**Analyzing the efficiency of Large Language Model AIs for NBA Money Line Sports Betting**

**Abstract**

Artificial intelligence (AI) is technology that enables computers and machines to simulate human learning and decision-making [3]. A specific subset of models is Large Language Models, which attempt to mimic human language and understand it. These Large Language Models are very simple to use and thus should be explored for a multitude of tasks. An interesting concept is utilizing these models to try to make predictions. Specifically revolving around sports. Sports betting has become a huge market for the world, having a market size of $200 billion throughout the world [1]. If Large Language Models were effective, it could aid people in making significant amounts of money. This study delves into this idea, analyzing which of 3 LLM are most effective for NBA Moneyline (predicting the winner) sports betting, testing Microsoft Copilot, Gemini Flash 2.0, and Meta AI. Each of the AIs were given the same prompts, and varying amounts of information and guidelines. The study resulted in Meta AI with no extra data given being the most profitable, and Meta overall was the best choice for NBA Moneyline betting, consistently beating the bookkeeper.

**Introduction**

*Background:* Sports betting is defined as placing a monetary wager on one or multiple sporting events [1]. A bettor may choose to bet on the outcome of a game or may try to predict a player’s performance. This type of betting has become extremely appealing, as it is described by many to be both a science and an art [2]. The recency of sports betting has led to many different approaches. There is a phenomenon with sports betting that is not seen with many other types of gambling. People tend to believe that they can “beat the system” often, as there are many more factors involved in sports that are very difficult for the average person to predict, so a knowledgeable sports viewer may have a chance to profit.

Artificial intelligence (AI) is technology that enables computers and machines to simulate human learning and decision-making [3]. AI has the ability to work with incredibly complex problems that are difficult for people to conceptualize on their own. It has been used countless times to predict things such as human behavior or the next possible actions of a user. AIs can be created and designed for many purposes. One of the many types of AIs that has been developed is called a Large Language Model. These models are very complex in nature, but their purpose is to attempt to understand human language and be able to respond in the human language. These AIs are specifically built for conversation and prediction.

*Significance:* Sports betting has become a huge market for the world, having a market size of $200 billion throughout the world [1]. Predicting the outcome of sporting events has traditionally been seen as a difficult task, due to the complex relationships between variables of interest. Attempts to make accurate predictions are fraught with biases owing to the bounded rationality within which human decision-making functions [2]. AI, with its unparalleled ability to analyze vast datasets and discern patterns beyond human capability, is emerging within the field of sports betting [4]. Powered by AI, people are beginning to make breakthroughs to make sports betting profitable. With how large the market is for sports betting, any sort of edge that a bettor can have over the system can quickly become incredibly lucrative and change their life. This effect would be compounded if the edge that can be achieved is accessible and easy to understand. The objective of this research project is to see which of 3 chosen large language model AIs can best be utilized to boost profit and/or accuracy of bets. The 3 models that were used for this study are Microsoft Copilot, which is built using GPT-4, Gemini 2.0 Flash, and Meta AI, which utilizes Llama 3. These models have all been built to handle a broad variety of tasks and seamlessly conversate with the user, so they will be interesting additions to the study.

*Related Work:* Looking at the related work for this project, some previous experiments can be found and analyzed. One experiment conducted by Ondřej Hubáček , Gustav Šourek, Filip Železný and others [5] utilized a three part model to try to create a model that could consistently beat the book keepers and make profit. The model was successful, especially when it was uncorrelated with the bookkeepers themselves, generating profit in every model tested where this was the case. This experiment, however, was only run on NBA games, so it may not be as successful in other sports. Another experiment done by Louis Rosenberg and Gregg Willcox [6] tested if systems modeled after swarms of creatures like bees could be effective to predict sports matches. These models are called Artificial Swarm Intelligence models. Looking at 200 NHL games, Vegas bookkeepers were correct 62% of the time and had a 41% loss of profit, while the ASI model was correct 85% of the time, and had a 170% gain in profit. 200 games, however, is a very small sample size for data of this caliber, and questions may arise if this success is applicable to all sports or just the outcome of NHL games. Another experiment done by Arnu Pretorius and Douglas A. Perry [2] tested to see if a machine learning model could perform 2 large groups of experts trying to predict 2015 World Cup games. These results were less conclusive than the previous two experiments mentioned above, concluding that there wasn’t enough data to show that the machine model was more accurate, but it was at least on par with the 2 groups of experts, and generated slightly more profits when that was accounted for. More research is needed to verify and build off these results.

*Summary of study:* In this paper, 3 separate AI LLM will be analyzed according to accuracy and profitability. Each AI will be given the same prompts as the others, and each AI will have 3 separate data sets: prediction with no extra info or guidelines, prediction with extra info, and prediction with upsets involved. The results will be displayed in a series of bar graphs, compared to each other, and analyzed. Utilizing this data, a conclusion will be presented on which is the most effective for NBA Moneyline sports betting.

**Materials and Methods:**

The 3 models that were used for this study are Microsoft Copilot, which is built using GPT-4, Gemini 2.0 Flash, and Meta AI, which utilizes Llama 3. Each AI was given 3 separate series of prompts every day, each of which was recorded in a document on GitHub which can be accessed here: <https://github.com/KonnorBoucher/Senior_Research_Project/tree/main>. Each set of prompts led to three predictions for each AI, with 9 different predictions total across all 3 AIs for each game. The first series of prompts asked the model which team will win, team 1 or team 2. The second series of prompts were based off the previous prompts and asked what the most likely upsets are. If more than 4 games were played for the day, 2 upsets were chosen. Otherwise, only 1 was chosen. The third series of prompts required a new instance of each AI to be created, and each AI would subsequently be asked which team was going to win, team 1 or team 2, but the result of the most recent matchup would be given (ex. “Predict who will win [team 1] at [team 2] tonight, [team 2] won 89 to 76 during their last meeting on [date]”) The results for the predictions were placed into a .csv file, which can be accessed on GitHub here: https://github.com/KonnorBoucher/Senior\_Research\_Project/tree/main

Using this data, accuracy was calculated by comparing the prediction of the game to its outcome. To calculate profits for each prediction set, it was assumed that each prediction would be associated with a bet of $5. DraftKings betting odds were used to calculate the profits for each. These odds can be gathered here: <https://sportsbook.draftkings.com/leagues/basketball/nba?msockid=146c6d591a7f646005c9799d1b3065e2>. Each set of predictions, along with the associated betting odds were gathered on the day of the games before they were played, and the outcomes of each game were gathered the next day.

To calculate profits and organize data, a python program was created. The program used the following procedure: if the odds of the team that won were negative, the following formula was used: Bet placed + (bet placed / (odds / -100)). If the odds were instead positive in the case of an upset, the following formula was used: Bet placed + (bet placed \* (odds / 100)). Each prediction, as mentioned in the materials and methods section previously, is accompanied by a $5 bet. The program can be found here: <https://github.com/KonnorBoucher/Senior_Research_Project/tree/main>

**Results**

A total of 115 NBA games were predicted from a period from 3/30/25 to 4/13/25. Each AI had 3 sets of predictions, with a total of 9 prediction sets, and 1035 separate predictions. Using these predictions, we calculated the accuracy of each prediction set and found that Meta, with no extra data or guidelines, was by far the most accurate, beating the bookkeeper by a wide margin. Copilot with no data or guidelines was the least accurate model, being very inaccurate. (**Fig 1).**

A bar graph with blue bars

AI-generated content may be incorrect.**Figure 1: Accuracy of each prediction set.** Graph shows percentages based on 115 NBA games spanning March 30 – April 13 (see **Methods** for details).

We also found that Meta was the most accurate when averaging the accuracy across all 3 input types for each AI, followed by Gemini, and Copilot. This clearly highlights Copilot as the worst option out of the three, while Gemini and Meta are both similar when only taking accuracy into account. (**Fig 2**).

A graph with blue bars

AI-generated content may be incorrect. **Figure 2: Accuracy for each AI Model:** Graph shows accuracy percentages for each LLM across all input types.

In addition, the average accuracies of each input type across all 3 models were analyzed, and the results show that across all 3 models, the models with info given on the last matchup were most accurate, followed by models with nothing given, followed by models that accompanied upsets (**Fig 3**). Upset inclusive models are inherently less accurate than ones that just pick the most likely winner, so this is to be expected. While this data seems significant at first glance, when context is taken, this data is skewed by copilot’s ineffectiveness.

A graph with purple bars

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**Figure 3: Accuracy Across each Input Type:** Graph shows accuracy percentages for each input type across all models.

When looking at the profits of each model, we found that Meta with no extra data or parameters, performed better than any other prediction model, accruing $67 in profit. Prediction models using copilot performed consistently worse than Gemini or Meta models. (**Fig 4)**.

A graph with red and green bars

AI-generated content may be incorrect.**Figure 4: Profits for each model.** Graph shows the profits of each model in a bar graph. These profits are compared to the bookkeeper’s profits.

Looking at the average profits for models across the 3 input types, Meta is the most profitable LLM, followed by Gemini the Copilot (**Fig 5**). Copilot once again is not a viable option for sports betting as it had a $60 loss across the testing period.

A graph with red and green squares

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**Figure 5: Profits for each model across all 3 Input Types:** Graph shows the average profit for each model across all 3 input types.

Lastly, profits across all input types were analyzed, where it is shown that giving data is the most profitable, followed by incorporating upsets, followed by models with nothing extra given or needed. (**Fig 6**). While this data seems significant at first glance, when context is taken, this data is skewed by copilot’s ineffectiveness.

A graph of green and red rectangles

AI-generated content may be incorrect.**Figure 6: Comparing profits for each prompt type** Graph shows the average profit of each prompt type, showcasing which was most effective.

**Discussion**

These results clearly show that there is some value in utilizing Large Language Models for prediction, as two out of the three AIs chosen were seen to be consistently able to create profit across 115 games. These results are incredibly interesting, as LLMs were not designed to predict at all, only to conversate and understand language. Why each of these models is more successful than others is a mystery without explicitly knowing the inner workings of these models, but with this evidence it’s clear that AIs can be utilized to create profit. A previous experiment, conducted by Ondřej Hubáček , Gustav Šourek, Filip Železný and others [5], found that models using machine learning could be profitable when predicting NBA games. This model was explicitly created to make predictions and bets, and while it is more successful than the LLMs chosen, the fact that both are profitable in theory is incredibly interesting.

The results from this study will hopefully be incredibly useful for helping not only new sports bettors make profits but will help experienced sports bettors make more informed decisions as well. With the recent rise of AI, it previously would have been difficult to know which AI is most trustworthy and effective for predicting matchups. In addition, it is clearer what should be given and asked of the AI’s being used to render them more effective. Although the data and results gathered are no doubt significant, there are some limitations that are important. Firstly, the sample size for both the number of games and the date range for the games was small. This small sample size means this experiment should be repeated to verify the results. Secondly, this study was only done of NBA games and purely focused on the outcome. Because of this, a conclusion cannot be made on the efficacy of AI in sports betting as a whole, a conclusion can only be made on the efficacy of AI with regards to predicting winners of NBA games.

There are many avenues for extensions of this work that can be explored. The experiment done by Louis Rosenberg and Gregg Willcox [6] could possibly be replicated, instead focusing on NBA games instead of NHL games. Another study done by René Manassé Galekwa, Jean Marie Tshimula, Etienne Gael Tajeuna, and Kyamakya Kyandoghere [7] proposes that future AI models should treat sports betting like a financial portfolio, and optimize the models to minimize risk. A model created with these design philosophies in mind could be extremely useful and effective, so this avenue should be explored. There is one more, slightly different, avenue that could be explored. A paper done by Aladár Kollár [8] explains 3 types of machine learning models, ANN, SVM and Markov Chain with respect to sports betting. A study comparing these 3 types of models to see which is most effective for predicting NBA games would be incredibly interesting and impactful.

The goal of this paper was to see if utilizing Large Language models was viable and profitable for sports betting. Through careful testing of three separate AI LLMs, Meta, Gemini, and Copilot, it was shown that LLM can be incredibly effective and profitable. Meta specifically showed a significant amount of promise when analyzing results, while Copilot performed very poorly. On top of these findings, it was clear that giving extra data to these models often harbored good results. Future studies may want to explore more drastic prompt engineering or give varying amounts of data to delve further into this. The most interesting idea that arises from this study is creating specifically trained machine learning models for sports betting. If broadly designed LLMs can be effective for prediction, how effective can a more narrow-minded model be? That is a very interesting question that is hopefully answered in the future. Overall, this study was incredibly successful in showing how effective LLMs can be for prediction and will hopefully motivate more studies on AI and sports betting specifically.

**References**

[1] R. Etuk, T. Xu, B. Abarbanel, M. N. Potenza, and S. W. Kraus, “Sports betting around the world: A systematic review,” *J. Behav. Addict.*, vol. 11, no. 3, Art. no. 3, Sep. 2022, doi: 10.1556/2006.2022.00064.

[2] A. Pretorius and D. A. Parry, “Human Decision Making and Artificial Intelligence: A Comparison in the Domain of Sports Prediction,” in *Proceedings of the Annual Conference of the South African Institute of Computer Scientists and Information Technologists*, in SAICSIT ’16. New York, NY, USA: Association for Computing Machinery, Sep. 2016, pp. 1–10. doi: 10.1145/2987491.2987493.

[3] “What Is Artificial Intelligence (AI)? | IBM.” Accessed: Feb. 24, 2025. [Online]. Available: https://www.ibm.com/think/topics/artificial-intelligence

[4] N. Sahota, “The Game Changer: How AI Is Transforming The World Of Sports Gambling,” Forbes. Accessed: Feb. 24, 2025. [Online]. Available: https://www.forbes.com/sites/neilsahota/2024/02/11/the-game-changer-how-ai-is-transforming-the-world-of-sports-gambling/

[5] O. Hubáček, G. Šourek, and F. Železný, “Exploiting sports-betting market using machine learning,” *Int. J. Forecast.*, vol. 35, no. 2, pp. 783–796, Apr. 2019, doi: 10.1016/j.ijforecast.2019.01.001.

[6] L. Rosenberg and G. Willcox, “Artificial Swarm Intelligence vs Vegas Betting Markets,” in *2018 11th International Conference on Developments in eSystems Engineering (DeSE)*, Sep. 2018, pp. 36–39. doi: 10.1109/DeSE.2018.00014.

[7] R. M. Galekwa, J. M. Tshimula, E. G. Tajeuna, and K. Kyandoghere, “A Systematic Review of Machine Learning in Sports Betting: Techniques, Challenges, and Future Directions,” Oct. 28, 2024, *arXiv*: arXiv:2410.21484. doi: 10.48550/arXiv.2410.21484.

[8] A. Kollár, “Betting models using AI: A review on ANN, SVM, and Markov Chain,” Mar. 21, 2021, *Open Science Framework*. doi: 10.31219/osf.io/mr2v3.