GraphEIV: A Framework for Estimating the Expected Immediate Value in Basketball Using Graph Neural Networks

Bruno M. Sá-Freire*[1,2], Gabriel R. G. Barbosa*[1,2], João Lucas L. Gonçalves*[1,2], Jake Schuster[2], and Hugo Rios-Neto (✉)[1,2]

[1] Universidade Federal de Minas Gerais, Belo Horizonte, Brazil
{bruno290103,grgb,jllgoncalves23,hugoriosneto}@ufmg.br
[2] Gemini Sports Analytics, Raleigh NC 27603, USA
jake@geminisports.ai

Abstract. Basketball is a fast-paced and strategic sport where each possession involves a series of complex decisions and actions. Analyzing and understanding these intricacies is essential for effective performance evaluation. This study introduces a novel framework, Expected Immediate Value, for evaluating basketball possessions from tracking data using Graph Neural Networks. We take inspiration from the Expected Possession Value framework for predicting points scored as an immediate consequence of the current game state. We develop four specific models to enhance the interpretability and composition of metrics: xFG (probability of a shot being successful), xNAT (next action - pass or shot), xR (probability of a player receiving the ball), and xTO (likelihood of a turnover). Our approach provides a comprehensive evaluation of player movements and decisions. This framework offers deeper insights into possession dynamics and supports strategy optimization in basketball.

Keywords: Basketball analytics · Deep learning · Graph neural networks.

1 Introduction

Basketball is a dynamic sport where small actions during each possession can significantly impact larger outcomes. While traditional metrics such as box score statistics and play-by-play data fail to capture such contributions, optical tracking data creates opportunities to evaluate player contributions to game-action outcomes more comprehensively. This paper presents a framework by which tracking data can be leveraged to optimize team and player strategies in basketball. [5][6][1][2][8]

Challenges arise when estimating the value of actions in basketball. The Expected Possession Value (EPV) in basketball represents the expected number of points that will be scored as an immediate consequence of the current game

* These authors contributed equally to this work.

state. Our work takes inspiration from the foundational EPV framework introduced by [2], which predicts the outcomes of basketball possessions through a stochastic process model.

The original EPV framework [2] models the probabilities associated with each possible state transition by considering data of each individual player, their tendencies, and style of play. While this design decision allows for detailed and personalized models, it also introduces limitations. For instance, the need for individual player data and cooperative stats, such as "probability passing maps" for each position, can be restrictive due to the fluidity of positions and team tactics in modern basketball. Moreover, the original EPV framework did not utilize deep learning techniques, which have advanced significantly since 2016. This presents an opportunity to build upon modern techniques to develop new frameworks for evaluating actions in basketball.

In this study, we propose a modular approach, using Graph Neural Networks (GNNs) to create four separate models to estimate the necessary probabilities that compose the Expected Immediate Value (EIV) framework. EIV calculates the immediate expected points a team can score at any given moment, assuming that the player currently in possession of the ball will either shoot or pass to a teammate who will then shoot. The decision to create the EIV framework, rather than improving the EPV, was in large part due to the data limitations we faced. These are thoroughly discussed in Section 3 and Section 7.

The main contributions of this paper are:

- Introduction of GNNs applied to the estimation of EIV in basketball, providing a novel approach to capture the intricate spatial and temporal relationships of the game.
- Development of new basketball metrics by aggregating predictions from our framework composed of four distinct models, enabling new advanced statistics for performance analysis.
- Given better data annotation, we provide a clear path for others to build upon our work to create an EPV framework that leverages the base architecture and model components we utilized.

2 Related Work

In [2], the first implementation of EPV in basketball, the authors define the metric as the "expected number of points the offense will score on a particular possession conditional on that possession's evolution up to time t". Their approach was stochastic, with multi-resolution modeling, to predict possession states in macro level using Markov chains (to maintain stochastic consistency) and a full resolution model for sensitivity to fine-grained details of data.

The inclusion of various player-specific features in the estimator was justified by improved accuracy when predicting decisions and movement. However, when it comes to general models for evaluating player decision-making and efficiency, there may be more utility in developing a player-agnostic model capable of pinpointing outliers among a given population of players.

Deep Hoops [8] is an architecture that uses deep learning to assign value to actions in basketball. A Long Short-Term Memory (LSTM) network was fed with player embeddings to predict the probability of the final action of each possession, where the possibilities are field goal attempts, shooting fouls, non-shooting fouls, and turnovers. The value of each final action was fixed as the average points which it led to. Finally, game states were evaluated by weighing the average value of each final action by the probability of each outcome.

A limitation presented in [8] is the lack of assigning values to shots that are dependent on the current game state, rather than a pre-defined average value. By fixing shot values, the expected value from a shot depends only on the probability of a shot being attempted, rather than upon its value or difficulty.

Similar to [2], a framework for evaluating the expected value of possessions in soccer was presented [4] in 2021. The authors consider the probability of a pass to all possible receivers and the probability of possible ball-drives and shots. These probabilities are then used as weight-averages to sum outcome values and determine a possession value. The framework uses low-level spatial data as input, from which 13 layers of sparse field-wide matrix representations are created and fed into a Convolutional Neural Network (CNN) that also estimates a field-wide matrix representation.

This approach may lead to problems when converting low-dimensional tracking data into high-dimensional sparse data [9]. To address this issue, GNNs have been used to represent game states of soccer in predictive models [9][7][10]. By representing players as nodes and the relationships between them as edges, it becomes possible to feed neural networks with representative information.

3 Data

For this study, we utilized a tracking data dataset consisting of 576 games from the 2015-16 NBA season, provided by SportVU[3]. This dataset includes the positions of all ten players on the court, along with the ball's coordinates, at a resolution of 25Hz. The high resolution of the tracking data enables detailed analysis of player movements and interactions during each possession.

However, the data lacks annotations of the actions that happen throughout the game, which makes it challenging to accurately interpret the context and meaning behind the data points. This lack of annotations means that the precise actions being taken by players (such as passes, shots, screens, or defensive maneuvers) are not directly recorded in the dataset. Consequently, identifying and classifying these actions becomes a complex task, often requiring additional processing or manual annotation to generate labels that can be used for supervised learning tasks. This adds a significant layer of complexity to the data analysis process.

Without clear labels, it is challenging to train models that can recognize specific actions or events with high accuracy. Heuristic methods, clustering techniques, or semi-supervised learning approaches to infer the actions from the raw

[3] https://github.com/linouk23/NBA-Player-Movements

positional data could help mitigate the challenge. Still, these methods introduce noise and uncertainty into the analysis, as these inferred labels might not always correspond perfectly to the actual events on the court.

We found an external play-by-play dataset[4] with annotations of some types of actions. Nevertheless, they were not synchronized to the timestamp of when the player started performing the action, but rather to the identifier of the play. This required us to develop rule-based algorithms to accurately identify the timing of certain events. The algorithms were designed to detect shots, passes, and pass turnovers, achieving a 71% average detection rate for all events.

In Section 7, we more thoroughly discuss how the lack of annotations limited our modeling approach for this work, and how one with better data could extend our work to build an EPV framework.

4 EIV Framework

This section defines the proposed GraphEIV framework for basketball. The primary task of this framework is to estimate the immediate expected amount of points a team can score at a given moment, considering the player with the ball will shoot or pass to someone who will catch and shoot. To do so, we estimate the chances of each of the actions happening and their chances of success.

Let G_t be the game state at time t. Let S be the number of points scored as a direct consequence of an action A taken at time t. The EIV of a basketball possession at time t is defined as $EIV_t = \mathbb{E}[S|G_t]$. We can expand it to:

$$\mathbb{E}[S|G_t] = \sum_{a \in A} \mathbb{E}[S|A = a, G_t] \cdot \mathbb{P}(A = a|G_t) \tag{1}$$

In this work, due to limited data annotation, we define the set of possible actions to be taken by the player with the ball to only passes and shots, $A = \{\rho, \zeta\}$, where ρ represents a pass and ζ a shot. Also, let $P(l)$ be a function that returns the points value of a field goal from location l. We can further expand Equation 1:

$$\begin{aligned} \mathbb{E}[S|G_t] = {} & P(l_c) \cdot \mathbb{P}(O = o_+|A = \zeta, G_t) \cdot \mathbb{P}(A = \zeta|G_t) \\ & + \sum_{r_i = r_1}^{r_4} P(l_{r_i}) \cdot \mathbb{P}(O = o_+|A = \rho_{r_i}, G_t) \cdot \mathbb{P}(A = \rho_{r_i}|G_t) \cdot \mathbb{P}(A = \rho|G_t) \end{aligned} \tag{2}$$

where o_+ represents a positive outcome O, r_i the receiver i and ρ_{r_i} a pass to receiver r_i. The EIVs of the four potential receivers are summed.

4.1 Base Architecture

To derive the total EIV value of any given game state, the probabilities from Equation 2 are calculated with four classifier models, which will be described

[4] https://github.com/airalcorn2/baller2vecplusplus/blob/master/events.zip

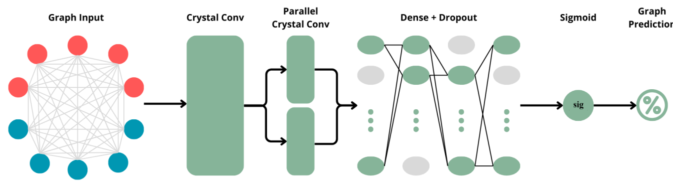

Fig. 1. Architecture of the base GNN model: one Crystal Convolutional Layer (CCL) followed by two Parallel CCLs. This is succeeded by four Dense Layers, with a 0.5 dropout applied after each layer, and a Sigmoid output.

in detail in the next section. The four models share the same base GNN architecture and use fully connected graphs as input, differing only in which players are included in the input graphs. Each model was trained separately. The base architecture can be visualized in Figure 1.

4.2 Individual Models

The four individual models developed are: expected next action taken (xNAT), expected receiver (xR), expected turnover (xTO), and expected field goal (xFG). xR and xTO are combined to create the expected pass outcome (xPO) component, while xFG is also applied to obtain the expected field goal receiver (xFGR). The predictions generated by each model can be visualized through plots like the ones in Figure 2.

The xNAT model is designed to predict whether the player will pass or shoot as their next action. In Equation 2, this is represented by the term $\mathbb{P}(A|G_t)$, where $A = \{\rho, \zeta\}$. This is achieved through supervised binary graph classification, where each input graph represents the game state immediately before a shot or pass is made. The input of this model is a fully connected graph, where all 10 players are connected to each other. The target label is 1 if it is a shot and 0 if a pass.

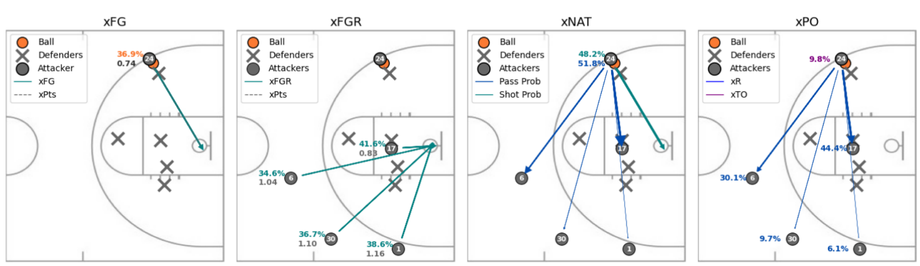

Fig. 2. Visualization of the four expected values that compose the EIV framework. Blue indicates passing probabilities; teal indicates shooting probabilities; purple represents turnover probability; and black text represents the expected points from a shot (xFG).

	Node Features					Edge Features	
Model	Position (x,y)	Velocity (x,y)	Distance to Basket	Is Attacking (bool)	Is Player with Ball (bool)	Are Teammates	Distance Between Players
xNAT	✓	✓	✓	✓	✓	✓	
xR	✓	✓	✓	✓	✓	✓	
xTO	✓	✓		✓	✓	✓	
xFG	✓	✓	✓	✓			✓

Table 1. Model features. Each model uses a subset of the node features: the players' x and y coordinates, their velocities in x and y directions, distance to the basket, a boolean to indicate if the player is from the attacking team, and a boolean to indicate whether the player is in possession of the ball. The edge feature can be either the distance between players or a boolean that indicates whether the connected nodes are teammates.

The expected pass outcome (xPO) value is a composite of two separate models: xR (expected receiver), which predicts the probability of passing to each of the four potential receivers; and xTO (expected turnover), which predicts the probability of the pass resulting in a turnover. The outputs of these two models are subsequently merged and normalized to create the xPO prediction. In Equation 2, the probability of a pass to receiver r_i is given by $\mathbb{P}(A = \rho_{r_i}|G_t)$.

The xR model represents the game state on a per-receiver basis, each frame yielding four different inputs. The input graph for xR consists of a fully connected graph with all five defenders, the player with the ball, and one potential receiver. The label is 1 if the potential receiver is the actual receiver and 0 otherwise. Also, The input graph for the xTO model contains all players on the court, with the label being 1 if the outcome is a turnover and 0 otherwise.

The xFG model predicts the probability of a shot being successful, regardless of whether it is a 2-point or 3-point shot. The objective of the model is to analyze the interaction between the shooter and defenders to determine the likelihood of the shot being successful. In Equation 2, it is the term $\mathbb{P}(O = o_+|A = \zeta, G_t)$. This model represents the game state as a graph, with the shooter and five defenders as nodes. The graph label is 1 if the shot is made and 0 if it is missed.

Initially, we built a separate model, xFGR, to predict the probability that a receiver would score a catch-and-shoot shot, given they received a pass. However, training a model exclusively with plays which ended in a catch-and-shoot heavily biased the model towards high scoring probabilities. To obtain more realistic results, the xFG model was used by using each potential receiver, instead of the player in possession, as a node in the input graph. In Equation 2, such probability of a receiver r_i scoring after a pass is given by $\mathbb{P}(O = o_+|A = \rho_{r_i}, G_t)$.

This modular approach allows for better calibration of task-specific models. It also allows for combining different models' predictions to create standalone metrics such as the ones explored in Section 6.2. Table 4.2 details the features of each model. Only frames where the team in possession is in the attacking half were included in the training and test sets.

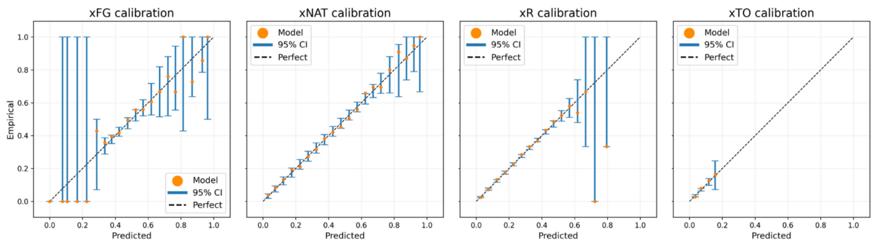

Fig. 3. Calibration plots for the four predictive models (xFG, xNAT, xR, xTO) used in the EIV framework. Each plot shows the relationship between predicted probabilities (x-axis) and empirical probabilities (y-axis) with 95% confidence intervals. The dashed line represents perfect calibration. Orange points indicate model predictions.

5 Model Validation

Since all models are binary classifiers whose training loss function was the Binary Cross Entropy (BCE), the same performance metrics can be used to compare each model, as shown in Table 5. Although all models performed better than a naive baseline that predicts the class distribution [3] (Normalized Bier Score (NBS) < 1), xNAT and xR were the most performant out of the four models.

In Figure 3, the calibration curve of all models is shown. The results indicate well-calibrated models, with predictions within the 95% confidence interval. Note that the confidence intervals are narrower for prediction ranges with more samples and are, therefore, more relevant. Also, note that prediction ranges without calibration points have no samples.

6 Applications

This section presents two possible applications of GraphEIV, in different granularities. First, by analyzing EIV on a single-play basis, then by aggregating metrics derived from the framework.[5]

[5] https://graph-epv-bc5247578fd6.herokuapp.com/

	xFG	**xNAT**	**xR**	**xTO**
BCE	0.58	0.51	0.60	0.67
ROC-AUC	0.75	0.78	0.73	0.65
Accuracy	0.68	0.78	0.67	0.58
F1-score	0.68	0.78	0.67	0.56
NBS	0.97	0.80	0.83	0.95

Table 2. Model performance metrics

6.1 Single-Play

EIV quantifies the shot and catch-and-shoot values of each moment in a possession, allowing us to analyze the probability and value of potential actions to determine if players are making valuable decisions on a per-play basis.

In Figure 4, we observe a sequence of frames where player #24 possesses the ball and dribbles toward the basket. In the first two frames (A and B), #24 is far from the three-point line, resulting in a low probability and value for a shot. The most probable action here is passing to the closest teammate, #17. Players on the defensive court have zero probability of receiving a pass, as it would be a violation. Consequently, the EIV starts to drop due to the low-value potential actions. As #24 dribbles closer to the three-point line in frames C to E, the probability of taking a shot increases, with the value of a potential shot increasing more rapidly. By Frame E, the shot value peaks at 1.10 as #24 is closest to the three-point line, making a three-point shot highly valuable. During this movement, the increase in shot value for both #24 and his potential receivers leads to a rise in EIV. As #24 moves into the two-point zone in Frame F, the EIV experiences a slight drop. This occurs because the value of #24's potential shot decreases, while his teammates' shot values increase as they approach the three-point line.

This approach enables a detailed examination of how well players optimize their actions to maximize scoring opportunities. By analyzing each decision in the context of its probability and value, the EIV framework helps identify whether players are making high-value choices that enhance the team's overall performance. This real-time evaluation of decision-making allows identifying strengths and areas for improvement in both individual and team strategies.

6.2 Aggregated Metrics

This section delves into the synthesis of individual model outputs to form comprehensive performance metrics, thereby providing a holistic view of a player's contribution over multiple possessions. These aggregated metrics are vital in bridging the gap between granular, moment-to-moment analysis and overarching strategic insights, enabling teams to make data-driven decisions that enhance overall performance and drive scouting strategies.

The first two metrics presented derive from the fact that the total EIV value is given by the sum of the expected value of a shot, $\mathbb{E}[S|A = \zeta, G_t]$, and the expected value of a pass, $\mathbb{E}[S|A = \rho, G_t]$. Therefore, it is possible to define Shot Value Above Expected as the difference between the points scored from a shot and the expected value of a shot, $P(l) \cdot \mathbf{1}_{\{O=o_+\}} - EIV_\zeta$. Another metric derivable from the EIV definition is Pass Value Wasted, given by the $\mathbb{E}[S|A = \rho, G_t]$ when the player in possession opts for a shot.

Comparing both metrics in Figure 5, it is possible to evaluate which players add more value with their shots than they waste by choosing to shoot. Stephen Curry, for example, is positioned well above the identity line, indicating that

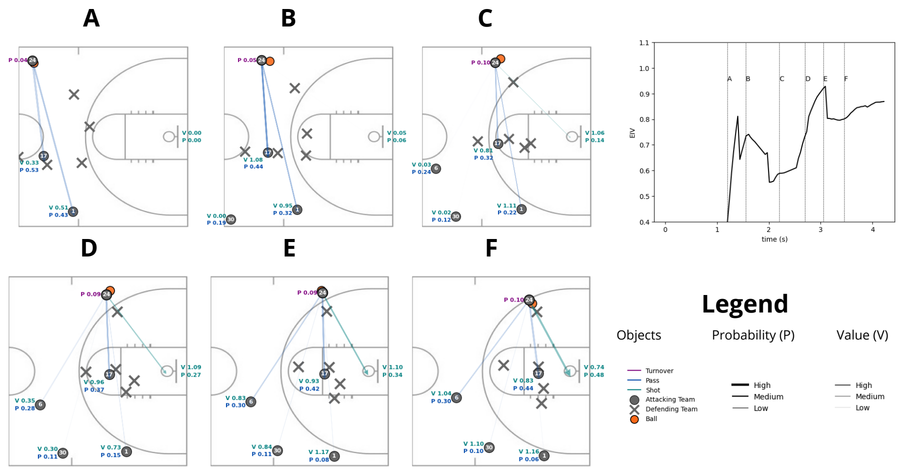

Fig. 4. Application of EIV in evaluating a single play. The sequence (A-F) shows some moments of a basketball possession with player positions, probabilities (P), and values (V). The EIV graph tracks the expected possession value over time, reflecting the impact of each action on the likelihood of scoring. The legend explains the symbols and color coding used for players and actions.

his average shot adds more value than expected, greatly compensating for the potential value of passes he forgoes.

Lastly, we present Dribbling Touch Value (DTV), given by $EIV_{t+\Delta t} - EIV_t$, the difference in EIV from the moment a player makes a shot/pass decision, at time $t + \Delta t$, and the EIV from the moment he first touched the ball, at time t. By aggregating DTV throughout the season, it is possible to determine which players bring the most value when dribbling and driving. Figure 6 shows players' contribution through dribbling touches. James Harden and LeBron James, known for their ball-driving skills, are highlighted on the upper right.

7 Challenges & Discussion

As aforementioned, the dataset presented several limitations. Primarily, the annotated event data did not align with the game and shot clocks of the tracking data, which required the development of rule-based algorithms. If the tracking data was synchronized, the need for rule-based algorithms would be eliminated, leading to more accurate models due to training with ground-truth target variables.

Additionally, the data lacked crucial information on dribbling and driving. Therefore, the decision was made to take only the immediate expected value of the current game state into account. As a consequence, the xNAT model

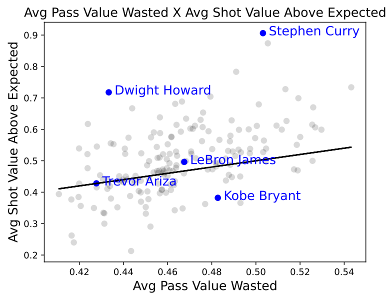

Fig. 5. Scatter plot of players' season average stats, depicting pass value wasted versus shot value above expected.

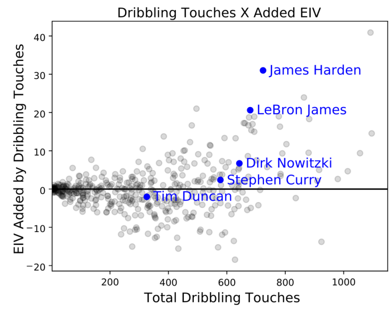

Fig. 6. Scatter plot of players' season aggregate stats, depicting total dribbling touches versus EIV added.

considers only shot and pass probability. However, dribbles were identified via rule-based algorithms and evaluated using variation in EIV (Figure 6). Reliable data on fouls was also missing, which prevented other types of turnovers from being considered as possible outcomes of a game state, such as offensive fouls or traveling turnovers, or to consider other possible possession outcomes, such as shooting fouls.

A point of discussion might be not including the shot technique as a feature of the xFG model. From a basketball standpoint, it seems obvious that the type of shot a player performs greatly influences their probability of success. For instance, a floater and a fadeaway from the same location inside the paint should have different average conversion rates. However, from a modeling perspective, it makes sense to represent the game state as the last moment before the decision of performing the action was made, not before the action was taken. This means that a game state whose outcome is a shot does not come right before the ball leaves the shooter's hand but the moment they start bringing the ball upwards from dribbling or receiving a pass. At that time, it is not possible to know precisely which technique a player will use, or even if they will shoot at all. So, the game state as a whole is evaluated before the action itself is taken.

The estimation of $\mathbb{E}[S|A = \rho, G_t]$, that is, the expected value of passing the ball in the current game state, is another interesting point of discussion and modeling decision we had to make. While estimating the long-term possession value of passing to each of the players could make more sense from a theoretical standpoint, in practice, we would have various scenarios where a pass does not have any impact on the possession outcome, meaning the current game state passed on as input would not be very representative of what contributed to scoring, its associated target. This, in turn, would cause training examples to be very noisy, that is, being uninformative regarding the expected value it would generate. Given all the noise already created by the required rule-based algorithms and not having data on dribbling and driving, we decided on an approach where the current game state would be sufficiently representative of the possible outcome.

We acknowledge that having a model that estimates the probability of a catch-and-shoot, that is, that a player receiving a pass would shoot without dribbling the ball, makes sense within the EIV framework. However, considering the probability of a shot attempt would also require considering the expected value of other possible actions, such as a pass. To do so, the EIV framework would need to be applied for every possible sequential outcome. This approach is both computationally unfeasible and would require too many assumptions regarding the game state in future actions. Therefore, it was determined to attribute value only to the immediate shot following the pass.

If the data limitations above are not an issue, the EIV framework can be easily extended to an EPV framework by considering more elaborate sets of possible actions and outcomes. In this case, Equation 1 would include the additional possible actions, and Equation 2 be extended with the additional possession outcomes.

Finally, even though EPV generates more metrics, EIV yields useful metrics by itself, such as points above expected, value of dribbling touches, and decision evaluation. The representation of frames as graphs in a GNN architecture is also an asset that brings new possibilities to action evaluation in sports. This approach is used here in the EIV framework but could also serve as the foundation for new EPV frameworks in the future.

8 Conclusion & Future Work

In this study, we introduced GraphEIV, a novel framework employing GNNs to estimate the EIV in basketball. Our modular approach not only enhances the interpretability of our metrics but also allows for a more granular analysis of player decisions and game dynamics, which can also be aggregated to evaluate teams and players over longer periods. The validation results indicate that our models are statistically relevant and well-calibrated, demonstrating their robustness and reliability.

In future works, with better-annotated data, the inclusion of fouls and rebounds would allow for the framework to be decomposed in a way that better represents possible outcomes of basketball possessions, thus, leading to EPV estimation. Also, utilizing a sequence of past frames up to the current one to represent the current game state, rather than only the current frame, could improve model performance given the appropriate GNN architecture.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

References

1. Alarcón Román, A.: Development of value metrics for specific basketball contexts: evaluating player contribution by means of regression. B.S. thesis, Universitat Politècnica de Catalunya (2022)
2. Cervone, D., D'Amour, A., Bornn, L., Goldsberry, K.: A multiresolution stochastic process model for predicting basketball possession outcomes. Journal of the American Statistical Association **111**(514), 585–599 (2016)
3. Decroos, T., Davis, J.: Interpretable prediction of goals in soccer. In: Proceedings of the AAAI-20 workshop on artificial intelligence in team sports (2019)
4. Fernández, J., Bornn, L., Cervone, D.: A framework for the fine-grained evaluation of the instantaneous expected value of soccer possessions. Machine Learning **110**(6), 1389–1427 (May 2021). https://doi.org/10.1007/s10994-021-05989-6, http://dx.doi.org/10.1007/s10994-021-05989-6
5. Lucey, P., Bialkowski, A., Carr, P., Yue, Y., Matthews, I.: How to get an open shot: Analyzing team movement in basketball using tracking data. In: Proceedings of the 8th annual MIT SLOAN sports analytics conference (2014)
6. Papalexakis, E., Pelechrinis, K.: thoops: A multi-aspect analytical framework for spatio-temporal basketball data. In: Proceedings of the 27th ACM International Conference on Information and Knowledge Management. pp. 2223–2232 (2018)
7. Sahasrabudhe, A., Bekkers, J.: A graph neural network deep-dive into successful counterattacks. In: Proceedings of the 17th annual MIT SLOAN sports analytics conference (2023)
8. Sicilia, A., Pelechrinis, K., Goldsberry, K.: Deephoops: Evaluating micro-actions in basketball using deep feature representations of spatio-temporal data. In: Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining. pp. 2096–2104 (2019)
9. Stöckl, M., Seidl, T., Marley, D., Power, P.: Making offensive play predictable-using a graph convolutional network to understand defensive performance in soccer. In: Proceedings of the 15th MIT sloan sports analytics conference (2021)
10. Wang, Z., Veličković, P., Hennes, D., Tomašev, N., Prince, L., Kaisers, M., Bachrach, Y., Elie, R., Wenliang, L.K., Piccinini, F., et al.: Tacticai: an ai assistant for football tactics. Nature communications **15**(1), 1906 (2024)