610	-0.568	-0.251	-0.215

Program:	HLM 7 Hierarchical Linear and Nonlinear Modeling
Authors:	Stephen Raudenbush, Tony Bryk, & Richard Congdon
Publisher:	Scientific Software International, Inc. (c) 2010
	techsupport@ssicentral.com www.ssicentral.com

Module:	HLM3.EXE (7.01.21202.1001)
Date:	22 March 2017, Wednesday
Time:	17:17: 8

Specifications for this HLM3 run

Problem Title: no title

The data source for this run = finaltest
The command file for this run =
C:\Users\EFilho\AppData\Local\Temp\whlmtemp.hlm
Output file name = C:\Users\EFilho\Desktop\hlm3.html
The maximum number of level-1 units = 35
The maximum number of level-2 units = 35
The maximum number of level-3 units = 34
The maximum number of iterations = 100
Method of estimation: full maximum likelihood
The outcome variable is FINALRAN

Summary of the model specified

Level-1 Model

$\mathrm{FINALRAN}_{ijk} = \pi_{0jk} + e_{ijk}$

Level-2 Model

$\pi_{0jk} = \beta_{00k} + \beta_{01k}*(TEAMS\_WI_{jk}) + \beta_{02k}*(TEAM\_INT_{jk}) + r_{0jk}$

Level-3 Model

$\beta_{00k} = \gamma_{000} + \gamma_{001}(COUNTRY_k) + u_{00k}$

$\beta_{01k} = \gamma_{010}$

$\beta_{02k} = \gamma_{020}$

Mixed Model

$FINALRAN_{ijk} = \gamma_{000} + \gamma_{001}*\mathrm{COUNTRY}_k + \gamma_{010}*\mathrm{TEAMS\_WI}_{jk} + \gamma_{020}*\mathrm{TEAM\_INT}_{jk} + r_{0jk} + u_{00k}$

For starting values, data from 35 level-1 and 35 level-2 records were used

Final Results - Iteration 848

Iterations stopped due to small change in likelihood function

$\sigma^2 = 0.19000$

τ_π

INTRCPT1,π_0 25.47088

Standard error of τ_π

INTRCPT1,π_0 28.05350

Random level-1 coefficient	Reliability estimate
INTRCPT1,π_0	0.993

τ_β

INTRCPT1

INTRCPT2,β_{00}

2.04252

Standard error of τ_β

INTRCPT1

INTRCPT2,β_{00}

27.49540

Random level-2 coefficient	Reliability estimate
INTRCPT1/INTRCPT2,β_{00}	0.076

The value of the log-likelihood function at iteration 848 = -1.077834E+002

F inal estimation of fixed effects:

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	21.209697	1.857780	11.417	32	<0.001
COUNTRY, γ_{001}	0.098891	0.033801	2.926	32	0.006
For TEAMS_WI, β_{01}					
INTRCPT3, γ_{010}	-6.390354	2.787937	-2.292	33	0.028#
For TEAM_INT, β_{02}					
INTRCPT3, γ_{020}	-1.262954	0.292660	-4.315	33	<0.001#

The p-vals above marked with a "#" should regarded as a rough approximation.

F inal estimation of fixed effects (with robust standard errors)

Fixed Effect	Coefficient	Standard error	t-ratio	Approx. $d.f.$	p-value
For INTRCPT1, π_0					
For INTRCPT2, β_{00}					
INTRCPT3, γ_{000}	21.209697	1.921046	11.041	32	<0.001
COUNTRY, γ_{001}	0.098891	0.033272	2.972	32	0.006
For TEAMS_WI, β_{01}					
INTRCPT3, γ_{010}	-6.390354	1.163960	-5.490	33	<0.001#
For TEAM_INT, β_{02}					
INTRCPT3, γ_{020}	-1.262954	0.248937	-5.073	33	<0.001#

The p-vals above marked with a "#" should regarded as a rough approximation.

F inal estimation of level-1 and level-2 variance components

Random Effect	Standard Deviation	Variance Component	$d.f.$	χ^2	p-value
INTRCPT1,r_0	5.04687	25.47088	too few df to compute		

F inal estimation of level-3 variance components

Random Effect	Standard Deviation	Variance Component	$d.f.$	χ^2	p-value
INTRCPT1/INTRCPT2,u_{00}	1.42917	2.04252	32	35.12220	0.322

Statistics for the current model

Deviance = 215.566881

Number of estimated parameters = 6

Exploratory Analysis: estimated level-3 coefficients and their standard errors obtained by regressing EB residuals on level-3 predictors selected for possible inclusion in subsequent HLMruns

Level-1 Coefficient	Potential Level-3 Predictors				
INTRCPT1/INTRCPT2,β_{00}					
	V3_A	V4_A	V6_A	V7_A	BUDGETRE
Coefficient	-0.020	-0.020	-0.000	-0.035	-0.000
Standard Error	0.036	0.028	0.000	0.152	0.000
t-value	-0.559	-0.702	-0.590	-0.228	-0.146