Revisiting Expected Possession Value in Football: Introducing a U-Net Architecture, Reward and Risk for Passes, and a Benchmark

Thijs Overmeer[1,2][a], Tim Janssen[3][b] and Wim P. M. Nuijten[1,2][c]
[1]*Eindhoven AI Systems Institute, Eindhoven University of Technology, Eindhoven, The Netherlands*
[2]*Department of Mathematics and Computer Science, Eindhoven University of Technology, Eindhoven, The Netherlands*
[3]*Royal Dutch Football Association (KNVB), Zeist, The Netherlands*

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Abstract: This paper presents an Expected Possession Value (EPV) model for football with three main new components: a U-Net-inspired convolutional neural network architecture, ball height as a feature, and a dual-component pass value model that analyzes reward and risk. We furthermore introduce the Overmeer–Janssen–Nuijten Pass Expected Possession Value benchmark (OJN-Pass-EPV benchmark), which enables a quantitative evaluation of EPV models by using pairs of game states with given relative EPVs. The presented EPV model achieves good results in model loss and Expected Calibration Error on a dataset containing Dutch Eredivisie and 2022 FIFA Men's World Cup matches and correctly identifies the higher value state in 78% of the game state pairs in the OJN-Pass-EPV benchmark, demonstrating its ability to accurately assess goal-scoring potential. Our findings enable more precise EPV estimations, support risk-reward analysis for passing decisions, and establish quality control standards for EPV models.

1 INTRODUCTION

Football analytics is increasingly important for gaining a competitive edge. This paper focuses on a specific metric in the expanding realm of football data analysis: Expected Possession Value (EPV). EPV quantifies the net probability of goal outcomes within a fixed time horizon: the probability that the team in possession scores minus the probability that they concede within τ seconds. Following Fernández et al. (2021), who propose a horizon consistent with the average possession duration, we set $\tau = 15$ seconds in this study. The resulting value is a continuous, zero-centered measure of goal-scoring potential with range in $[-1, 1]$.

This work addresses four key research questions (RQs) in EPV modeling:

First, can we develop a high-quality EPV model using modern deep learning architectures? We investigate whether U-Net convolutional neural networks, successful in medical imaging and other spatial domains, can capture the complex spatial patterns in football. For this, we introduce OJN-EPV (Overmeer–Janssen–Nuijten Expected Possession Value), a U-Net–type architecture focused on pass EPV, tested on the Dutch Eredivisie dataset and the 2022 FIFA Men's World Cup dataset.

Second, does incorporating ball height as a feature improve pass prediction? We examine whether adding the vertical dimension enables the model to distinguish between aerial and ground passes, potentially improving prediction accuracy for different types of passing scenarios.

Third, can decomposing pass value into risk and reward components provide more actionable insights? We define reward as the probability of scoring and risk as the probability of conceding within 15 seconds, for both successful and unsuccessful passes.

Fourth, how can we establish standardized evaluation methods for EPV models? We introduce the Overmeer–Janssen–Nuijten Pass Expected Possession Value benchmark (OJN-Pass-EPV benchmark), consisting of 50 expert-validated pairs of game states for relative pass-value comparison.

[a] https://orcid.org/0009-0003-9108-1909
[b] https://orcid.org/0000-0002-8050-1176
[c] https://orcid.org/0000-0003-0351-2768

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1.1 Main Contributions

Based on our research questions, this work delivers the following contributions:

- A U-Net-based EPV model achieving strong performance across all components: pass success, pass likelihood, and pass value prediction with low loss and strong calibration.
- Empirical validation that ball height improves pass likelihood predictions, enabling the model to distinguish aerial from ground passes while accounting for their inherent uncertainty.
- Decomposition of pass value into interpretable reward and risk components, enabling tactical analysis of volatility in passing decisions beyond a single metric.
- The OJN-Pass-EPV benchmark with 50 expert-validated game state pairs, establishing the first standardized quantitative evaluation framework for EPV models.

2 RELATED WORK

Quantifying the value of actions in football follows two main lines: event-only models and tracking-based models. Event-only approaches leverage the broad availability of event data, while tracking-based models exploit full-player spatio temporal data to capture off-ball context.

Event-based metrics such as Rudd's Markov models (Rudd, 2011), VAEP (Decroos et al., 2019), Expected Threat (xThreat) (Singh, 2019), and ECOM (Bransen et al., 2019) estimate the added value of actions from *event data*. They scale well across competitions but cannot distinguish game states that share identical on-ball actions yet differ in off-ball positioning, which limits their ability to evaluate relative pass value in otherwise similar situations.

Tracking-based approaches combine *tracking data* with events to model spatial dynamics. Metrics such as Dangerousity (Link et al., 2016) and expected pass (Anzer and Bauer, 2022) incorporate for example player locations and velocities, offering richer context. However, many works either simplify representation (e.g., coarse zones) or only partially encode the full game state, and the resulting models are not always transparently interpretable for practitioners.

Fernández et al. (2019) introduce Expected Possession Value (EPV) to football as a tracking-based framework that estimates, at each event of a pass, dribble, or shot, the net probability of scoring minus conceding within a fixed horizon. EPV decomposes possession into actions (passes, carries, shots) and produces spatially interpretable surfaces, including pass value within a fixed horizon (commonly 15 seconds) and pass success probabilities. Fernández et al. (2021) further refine components such as pass likelihood, dribble and shot evaluation, and action selection, and evaluate models with calibration and loss metrics.

Beyond single-number value, prior work has examined risk–reward trade-offs for passes using tracking data (Goes et al., 2022; Power et al., 2017), typically defining risk via interception likelihood and reward via tactical outcomes. Our perspective differs in objective: we define reward and risk directly in terms of future goal scoring and conceding probabilities within a 15-second horizon, yielding spatial value surfaces for both successful and unsuccessful passes.

Two gaps remain salient. First, ball height is rarely modeled, despite empirical differences between aerial and ground passes (Håland et al., 2020). Second, standardized *relative* evaluation for pass EPV is lacking; existing works predominantly report aggregate loss and calibration, which do not capture whether a model ranks two closely related states in the expert-expected order. Our work addresses both by incorporating ball height explicitly, and by introducing an expert-validated benchmark of paired game states for relative assessment.

3 METHODOLOGY

3.1 Data Collection

The data used in this study are sourced from the Koninklijke Nederlandse Voetbalbond (KNVB), providing tracking data from TRACAB, and event data from OPTA, which encompasses the 2021/22 and 2022/23 seasons of the Dutch Eredivisie, in addition to data from the 2022 FIFA Men's World Cup.

Our analysis utilizes data from 624 Eredivisie matches and 63 2022 FIFA Men's World Cup matches. This combination captures a diverse array of performance levels and playing styles, thereby providing a robust foundation for OJN-EPV.

3.2 Data Preprocessing and Feature Engineering

We transform the raw event and tracking data for integration into our models through the following steps:

- *Coordinate Normalization and Grid Scaling:* Player and ball coordinates are first normalized to a standard pitch dimension (105m x 68m) based on the venue information associated with each match, addressing variations in actual pitch sizes. These normalized coordinates are then scaled to fit a 104×68 grid representation for efficient processing in NumPy and TensorFlow. Velocities are smoothed using a Savitzky-Golay filter to reduce noise.

- *Direction Standardization and Cleaning:* We standardize the data by ensuring all attacks proceed uniformly from left to right. Additionally, we remove instances of players recorded outside the pitch boundaries to improve data integrity.
- *Real Playing Time Calculation:* To accurately assess pass value, we calculate the actual playing time, excluding periods when the ball is out of play. This ensures that our evaluation window of 15 seconds following each pass reflects only the active duration of the game, providing a more precise assessment of in-game actions.
- *Data Alignment:* To ensure synchronicity, we align the event data with the tracking data. This ensures that each pass event is accurately reflected in the tracking data, enabling precise spatial and temporal analysis. The tracking data includes ball height (z-axis). Positional data from optical tracking systems inherently contains noise (with typical errors around 7–8 cm (Linke et al., 2020)); our 1 m grid resolution is robust to such deviations in the (x, y) positions.

For the pass likelihood, pass success, and pass value models, we use the features described in Fernández et al. (2021) and additionally incorporate the z-value (height) of the ball.

3.3 Model Architecture

We select a U-Net–type architecture (Ronneberger et al., 2015) due to its proven effectiveness in image segmentation tasks, which share similarities with predicting dense, spatially-aware surfaces like pass EPV across the pitch. The U-Net's encoder-decoder structure with skip connections allows the model to capture both fine-grained local details (e.g., player proximity) and broader global context (e.g., overall team formation), which are both crucial for accurate EPV estimation.

Our pass OJN-EPV model takes a multi-channel grid representation of the game state over the pitch with dimensions (104×68) and produces a single output grid of the same size. Each cell corresponds to the predicted quantity at that location (e.g., pass success probability, pass likelihood, or pass value). The model comprises encoder and decoder blocks with max pooling, replication padding, attention gates, and concatenation layers. A diagram is provided in Figure 1.

Each encoder block applies two repetitions of: replication padding, a convolution with a 5×5 kernel, batch normalization, and a LeakyReLU activation (alpha $= 0.1$). The number of filters per block is 16, 32, and 64 in the contracting path, then 32 and 16 in the expanding path to mirror the U-shape. Decoder blocks consist of upsampling, replication padding, a 5×5 convolution with the corresponding number of filters, batch normalization, and LeakyReLU (alpha $= 0.1$).

Downsampling is performed by max pooling after the first two encoder blocks; pooling is omitted after the third to preserve spatial resolution. The most contracted feature maps are 26×17.

In the decoder, feature maps are upsampled. Attention gates modulate the high-resolution encoder features using a gating signal from the decoder before concatenation. The concatenated features are then processed by the decoder convolutional blocks, combining local detail with global context.

The final layer uses a sigmoid activation for the *pass success* model and softmax over the 104×68 grid for the *pass likelihood* model. For *pass value*, we employ a softmax per grid cell with three classes indicating outcomes within 15 seconds: goal for the passing team, no goal, or goal for the opponent.

3.4 Model Training and Evaluation

We split the matches into training, validation, and test sets using an 80-10-10 split for Eredivisie matches and a 60-20-20 split for 2022 FIFA Men's World Cup matches. Due to the smaller size of the 2022 FIFA Men's World Cup dataset, we assign a higher percentage of samples to the validation and test sets to enhance their statistical relevance. Table 1 shows the distribution of successful and unsuccessful passes across both datasets.

We first train on the larger Eredivisie dataset and subsequently fine-tune on the 2022 FIFA Men's World Cup data. The training employs a cyclic learning rate, which fluctuates between a base learning rate of 1×10^{-6} and a maximum learning rate of 1×10^{-4} following a triangular policy with a full cycle lasting 8 epochs (Smith, 2017). This method helps to avoid local minima. Subsequently, we fine-tune the model using data from the 2022 FIFA Men's World Cup, where the maximum learning rate is decreased to 1×10^{-5}.

A batch size of 128 is used for all OJN-EPV models. Training stops when the validation loss does not

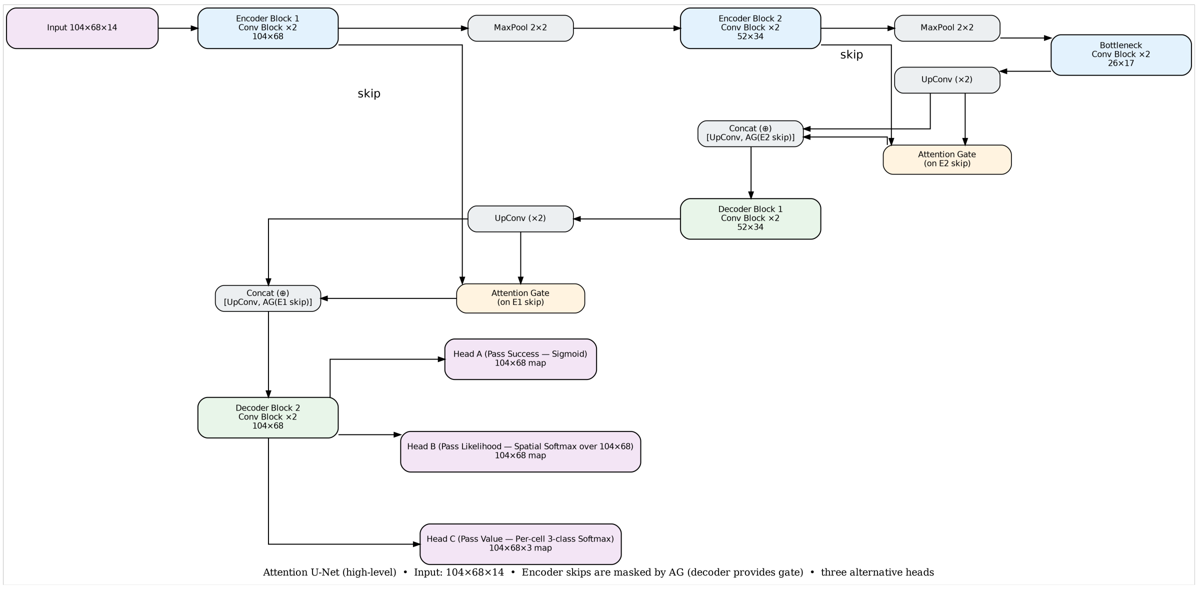


Figure 1: High-level U-Net architecture with encoder–decoder and skip connections used in OJN-EPV.

Table 1: Comparison of Successful and Unsuccessful Passes.

Dataset	Total	Train	Val	Test	% Success
Eredivisie	507,953	406,495	49,542	51,916	79.79%
2022 FIFA Men's World Cup	58,569	34,093	11,787	12,689	81.52%

improve for 8 consecutive epochs. After training converges, we select the epoch that provides a suitable balance between the loss and expected calibration error (ECE). The Adam optimizer with default settings in TensorFlow 2.18 is employed for all models.

Both pass success and pass value models employ temperature scaling as a post-processing step. The optimal temperature value, ranging from 0.1 to 2 with a step size of 0.1, is selected to minimize the ECE on the validation set.

3.5 Optimal Pass Location Identification

To operationalize OJN-EPV for evaluating passes (as visualized in Figure 4), we create a pitch-wide surface that combines pass success, pass value, and the likelihood of a pass arriving at each location. We restrict the outputs to reasonably probable destinations using a likelihood threshold.

Definition 1 (OJN-EPV Output). The model output for location (x,y) is:

$$\text{Output}(x,y) = \begin{cases} V(x,y) & \text{if } L(x,y) > 0.001 \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

$$\text{where } V(x,y) = S(x,y)V_s(x,y) + (1 - S(x,y))V_u(x,y) \tag{2}$$

$$V_s(x,y) = P_{\text{score}}(x,y|\text{success}) - P_{\text{concede}}(x,y|\text{success}) \tag{3}$$

$$V_u(x,y) = P_{\text{score}}(x,y|\text{no success}) - P_{\text{concede}}(x,y|\text{no success}) \tag{4}$$

with:

- $V(x,y)$: estimated value of a pass that ends up at location (x,y)
- $L(x,y)$: likelihood that a pass ends up at location (x,y)
- $S(x,y)$: probability of a successful pass to (x,y)
- $P_{\text{score}}(x,y|\text{success})$: probability of scoring after a successful pass to (x,y)
- $P_{\text{concede}}(x,y|\text{success})$: probability of conceding after a successful pass to (x,y)
- $P_{\text{score}}(x,y|\text{no success})$: probability of scoring after an unsuccessful pass to (x,y)
- $P_{\text{concede}}(x,y|\text{no success})$: probability of conceding after an unsuccessful pass to (x,y)

We set $L(x,y) > 0.001$ as a practical threshold in Definition 1. This hyperparameter can be adjusted: lower values surface less likely (but potentially more creative) options, whereas higher values restrict recommendations to more traditional and realistic destinations. This output definition enables the identification of optimal pass locations by evaluating $\text{Output}(x,y)$ across all feasible locations on the pitch. The location with the highest output value represents the model's recommendation for the most valuable pass option, accounting for both the probability of successfully executing the pass and its expected impact on scoring/conceding probabilities. This practical application is demonstrated in our analysis of real game situations (see Figure 4 in Section 5).

3.6 Benchmark Creation and Evaluation

To enable quantitative evaluation of the performance of EPV models, we create the OJN-Pass-EPV benchmark. This benchmark consists of 50 modified game state pairs, where we use a real game state and realistically alter aspects of it (e.g. player positions and velocities). While this number is modest, it represents a first step towards standardized quantitative evaluation of pass EPV models, focusing on challenging scenarios identified by experts.

We rely on a panel of three football experts, including members of the Royal Dutch Football Association (KNVB) with backgrounds in performance and data analysis, to assess which of the two game states in each game state pair has a higher pass EPV. This approach follows guidelines from Davis et al. (2024), who emphasize expert evaluation as essential for sports analytics validation. We focus on relative EPVs rather than absolute EPVs, as the latter are often more subjective. In designing the benchmark, we select game state pairs that we expect to have widely accepted relative values, and we only include game state pairs in the benchmark set if all three football experts agree on their relative value.

To obtain the performance of OJN-EPV on the benchmark, we first create a single scalar pass EPV for a game state. For this, we take the prediction of pass EPV over endpoints with respect to the pass likelihood as in Definition 2 and compare the scalar pass EPV of one game state with the modified game state. We then report the percentage of cases where our model ranks the game state either lower or higher in correspondence with the ratings of the experts.

Definition 2: Scalar Pass EPV.

$$\text{EPV}_{\text{pass}} = \sum_{x,y} L(x,y)\,V(x,y) \qquad (5)$$

with $V(x,y)$ as in Definition 1.

4 RESULTS

This section presents our main results and findings, beginning with a feature ablation study. Building upon the optimal feature set identified, we subsequently present the results of an architectural study aimed at determining the ideal number of parameters for OJN-EPV. The best-performing architecture is then employed to evaluate the performance of the resulting model. Losses and calibration metrics in this section are computed on held-out splits of the Eredivisie and 2022 FIFA Men's World Cup datasets (Tables 2 and 3). The OJN-Pass-EPV benchmark in Section 4.6 is a separate, expert-validated set of 50 paired game states used only for relative evaluation.

4.1 Feature Ablation Study

In our feature ablation study, we investigate the effects of various feature combinations on model performance. Across all models, adding features beyond the fundamental features (i) player positions and velocities, (ii) distance to the ball for every location, and (iii) ball height, yield only negligible performance gains in aggregate metrics such as loss and ECE. In practice, the only additional features we include are *distance to goal* and *angle to goal*. Closer inspection of the value models, including visual evaluations of predicted probability surfaces, reveals that these two features substantially improve contextual accuracy. Without them, the model underestimates value in scenarios near the penalty area. We retain these features specifically because they improve benchmark performance even when global loss and calibration change only marginally.

4.2 Architecture Study

To validate the model architecture, we examine various setups, specifically focusing on the number of filters (8, 16, 32) and the filter dimensions (3x3, 5x5). We find that using only 8 filters significantly reduces performance for all models except the pass value models. For the models using 32 filters, we find that these models do show slightly better performance compared to the models using 16 filters, but due to only slight improvements and significantly more parameters, we choose to use 16 filters with dimension 5x5 for the OJN-EPV model. This configuration results in 372,355 parameters for the pass success model, 372,359 for the pass likelihood model, and 373,201 parameters for both pass value models (successful and unsuccessful).

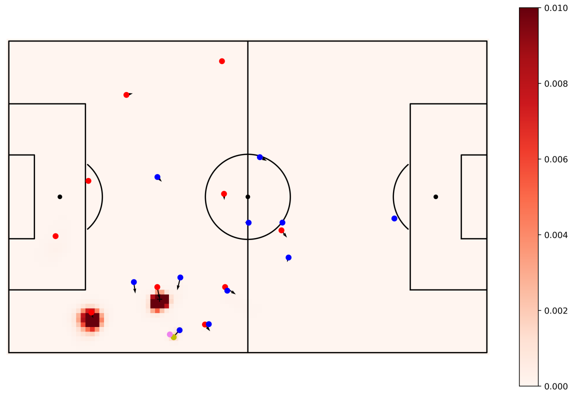
4.3 Model Performance

This section assesses the performance of the OJN-EPV model, focusing on the loss and calibration metrics. We use ECE with 10 bins as the calibration metric. To enhance model calibration, we apply temperature scaling to the pass success and pass value models. All models, except one, demonstrate optimal calibration with a temperature of 1.0, indicating no need for temperature scaling. Only the value unsuccessful model, trained and validated on the Eredivisie data, exhibits improved calibration with a temperature value of 1.1. We do not report ECE for the pass likelihood surface, because it is a spatial distribution (softmax over 104×68 endpoints) rather than a binary probability; bin-based calibration is not well-posed for this output. Table 2 presents the overall performance metrics for models trained on Eredivisie data, while Table 3 shows results for models fine-tuned on 2022 FIFA Men's World Cup data. Loss and ECE curves remain stable over epochs, indicating consistent convergence behavior.

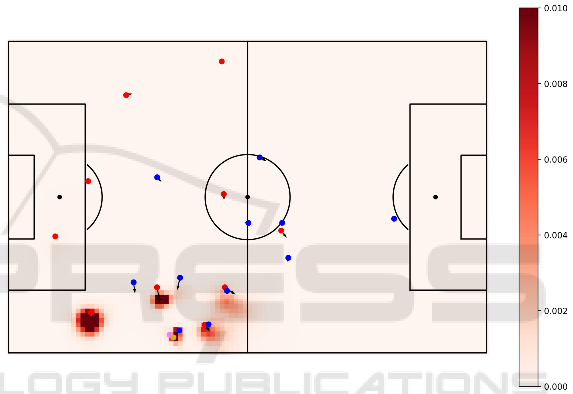
The detailed loss per class based on the value model, as shown in Tables 4 and 5, provides a comprehensive representation of the model's nuanced understanding of pass outcomes. Low loss and calibration scores demonstrate the model's proficiency in accurately forecasting whether a pass will result in scoring a goal, conceding a goal, or no goal at all within a window of 15 seconds for the team in possession of the ball.

4.4 Influence of Ball Height on Predictions

Incorporating the ball's height (z-axis) into the model significantly impacts the pass likelihood predictions by adding the crucial vertical dimension to the analysis. Figure 2 illustrates this by contrasting two scenarios: a ground pass (Figure 2a) and an aerial pass with the ball at 2 meters high (Figure 2b). When trained without the ball height feature on the Eredivisie dataset, the pass likelihood model achieves a loss of 4.7478, compared to 4.7225 with ball height included (as shown in Table 2). While this aggregate metric shows only minor changes, reflecting the relative rarity of aerial passes, Figure 2 demonstrates the practical importance of considering ball height for specific passing situations, where the model recognizes that aerial passes can be made over opponents while also showing increased uncertainty about the pass destination.



(a) Ground pass scenario (z=0 m). Red team in possession; yellow dot marks the ball carrier belonging to the red team; pink dot marks the ball.



(b) Aerial pass scenario (z=2 m). Same game state as top panel but with the ball at 2 meters in the z-axis.

Figure 2: Impact of ball height on pass likelihood prediction. Top: ground pass (z=0 m) with blocked passing lanes; Bottom: same state with an aerial pass (z=2 m) that can be played over defenders. Aerial passes yield broader, more diffuse likelihoods, reflecting lower precision relative to ground passes.

4.5 Risk and Reward Decomposition

Decomposing pass EPV into reward and risk components offers a more nuanced perspective on the complexities of passing decisions in football. By separating the potential positive and negative impacts of a pass, we can gain deeper insights into the underlying volatility of seemingly straightforward game states. Figure 3 depicts one such game state, where the decomposition of EPV reveals the trade-offs inherent in a passing decision.

In this game state, the pass value model trained on successful passes assigns a slightly negative overall value (i.e., -0.0047) for the end location of the

Table 2: Loss and ECE on both datasets for models trained on Eredivisie data. Note: ERE = Eredivisie; WC = World Cup.

Model	Loss (ERE)	ECE (ERE)	Loss (WC)	ECE (WC)
Pass Success	0.1558	0.0024	0.1355	0.0122
Pass likelihood	4.7225	-	4.4528	-
Pass Value (Successful)	0.0689	0.0016	0.0835	0.0060
Pass Value (Unsuccessful)	0.0663	0.0042	0.0726	0.0056

Table 3: Loss and ECE on both datasets for models fine-tuned on 2022 FIFA Men's World Cup data. Note: ERE = Eredivisie; WC = World Cup.

Model	Loss (ERE)	ECE (ERE)	Loss (WC)	ECE (WC)
Pass Success	0.1568	0.0090	0.1326	0.0047
Pass likelihood	4.7227	-	4.4367	-
Pass Value (Successful)	0.0687	0.0024	0.0836	0.0065
Pass Value (Unsuccessful)	0.0671	0.0045	0.0740	0.0050

pass marked with a "+". This implies that even if the pass is completed, the blue team is still considered more likely to score within 15 seconds than the red team. Building on nuanced risk-reward assessments in passing, such as Goes et al. (2022) who quantified risk via interception probability and reward through multiple tactical factors, our analysis, grounded in the EPV framework, offers a complementary perspective focused on ultimate outcomes. Instead of solely focusing on pass completion or immediate tactical advantage, we decompose the predicted pass value into 'reward' (the probability of scoring within 15 seconds) and 'risk' (the probability of conceding within 15 seconds). This direct link to future goal events allows for evaluating the potential volatility and net goal impact inherent in different passing options, distinct from the immediate risk of turnover or specific tactical gains. Even a successful pass can lead to an unpredictable game state, potentially detrimental for the team in possession, depending on factors such as opponent pressure. This assessment is based on potential outcomes: the blue team has a 0.0199 probability of scoring compared to 0.0152 for the red team. This analysis illustrates the complex trade-offs that can be present in passing decisions.

OJN-EPV quantifies these potential outcomes (reward vs. risk for different options) to inform player and coach decision-making, rather than prescribing a single 'best' action, which may depend on factors beyond the model's scope (e.g., game state, tactical instructions, individual player risk tolerance).

4.6 Benchmark Performance and Validation

Before incorporating distance to goal and angle to goal features in our pass value models, the benchmark performance for the model trained only on the Eredivisie dataset is 68% on the OJN-Pass-EPV benchmark, rising to 70% after fine-tuning on the 2022 FIFA Men's World Cup data. Once we add these two features, the global loss and calibration metrics do not show a pronounced improvement. However, the benchmark performance for both the Eredivisie-trained and 2022 FIFA Men's World Cup fine-tuned models increases to 78%.

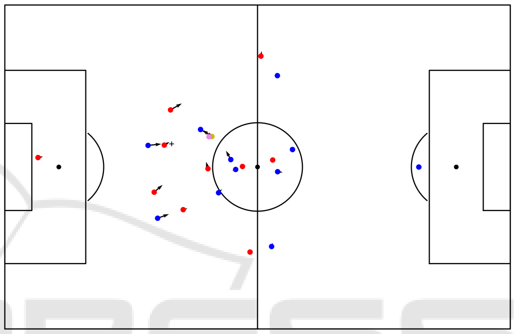


Figure 3: Pass value decomposition in a single game state. Red team is in possession; the ball carrier is marked with a yellow dot; the intended pass destination is marked by "+". The example illustrates how OJN-EPV can assign slightly negative overall value even for a completed pass when conceding risk outweighs reward in the horizon of 15 seconds.

5 DISCUSSION

This section discusses our findings and their implications for football analytics.

5.1 Technical Achievements

5.1.1 U-Net Architecture Performance

Our results indicate that the U-Net architecture delivers strong performance on the OJN-Pass-EPV bench-

Table 4: Pass value model - loss and ECE by class for model trained on Eredivisie data.

Class	Loss (Eredivisie)	ECE (Eredivisie)	Loss (WC)	ECE (WC)
Scoring goal (Successful)	0.0590	0.0018	0.0689	0.0048
No goal (Successful)	0.0660	0.0040	0.0791	0.0035
Conceding goal (Successful)	0.0096	0.0023	0.0144	0.0022
Scoring goal (Unsuccessful)	0.0379	0.0060	0.0357	0.0074
No goal (Unsuccessful)	0.0620	0.0105	0.0663	0.0134
Conceding goal (Unsuccessful)	0.0271	0.0041	0.0362	0.0062

Table 5: Pass value model - loss and ECE by class for model fine-tuned on 2022 FIFA Men's World Cup data.

Class	Loss (Eredivisie)	ECE (Eredivisie)	Loss (WC)	ECE (WC)
Scoring goal (Successful)	0.0590	0.0011	0.0693	0.0057
No goal (Successful)	0.0658	0.0032	0.0793	0.0042
Conceding goal (Successful)	0.0093	0.0021	0.0141	0.0020
Scoring goal (Unsuccessful)	0.0385	0.0064	0.0366	0.0081
No goal (Unsuccessful)	0.0619	0.0095	0.0661	0.0125
Conceding goal (Unsuccessful)	0.0272	0.0039	0.0365	0.0058

mark. Its effectiveness stems from the U-Net's ability to first capture broad, contextual information like the overall team formation in its encoder, and then re-integrate fine-grained local details, such as player proximity, using skip connections to produce a spatially precise output.

The choice of 16 filters with 5x5 kernels balances model complexity and performance. While 32 filters give marginal gains, the parameter cost is disproportionate.

5.1.2 Ball Height Impact

Incorporating ball height improves the model's ability to distinguish between ground and aerial passes. As shown in the Results, the model recognizes that aerial passes can bypass defenders while exhibiting increased spatial uncertainty, aligning with domain knowledge that headers are less precise than ground passes.

5.1.3 Risk-Reward Decomposition

Decomposing pass value into separate reward and risk components provides a more nuanced view than single-value EPV approaches. By quantifying the probability of scoring (reward) and conceding (risk) for both successful and unsuccessful passes, the model surfaces the volatility of different options.

5.2 Methodological Considerations

5.2.1 Benchmark Design

The OJN-Pass-EPV benchmark represents a first step toward standardized evaluation in EPV modeling. By focusing on relative comparisons between paired game states rather than absolute values, we reduce subjectivity in target labels. Unanimous expert agreement ensures high-confidence ground truth, though it limits the set to 50 pairs. The public repository includes the 50 paired states and the expert selections.

5.2.2 Training Strategy

We train on Eredivisie data and fine-tune on 2022 FIFA Men's World Cup data; similar qualitative behavior across both suggests the model captures general football principles rather than competition-specific patterns.

5.3 Comparison with Previous Work

Attempting to implement the Fernández et al. (2021) model as a baseline encountered vanishing gradients during training, preventing a direct comparison and motivating our U-Net approach with skip connections and LeakyReLU activations (Glorot et al., 2011).

The OJN-Pass-EPV benchmark provides a quantitative measure previously unavailable in the field. Incorporating distance and angle to goal improves relative value assessment even when aggregate loss and calibration metrics change only marginally.

5.4 Practical Implications

We illustrate how our model can be employed as a decision support tool, utilizing Definition 1 by evaluating the model surface across the pitch (Figure 4). In this figure, we demonstrate the locations that our model estimates to be optimal based on the current game state. As previously discussed in subsection 4.5, these outputs should be considered a supportive tool for practitioners, taking into account current limitations, such as the model's player-agnostic nature.

Beyond benchmark accuracy, OJN-EPV supports player- and team-level decision profiling. At the player level, analysts can quantify a risk profile by measuring the share of high-variance options (high risk–high reward) selected relative to available alternatives, and detect systematic biases toward conservative choices. At the team level, aggregated risk–reward tendencies reveal phase- or opponent-specific strategies (e.g., increased aerial risk under high press). These diagnostics help align coaching intent with on-pitch execution.

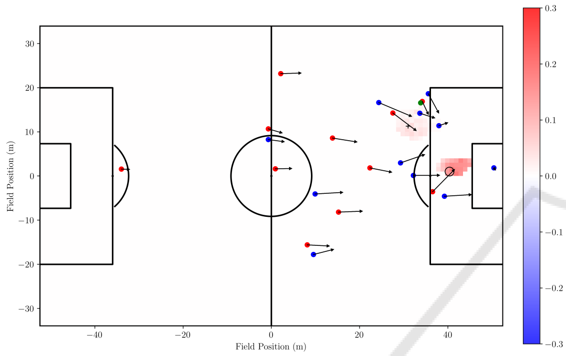


Figure 4: Decision analysis with OJN-EPV. Red team is in possession; the ball carrier is marked with a yellow dot. The player's actual pass destination is marked by "+"; the model-recommended optimal location is circled (Definition 1). The comparison highlights potential areas for decision-making refinement.

OJN-EPV supports applied analysis across the match cycle: pre-match scouting of opponent passing patterns, half-time assessment of risk-taking shifts, post-match comparison of actual decisions to model surfaces.

5.5 Limitations & Future Work

Three benchmark errors are attributable to offside; rule-aware masking of offside receivers at pass start would likely correct these cases. Offside is defined for receivers at pass start, not for abstract endpoints, so a location-only mask is inadequate. A practical remedy is a post-processing step that assigns candidate endpoints to intended receivers and sets $S(x,y) = 0$ for receivers who are offside at pass start.

Future work includes implementing explicit offside handling via receiver-aware masking, expanding the OJN-Pass-EPV set beyond 50 pairs, increasing spatial resolution beyond 1 m to capture finer nuances, and developing player-specific models that account for individual abilities and preferences.

6 CONCLUSION

We present OJN-EPV with four core contributions: a U-Net architecture for spatial EPV at modest scale (372K parameters), incorporation of ball height to distinguish aerial from ground passes, a risk-reward decomposition defined for both successful and unsuccessful passes, and the OJN-Pass-EPV benchmark of 50 expert-validated pairs for standardized, relative evaluation.

Our model demonstrates strong performance across both Eredivisie and World Cup datasets, achieving low loss, robust calibration, and 78% accuracy on our benchmark. These results affirm the value of each contribution: the U-Net architecture produces high-quality spatial EPV surfaces, ball height integration refines pass predictions, the risk-reward framework offers actionable insights, and the benchmark provides a necessary tool for standardized evaluation, thereby answering RQ1–RQ4.

To foster transparency and drive further innovation, the OJN-Pass-EPV dataset is publicly available at https://github.com/EAISI/OJN-EPV-benchmark. This resource provides the community with a standardized tool to rigorously compare and validate new EPV models, moving beyond aggregate metrics toward expert-aligned relative assessments. Ultimately, this work not only introduces a novel, high-performing EPV model but also establishes a more robust methodological foundation for its evaluation, setting a new baseline for future research in football analytics.

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