Giving answers or educating?

– Evaluation of an automated tracking system and its possibilities to educate game intelligence in Swedish elite football players.

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Abstract

The aim of the study was to evaluate an automated tracking system and its possibilities to increase knowledge and awareness (future described as educate) in game intelligence among Swedish male elite football players. The study involved both qualitative and quantitative aspects. The quantitative part consisted of observing offensive passes performed by three male players, average age 25.3 (±1.5) years, weight 75.7 (±2.1) kg and height 181 (±4.4) cm. All of the players offensive passes were judged and categorized, based on criteria by the practitioner with footballing knowledge and by the automated tracking system. Pass probability (PP) and pass probability times pass impact (PP x PI) was observed since they indicate the possibility for a pass to succeed but also its impact, which could be associated with the game intelligence ability, knowledge of situational probability. The results showed a significant association (p<0.05) between PP and PP x PI. Hence, the null hypothesis could be rejected. Additionally, pass probability (PP) was a more accurate method than pass probability times pass impact (PP x PI) and results also showed that the players made more accurate decisions than the automated tracking system.

The qualitative part of the study consisted of three recorded sessions with the player, where the automated tracking system was used as an educational tool. The players were shown different situations which they then discussed. Results indicated that most of the player quotes could be associated to visual search behavior (n=24). Although, an improved automated tracking system was used, there are still limitations with the automated tracking systems accuracy which could affect the results. This article provides a very preliminary step in the study of automated tracking systems as an educational tool and suggests an approach based on discussions with players, rather than only relying on answers given by the automated tracking system. However, the research area within automated tracking systems is relatively unexplored and results should be interpreted with caution. Therefore, future studies are necessary to determine how much an automated tracking system could improve game intelligence.

Keywords: Automated tracking system, Game intelligence, Football analytics.
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1. Introduction

For a long period, football has generated curiosity and enthusiasm among players, coaches, spectators and researchers. Football is a complex sport which involves both physiological and psychological abilities. Applying both these abilities, with great quality and quantity, is crucial for becoming a successful player (Bloomfield, Polman & O’Donoghue, 2007; Dellal et al., 2011; Bangsbo, Mohr & Krstrup, 2006). The purpose of the sport could simply be stated as scoring more goals than you concede, but ultimately the when breaking the sport down, its complexity is revealed.

Mann, Williams, Ward and Janelle (2007) examined young elite and novice football players and found a significant difference in physical performance between expert and novice football players. Similar differences in physical performance have also been identified between Championship, Premier League and Champions League teams. However, the authors in that study concluded that physical performance may not indicate superiority between divisions and leagues, just differences in physical performance (Di Salvo, Pigozzi, González-Haro, Laughlin & Witt, 2012). Instead, decision making could be a more accurate variable explaining the difference between levels (Vaeyens, Lenoir, Williams & Philippaerts, 2007). Thus, football is a lot about running, it also involves the knowledge and intuition of when and where to run (Di Salvo et al., 2012) and according to Vestberg, Reinebo, Maurex, Ingvar and Petrovic (2017) differences in the executive functions (e.g. decision making) among young elite football players may be a good predictor for future success. Hence, the psychological ability could play a crucial part in football (Williams, 2000).

One of many psychological functions is the perceptual-cognitive function, which involves prediction and decision-making abilities (Casanova, Oliveira, Williams & Garganta, 2009). However, in the world of sport, these abilities are more known as components of game intelligence (Stratton, Reilley, Richardson & Williams, 2004). When optimizing decisions in football, considerations regarding time, space, players and the position of the ball should be made (Meusen, 2020). According to Williams (2000), game intelligence could be a crucial component for high-level performance in football and involves the abilities, advance visual cue utilization, pattern recall and recognition, visual search behavior and the knowledge of situational based probabilities (Casanova et al., 2009).
2. Background

2.1 Game intelligence

In the following sections, definitions and previous research in the field of game intelligence will be presented.

2.1.1 Advance visual cue utilization

Advance visual cue utilization refers to a player’s ability to anticipate possible outcomes for an opponent, based on their body angles and movements e.g. body posture or kicking technique (Williams, 2000). High levels of advance visual cue utilization lead to great benefits in ball sports (Abernethy, 1987) since experienced players tend to be superior in comparison to inexperienced players in advance visual cue utilization (Williams & Burwitz, 1993; Nakamoto & Mori, 2012).

2.1.2 Pattern recall and recognition

Pattern recall and recognition is defined as the ability to recognize match situations e.g. positions of opponents during a cross (Casanova et al., 2009). Pattern recall and recognition can be based on dynamic situations where actions are structured, e.g. situations when the ball is on the pitch or unstructured situations, e.g. when player is having a water or injury break (Williams, 2000). The capability of recalling and recognize football-specific information could contribute to a superiority against the opponent, since predictions of outcomes based on experience could be made.

Studies have investigated players in different levels and their ability to recall situations (Abernethy, Baker & Côté, 2005). Players were shown short sequences from a game and shortly after, they were supposed to recall the situation from the clip as accurately as possible. Research indicated that more skillful players tend to recall situations more accurate
than less skilled players (Williams, Hodges & Barton, 2006; Smeeton, Ward & Williams, 2004; Alain & Proteau, 1980).

2.1.3 Visual search behavior

Visual search behavior refers to a player’s ability to adjust focus to the most relevant information. The difference between visual search behavior and advance visual cue utilization is that the advance visual cue utilization regards anticipations of actions made by opponents. A player with high level of visual search behavior knows where and when to look during situations (Williams, 2000). The ability to extract relevant information under a short period could contribute to an advantage since research has shown that there are variations in search patterns between professional and novice football players, where a professional player is able to process information quicker and more accurate than a novice player (Casanova et al., 2009).

2.1.4 Knowledge of situational probabilities

Knowledge of situational probabilities involves the ability to extract relevant information from an event and anticipate possible outcomes. e.g. the optimal position in order to score based on where the ball possibly will land and position of the opponents. High skilled professional players tend to have high knowledge regarding the possibility for future situations based on the current situation compared to novices (Casanova et al., 2009). Knowledge of situational probabilities can appear in different ways, specific and general (Williams, 2000). A general example could be a situation where the center back has the ball, with the possibility to play the other center back, full back or the central midfielder. This is a common situation that is similar, pretty much independent of team or player. However, the specific knowledge of situational probability regards tendencies that opponents might have for example the left footed right winger who always wants to cut in for a shot or the striker who is weak on the head. When comparing skilled and less skilled football players, the skilled completes more accurate and faster anticipations for possible future outcomes (Williams, 2000).
2.2 Football analytics

Football analytics has been a part of the game for a long time. In the 1950s, Charles Reep collected statistics manually with the purpose of identifying the key to scoring goals (Sykes & Paine, 2016). However, football analytical systems have not until recently developed rapidly, not only in football but also in basketball, American football, baseball and ice hockey (Nistala & Guttag, 2019; Czuzoj-Shulman, Boucher, Bornn & Javan, 2019; Burke, 2019; Berry & Fowler, 2019). The primary purpose of sport analytics today, is to provide coaches with information and preferable tools to evaluate and develop tactics. Apart from that, football analytics could be beneficial when scouting opponents, by identifying their way of playing (Amatria, Dios, Pérez-Turpin, Gomis-Gomis, Elvira-Aranda & Suárez-Llorca, 2019) and recruiting players to your team that could enhance team chemistry on the pitch (Bransen & Van Haaren, 2020; Gavião, Sant’Anna, Alves Lima & de Almada Garcia, 2019).

Automated tracking systems are primarily based on collective movement, event data and coordinates of the players’ and the ball and its location, which then contributes to modelling models (Sumpter, Mann & Perna, 2012; Nitala & Guttag, 2019). Expected goals (xG) is one famous module, generated by an automated tracking system, which estimates the quality of a goal scoring chance (Spearman, 2018). Automated tracking systems strive to eventually provide the coaching staff with information that could facilitate and improve tactical decisions. Currently, there is a lack of studies validating automated tracking systems since clubs and organizations use and create their own automated tracking system. However, assumptions could be made based on sport conferences, that there are associations between the automated tracking systems, developed by the clubs due to similarities in equations.

2.2.1 Principles

The automated tracking system used in this study is based on two different principles. The first one is the zonal principle, identified by coaches and analysts at F.C. Barcelona, who defined relative positions to the ball (Seirul·lo, F. 2010). From each situation in football, zonal principles could be applied, where the different zones are intervention, mutual-help and cooperation zone. Intervention zone includes the ball holding player and the defenders with
the possibility to intercept the ball immediately. Mutual-help zone involves the players who are relatively close to the ball, but without possibility to intercept it immediately. These players are further away than the ones in the intervention zone, but still close enough to receive a pass in the nearest future. In this study, a pass is defined as when a player (i.e. passer) is kicking the ball towards a teammate (i.e. receiver) who then intercepts the ball trajectory. This zone includes both the attacking and defending team. Cooperation zone is the resisting area for the player outside mutual-help zone. Players in this area will not receive a pass in a few seconds, instead the attacking players in this area strive to control space and identify dangerous areas while the defending team strives to minimize the area for the attacking team.

The other principle underlying for the automated tracking system was based on the behavior as football player; striving for optimizing pitch control, pass possibility or pass impact (Peralta Alguacil, Fernández, Piñones Arce and Sumpter, 2020).

Figure 1. Illustration of a real game situation in the Spanish first division between F.C. Barcelona (red dots) and Real Betis (green dots) which illustrates the different zones and the direction of the players and the ball (black dot).
2.2.1.1 Pass impact

Pass impact (PI) measures a pass and how much it contributes to a goal. How much it increases the likelihood for a goal in the nearest future is displayed with a numeric value, on a range from 0 to 1, for more information see Appendix A.3 (Peralta Alguacil et al., 2020). Pass impact has been applied to this study, since a player with repetitive high pass impact probably predicts optimal outcomes well. This ought to be associated with the game intelligence ability, knowledge of situational probabilities. Researchers have tried to examine the impact for a pass by computing different models. However, limitations have brought up for discussing among researchers (Decroos, Bransen, Van Haaren & Davis, 2019). Altman (2015) generated a model which only assessed pass impact based on goals and assist and Mackay (2017) excluded passes that could increase the chances for scoring a goal in the next couple of seconds and excluded players who were able intercept the ball trajectory.

Decroos et al. (2019) decided to modify the work of Altman and Mackay and adjusted for the limitations. The modifications involved a more accumulated measurements of both offensive and defensive action as well as its impact. However, limitations still existed since these calculations did not compute the ball trajectory optimally (Peralta Alguacil et al., 2020) and
moreover only valued the on-ball actions (Decroos et al., 2019). A modified model for pass impact by Peralta Alguacil and colleagues, with a new ball trajectory and integration of historical data provided by Twelve Football, will be applied to this study.

Figure 3 and 4 below, illustrates that impact changes depending on position of the ball (blue dot). The white color indicates a “0-impact-pass” which will not enhance the chances of scoring, while the black color indicates a “1-impact-pass”, a pass that is guaranteed to contribute to a goal. A pass can shape any value on a possibility scale from 0 to 1.

Figure 3. Pass impact when the position of the ball (blue dot) is at the right side in offensive position. The heat map describes the probability for a pass to lead to a goal. See appendix A.3 for calculation of pass impact.
Figure 4. Pass impact when the ball (blue dot) is central outside the penalty box. The heat map describes the probability for a pass to lead to a goal. See appendix A.3 for calculation of pass impact.

2.2.1.2 Pass probability

The purpose of pass probability (PP) is to assess the possibility for a pass to be completed. The measurement is based on how long time it takes for a teammate to intercept the ball trajectory. A numeric value between 0 and 1 displays the possibility for a pass to be completed (for further explanation see Appendix A.1). However, it has been discussions between data analysts when modelling pass probability, some suggest that machine learning, based on real football data is an optimal method for modelling pass probability (Gudmundsson & Wolle, 2014). However, the method has been criticized for not being concrete enough (Spearman, Basye, Dick, Hotovy & Pop, 2017). Another modelling method of pass probability is time-to-intercept, where the idea is to calculate how long time it would take for a player to intercept the ball trajectory (Spearman et al., 2017). Peralta Alguacil et al. (2020) refined Spearman’s modelling method by changing the calculation for the ball trajectory and improved the algorithm. The model generated by Peralta Alguacil and co-researchers will be applied in this study.
When modelling pass probability, the practitioner defined a pass as, when a ball holding player (i.e. passer) is kicking the ball, which later gets intercepted by a teammate (i.e. receiver) (Spearman et al., 2017; Peralta Alguacil et al., 2020; Gudmundsson & Wolle, 2014). Pass probability has been applied to this study to facilitate the investigation of game intelligence and its involving abilities, such as knowledge of situational probability.

Figure 5. A real match situation from 2019 between Hammarby IF (green) and IFK Göteborg (black). The central midfielder was playing a breakthrough pass into the penalty area, at the same time as the Hammarby striker is completing a diagonal run for intercepting the ball trajectory. The green area indicates a high possibility for a pass to be completed, while the red area represents a low possibility for a completed pass.

2.2.1.3 Pass probability times pass impact

Pass probability times pass impact (PP x PI) is a combination of pass probability and pass impact, developed by Peralta Alguacil et al. (2020). The purpose of PP x PI is to assess the possibility for a pass to be received and a goal resulting from that pass. Since the pass involves both decision-making and prediction of outcome it could principally be associated with the game intelligence ability; knowledge of situational probabilities. Hence, PP x PI will possess a vital part of this study. Peralta Alguacil et al. (2020) concluded in their study that
PP x PI has high accuracy and is the best predictor for actions in the mutual help zone. However, there are limitations with studies examine PP x PI since it is such a new method.

![Figure 6](image)

**Figure 6.** Pass impact times pass probability from a real game between Hammarby IF and Malmö FF, were the ball (black dot) is outside the right corner of the penalty box with players able to intercept the pass. See appendix A.1 and A.3 for calculations of pass impact.

### 2.2.1.4 Pitch control

Pitch control (PC) assess the position of a player in relation to teammates, opponents and the goal. A numeric value between 0 and 1 represents how much control a specific player has over an area and how valuable the area is. A heatmap of players movements during a game has been a part of sport analytics for a while. However, heatmap does not provide with any value for the locations that players cover during a game, instead it highlights the movement pattern of the player (Fernández et al., 2019). Research has assumed that controlling space in crucial areas is beneficial for increasing the chances of scoring and reduce the probability of conceding goals (Pollard, Ensum & Taylor, 2004). Controlling the majority of the pitch could contribute to more options for the team in possession. Hence, researchers have tried to assess and identify optimal positions for increasing pitch control (Peralta Alguacil et al., 2020). Recent studies have generated pitch control models based on Voronoi diagrams (Kim, 2004; Fernández & Bornn, 2018; Rein, Raabe & Memmert, 2017) which indicates a point
and the distance to the nearest points around it (Kim, 2004). With support from Voronoi diagrams, an area controlled by a player could be highlighted (Fonseca, Milho, Travassos & Araújo, 2002; Kim, 2004). However, Voronoi diagrams only define strict boundaries, independent on the influence from other players, their movement (Fernández & Bornn, 2018) and additionally, the area occupied by the player lacks a value within the automated tracking system (Fernández et al., 2019). A more continuous calculation was generated for estimating pitch control and its value (Fernández & Bornn, 2018; Fernández et al., 2019; Peralta Alguacil et al., 2020), which will be implemented into this study, for calculation, see Appendix A.2.

Pitch control could primary be used to evaluate an idea, well described by the Dutch former footballer Johan Cruyff “*When you play a match, it is statistically proven that players actually have the ball 3 minutes on average ... So, the most important thing is what do you do during those 87 minutes when you do not have the ball.*”. Hence, pitch control could evaluate both on and off ball actions and assess players contribution during games.

Figure 7 displays pitch control between Hammarby IF (green) and Helsingborg IF (red) the white spaces indicates an area where the players have equal control over. With help from this figure coaches and players could get a clear picture of area covered during specific situations.
2.2.3 Football analytics as an educational tool for game intelligence

An equipment with the capability of increasing knowledge or awareness in a selected knowledge area could be considered as an educational tool. In this thesis the word educational tool will describe the automated tracking systems possibility to increase either knowledge or awareness for game intelligence.

Hammond (2004) assumed video-based feedback (VBF) contributes to a more holistic perspective in sport. VBF could be used for critical reflection, increasing knowledge, challenging and improving players with help from on pitch errors (Middlemas & Harwood, 2018). Mazzelli and Nason (2019) investigated if an automated tracking system could be used as an educational tool for players and when it should be applied. Their study suggested that feedback should be provided selectively, with the conclusion, practice what you wish to improve.

Peralta Alguacil et al. (2020) examined the accuracy of the automated tracking system together with the head and assistant coach for Hammarby IF. The researchers selected sequences and presented them for the coaches. Their conclusion indicated that pitch control could be an appropriate tool for tactical discussions and presenting feedback for players. However, a learning process could be necessary for the players (Peralta Alguacil, et al., 2020) since social climate affects the outcomes of visual feedback as an educational tool. Meeting should preferably be held face-to-face and under circumstances were players are trusting their leaders and teammates (Middlemas & Harwood, 2018).

Different feedback delivery strategies can be applied, where sessions can be held with team or person-to-person focus, where different strategies seem to evoke different outcomes. Although video-based feedback could increase the knowledge regarding tactics and own behavior, coaches should be aware that players respond differently to feedback. Awareness from coaches is therefore vital when applying a strategy (Middlemas & Harwood, 2018). A study has shown that absence of trust and will to receive feedback, due to negative climate, could be harmful and lead to negative consequences for players improvements (Pensgaard &
Duda, 2002). Mackenzie and Cushion (2013) suggests that feedback may only be advantageous if the individual understands what has been delivered and is able to interpret the information correctly. Therefore, teaching strategies may and ought to differ from person to person (Raab, 2007). Video based feedback could also be used by coaches to evaluate performance and confirming players tactical awareness (Middlemas & Harwood, 2018). In order to develop game intelligence in sport, experience-based exercises are a vital component (García-González et al., 2013). Nimmerichter et al. (2015) found that VBF two times a week could be beneficial for develop decision-making. Furthermore, decision-making is the most developable ability when utilizing VBF (García-González, Perla Moreno, Moreno, Gil and del Villar, 2013; Nimmerichter, Weber & Haller, 2015). Additionally, VBF could increase performance among national team athletes in different sports (Baker et al., 2003) for instance, in tennis (García-González et al., 2013). If an automated tracking system could be used as an educational tool, football players could improve their performances (Vestberg et al., 2017; Vaeyens, 2007). However, there is a lack of studies examining automated tracking systems possibility to educate game intelligence.

2.3 Aim

The general aim of this study was to investigate if an automated tracking system could be used as an educational tool for game intelligence in Swedish male elite football players. Investigation will consist of validating the accuracy of the automated tracking system and investigate players’ perceptions of the automated tracking system.

2.3.1 Research question

1) Does pass probability times pass impact (PP x PI) make a better prediction than pass probability of the actions of the players (PP)
2) Are the players making better decisions than the system
3) Can the automated tracking system be used as a tool for educating game intelligence among Swedish male elite football players?
2.3.2 Hypothesis

$H_1$: There is a significant association between PP and PP x PI for estimating optimal solutions for a pass, generated by the automated tracking system.

$H_0$: There is no significant association between PP and PP x PI for estimating optimal solutions for a pass, generated by the automated tracking system.
3. Method

The purpose with the method was reaching the aim of the study by generating a method that could contribute to examination of the three research questions. The first research question, 1) *Does pass probability times pass impact (PP x PI) make a better prediction than pass probability* was generated to evaluate the accuracy of the system. Since, if the system could educate (i.e. improve knowledge and awareness) in game intelligence, the figures generated by the system should be trustworthy. Pass probability was selected since its new methods claims to be more accurate than similar equations (Peralta Alguacil et al., 2020).

Furthermore, the research question wants to compare which of the two categories, PP and PP x PI that makes the best prediction. Where the best prediction was defined as most accurate in suggesting the best pass for a situation.

The second research question 2) *are the players making better decisions than the system?* Was designed to investigate if the decisions (i.e. pass executed by the player) by the player was better than the pass proposed by the automated tracking system. Determination of the best decision was based on a judgment by the practitioner. Where the practitioner refers to the author in this study. By examine the second research question, information regarding differences in game intelligence between the player and the automated tracking system could be collected. If the player made better decisions than the system, discussions could be brought up regarding if the system is appropriate for educating something that the player is superiority in.

The last research question 3) *Can an automated tracking system be used as a tool for educating game intelligence among Swedish male elite football players?* As previously described the definition for educating was increasing knowledge or awareness in the area of game intelligence. The purpose with the third research question was to examine the automated tracking system’s possibility to educate game intelligence based on players’ perceptions.

The purpose of the hypothesis was to investigate the associations between PP and PP x PI for estimating the optimal pass, where the definition for optimal would be the best possible solution with regards to the judgment criteria in figure 9. PP and PP x PI was compared to
see if PP x PI could be as accurate as the improved PP. Since, PP x PI involves PI more valuable information regarding the pass performed by the player will be received.

To create results for the research questions and hypothesis, a mixed method containing both qualitative and quantitative data (Creswell, 2005) was applied, for beneficial knowledges and understandings (Nelson & Groom, 2011) within the area. In order to validate the accuracy of the automated tracking systems, quantitative data was collected. Meanwhile, the evaluation of the automated tracking systems possibility to educate game intelligence required qualitative data. Mixed methodology is known for increasing validity and strengthen the conclusion (Creswell & Plano Clark, 2011). Thus, its advantageous, criticism have been raised for mixed methodology, such as time requirements, complexity and lack of previous research (Schoonenboom & Johnson, 2017).

3.1 Quantitative

3.1.1 Sample

This quantitative part was in collaboration with a Swedish elite football team. Hence, a convenience sample was applied for facilitating the recruitment process. However, criticism regarding convenience sample has been raised since it could lead to selection bias and limitations in generalizability (Burns & Grove, 2005). When recruiting participants, the aim was to involve players who completed as many passes as possible in all types of directions. It was therefore more important to have high numbers of passes than observing plenty of players performing few passes. Central midfielders have shown to perform plenty of passes (Gruber, 2018) with some amount of impacts. Although defenders perform plenty of passes the impact of these passes are mostly low since most of the passes are played on their own pitch half to another defending colleague. Including players who had been performing low amounts of passes could lead to incorrect data since a pass, for example, could have accidently or luckily have been completed. Furthermore, a player playing 90 minutes probably completes more passes, than a player who played the last 15 minutes. Therefore,
observation of players who were assumed to complete a lot of passes, in different directions was crucial for this study. Due to time limitations and a striving for excluding non-representative data, criteria regarding games and minutes were applied.

A Swedish top division team during 2019 with 26 players had to fulfill several inclusion and exclusion criteria, in order to contribute to the study. Players had to, during the season 2019, 1) Be positioned as midfielder; 2) Play at least 50 percentage of the games in the league; 3) Play at least 75 minutes of the games they were involved in.

Out of 26 players, ten were positioned as midfielders, four of them played at least 50 percentage of the games and three played at least 75 minutes of the games they were involved in (see figure 8). Hence, the inclusion and exclusion criteria led to three participants for the quantitative study.

![Diagram](image)

**Figure 8.** Illustrating recruitment procedure.
3.1.2 Participants

Three male elite football players participated in this study. Average age was 25.3 (±1.5) years, weight 75.7 (±2.1) kg and height 181 (±4.4) cm. Players played as midfielders, two of them as central midfielder and one on them as a winger.

Table 1. Description of the participants.

<table>
<thead>
<tr>
<th>Gender</th>
<th>Age (years)</th>
<th>Weight (kg)</th>
<th>Height (cm)</th>
<th>Position</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>25.3 (±1.5)</td>
<td>75.7 (±2.1)</td>
<td>181 (±4.4)</td>
<td>Midfielders</td>
</tr>
</tbody>
</table>

3.2 Procedure

Games from the Swedish top division 2019, were downloaded from www.arenaplay.se and re-watched in a video player (QuickTime Player version 10.5, Apple Inc., CA, US).

Minute, second and frame for all passes on the offensive half, made by the players were registered. A pass was defined as, when a ball holding player (i.e. passer) is kicking the ball, which trajectory later gets intercepted by a teammate (i.e. receiver). The numbers for each pass were then inserted into the automated tracking system (Spyder, Python Version 3.7, Amsterdam, Netherlands). Hence, plots of PP and PP x PI could be generated and contributed to a numerical value for PP and PP x PI (see appendix A.3 and A.1 for calculation) for each situation. The number calculated from pass impact times pass probability indicated the numeric value of the pass and its possibility on a probability scale between 0 and 1, while the numerical value for pass probability indicated the probability for the pass on a probability scale from 0 to 1, both calculations were performed for the same situation. The practitioner then judged the optimal pass suggested by the automated tracking system in relation to the pass executed by the player.

For each situation four categories were selectable, the most suitable category was determined and judged by the practitioner with footballing knowledge, which also is the author to this
study, but future known as practitioner in this study. The practitioner decided the most suitable of the following categories based on criteria from figure 9.
1) Optimal for the practitioner and the system (OFPAS);
2) Optimal for the system not practitioner (OFSNP);
3) Optimal for the practitioner not the system (OFPNS);
4) Optimal for either of the practitioner or system (NOFE).
The definition for optimal was the best possible decision/pass performed by the player.

Score for each category was set were scores of 0 was equal to NO and scores of 1 was equal to YES. 0’s and 1’s was inserted into each category for every situation. Application of categories facilitates the evaluation of the system, but also the possibility to identify flaws. The author considered that OFPAS indicated that the decision was right according to the system, the practitioner and the player, no flaws could be identified. However, NOFE indicated that the decision was incorrect according to the practitioner and the system, hence the pass executed by the player was a bad decision and the fault could be identified with the player. Furthermore, OFPNS could indicate that the pass was correct according to the practitioner but not according to the system. The player therefore performed the correct pass, however flaws could be identified in the system, which indicates that the automated tracking system has its limitations.

Decision regarding the practitioner’s decision was based on several criteria and questions:
1) Body angle of the passing player;
2) Moving direction of the passing player;
3) Velocity of the passing player;
4) Possibility to see the teammate;
5) Is the teammate allowed to receive a pass in that area? (i.e. offside rule) 6) In which of the zones is the receiving player?
7) What type of pass is required for the ball to be played? The data was then analyzed with the statistical method, see following section.
Table 2. Fictive table of the results from the re-watched situations, where each pass generated a numeric value from the automated tracking system. Min = minute, Sec = second, PP = pass probability, PI = pass impact, OFPAS = optimal for practitioner and the system, OFSNP = optimal for system not practitioner, OFPNS = optimal for practitioner not system, NOFE = neither optimal for either.

<table>
<thead>
<tr>
<th>Min</th>
<th>Sec</th>
<th>Frame</th>
<th>Value</th>
<th>Action</th>
<th>Optimal for practitioner and system</th>
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<td>9</td>
<td>24</td>
<td>0.149</td>
<td>PP x PI</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>72</td>
<td>50</td>
<td>12</td>
<td>0.647</td>
<td>PP</td>
<td>1</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Figure 9 illustrates an example of how a judgement by the practitioner could be made. The ball inside the red circle is having the ball and plays it at the direction of the area. Was this the optimal decision? According to the automated tracking system in figure 10. The pass should have been played to the left winger (yellow circle). However, the player in the red circle did not have the possibility to see the teammate, the body angle of the passing player was not optimal and since the player in the yellow circle has very low speed, the probability of the player inside the yellow circle to get a clear chance is very low. The pass performed by the player inside the red circle was therefore optimal according to the practitioner, but not the system (OFPNS). This was an example of how judgments could be made.
Figure 10. Illustration of judgment process from a television perspective.

Figure 11. Illustration of judgment process from a PP x PI view.
3.3 Statistical method

Answers from the quantitative part will result in binary numbers and are answers of discrete values (Hassmén & Hassmén, 2014) of either 0 or 1. Chi-square test (χ²-test) is used for identifying associations in discrete values. The test examines the hypothesis and evaluates potential associations or non-associations (Boslaugh, 2008). In order to reject or accept the null hypothesis in this study, the χ²-test for independence will be applied and p-value will be set at 0.05 (p<0.05).

3.4 Ethics

All data from the participants were collected from open access data and all information regarding inclusion criteria could be found at the Swedish Football Federation. The researcher was aware that there is a risk that the data could lead back to the players and affect them and their careers. Therefore, all players have been anonymized and any information that could lead to the players identity has been detached to secure personal safety for the participants. Apart from that all data will be saved on a locked computer that only the practitioner could access until the end of the thesis. The data will then be removed from the computer and imported to an USB-stick, only accessed by the practitioner. Before the presentation, players where informed with the purpose of the study and was informed that they had the possibility to terminate the meeting without giving any reason and it would not affect their position in the team. Finally, the researcher had no interest of conflicts and no sponsoring for this thesis was received.

3.5 Qualitative

The purpose of the qualitative method was to provide an answer for the third research question, can an automated tracking system be used as an educational tool in game intelligence? In order to determine its possibilities, a deeper knowledge regarding the players’ perceiving and perceptions of the automated tracking system will be crucial.
Therefore, a phenomenography approach has been applied, to gain and increase the understanding of the relationship between the human world and human perceptions (Hassmén & Hassmén, 2014). Where the phenomenon in the qualitative method for this study is the player and their perceptions of the automated tracking system and how it affects their knowledge and awareness of game intelligence.

3.5.1 Sample

Two men’s football team representing the Swedish top division and second division participated in the qualitative part of the study. The players were selected to participate by coaches based on their playing positions. All players in the team had the possibility to attend to the meetings with the practitioner. However, players involved in the selected situations were highly recommended to participate by their coach, meanwhile players not involved did not receive any specific recommendation.

3.5.2 Participants

All players participating in the meetings with practitioner were from either a part of a team in the Swedish top or second division season 2019. During the first meeting seven players from the Swedish top division team participated. A total of three occasions where held between 2nd of March 2020 to 3rd of April 2020. Validity was strengthened by separating the meetings into three different sessions. Hence, all data would not be collected at the same time by the same people and also contributed to a preferable discussion due to the size of the groups. However, person-to-person sessions, which seems to be the most beneficial (Middlemas & Harwood, 2018) was not possible because of time limitations. Only one player participated in more than one meeting. A total of 23 players participated with the average age of 22.2 (±4.7) years old. The players could be positioned as either goalkeeper, defender, central midfielder, winger or attacker.
Table 3. Description of participants from the first session.

<table>
<thead>
<tr>
<th>Meeting 1</th>
<th>2nd of March 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (n=)</td>
<td>Age (years)</td>
</tr>
<tr>
<td>7</td>
<td>28.2 (±3.4)</td>
</tr>
</tbody>
</table>

Table 4. Description of participants from the second session.

<table>
<thead>
<tr>
<th>Meeting 2</th>
<th>1st of April 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (n=)</td>
<td>Age (years)</td>
</tr>
<tr>
<td>11</td>
<td>19.3 (±2.1)</td>
</tr>
</tbody>
</table>

Table 5. Description of participants from third session.

<table>
<thead>
<tr>
<th>Meeting 3</th>
<th>3rd of April 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (n=)</td>
<td>Age (years)</td>
</tr>
<tr>
<td>5</td>
<td>20.0 (±0.7)</td>
</tr>
</tbody>
</table>

Table 6. Description of summary for participants from all sessions.

<table>
<thead>
<tr>
<th>Total of three meetings</th>
<th>2nd of March - 3rd of April 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants (n=)</td>
<td>Age (years)</td>
</tr>
<tr>
<td>23</td>
<td>22.2 (±4.7)</td>
</tr>
</tbody>
</table>

3.5.3 Procedure

The teams were divided into smaller groups to create an environment more suitable for discussions, where players most affected by the situations participated, e.g. defenders are most affected of defensive crosses. The sessions were scheduled in the afternoons and took approximately 45 to 60 minutes. The first meeting was held at the training facility after the players had finished their practice and lunch. The second and third meeting where held through Zoom Video Communication (version 4.6.7, CA, US) due to COVID-19. The attending players were un-familiar with the program and internet problems complicated the communication. Noticeably was that, compared to the first group the second and third had not been interacted with the automated tracking system previously.
The procedure for each session was structured in the same way. The practitioner started with selecting different situations to observe and divided them into different action groups, based on the Swedish FAs player development plan, were they believe that, in football, players are either in attack, defense or transition phase. Attack could be divided into either build up phase, creating goal chances or finishing and counterattacks, meanwhile, defense could be divided into recover the ball, prevent build ups or prevent goal scoring chances. In this study, the practitioner changed the terminology based on the Swedish FA model. The researcher selected six different categories: defense outside box, defending crosses, defenses in offense, attacking crosses, space creation and attacking runs. All could be linked to the Swedish FA model (see figure 12).

Figure 12. Illustration of the categories in football according to the Swedish FA (orange, blue and green) and how they are linked to the categories in this study (lighter colors).

Three games from the season 2019, were downloaded from Arenaplay.se and re-watched in a video player (QuickTime Player version 10.5, Apple Inc., CA, US), Minute, second and frame were registered for the actions. The length of a situation was based on possession chains and started when the players where close to the area involving the observed situation and ended when opponents had two consecutive touches on the ball. The video clips were approximately ten seconds, due to time limitations and focusing capacity among players. Only three to four videos were selected — one good, one bad and one decent, based on the practitioner’s opinion. The sequences then lead to plots of pitch control, pass impact and pass
possibility, generated in the automated tracking system (Spyder, Python version 3.7, Amsterdam, NL) which then were inserted into a power point presentation. A detailed description for each situation was completed before presenting it to the players. The purpose of the description was to apply awareness of self-perception and to prevent confirmation bias in the practitioner.

3.5.3.1 Presentation

Before the start of each presentation, players were informed about the purpose of the study. The sessions were recorded in audio for educational and research purposes. The practitioner implemented a socratic approach during presentation for the players. The procedure went as following: 1) Players started by watching the approximately ten second clip with the opportunity to re-watch the clips. 2) A frame from where the situation occurred e.g. defensive cross was then shown. 3) Players were then asked how they experienced the situations and why they did experience it in a certain way. 4) Same situation was then showed but as a plot of pitch control, 5) the researcher then summarized the players discussion to confirm the understanding of the discussion. 6) Afterwards, a picture of pass probability, from the same frame as earlier where shown 7) followed by a picture of pass impact and eventually 8) a picture of the pass impact followed by a summarizing was held. The presenter was in charge of the discussions and decided when players were allowed and not to discuss with each other. This procedure was implemented for all situations for each category. A semi-structured interview approach was applied where some questions was decided, such as letting the player explain their perceptions of each situations while other questions appeared depending on the players answers.
Table 7. Description of the procedure during presentations.

<table>
<thead>
<tr>
<th>Step</th>
<th>Action</th>
<th>Description</th>
<th>Purpose</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Watching the clip</td>
<td>A holistic understanding for the situation.</td>
<td>Getting an overview of the entire clip.</td>
</tr>
<tr>
<td>2</td>
<td>Watching a picture</td>
<td>Watching the specific action from the situation.</td>
<td>Clarify what situation that should be focused.</td>
</tr>
<tr>
<td>3</td>
<td>Pitch control and discussion</td>
<td>Watching the situation from a pitch control</td>
<td>Providing an insight on how pitch control affects the team.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>perspective.</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Pass probability and discussion</td>
<td>Watching the situation from a pass probability</td>
<td>Providing an insight on how pass probability affects the team.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>perspective.</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>Pass impact and discussion</td>
<td>Watching the situation from a pass impact</td>
<td>Providing an insight on how pass impact affects the team.</td>
</tr>
<tr>
<td></td>
<td></td>
<td>perspective.</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Summary</td>
<td>Summarizing vital points made.</td>
<td>Confirm transferred information</td>
</tr>
</tbody>
</table>

The reason for applying this procedure was based on four categories, information, analyzing, reflecting and concluding. The first part contains information were the researcher present the purpose of the meeting. The focus was to prepare the players for the procedure and its purpose. The players were then supposed to analyze the sequences, the author provided visual information regarding situations from recent games to facilitate the analyzes and evaluations. Hence, reflection was applied to discuss their thoughts and reflections which could help the author to understand the players perceptions. The final part contained a conclusion to summarize what had been said and confirm that the information was transferred correctly.
3.5.3.2 Thematizing

When the presentation for the players was completed, interview data had been produced. An appropriate way for presenting the result was conducted by coding the data into different themes. Criteria, based on the work of Whittemore, Chase and Mandle (2001) were applied to increase the validity for the study. The researcher applied a pros and cons triangulation, where arguments for the interpretation’s and its reliability were discussed and weighted against each other.

Selected data for the result had to fulfill two criteria, 1) it had to be of relevance for the research question and, 2) the answer had to be generated from step 3, 4 or 5 from the presentation (see table 6). Since these answers cannot inform the researcher if the players’ anticipations were based on the automated tracking system. All answers were separated into two different categories. Players who understood the system and players who did not understand it. The players who understood the system were then placed into sub-categories associated to the game intelligence, advance cue utilization, pattern recall and recognition, visual search behavior and knowledge of situational probability. Finally, answers were placed into suitable sub-categories. Noticeably was that one answer could be selected into more than one subcategory. However, answers associated with not understanding the system could not be placed into any sub-category. If an answer ended up in a sub-category, this theme would receive one point and all the points would later be summarized (see figure 13).

![Figure 13. Showing the procedure for thematizing.](image-url)
4. Results

The following section will firstly present the results from the quantitative method, which has been evaluating the accuracy of automated tracking system. The second part will involve the qualitative results generated from the players’ perception regarding the automated tracking system.

4.1 Quantitative

Pass probability (PP) and pass probability times pass impact (PP x PI) were observed 186 times, 93 for each action. The observations led to following results based on the practitioner’s interpretations and judgements, NOFE (n=19), OFPAS (n=52), OFPNS (n=21), OFSNP (n=1). Regarding action PP x PI, NOFE (n=24), OFPAS (n=10), OFPNS (n=57), OFSNP (n=2). The total value for PP and PP x PI was NOFE (n=43), OFPAS (n=62), OFPNS (n=78), OFSNP (n=3) and a total of 186 observations.

Table 8. Result of PP, PP x PI and PP + PP x PI. Were PP = Pass probability, PI = Pass impact, NOFE = Neither optimal for either, OFPAS = Optimal for practitioner and system, OFPNS = Optimal for practitioner not system, OFSNP = Optimal for system not me.

<table>
<thead>
<tr>
<th>Category</th>
<th>NOFE</th>
<th>OFPAS</th>
<th>OFPNS</th>
<th>OFSNP</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Action</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PP</td>
<td>19</td>
<td>52</td>
<td>21</td>
<td>1</td>
<td>93</td>
</tr>
<tr>
<td>PP x PI</td>
<td>24</td>
<td>10</td>
<td>57</td>
<td>2</td>
<td>93</td>
</tr>
<tr>
<td>Total</td>
<td>43</td>
<td>62</td>
<td>78</td>
<td>3</td>
<td>186</td>
</tr>
</tbody>
</table>

The chi-squared test of the results displayed a score of 45.982 for Pearson Chi-Square, when the degrees of freedom (df) was set to 3. The asymptotic significance which represent the p-value was .000. Meanwhile, the likelihood ratio showed a value of 49.351 with a df at 3. Hence, the results indicated that the null hypothesis can be rejected, due to a significant association (p>0.05) between the groups (see table 9).
Table 9. Result of the Chi-squared test of 186 valid cases and a degrees of freedom (df) set to 3 indicated a Chi squared test score of 45.982. A significant association (P = .000), p>0.05.

### Chi-Squared Tests

<table>
<thead>
<tr>
<th></th>
<th>Value</th>
<th>Degrees of freedom</th>
<th>Asymptotic Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pearson Chi-Square</td>
<td>45.982</td>
<td>3</td>
<td>.000</td>
</tr>
<tr>
<td>Likelihood Ratio</td>
<td>49.351</td>
<td>3</td>
<td>.000</td>
</tr>
<tr>
<td>N of Valid cases</td>
<td>186</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

An illustrative comparison of the actions, PP and PP x PI (see figure 14) displayed the differences between and within the categories and actions. Results indicated that OFSNP was higher for PP x PI (n=2) than PP (n=1), OFPNS was higher for PP x PI (n=57) than PP (n=21), OFPAS was higher for PP (n=52) than PP x PI (n=10) and NOFE indicated a higher value for PP x PI (n=24) than PP (n=19).

Results of PP and differences within the group indicated that, OFPAS had the highest value (n=52), followed by OFPNS (n=21) and NOFE (n=19) while OFSNP had the lowest value (n=1). A total of 93 observations for PP was completed.

The results of PP x PI and differences within the group displayed that OFPNS had the highest value (n=57), followed by NOFE (n=24) and OFPAS (n=10), lowest value was provided by OFSNP (n=2) for a total of 93 observations.
Results of correct decisions (OFPAS and NOFE) and incorrect decisions (OFPNS) by the automated tracking system indicated that 77 percent of the decisions were correct, and 23 percent of the decisions were incorrect for PP. While, PP x PI displayed that 37 percent of the decisions were correct (OFPAS, and NOFE) while 63 percent of the decisions were incorrect (OFPNS).

**Figure 14.** Illustration of differences between PP and PP x PI. OFSNP = Optimal for system not practitioner, OFPNS = Optimal for practitioner not system, OFPAS = Optimal for practitioner and system, NOFE = Neither optimal for either.

**Figure 15.** Illustration of correct decisions by the system for PP and PP x PI. PP = Pass probability, PP x PI = pass probability times pass impact, OFPAS = optimal for practitioner and system, NOFE = neither optimal for...
either and OFPNS = optimal for practitioner, NOFE = neither optimal for either and OFPNS = optimal for practitioner not system.

Result from comparison between the system and the player indicated that the player had 52 percent correct decisions, while the automated tracking system had 48 percent, for PP. Meanwhile, PP x PI indicated that the player had 72 percent accurate decisions and the system 28 percent (see figure 16).

![Result of correct decisions by the system for PP x PI](image1)

**Figure 16.** Illustration of differences between the system and the players for PP, and PP x PI. OFPNS = Optimal for practitioner not system, NOFE = Neither optimal for either, PP = Pass possibility, PP x PI = Pass possibility times pass impact.

### 4.2 Qualitative

Following section is presenting the qualitative results, followed by quotes from the players. Out of 23 participants, 10 provided with answers that could be associated with categories for game intelligence, which indicates that 13 did not contribute to the discussions, spread over three occasions. If an answer could be associated with a quote it would receive one point. Noticeably, one answer could be associated with more than one category. Advanced visual cue utilization received 9 points, pattern recall and recognition received 5 points, visual search behavior received 24 points, knowledge of situational probabilities received 12 points and players not understanding the system received 3 points. A total of 13 players from three sessions did not contribute to the discussion.
Figure 17. Illustration of all points (n=54) and answers (n=32) generated by 10 participants and its distribution between advance visual cue utilization (n=9), pattern recall and recognition (n=5), visual search behavior (n=24), knowledge of situational probability (n=12) and players not understanding the system (n=3).

4.2.1 Anticipating a potential outcome for the opponent

In a couple of the answer, the responders indicated that the system could facilitate to anticipate a potential outcome for an opponent. This category could be associated with advanced visual cue utilization which is a part of game intelligence (Stratton et al., 2004). The answers appeared when identifying actions from sequences.

In the situation below (see figure 18), the ball (black dot) is at the left bottom corner and the player in blue is about to make a cross. The blue color indicates area controlled by one team, while the green area displays area controlled by the other team. White color shows that the area is equally covered. In the quote below, the player is anticipating an outcome for when the ball has been crossed into the box and cleared away by the green team.
"Exactly... if we clear we get it straight back in the face because no matter where we clear that it is going to be blue ball. 9 has it, 13 has it even 30 has it if we clear it that way. So, we need to get in better positions to not get that ball straight back into the box." - Quote for figure 18.

Figure 18. Illustration of pitch control during a crossing situation when the ball (black dot) is under control by the blue team in the bottom left corner.

The figure displays a situation, where the ball (black dot) is under control by the blue team in the bottom of the penalty box. The ball holding player is making a cross. The different colors (blue and green) indicates area controlled by each team, while the white colors indicate areas equally controlled. In the quote below, the player anticipates a possible outcome.

"I mean according to the system; we are covering dangerous areas. But on the top of the box there are two guys who can get the rebound." - Quote for figure 19.
4.2.2 Processing the current situation based on experience

In other descriptions, depictions of how players previous experience affects their opinions can be identified. Casanova et al. (2009) defined this ability as pattern recall and recognition which meant that players can anticipate outcomes by recalling and recognizing patterns from before.

The picture below is the same as figure 19. However, the player made a different observation with another perception of the figure. In the quote below the player refers to number 33 (yellow circle) and the possibility for “him” (orange circle) to defend that player if 33 gets the ball.

“I think if they play the ball back to number 33, he has time to get there. And the amount of balls, I mean in my experience, that are cleaned out from the penalty to the area in top of the box, is very likely.” - Quote for figure 20
Figure 20. Illustration of pitch control during a crossing situation. Yellow circle indicates number 33, while the orange circle refers to “he” in the quote.

A third observation, for the same situation (figure 19, 20 and 21), was made by one of the players. This quote appeared in a different meeting although it reminds a bit of figure 20. The player is anticipating that when the ball (black dot) is played into the box, defenders will clear it and it will probably end up in the top of the box. However, the player assumes the penalty spot (uncolored circle in the center of the penalty box) to be the most important area to control.

"My only issue with that pitch control is that most clearances, bad clearances end up in top of the box where they are now. I want us to control our penalty spot, because that is where the most of our goals is conceded." - Quote for figure 21
4.2.3 Adjusting focus to the relevant information

Some of the participants highlighted relevant information for the different situations. Adjusting focus to relevant information during situations is the definition of visual search behavior (Stratton et al., 2004).

In figure 22, the blue team is having the ball under control in the bottom right corner. The ball holding players is about to make a cross into the box. The green area illustrates the control by one team, meanwhile the blue color indicates the area controlled by the other team. Equally controlled area will be displayed with a white color. In this situation the green team (defenders) are not having full control over their own penalty box. The player is suggesting Thomas (orange circle) to take two steps in to make the box green, which refers to defenders having control of the penalty box.

“It should become green if Thomas takes just two steps” - Quote for figure 22
Figure 22. Illustrates pitch control during a crossing situation with the ball (black dot) in the bottom right corner and the suggested action for Thomas (orange circle).

When the ball (black dot) is in the bottom for the penalty box (see figure 23), the player indicates that the defending positions in the penalty box is good. However, in the previous slide the players could see the same action in a television format. The player then observed that the defenders were just watching the ball and forgot about the attackers, which is not possible to see in a figure generated by the automated tracking system.

“The thing is, what happens everyone is that they are ball watching ... But I mean generally it’s a good position.” - Quote for figure 23
4.2.4 Extracting relevant information and anticipating outcomes

Other results indicated that players could extract relevant information and anticipate outcomes for different situations. This strategy indicates the knowledge of situational probabilities. Were players based on information could anticipate outcomes for players in their own team.

In figure 24 the ball (black dot) is under control by the attacking team (blue dots) in the bottom of the penalty box, while the green dots are defending. In the quote below the player has identified the positioning for central defenders (orange circle), central midfielders (red circles) and number 20 (yellow circle). The player extracts relevant information, anticipates potential outcomes and present solutions.
“"It is for central defenders to be central in most amount of time. Cause it is always easier to be central and then pushing out. In worst case scenario this guy flicks it back to 20, we are still in good position to control our box. So, if we can get our central midfielders in central positions when crosses are coming a think, we are in lot of better chances in controlling the areas that are most important." - Quote for figure 24

Figure 24. Illustration of pitch control during a crossing situation where the ball (black dot) is in the bottom of the penalty box. The positions of the central defenders (orange circle), central midfielders (red circle) and number 20 (orange circle) is highlighted.

The participants were good at identifying different movements within the same situations. Figure 22 is the same as figure 20 but from a different meeting. The ball (black dot) is in the bottom corner, under control by the blue team, while the green team is defending. The quote below indicates that the player has identified the positioning of the goalkeeper (orange dot). By extracting relevant information, the player is also making anticipations of outcomes based on previous experience and the current situation.

“"The goalkeepers positioning is too far to the first post. I mean in normal goalkeeping, what we learn stuff, when the cross is played so deep, is that we should be towards the middle and further out. So, if he would cross it, it would be much harder to play a ball towards the small area.” - Quote for figure 23
4.2.5 Players not understanding the system

In some of the answers, players indicated that they did not understand the system. Players who did not understand the system could not be selected into any of the four categories presented in the qualitative results above.

One example of when one player was not understanding the system could be displayed with help from figure 26. The ball (black dot) is in the bottom left corner and under control by the blue dots (attacking team) while the green dots are defending. The ball holding player is playing a cross into the box. This figure illustrates the pass possibility and its impact of increase in goal scoring. The white color indicates a low impact, the yellow shows a medium impact and red displays a high impact. In the figure the players started to discuss which player that is most dangerous, Charles (orange dot) or Mike (purple dot). The discussion was brought up since Charles is one of the best strikers in the league. However, Charles is not in the most dangerous area according to the system, who cannot compute the characteristics for each player.
"The most dangerous guy in their team is Charles!

" – No, it’s Mike?

“ – Yeah I know, but in the end, it is Charles.” - Quote for figure 24

Figure 26. Illustration for pass possibility times pass impact. The ball (black dot) is in the bottom left corner. Charles (orange circle) and Mike (purple circle) is highlighted.

In figure 27, the ball (black dot) is under control by the attacking team (green dots) outside the right corner of the penalty box. The defenders (blue dots) are trying to prevent the attack. White color indicates a pass with low probability and/or low impact, yellow displays a pass with medium probability and/or impact while red indicates a pass with high probability and/or impact. The quote indicates that the player did not understand the colors and therefore not the system.

“Hmm…is the red good?” - Quote for figure 25
Figure 27. Illustration of pass possibility times pass impact. The ball (black dot) is outside the corner of the penalty box. The green dots are attacking while the blue is defending.

The last quote appeared in a transition watching a clip in television format to showing a generated plot, the player was keen to get (according to him) the answer from the automated tracking system.

“And now we want the answer!” - Quote without figure.
5. Discussion

Following section opens for discussing if the automated tracking system could be used as an educational tool for game intelligence among Swedish elite football players. The discussion is divided into two parts — one qualitative and one quantitative.

5.1 Quantitative

The results indicated that there is a significant (p<0.05) association between PP and PP x PI. Hence, the null hypothesis could be rejected. This indicates that there are similarities in PP and PP x PI, which could probably be explained by both categories existing of PP. However, differences between and within the groups could be identified in figure 14. The analyze of 93 PP situations showed that OFPAS became the action with the highest score (n=52) and formed 56 percent of the results for PP. OFPAS could indicate that the pass executed was correct according to the practitioner, automated tracking system and the player. However, the score of OFPAS for PP x PI was a lot lower (n=10), instead OFPNS formed the majority (61 %) of the answers (n=57). OFPNS could indicate that the pass executed by the player was correct according to the practitioner, but not by the system. When analyzing the situations, several criteria were applied (see figure 9) which contributed to identify limitations in the automated tracking system. However, all situations are based on the practitioner’s judgement which enhances the risk for subjectivity bias. If it would have been possible, the practitioner would have created a group of people controlling the situations together, in order to decrease the risk for subjectivity bias. This was unfortunately not possible in this study due to restrictions, instead the practitioner applied criteria for the judgments, but also repeated the analyzing parts to see if the perception of the situation differed from time to time. This was made to enhance the chances for the correct judgment and thereby decrease the risk of subjectivity bias.

According to the results in figure 15, PP is more accurate regarding decisions, than PP x PI. The system had 77 percent correct decisions for PP, but only 37 percent correct decisions for PP x PI. The evaluation of the accuracy was formed by comparing the amount of correct
decision made by the system (OFPAS and NOFE), against the amount of incorrect decisions by the system (OFPNS). The practitioner assumed that the system and researcher agreed at two categories NOFE and OFPAS. NOFE indicated that the pass performed by the player was neither optimal according to the practitioner nor the system, while OFPNS indicated that the pass played was correct and the suggestion by the system was incorrect.

In this study only three players were participating due to strict inclusion and exclusion criteria which could lead to questions regarding the statistical power. However, it is not the number of participants that is of interest for the practitioner. Instead it is the number of passes that is of interest, since that is part being analyzed and observed not the players in itself. 186 players completing one pass would probably increase the power, but it would also increase the risk inaccurate data, due to that single pass being a mistake (e.g. bad hit). According to the practitioner, analyzing few players completing many passes is better than plenty of players completing few passes.

Illustrations of differences in correct decisions between the system and the players can be observed in figure 14. The results indicated similarities between the system (48 %) and player (52 %), with a small advantage for the players when measuring correct decisions according to the evaluator. However, for PP x PI, the player had a clear superiority (72 %) against the system (28 %), which indicates that the player is making better decisions than the system (i.e. the pass executed by the player was better than the suggested pass by the system). OFPNS was the category deciding when the player made a correct decision and NOFE was the category deciding when the system made the correct. OFPNS indicates that the pass executed by the player was correct according to the evaluator but not the system, while NOFE indicates that the evaluator and the system assumed that the pass was incorrect performed by the player.

Peralta Alguacil and colleagues modified and improved the automated tracking system by developing a more accurate ball trajectory and implemented historical data from three consecutive seasons in the Spanish league, English league and Champions league, with the purpose to avoid previous limitations with automated tracking systems, such as assessments only on goals and assist (Altman, 2015) and exclusion of passes that could lead to a goal in the near future (Mackay, 2017). However, new limitations could be identified and the reason
for the differences between PP and PP x PI. Firstly, the system lacked the possibility to identify body angle. In some situations, the optimal pass according to the system, could be limited for the player to perform, for example, the automated tracking system excluded the fact that the ball holding player was running with high speed in the opposite direction and with the back faced against the receiver. Although, it is not impossible to perform a pass with the back against a teammate, the possibilities should be highly affected. Secondly, the system lacks knowledge regarding the offside rule and sometimes suggests that a pass to an offside standing player would be a great decision. Thirdly, as seen in figure 4, when the ball is central outside the box, a pass to the corner has similar impact as a pass to the top of the penalty box, indicates that there is still room for improvements. In fact, improvements have been made by the club and a new pass impact model has been generated (see appendix A.3.1).

When the analyze of situations were completed, the results were presented in binary number. However, binary numbers could cause problems since they do not indicate to any degree, instead it only provides with information equal to yes or no. Evaluations of situations could be of almost equal value, hence presenting to what degree the differences occur could get a different picture of the results. Noticeably, all analyzes was made by the researcher thus, there was no conflict of interest, results should be interpreted with caution due to the subjective estimation.

The lack of previous research and the fact that the automated tracking systems are developed within the club, could lead to differences in accuracy between the systems. Hence, more research is needed in order to generalize these results.

5.2 Qualitative

The results from the qualitative part indicated that an automated tracking system could be beneficial as an educational tool for game intelligence. Thus, most of the points represented visual search behavior, based on the results in the qualitative part, caution should be applied when interpreting the results.
A limitation was that, for some questions, players did not contribute in the discussions. Out of 23 players participating in the meetings, only 10 provided with answers. This led to a lack of understanding for the perception and knowledge in the automated tracking system for the non-responding. Hence, these players could thereby not be placed into any category. A reason why the participants did not get involved in the discussion could be because of the group size. According to Middlemas and Harwood (2018) meetings are preferable as person to person session, instead of larger groups and the fact that players should be treated differently in these situations for optimal outcomes (Raab, 2007). According to Mackenzie and Cushion (2013), making the group smaller it becomes easier to confirmation the players understandings. However, a person to person session requires more time and was in this study not performable, due to time limitations.

Other reasons why some participants were less involved could be the social climate. A negative environment where the participants feel insecure could be a limitation, (Pensgaard & Duda, 2002) it is therefore important to build trust and hold meetings in locations that are well known to the players (Middlemas & Harwood, 2018). Unfortunately, due to COVID-19 sessions were forced to become digital meetings, with players not having experience of Zoom video communication programme. Additionally, the groups participating in the second and third meeting were unfamiliar with the automated tracking system, something that could affect their contribution to the sessions negatively (Middlemas & Harwood, 2019; Peralta Alguacil et al., 2020). When comparing the Zoom sessions and the sessions held face to face with the players, the activity was much higher during the face to face meeting. In fact, only one player lacked commitment during the meeting held at the training facility, compared to sometimes three, four or five players not getting involved in discussions during Zoom sessions. The results from the qualitative part should therefore be interpreted with caution since the is a risk that the non-responding players either do not understand or do not feel comfortable about speaking in that group. Both outcomes would be harmful when striving to educate game intelligence (Middlemas & Harwood, 2018).

In spite of, inexperience of the automated tracking system, the results indicated that most of the responding players understood the automated tracking system. Regarding the non-responding it will remain unknown regarding their perceptions and understandings. In the qualitative results, players defined optimal solutions and possible outcomes with help from the colors in plots, generated by the automated tracking system. Using the colors and
discussing how the colors would change depending on positions could lead to an understanding for the system. This strengthens the idea of Mazzelli and Nason (2019) that an automated tracking system could be used as a feedback tool for players. Meanwhile, other players identified limitations within the system since it did not consider the differences in qualities between the players. In one situation a more dangerous striker in the opponent team (according to the players) was almost left alone in the penalty box, which led to a discussion regarding who was the most dangerous player in a subjective and objective opinion. The discussion ended by players highlighting that although the player was the best when it came to scoring goals, he is not in the most dangerous area at that situation. The conclusions made, highlights their trust for the system. Although, the system fails to recognize each player and their differences, the positions of the players are probably of higher impact. According to Hammond (2004) a video-based system contributes with a more holistic perspective and similarities could also be identified in this study by the automated tracking system. The automated tracking system gives the players a clear overview for the situations, however limitations seems to appear within the details. Nimmerichter et al. (2015) recommended that two times a week regularly was beneficial for developing decision makings. Due to COVID-19 the regularity of the three sessions in this study were affected. However, the results indicate that also less occurrences seem to have an effect in educating game intelligence.

The practitioner implemented different themes for the sessions. The different themes could, according to Mazzelli and Nason (2019) develop decision making in the selected area. If coaches wish to improve game intelligence for defensive actions among their players, then defensive crosses could be the topic for that session.

Could trusting the automated tracking system be harmful? “Show us the answer!” was a quote from one of the players. A risk when using an automated tracking system is that the player trusts and relies on the system too much. In the previous section, it was described how the players valued the position of a player higher than the actual player. Thus, the system has made great improvements the last decades, caution and respect should be applied when using it in sport contexts. The purpose of the automated tracking system is to be a tool for coaches which strives to improve in tactics (Amatria et al., 2019). However, as shown in the quantitative results there are still some limitations within the system. Relying too much on the system could have a negative effect on game intelligence, since the system is not accurate.
enough. However, the automated tracking systems seems to improve critical reflection and anticipating future outcomes, just like Middlemas and Harwood (2018) discovered for video-based feedback.
6. Conclusion

Sport analytics have previously been used for scouting opponents, improving tactics (Amatria et al., 2019) or optimizing the recruitment of new players (Bransen & Van Haaren, 2020). The aim of this study was to evaluate if an automated tracking system could be used as a tool for educating game intelligence in Swedish male elite football players. A mixed method, consisting of a quantitative and a qualitative part was applied. The results indicated that there is a significant (p<0.05) different between PP and PP x PI.

The results showed that pass probability makes better prediction than pass probability times pass impact and the player is probably making better decisions than the system. However, limitations with the system was identified that could affect the results. The researcher could not ensure that the players with limited contribution during sessions understood the system, this led to that they were not a part of the evaluations in this thesis. Furthermore, some players showed tendency to overrate the system.

An automated tracking system could be used as an educational tool, with the purpose to increase knowledge and awareness regarding the decisions players make during games. However, its effects remain unknown due to the systems limitations. If implementing an automated tracking system, it is important to acknowledge that the system only is a tool who do not provide any guaranteed answers, a recommendation is therefore to discuss the situations in meetings. Data analytics are opening a new chapter within the sports that could help us improve and understand, not only football but plenty of other sports. However, an automatic tracking system is often developed and kept within football clubs, which make it difficult for the research community to access and apply the information into research. A next step to develop this research area could thereby be for clubs to corporate with the academia and make the data more accessible. This could favor future research, which is needed to determine how much the system could improve game intelligence.
References


Pensgaard, A. M., & Duda, J. L. (2002). "If we work hard, we can do it” a tale from an Olympic (gold) medalist. *Journal of Applied Sport Psychology*.


Appendix

Following section displays the calculations for the system generated by Peralta Alguacil and colleagues, which have been applied to this study.

A.1 Pass probability

The purpose of pass probability is to provide with information regarding a pass to be successful, a pass was defined as, when a ball holding player (i.e. passer) is kicking the ball, which later gets intercepted by a teammate (i.e. receiver). The model for pass probability in this study was an adjustment of Spearman’s method. Spearman and colleagues computed the ball movements based on a formula that considered aerodynamic drag to be responsible for deceleration of the ball movement, however Spearman decided to exclude the Magnus force.

Equation 1. Equation for pass probability by Spearman and co-workers.

\[ \ddot{r}_{\text{aero}} = \frac{1}{2m} \rho C_D A \dot{r}^2 \]

The mass of the ball was set to 0.42 kilograms \((m = 0.42 \text{ kg})\) and its density of air was 1.225 kilograms per cubic meter \((\rho = 1.225 \text{ kg/m}^3)\). The drag coefficient was 0.25 \((C_D = 0.25)\) while the cross-section area of the ball was set to 0.038 squared meters \((A = 0.038 \text{ m}^2)\). Assumptions were made that the passes were ground passes, hence friction was added to the model, which is illustrated below.

Equation 2. Calculation for friction by Peralta.

\[ \dot{r}^2 = -\mu g \dot{r} \]
Weather conditions are changing and affecting the surface of the pitch in different ways. An estimated value for the height of the grass was set to 0.55 ($\mu = 0.55$) which is the median value of the interval for FIFA’s recommendations regarding high quality artificial grass surfaces. Although, passes are considered to be ground passes, Peralta Alguacil et al. (2020) discovered that the ball travels in the air the first two thirds of its trajectory and the last on the ground. Aerodynamics was therefore implemented on the first two thirds and added friction to the last third, which is explained in equation 3.

**Equation 3.** Formula for ball trajectory.

$$
\vec{r} = \begin{cases} 
-\frac{1}{2m} \rho C_D A \vec{r}, & t \leq \frac{2t_{\text{max}}}{3} \\
-\mu g \vec{r}, & t > \frac{2t_{\text{max}}}{3}
\end{cases}
$$

Pass probability is actually calculating the time to interception by considering players to be object with movements. This was described by an equation of motion with a driving force, exerted by the players' legs and a drag defining their maximum possible velocity.

**Equation 4.** Formula for maximum possible velocity.

$$
m \frac{d}{dt} \vec{v} = \vec{F} - k \vec{v}
$$

whose solution is given by:

**Equation 5.** Solution for maximum possible velocity.

$$
\vec{x} - \vec{x}_0 = V_{\text{max}} \left( t - \frac{1 - e^{-at}}{\alpha} \right) \vec{e} + \frac{1 - e^{-at}}{\alpha} \vec{v}_0
$$
Where $V_{max} = F/k = 7.8 \, m/s$ is the maximum velocity that a player can reach, $\alpha = k/m = 1.3$ is the magnitude of the resistance force and $e^t$ is the unit vector that denotes the direction of the acceleration of the player.

With this result, it is possible to see that all the points that a player with starting position $x_0^*$ and initial velocity $v_0^*$ can reach are enclosed inside the circle with centre

**Equation 6.** Formula for starting position and initial velocity and how they are enclosed inside the circle with center.

\[
\ddot{x}_0 + \frac{1 - e^{-\alpha t}}{\alpha} v_0
\]

and radius

**Equation 7.** Formula for the radius of equation 6.

\[
V_{max} \left( t - \frac{1 - e^{-\alpha t}}{\alpha} \right)
\]

This makes the finding of the interception times for the players easier than with the minimization problem that Spearman proposed (Peralta et al., 2020). In order to obtain them the time must be discretized, in steps of 0.04 seconds and for each time step, checking’s of the already computed position of the ball were performed and calculations of the reachable area of the player. If the current ball position falls outside the circle, we advance to the next time step and repeat the process until the ball is in inside the player's reachable area; that moment determines the interception time.

Once the physical models behind the ball and the players have been established, the probabilistic model proposed by Spearman et al. can be used. Its main feature is the usage of a logistic distribution to determine the probability of a player getting the ball at time $T$ knowing his arrival time $t$. 

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\[ P_{\text{int}} = \frac{1}{1 + e^{\frac{T-t_{\text{int}}}{\sqrt{3}\sigma/\pi}}} \]

Note that this function does not compute the probability for a certain player to get the ball during a pass, but the probability of him being able to intercept the ball after \( T \) seconds (without considering the rest of the players). Furthermore, another consideration that is made is that a player has to be in the vicinity of the ball for a certain time in order to have control over it, this is modelled with the term:

![Figure A1. Pass probabilities and interception points inside (with blue markers) and outside (white markers) the possible ground-pass area around the ball.](image)

\[ P(t) = 1 - e^{-\lambda t} \]

With the combination of these two, the final system of differential equations that gives the probability for each player to receive the pass is built as follows,

\[ \frac{dP_j}{dT}(T) = \left( 1 - \sum_k P_k(T) \right) P_{\text{int},j}(T)\lambda \]
In order to analyze the pass probabilities for any given match moment \( a \), total of 750 potential passes are calculated, distributed over 50 angles all around the ball and 15 pass speeds between 1 and 20 m/s. For each of these passes the probabilities of pass success together with their respective interception point, i.e., the location on the pitch where it is most likely to be received, are computed and a heatmap is generated showing the probability that a teammate of the player passing the ball will receive it. Figure 1c shows the points calculated in one example in a match between FC Barcelona and Real Betis.

Since the simulations that we perform are based on ground passes, it is clear that there will be some areas on the pitch (mainly all of the points that lay behind a player) that cannot be reached with one of these passes, either because the ball is always intercepted before it gets there or because a really strong pass is needed for the ball to get there and there is no possibility of interception due to its speed. The points that bound the reachable area with a ground pass are what we call the "last interception points".

**A.2 Pitch control**

Pitch control was proposed by Javier Fernández and Luke Bornn. In their work they follow a different approach than Spearman's, basing it on what they call "player influence areas" instead of arrival times. The player influence at a certain point on the pitch \( p \) at time \( t \) is determined by the position and speed of the player. Same formula was applied by Peralta defined by:

\[
I_i(p, t) = \frac{f_i(p, t)}{f_i(p(t), t)}
\]

Where,

\[
f_i(p, t) = \frac{1}{\sqrt{(2\pi)^2 \det(COV_i(t))}} \exp\left(-\frac{1}{2} (p - \mu_i(s_i(t)))^T COV_i(t)^{-1} (p - \mu(t))\right)
\]
Pitch control is also a way of mimicking long passes in an easier and, possibly, more trustful way than simulating the trajectory of a long ball in the air for two main reasons: the first one is that factors that are unknown with the datasets that wind speed and direction or ball spin play an important role in these passes and, even if we could perfectly model the flight of the ball, not all the players have the same skills when sending high passes and modelling this "player accuracy factor" properly would be almost impossible.

We thus also use pitch control to extrapolate the pass probability model in section A.1. A grid of points is created outside the zone that is already covered by possible ground passes and, for each of them, we calculate pitch control. Figure A1 shows an example of this extrapolation for a frame of the same game between FC Barcelona and Real Betis.

A.3 Pass impact

To measure impact of a pass, a model developed by the company Twelve was applied. Twelve have gathered event data from three historical seasons of the Premier League, La Liga and Champions League.

Two logistic regressions were fitted in order to assign a value to each pass. The first regression is obtained by assigning each possession chain a value, which gives the probability of a pass leading to a shot. Another regression is then computed for estimating the probability of a shot leading to a goal. The two logistic regressions are then multiplied and describes the probability of a pass of and how likely it is to result in a goal. Hence, the definition of pass impact.

A.3.1 Pitch impact 2.0

A new model for pitch impact was generated during this study, figures below displays the differences between the new model (figure A.2) and the old (figure A.3). Both models are still based on historical data from three seasons in Premier League, Champions League and La Liga (Spanish League). The formula for the exact equation has not been accessed by the researcher.
Figure A.2. The updated version of pass impact

Figure A.2. The pass impact model used in the study.
Literature search

Purpose and research question:

**Purpose:** To evaluate if an automated tracking system could be used as a tool for educating game intelligence to Swedish male elite football players.

**Research question:** 1) Does pass probability times pass impact (PP x PI) make a better prediction than pass probability (PP), 2) are the players making better decisions than the system and 3) can the automated tracking system be used as a tool for educating game intelligence among Swedish male elite football players with an automated tracking system?

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“Visual feedback in football”

Comments:

It was hard to find previous research on automated tracking systems in football, especially on its possibility to develop game intelligence. Help from the supervisor and colleagues facilitated the process. A lot of information was also found from “related articles” and SLOAN MIT sport conference.