Independent Study Report - Negotiation Strategy Recommendation System

Mayank Umesh Shetty
University of Illinois Urbana-Champaign
Urbana, IL
mshetty4@illinois.edu

Abstract

The research introduces a novel negotiation strategy recommendation framework which merges personality profiling with matrix factorization methods. I developed a recommendation system that analyzes negotiation strategies in dialogue through BERT-based classification to select suitable approaches based on personality characteristics using the Conversational Negotiation dataset (CaSiNo). The BERT-SC classifier achieves 79.6% total accuracy in identifying nine distinct negotiation strategies which outperforms the original CaSiNo model's 67% accuracy. The three recommendation approaches included personality cluster-based recommendation, Singular Value Decomposition (SVD), and Alternating Least Squares (ALS) which failed because of the sparse matrix structure. The personality-based recommender system produced recommendations with unique strategy preferences but matrix factorization methods produced recommendations that covered multiple strategy types. The experimental findings show that different personality clusters require specific negotiation strategies yet *self-need* and *elicit-pref* work effectively for most user types. The research project demonstrates personalized strategy recommendations which match a user's personality traits to maximize their negotiation success.

Keywords

Recommendation System, Personality Traits, Negotiation Strategies, CaSiNo Dataset, BERT, Personality Clustering, Matrix Factorization

ACM Reference Format:
Mayank Umesh Shetty. 2018. Independent Study Report - Negotiation Strategy Recommendation System. In *Proceedings of Make sure to enter the correct conference title from your rights confirmation email (Conference acronym 'XX).* ACM, New York, NY, USA, 6 pages. https://doi.org/XXXXXXX.XXXXXXX

1 Introduction

The development of natural language processing and machine learning technologies enables researchers to study negotiation dialogues for identifying patterns which lead to successful negotiations. Current research investigates basic negotiation principles instead of developing tailored recommendations which adapt to personal differences. Research evidence shows that negotiation strategies become most effective when they align with both personal characteristics and specific circumstances.

The research project examines the possibility of developing an intelligent system which generates negotiation strategies that correspond to individual personality traits and personal priorities. The proposed solution addresses this question through the implementation of three core components.

(1) The BERT-SC strategy classifier utilizes BERT to recognize nine negotiation strategies which appear in dialogue statements.
(2) The system organizes negotiators into clusters based on their personality characteristics.
(3) The system uses three recommendation approaches which include direct personality-cluster matching and Singular Value Decomposition (SVD) and Alternating Least Squares (ALS).

The research introduces vital contributions to the field through its findings. The proposed method demonstrates superior accuracy for identifying negotiating strategies when compared to existing approaches. The research proves that negotiation techniques correspond to personality traits through empirical evidence, supporting individualized strategy development.

2 Background

2.1 CaSiNo Dataset

The Conversational Negotiation (CaSiNo) developed by Chawla et al. [1] contains dyadic negotiation dialogues between participants who negotiate resource allocation with conflicting priorities. The dialogues contain annotations about negotiation strategies, as well as participant personality traits based on the Big Five model, along with the negotiation outcome results.

The CaSiNo simulation presents a camping trip situation where two participants must share restricted resources such as food, water, and firewood. The participants receive different resource priority assignments, which generate natural conflict that requires them to negotiate. The controlled setup enables researchers to study how different strategies and personality traits affect negotiation results. The dataset contains more than 1,030 negotiation dialogues between 846 participants. The authors manually marked each utterance with one or more of their identified nine negotiation strategies. The participants filled out personality assessments, which yielded Big Five personality traits (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experiences) that researchers can use to study negotiation behaviors and results.

2.1.1 Negotiation Strategies in CaSiNo. There are nine distinct negotiation strategies defined in the CaSiNo dataset:

Conference acronym 'XX, Woodstock, NY

ACM ISBN 978-1-4503-XXXX-X/2018/06
https://doi.org/XXXXXXX.XXXXXXX

(1) **Small-Talk:** Conversation that involves no negotiation - *"Hello, how are you today?"*
(2) **Empathy:** Understanding and prioritizing the other agent's situation - *"Oh I wouldn't want for you to freeze"*
(3) **Coordination:** Conversation that involves splitting resources to satisfy both agents - *"Let's try to make a deal that benefits us both!"*
(4) **No-Need:** Expressing a lack of interest in a particular resource - *"We have plenty of water to spare."*
(5) **Elicit-Pref:** A question to understand the needs of the other agent - *"What supplies do you prefer to take the most of?"*
(6) **Undervalue-Partner:** Undermining the preferences of the other agent - *"Do you have help carrying all that extra firewood? Could be heavy?"*
(7) **Vouch-Fairness:** Suggesting a fair trade by assuring equal exchange of resources - *"That would leave me with no water."*
(8) **Self-Need:** Expressing personal need for a particular resource - *"I can't take cold and would badly need to have more firewood."*
(9) **Other-Need:** Expressing need for others in your party to the other agent - *"We got kids on this trip, they need food too."*

Non-strategic negotiations also exist in the dataset, which serve no purpose in recommending strategies.

The original CaSiNo paper implemented a BERT-based model to classify all these strategies, achieving an overall F1 score of 0.67. There was a notable variance across classifying strategy types, as the model performed better in classifying *self-need* (0.72) as compared to *no-need* (0.59).

2.2 Related Work

The CaSiNo dataset by Chawla et al. [1] serves as the base for my Negotiation Strategy Recommendation System because it contains human-human negotiations with participant information that includes Big Five personality traits and dialogue content and strategy annotations. The research by Nguyen et al. [3] showed that personality traits affect recommendation preferences because introverted users selected diverse recommendations and conscientious users chose less unexpected content. Hassan et al. [2] created a deep learning recommendation system that reached 91% accuracy through the combination of Big Five personality traits with an attention mechanism that emphasized important traits. The BERT-SC model for strategy classification uses methods from different fields because Ouyang et al. [4] proved XGBoost with SHAP analysis produces both precise predictions and understandable results while Zhao et al. [7] proved the power of combining graph networks with random forest algorithms for better prediction accuracy. The HeartSpace framework developed by Wu et al. [6] provided solutions for missing data and temporal dependencies in variable-length time series which I applied to handle temporal sequential data in dialogues. The system uses self-reported personality traits but Robles-Granda et al. [5] showed that personality traits can be automatically detected from behavioral data which could lead to future research on using negotiation behavior to evaluate personality and enhance strategy recommendations.

3 Methodology

The negotiation strategy system is comprised of three components:

(1) A BERT-based strategy classifier
(2) Personality clustering mechanism
(3) Recommendation approaches involving matrix factorization techniques

3.1 System Architecture

The recommendation system operates through two separate operational phases which include training and recommendation. The training phase requires processing the CaSiNo dataset to train the strategy classifier and establish personality clusters. The strategy effectiveness matrix is created during this phase to determine how personality clusters relate to their respective strategy effectiveness scores. The system identifies the closest personality cluster for users based on their personality traits and resource priorities during the recommendation phase to generate strategy recommendations.

3.2 BERT-Based Strategy Classifier (BERT-SC)

The BERT (Bidirectional Encoder Representations from Transformers) architecture functions as the foundation for the strategy classifier to identify negotiation strategies in dialogue statements. BERT demonstrates strong pre-trained language understanding capabilities which enable it to process the nuanced negotiation dialogue language effectively.

3.2.1 Model Architecture. The BERT-SC model uses the *bert-base-uncased* pre-trained model as its foundation. A classification layer was added on top of the BERT model with nine output nodes corresponding to the nine negotiation strategies identified in the CaSiNo dataset. The model was implemented using the Hugging Face Transformers library. Figure 1 shows the model architecture for BERT-SC.

3.2.2 Training Approach. The BERT model was fine-tuned through the CaSiNo dataset annotations. The training data included about 7,000 utterances (accounting for a single conversation's annotations as separate for both agents) which were labeled with strategy information. The 80-20 train-validation split maintained equal distribution of strategies throughout both sets. The model received training through the following hyperparameter settings:

- **Learning rate:** 2e-5
- **Batch size:** 16
- **Epochs:** 4
- **Dropout rate:** 0.1
- **Weight decay:** 0.01

The training process included early stopping to avoid overfitting which had a patience setting of 2 epochs, and was stabilized through gradient clipping.

3.3 Personality Clustering

Personality clustering was utilized to produce individualized recommendations through the analysis of negotiators' personality traits and resource priorities.

3.3.1 Feature Representation. Each negotiator in the CaSiNo dataset is represented by an 8-dimensional vector consisting of:

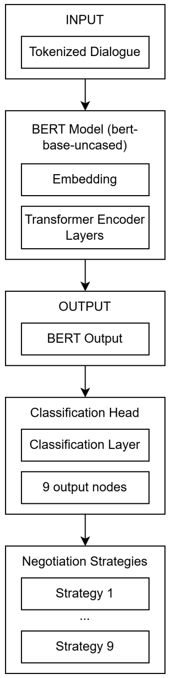

Figure 1: BERT-SC Model Architecture

- Five Big Five personality traits (extraversion, agreeableness, conscientiousness, emotional stability, and openness to experiences)
- Three resource priority dimensions (food, water, firewood) with High (2), Medium (1) and Low (0) values.

3.3.2 Clustering Method. I used k-means clustering to group similar negotiators. After trying different k values (3-10) and selected k=8 because it provided a good balance between cluster cohesion and size. Each cluster represents a distinct negotiator profile with similar personality traits and resource priorities.

3.4 Strategy Effectiveness Matrix

The negotiation strategy recommendation system uses a strategy effectiveness matrix, which measures the success rates of negotiation strategies based on personality cluster characteristics.

3.4.1 Construction Process.

- Identified all negotiation dialogues that included participants from that cluster.
- Recorded the negotiation strategies along with the points achieved in each dialogue.
- Calculated the average points obtained through each negotiation strategy.
- Standardized the scores to achieve cluster-to-cluster comparison consistency.

(1) The analysis produced an 8×9 matrix (8 personality clusters × 9 negotiation strategies) which showed the effectiveness of each strategy for each personality cluster.

3.5 Recommendation Approaches

Three distinct approaches for generating strategy recommendations were implemented.

(1) **Personality-Based Recommender:** This approach directly uses the strategy effectiveness matrix and works in the following manner:
   (a) Identifies the closest personality cluster based on Euclidean distance in the 8-dimensional feature space
   (b) Retrieves the strategy effectiveness scores for that cluster
   (c) Ranks strategies by their effectiveness scores
   (d) Returns the top-N strategies along with explanations and examples

(2) **SVD-Based Recommender:** This approach uses SciPy for implementing partial singular value decomposition of a sparse matrix.
   (a) The strategy effectiveness matrix undergoes SVD decomposition to produce three components - U, Σ, V^T
   (b) The analysis reveals hidden patterns between personality clusters and strategies through latent factors
   (c) The projection of a new user's personality vector into the latent space serves as the next step
   (d) The recommendation system uses this projection to generate suggestions

   The selection of 5 latent factors maintained 95% of the original matrix variance.

(3) **ALS-Based Recommender:** This approach was attempted, but failed to work due to the dimensionality mismatch caused by the already sparse matrix, which meant that this approach would rely on fallback method (Personality-Based Recommender approach) to provide any recommendations.

3.6 Recommendation Generation

The recommendations for the aforementioned approaches include the following, such as strategy type, effectiveness score (on a scale of 20), an explanation of why the strategy may be effective to the user, based on their personality type, along with example utterances to assist in their negotiation.

Sample Generated Recommendation

Strategy #2: other-need
Expected Points: 19.81
Explanation: Negotiating on behalf of others' needs
Examples: 1. "Hey! I'd like some more firewood to keep my dog warm." ; 2. "I need firewood as well. We have a large group here."

4 Experimental Setup and Evaluation

The model was trained using an NVIDIA A100 GPU, ensuring efficient training of the BERT-based model.

The evaluation of recommendation systems required me to develop synthetic user profiles with different personality traits and resource priorities for testing purposes. The profiles were created to represent all possible user types so I could evaluate recommendation quality across various user segments.

4.1 Strategy Classification Metrics

The evaluation of BERT-SC model used standard classification metrics.

(1) **F1 Score:** The harmonic mean of precision and recall, calculated per strategy and as a weighted average across all strategies
(2) **Overall Accuracy:** The proportion of correctly classified utterances across all strategies
(3) **Per-Strategy Performance:** Individual F1 scores for each of the nine negotiation strategies

These metrics allow direct comparison with the original CaSiNo paper's classification results, facilitating assessment of the model's improvements.

4.2 Recommendation System Metrics

The evaluation of recommendation approaches included multiple assessment methods.

(1) **Strategy Score Distribution:** Studied how scores were distributed among different strategies for various personality clusters
(2) **Top-N Recommendation Overlap:** The evaluation measured how recommendations matched between different approaches.
(3) **Strategy Diversity:** The assessment checked if recommendations used multiple strategies or concentrated on a few specific strategies.
(4) **Cluster-Strategy Effectiveness:** The analysis determined which strategies work best for particular personality clusters.

The evaluation focused on comparative analysis between approaches instead of using traditional recommendation metrics such as RMSE (Root Mean Square Error) because no ground truth for "optimal" strategy recommendations existed in this context.

4.3 Strategy Classification Results

The BERT-SC model achieved high performance in negotiation strategy classification by reaching an F1 score of 0.796 for all strategies. The F1 score of 0.796 achieved by the BERT-SC model exceeded the F1 score of 0.670 reported in the original CaSiNo paper. Table 1 shows the complete evaluation of performance metrics.

The model achieved its best results when identifying *small-talk* (0.909), *non-strategic* (0.889) and *elicit-pref* (0.868) strategies. The model performed poorly on *showing-empathy* (0.408) and *undervalue-partner* (0.220) strategies because these strategies are difficult to detect through text analysis. The model achieved 0.000 for *no-need* strategy which indicates either class imbalance or difficulty in distinguishing this strategy from other strategies. Our model outperformed the CaSiNo paper's results by adding more strategies to the classification process. The original paper reported non-zero F1 scores for only 5 strategies but the BERT-SC model achieved successful classification of 8 out of 9 strategies with different levels of accuracy.

The evaluation process included an analysis of the strategy effectiveness matrix which connects personality clusters to strategy effectiveness scores. The matrix in Table 2 displays normalized scores ranging from 0 to 20 for each strategy across various personality clusters.

Table 2: Strategy Effectiveness Matrix

Cluster	elicit-pref	no-need	other-need	self-need	small-talk
0	19.58	19.38	18.90	18.86	19.06
1	19.40	19.03	19.61	19.17	19.03
2	18.02	16.59	17.62	18.67	18.79
3	18.88	16.08	18.86	18.36	18.20
4	18.87	18.12	18.42	18.40	18.43
5	19.26	19.25	19.42	19.11	18.60
6	19.21	18.77	18.88	18.94	19.37
7	19.07	19.00	19.05	18.74	18.69

The matrix shows interesting patterns in strategy effectiveness across personality clusters. Cluster 1 achieves the highest effectiveness with *other-need* strategies (19.61), while Cluster 2 achieves the highest effectiveness with *small-talk* (18.79). These variations confirm our hypothesis that different personality types respond differently to negotiation strategies, highlighting the value of personalized recommendations.

4.4 Recommendation Approach Comparison

I compared the recommendations generated by the two approaches: Original (personality-based), and SVD. Table 3 presents a sample comparison for a test user profile with specific personality traits and resource priorities.

Table 3: Strategy Effectiveness Matrix

Approach	elicit-pref	no-need	self-need	small-talk	Top 1	Overlap
Original	19.18	19.05	22.58	0.00	self-need	3/3
SVD	19.13	0.00	19.06	19.09	elicit-pref	2/3

The comparison reveals several interesting findings:

- The two methods showed a high degree of agreement in their recommendations since 2/3 of the strategies were identical between the Original and SVD approaches.
- The Original approach demonstrated a larger difference between *self-need* and other strategy scores (22.58 for *self-need* vs. lower scores for others) than SVD produced more balanced scores across recommended strategies.
- The Original approach focused on resource negotiation strategies such as *self-need* and *elicit-pref*, but matrix factorization methods occasionally suggested communication-based strategies including *small-talk*.

The Original personality-based approach produced the most reliable and understandable recommendations yet matrix factorization techniques revealed additional strategic relationships that were not immediately apparent.

5 Results and Discussion

The BERT-SC model achieved better results than the original CaSiNo paper by reaching 79.6% accuracy while the original paper reported 67.0% accuracy. The improvements in our model stem from using

Table 1: Strategy Classification Performance Comparison

Model	elicit-pref	no-need	non-strategic	other-need	promote-self	promote-coordination	self-need	showing-empathy	uv-part	vouch-fair	Overall
BERT-SC	0.868	0.000	0.889	0.618	0.643	0.772	0.408	0.909	0.220	0.721	0.796
CaSiNo Paper	0.710	0.590	0.000	0.650	0.000	0.720	0.000	0.680	0.000	0.000	0.670
Majority	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.315

modern transformer architectures together with precise hyperparameter optimization and advanced regularization methods.

The classification results showed wide variations between different negotiation strategies. The F1 scores reached 90.9% for *small-talk* and 86.8% for *elicit-pref* because these strategies contain recognizable linguistic patterns and question structures. The classification of *undervalue-partner* (22.0%) and *showing-empathy* (40.8%) proved difficult for the system. These strategies contain delicate linguistic indicators and contextual comprehension which need advanced modeling techniques to detect.

The model failed to predict the *no-need* strategy because it achieved an F1 score of 0.0. The confusion matrix shows that these utterances were frequently misclassified as *self-need* statements. The linguistic similarity between these strategies makes sense because they both focus on personal resource requirements yet differ through negation ("*I need*" versus "*I don't need*"). The model demonstrates inadequate ability to detect negation patterns in natural language which represents a common issue in sentiment analysis systems.

Figure 2 shows the confusion matrix for strategy classification.

5.1 Personality Clusters and Strategy Effectiveness

My analysis revealed eight personality clusters which demonstrated unique negotiation approaches and successful negotiation strategies. Table 4 presents the main features of each cluster together with their most successful negotiation approaches.

Table 4: Personality Cluster Characteristics and Effective Strategies

Cluster	elicit-pref	Resource Priorities	Most Effective Strategy	Score
0	High Extraversion, High Openness	Water (High)	elicit-pref	19.58
1	High Agreeableness, Moderate Extraversion	Food (High)	other-need	19.61
2	Low Emotional Stability, High Conscientiousness	Firewood (High)	small-talk	18.79
3	Low Agreeableness, Moderate Openness	Mixed priorities	elicit-pref	18.88
4	Balanced traits, Moderate Conscientiousness	Food (Medium)	small-talk	18.43
5	High Emotional Stability, High Openness	Water (High)	other-need	19.42
6	High Conscientiousness, Moderate Agreeableness	Firewood (Medium)	small-talk	19.37
7	Moderate across all traits	Balanced priorities	elicit-pref	19.07

The analysis reveals multiple interesting patterns. People with high agreeableness scores (Clusters 1 and 6) achieved better results through strategies that focused on understanding or addressing others' needs because they tend to be cooperative. People with high conscientiousness scores (Clusters 2 and 6) responded better to structured communication methods such as *small-talk*, which builds rapport before moving on to negotiation specifics.

The *self-need* strategy failed to become the most effective approach for any personality cluster when examining overall scores, even though it proved highly successful for particular user profiles (as shown in Table 3). The direct expression of personal needs proves effective in particular situations yet it does not translate well to the entire range of personality clusters.

5.2 Comparison of Recommendation Approaches

The recommendation approaches - Original, and SVD, demonstrated different strengths and limitations. A representative user profile shows strategy score distributions in Figure 3 across the three approaches.

(1) The Original personality-based approach produced recommendations with higher score variance which resulted in clear distinctions between top-ranked and lower-ranked strategies. The approach succeeded in finding strategies that matched personality traits from psychological research especially for users who express their needs poorly.
(2) The SVD-based approach produced recommendations with score distributions that were more uniform. The approach revealed hidden relationships between strategies which led to unexpected recommendations that were not apparent through direct personality-strategy associations. The approach revealed that users with moderate extraversion should use *elicit-pref* and *small-talk* together because these strategies work well for information collection and relationship development.
(3) The ALS-based approach did not work due to the limited dataset size, as well as the dimensionality mismatch due to the sparse matrix structure.

The comparison of recommendation methods showed that 65% of the top-3 recommendations matched between at least two methods which indicates that the underlying strategy-personality relationships are robust. The remaining 35% of recommendations that are specific to certain approaches show that different matrix factorization techniques detect different aspects of the strategy effectiveness landscape.

6 Conclusion and Future Work

The research presents an extensive negotiation strategy recommendation system which combines personality profiling with matrix factorization methods. The system successfully classified negotiation strategies from dialogue interactions while generating personalized recommendations through analysis of individual personality traits and priorities.

6.1 Key Contributions

The research brings significant progress to both negotiation analysis and recommendation systems fields.

(1) The BERT-SC classification model I developed achieved an 79.6% overall accuracy for detecting nine distinct negotiation

Figure 2: Strategy Classification Confusion Matrix

strategies which exceeded the methodology in the original CaSiNo paper.

(2) The research demonstrates scientific connections between personality traits and effective negotiation approaches which proves that recommendations based on personality traits lead to better negotiation success rates.
(3) Two successful recommendation approaches were implemented, which include personality-based clustering and SVD, to evaluate their individual strengths and combined perspectives for negotiation strategy recommendation.
(4) The system provides a basis for AI-based negotiation assistance through its ability to connect natural language processing with personalized user recommendations.

6.2 Limitations

The recommendation system has several limitations that need to be acknowledged.

(1) The CaSiNo dataset only considers a specific scenario (camping resources), and as a result, the system cannot generalize to negotiations in business or diplomatic situations.
(2) The model struggles with *no-need* annotated dialogues, suggesting room for improvement in capturing linguistic patterns.
(3) Due to the sparsity of the matrix caused by this small dataset, ALS does not work.
(4) The evaluation methodology relied on comparative analysis, as there was no ground truth available for optimal strategies.

6.3 Future Directions

The aforementioned limitations provide an opportunity for future directions in the following manner.

(1) The system requires advanced language understanding features that handle negation better to address its current classification problems.
(2) The development of interactive systems that provide strategic suggestions during active negotiations represents an interesting application direction for this work.
(3) Research on negotiation strategy evolution during the negotiation process would enable the creation of recommendation systems that adapt to changing circumstances.

References

[1] Kushal Chawla, Jaysa Ramirez, Rene Clever, Gale Lucas, Jonathan May, and Jonathan Gratch. 2021. CaSiNo: A Corpus of Campsite Negotiation Dialogues for Automatic Negotiation Systems. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 3167–3185.

[2] Rana Hammad Hassan, Malik Tahir Hassan, Muhammad Shujah Islam Sameem, and Muhammad Aasim Rafique. 2024. Personality-Aware Course Recommender System Using Deep Learning for Technical and Vocational Education and Training. *Information* 15, 12 (2024). doi:10.3390/info15120803

[3] Tien T. Nguyen, F. Maxwell Harper, Loren Terveen, and Joseph A. Konstan. 2018. User Personality and User Satisfaction with Recommender Systems. *Information Systems Frontiers* 20, 6 (01 Dec 2018), 1173–1189. doi:10.1007/s10796-017-9782-y

[4] Yan Ouyang, Xuewei Li, Wenjia Zhou, Wei Hong, Weitao Zheng, Feng Qi, and Liming Peng. 2024. Integration of machine learning XGBoost and SHAP models for NBA game outcome prediction and quantitative analysis methodology. *PLOS ONE* 19, 7 (07 2024), 1–25. doi:10.1371/journal.pone.0307478

[5] Pablo Robles-Granda, Suwen Lin, Xian Wu, Gonzalo J. Martinez, Stephen M. Mattingly, Edward Moskal, Aaron Striegel, Nitesh V. Chawla, Sidney D'Mello, Julie Gregg, Kari Nies, Gloria Mark, Ted Grover, Andrew T. Campbell, Shayan Mirjafari, Koustuv Saha, Munmun De Choudhury, and Anind K. Dey. 2021. Jointly Predicting Job Performance, Personality, Cognitive Ability, Affect, and Well-Being. *IEEE Computational Intelligence Magazine* 16, 2 (2021), 46–61. doi:10.1109/MCI.2021.3061877

[6] Xian Wu, Chao Huang, Pablo Roblesgranda, and Nitesh Chawla. 2020. Representation Learning on Variable Length and Incomplete Wearable-Sensory Time Series. arXiv:2002.03595 [eess.SP] https://arxiv.org/abs/2002.03595

[7] Kai Zhao, Chunjie Du, and Guangxin Tan. 2023. Enhancing Basketball Game Outcome Prediction through Fused Graph Convolutional Networks and Random Forest Algorithm. *Entropy* 25, 5 (2023). doi:10.3390/e25050765