Appendix

A Related work

A.1 Predictive analysis of team sports using tracking data

In many team sports, including soccer, predictive analysis using tracking data (positional information of players and ball) is widely used [18,69]. Cervonet et al. expressed how much scoring is expected at the end of a basketball possession as EPV (Expected Possession Value) [8,9]. This method is also used in Soccer [17] and Handball [40,27]. There have also been many predictive analyses focusing on goals, for example, Chang et al. evaluated the difficulty of shots and the ability to shoot successfully separately [10], Lucey et al. estimated the probability of the occurrence of chances [32], and Fujii et al. used the Koopman Spectral Kernels to predict the probability of successful shots [19]. Furthermore, many studies evaluated players based on their scoring opportunities. McHale et al. evaluated players based on a single score without considering position and style of play [35,36]. In contrast, Pappalardo et al. evaluated player performance in a multidimensional and role-specific way [42], and Decroos and Davis used player vectors to identify players' playing styles [12]. Decroos et al. proposed VAEP (Valuing Actions by Estimating Probabilities), which evaluates player actions based on their impact on the result of the game while taking into account the previous context [11]. However, in soccer, scoring chances are rare situations, so predictive analysis based on scoring chances is not reliable. Therefore, some researchers have focused on defense by learning ball recovery probability and being attacked probability [61,63], and Umemoto and Fujii evaluated player positioning in defense using counterfactuals [62].

Many predictive analyses that focused on each type of action have also been conducted. Power et al. evaluated passes by estimating both the risk and reward of a pass [44]. Goes et al. evaluated passes based on whether they disrupt the opponent's defensive construction [22], and Bransen et al. evaluated passes based on how much they contributed to the xG based on similar past passing data [6]. Rahimian et al. predict and quantify Penetrative passes [45], and they built a predictive model of the intended recipient of the pass and the player who actually receives it [46], and Robberechts et al. quantify players' creativity [51]. Some researchers have also evaluated the receiver as well as the passer [31,20,13]. Robberechts quantified the pressure decisions as VPEP (Valuing Pressure decisions by Estimating Probabilities), based on the VAEP [50], and Merckx et al. automated the press analysis [39]. VanRoy et al. analyzed buildup tactics using Markov decision processes and described the defensive construction against buildup [65]. Furthermore, as a method for action prediction, a study based on Transformer, which is used to construct a language model, has been conducted [54,70,37,38]. In this study, the following space assessment approach is useful for evaluating player positioning for events that have no clear label and are difficult to predict, such as counter-attacks and counter-presses that occur from transitions.

A.2 Space evaluation for team sports

When evaluations are based on on-ball events, they often fail to assess off-ball players since only a subset of players is targeted. Moreover, off-ball time is longer than on-ball time, making it crucial to evaluate off-ball movement. Consequently, many studies have focused on evaluating off-ball movement. This evaluation has enabled the discovery of the value of players who were previously overlooked in event-based assessments. As a rule-based off-ball evaluation, Supola et al. evaluated off-ball cutting in basketball [58]. Lamas et al. showed that off-ball movement affects the probability of getting an open shot in basketball [29]. Wu et al. quantitatively evaluated off-ball offensive contributions by considering player position and team cooperation [67]. Link et al. evaluated space danger as the probability of a player scoring a goal at each moment of ball possession [30], and Fernandez evaluated moves that create space for teammates [16].

Off-ball evaluations using mathematical models are also being developed. In studies considering players' dominance areas, Voronoi partitioning has been performed by treating players as generating points. Taki et al. conducted a Voronoi partitioning that calculates the minimum arrival time while considering players' speed and acceleration, evaluating space based on dominance areas [59]. Additionally, regarding player motion models, Fujimura and Sugihara used a one-dimensional motion model [21], and Brefeld et al. proposed a method utilizing a model based on kernel density estimation [7]. Furthermore, Martens et al. used a data-driven motion model [33], and Naruzuka et al. used players' arrival time to weight the field [41].

The model proposed in this study is an extension based on OBSO (Off-Ball Scoring Opportunity) proposed by Spearman [56,57]. OBSO is a model that quantifies where a player should receive a pass to maximize scoring opportunities, using the positions of players and the ball. For more details, see Section B. Rios-Neto et al. extended OBSO to tracking data and provided a new perspective [49]. Additionally, the studies by Teranishi et al. [60], Yeung et al. [68], and Umemoto and Fujii [62] each proposed models that extend OBSO. The idea of OBSO also applies to other sports, with Kono and Fujii extending it to basketball [28] and Iwashita et al. extending it to ultimate [26].

The USO (Ultimate Scoring Opportunity) model [26] uses pitch-wide weighting for spatial evaluation. USO calculates spatial value based on a combination of PPCF (as used in OBSO), positional weight (w_{area}), and distance weight ($w_{distance}$). In the w_{area} component, spatial importance is assessed based on ease of scoring or passing, with the end zone—analogous to the goal in soccer—assigned a weight of 1. The weights for other locations are determined by the normalized angle subtended by the end zone. In contrast, the field value model proposed in this study uses distance in both the longitudinal and lateral directions rather than angles with respect to the goal. This difference stems from the structural disparity between ultimate and soccer. In soccer, using angular weighting results in extremely low values in the corners of the pitch, which is inappropriate for evaluating spatial value. Therefore, angular information was excluded from the weighting scheme, and instead, distance to the goal along each axis was used.

A.3 Research on transitions in soccer

In soccer, the decision-making during transitions, the moments of switching between attack and defense, has been considered important. Reep and Benjamin showed that transitions in the opponent's half have a high probability of leading to goals and significantly impact the overall performance of the team [48]. On the other hand, recent studies showed the importance of counter-attacks following ball recoveries in the defensive half. Barreira et al. showed that the effectiveness of an attack increases when a team connects passes after defensive actions such as tackles in their own half [4]. Liu et al. found that shots resulting from counter-attacks following ball recoveries in the defensive half have a significant impact on match outcomes [25]. These findings suggest that tactical changes and improvements in player skills have influenced the growing importance of ball recoveries in the defensive half, where more space is available. Wright et al. analyzed goals scored in the English Premier League and revealed that 65% of them resulted from transitions [66]. Furthermore, studies have been conducted on detecting transitions and evaluating counter-attacks that originate from transitions. Fassmeyer et al. utilized semi-supervised learning to detect counter-atacks and set-piece situations such as corner kicks [14]. Additionally, Hobbs et al. applied hierarchical clustering for transition detection and further assessed counter-attacks by calculating the defensive disorganization and the attacking threat level [24]. Moreover, Phatak et al. introduced the concept of Expected Counter, which predicts the success rate of counter-attacks and the defensive risk level [43]. Raudonius and Allmendinger evaluated individual players' contributions to counter-attacks using four metrics: the distance covered, the threat level of actions against opponents, the number of defenders bypassed, and the ability to control space on the field [47]. Gonzalez-Rodenas et al. found that vertical action within the first three seconds of winning the ball increased the probability of creating scoring opportunities and was effective in creating scoring opportunities on the counter only when the opposing defense was unbalanced [23].

On the defensive side, Peters et al. defined Rest Defence on a rule basis, and found that when Rest Defence works, it reduces the risk of shots by opposing teams or losing possession on a counter [2]. Additionally, in modern soccer, the concept of counter-pressing has become an essential factor that cannot be overlooked. Jürgen Klopp, who managed Liverpool FC until 2024 and achieved great success, popularized the tactical approach known as Gegenpressing [71], and Pep Guardiola, the manager of Manchester City, introduced the five-second rule in counter-pressing [3]. These managers have demonstrated success in the English Premier League, highlighting the importance of counter-pressing. Bauer and Anzer conducted a data-driven analysis of counter-pressing and revealed that successful counter-pressing significantly increases the goal-scoring rate, whereas failure leads to a substantial rise in conceding goals [5]. Vogelbin et al. analyzed the Bundesliga by dividing teams into three groups based on their rankings and comparing them. Their study demonstrated that the ability to quickly regain possession is a crucial factor in successful defensive performance [34]. In this study, we focused on space, which has not been widely considered in transition evaluation, and evaluated the space at the starting point of transitions.

B OBSO Framework

As described in Section 2, $P(S_r|D)$, $P(T_r|D)$ and $P(C_r|D)$ are represented by the Score model, PPCF (the Potential Pitch Control Field), and the Transition model, respectively. The score model is explained in Section B.1, PPCF in Section B.2, and the Transition model in Section B.3. The overview of this model is illustrated in the upper section of Figure 1. The implementation is based on the code at [52]. This framework is constructed by combining the Score model, PPCF, and the Transition model, enabling goal probability estimation at different points on the pitch. However, a limitation of this model is that it is designed to predict scoring opportunities, which results in generally low evaluations for positions far from the goal. To address this issue, we propose an improved model in Section 3.

B.1 Score model

Here we describe the Score model, which is one of the models that constitute OBSO. This model represents the importance of the pitch based on score prediction. In OBSO, it is represented as follows:

$$S(\vec{r}|\beta) = [S_d(|\vec{r} - \vec{r_g}|)]^{\beta}. \tag{8}$$

Here, $\vec{r_g}$ denotes the position of the goal, and $S_d(x)$ refers to a monotonically decreasing function concerning distance. By setting the parameter β , it expresses the idea that even at the same distance, scoring becomes easier if there is no defensive pressure. In this study, we used the grid data included in the code that implemented OBSO independently of the original authors [52] as the Score model.

In the Score model, locations closer to the goal are given relatively high evaluations, while areas farther from the goal are generally rated lower. As a result, it becomes unsuitable for evaluating space in situations where scoring is not the primary focus. To address this issue, we propose the field value model in our OBPV (Off-Ball Positioning Value) framework as a replacement for the Score model. The field value model considers the weight across the entire pitch, enabling spatial evaluation without solely focusing on scoring opportunities.

B.2 PPCF

Here we describe PPCF, one of the models that constitute OBSO and OBPV. This model represents the players' occupancy on the pitch—specifically, it can be interpreted as the probability that a player from the same team will be able to control the ball if it is passed to a given location. The control probability of player j at a specific location $\vec{r}$ at time t is expressed as follows:

$$\frac{dPPCF_j}{dT}(t, \vec{r}, T|s, \lambda_j) = \left(1 - \sum_k PPCF_k(t, \vec{r}, T|s, \lambda_j)\right) f_j(t, \vec{r}, T|s)\lambda_j. \quad (9)$$

Here, $f_j(t, \vec{r}, T|s)$ represents the probability that player j reaches location $\vec{r}$ within time T. To model this, we compute the expected arrival time $\tau_{exp}(t, \vec{r})$, which represents the time required to reach a certain location $/vecr$, assuming the player accelerates with a constant acceleration a from the initial velocity $\vec{v_j}(t)$ up to the maximum speed v. In a previous study, the values $v = 5m/s$ and $a = 7m/s^2$ have been used. In practice, the actual arrival time may vary due to various factors such as uncertainty in tracking data, the players' direction, awareness, and tactical decisions. To avoid modeling all these factors directly, we use the cumulative distribution function (CDF) of the logistic distribution to compute the probability that player j at time t can reach location $\vec{r}$ within time T, as shown in the following equation:

$$f_i(t, \vec{r}, T|s) = \frac{1}{1 + \exp\left(-\frac{T - \tau_{exp}(t, \vec{r})}{\sqrt{3}s/\pi}\right)}. \quad (10)$$

Here, $\sqrt{3}s/\pi$ represents the uncertainty in a player's arrival time. In this study, we set $s = 0.45$. λ_j denotes the control rate. A higher value of λ_j corresponds to a shorter time required to control the ball. This control rate is assumed to differ between the attacking and defending teams. The attacking team needs to control the ball accurately in order to shoot or make the next pass. In contrast, the defending team does not necessarily need to control the ball with high precision. To represent this distinction, we introduce the parameter κ. Using this parameter, the control rate is expressed by the following equation:

$$\lambda_i = \begin{cases} \lambda & (i \in A) \\ \kappa\lambda & (i \in B) \end{cases}. \quad (11)$$

Here, A denotes the set of attacking players, and B denotes the set of defending players. In a previous research, the values $\kappa = 1$ and $\lambda = 4.3$ were used, assuming that defending players also attempt to gain control of the ball before transitioning to attack. Based on this assumption, the same control rate was used for both attacking and defending teams in the calculations.

Then, by integrating Equation 9 over T from 0 to ∞, the PPCF for each player can be computed. Additionally, in case where a player from one team arrives significantly earlier than any player from the opposing team and sufficient time to control the ball, the PPCF for that team is set to 1, and that of the opposing team is set to 0.

B.3 Transition model

Here we describe the Transition model, one of the components of OBSO. This model represents where the next on-ball event is likely to occur. In OBSO, it is assumed that the ball behaves similarly to a two-dimensional Brownian motion. This assumption is based on the idea that the ball's movement changes due to interactions such as passes, headers, blocks, and interceptions by players. Accordingly, OBSO considers a two-dimensional normal distribution. Furthermore, it is assumed that the player making the pass aims to send the ball to a location less likely to be intercepted. To reflect this, the Transition model incorporates the PPCF modeled in Section B.2, and is represented by the following equation:

$$T(t, \vec{r}|\sigma, \alpha) = N(\vec{r}, \vec{r_b}(t), \sigma) \cdot [\sum_{k \in A} PPCF_k(t, \vec{r})]^{\alpha}. \tag{12}$$

In the implementation of OBSO used in this study, we set $\alpha = 0$ for simplification and directly used the two-dimensional normal distribution. However, in actual football games, the tendency of pass destinations varies depending on the location on the pitch—for example, passes from the side areas are often directed inward. To account for this, the transition kernel model proposed in this study divides the pitch into 18 regions and uses kernel density estimation based on the actual pass distributions within each area.

C Field value model

The field value model was constructed based on the following procedure. First, the following sigmoid function (Fig. 5 Left) is defined along the longitudinal direction of the pitch (X-axis).

$$weight(x) = \frac{1}{1 + \exp(-\frac{x+15}{30})}. \tag{13}$$

This function reflects the gradual change in importance across the pitch during an attacking phase, while maintaining high values near the goal area. At $X = -15$, which approximately marks the boundary between the defensive third (the third closest to the team's own goal) and the middle third of the pitch, the weight becomes $weight = 0.5$. The function is designed so that the weights are approximately 0.2 at one end of the pitch and 0.9 at the other. The slightly higher value than 0.2 at the lower end is due to the additional decrease in weight as the position moves closer to the sidelines.

In addition, a normal distribution is applied in the width direction of the pitch (Y-axis). The maximum value of this normal distribution is given by Equation 13, and the standard deviation is defined by Equation 14, where the variance decreases as the position moves farther from the goal along the X-axis. This function reflects the assumption that near the goal, the importance does not

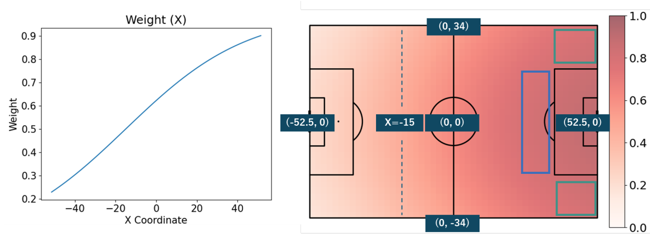

Fig. 5. Sigmoid function and field value model. (Left) The sigmoid function is applied along the X-axis of the pitch. (Right) Field value model when attacking from left to right. Darker red indicates higher importance, while areas closer to white represent lower importance. The weight decreases as the position moves away from the goal along the length of the pitch, and also as it moves toward the sidelines. The area adjacent to the penalty box, marked in green, and the vital area, marked in blue, are assigned higher values.

significantly change even if the position shifts toward the sidelines. In the equation, the constant 34 represents the distance from the center of the pitch to the sideline.

$$\sigma(x) = 34 \times \{1 + weight(x)\}. \tag{14}$$

Based on the above, the Field value at the position (x, y) is defined as follows:

$$w_{field}(x, y) = \exp\left(-\frac{y^2}{2\sigma(x)^2}\right) \times weight(x). \tag{15}$$

The field value model computed in this rule is illustrated on the right side of Figure 5. In the field value model, the areas adjacent to the penalty area (outlined in green) and the vital area (outlined in blue) are highly valued. These areas are considered highly important in soccer; thus, the model can be regarded as appropriately capturing their significance.

D Other supplementary figures

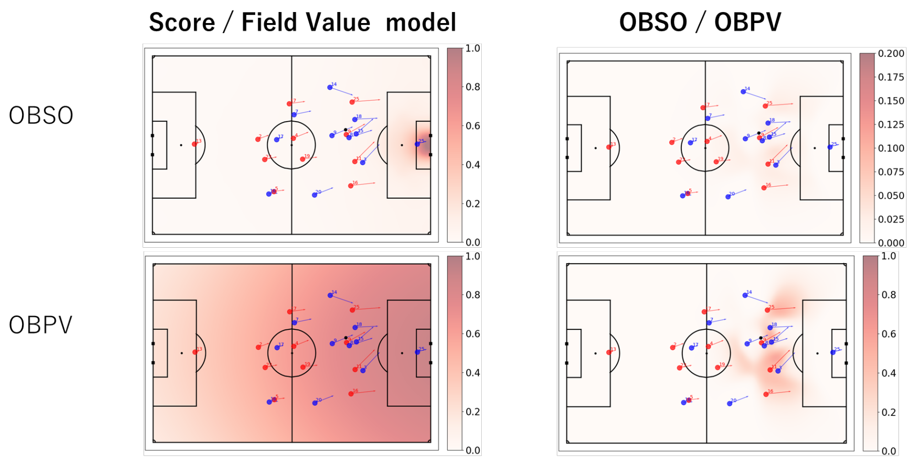

Fig. 6. Score model vs. Field value model. The upper row corresponds to OBSO (which uses the Score model, PPCF, and the Transition Kernel model), while the lower row corresponds to OBPV (which uses the field value model, PPCF, and the Transition Kernel model). In OBSO, the values tend to be smaller overall due to the influence of the Score model; therefore, the maximum value of the heatmap was set to 0.2. This value is considered appropriate for scenes near the goal.

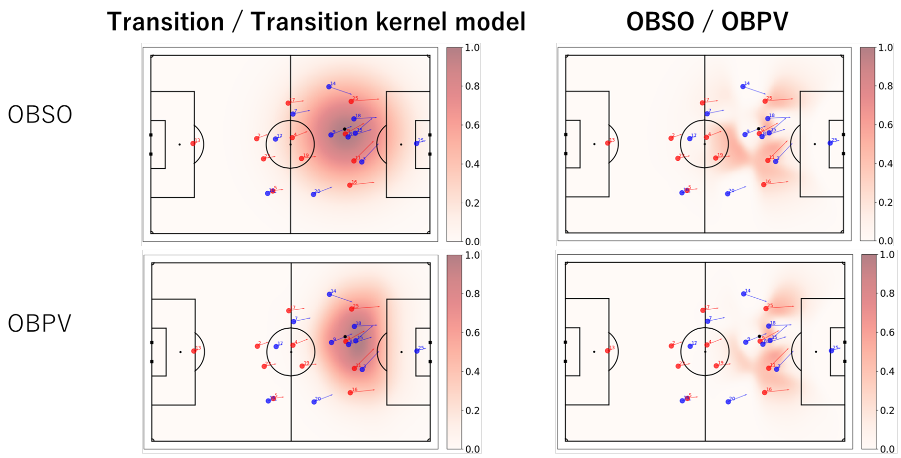

Fig. 7. Transition model vs. Transition kernel model. The upper row corresponds to OBSO (which uses the field value model, PPCF, and the Transition model), while the lower row corresponds to OBPV (which uses the field value model, PPCF, and the Transition kernel model).

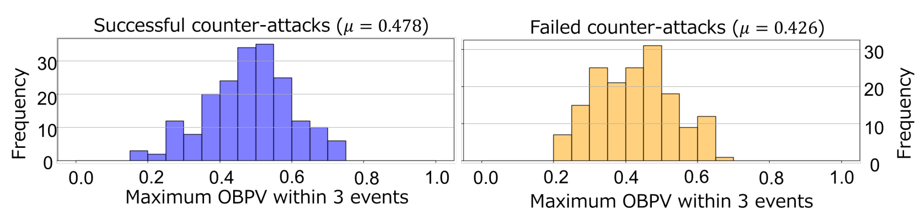

Fig. 8. OBPV of successful and failed counter-attacks. Successful counter-attacks showed higher OBPV values, with a statistically significant difference observed ($p < 1.0 \times 10^{-5}$).