SCIENTIFIC JOURNAL OF SPORT AND PERFORMANCE

ORIGINAL ARTICLE

Assessing the accuracy of large language models in extracting latest cricket information

Indika Wickramasinghe . *Associate Professor. Department of Mathematics. Prairie View A&M University. Prairie View, Texas, United States of America.*

ABSTRACT

The development of large language models (LLMs) is making waves across various fields, bringing numerous benefits and innovations. At the same time, cricket is growing rapidly in popularity worldwide. Given this context, it's a great moment to explore how well LLMs can keep up with the latest cricket knowledge. This study evaluates the performance of three LLMs Co-Pilot, ChatGPT, and Liner in generating accurate summaries of bilateral Test and One Day Internationals (ODI) cricket series played in 2024. The evaluation focused on three main tasks: reporting series results, identifying the top three batsmen with their scores, and listing the top three bowlers with their wickets. Among the models, Co-Pilot stood out, consistently delivering the highest accuracy across all tasks and formats, especially for matches involving Australia, India, and South Africa. ChatGPT showed mixed results, excelling in some areas but struggling with task-specific accuracy. Liner, on the other hand, had the lowest accuracy and faced significant challenges in providing relevant detailed cricket-related information. The study also noted instances where the models generated unrelated or incorrect outputs, highlighting the need to validate LLM-generated cricket data to ensure it is reliable and correct.

Keywords: Performance analysis, Large Language Models (LLMs), Cricket analytics, Artificial intelligence, Performance evaluation, Natural Language Processing (NLP), Sports data analysis.

Cite this article as:
Wickramasinghe, I. (2025). Assessing the accuracy of large language models in extracting latest cricket information. *Scientific Journal of Sport and Performance*, *4*(2), 268-284. https://doi.org/10.55860/GSLZ8291

Corresponding author. *Department of Mathematics. Prairie View A&M University. Prairie View, Texas, United States of America.*
E-mail: ipwickramasinghe@pvamu.edu
Submitted for publication January 09, 2024.
Accepted for publication March 11, 2025.
Published March 25, 2025.
Scientific Journal of Sport and Performance. ISSN 2794-0586.

doi: https://doi.org/10.55860/GSLZ8291

INTRODUCTION

Large Language Models (LLMs) are incredibly advanced neural networks, trained on massive amounts of text data, consisting of billions of parameters (Connor and O'Neill, 2023). They have three main features: architecture, scale, and transfer learning capabilities (Cook and Karakuş, 2024). The architecture determines how well they can process and understand language, while the scale refers to the amount of data and the number of parameters they are trained on. Transfer learning is a key feature that allows LLMs to apply their pre-trained knowledge to specific tasks with great flexibility and usefulness (Naveed et al., 2023; Vaswani et al., 2017; Romero, 2021; Yosinski et al., 2014). These models are designed to excel in recognizing, generating, and manipulating human language with exceptional skill (Naveed et al., 2023).

In recent years, LLMs have become transformative tools in Artificial Intelligence, performing exceptionally well in various natural language processing (NLP) tasks. Their applications include text summarization, language translation, code generation, and more. These capabilities have allowed LLMs to impact many fields, finding uses across different industries (Lewis et al., 2019).

The transformative impact of LLMs is evident in sectors like business (Olena, 2024), education (Mitchell et al., 2023), and healthcare (Haemmerli et al., 2023). However, their influence on sports a field with vast global engagement has received less attention. Cricket, one of the world's most popular team sports and it is played all around the globe (Wickramasinghe, 2014). Cricket related research has continuously evolved with the integration of AI technologies, which has enable to reshape the game at various levels.

Cricket has gained global popularity due to its unpredictable nature and the multiple factors that influence its outcome (Bandulasiri et al., 2016). LLMs can further enhance the sport's appeal by improving fan engagement, analytics, and content creation while providing AI-driven insights, multilingual coverage, coaching tools, and interactive experiences. However, their impact depends on the accuracy and reliability of the cricket-related information they generate. Given the growing influence of LLMs across various fields, it is crucial to explore their ability to produce accurate and up-to-date cricket knowledge. This study aims to examine the role, awareness, and application of LLMs in the globally celebrated sport of cricket, focusing on their effectiveness in generating information about the current game.

Impact of LLMs in Sports

Social media platforms like Facebook and YouTube have become essential resources for sports enthusiasts. They act as informal educational tools, helping people learn new skills and share knowledge (Connor and O'Neill, 2023). These platforms make sports-related information more accessible, serving as learning hubs for anyone looking to improve their understanding and performance.

Recent advancements in LLMs have further boosted sports engagement by offering fans interactive and self-directed learning opportunities. These models help users develop and refine their skills in an intuitive way. For example, Microsoft's Bing Chat goes beyond traditional search engine functions, allowing users to explore sports-related videos and images to aid in skill development (Mehdi, 2023; Qiu, 2024).

However, LLMs have notable limitations when it comes to processing complex sports scenarios. Xia et al. (2024) introduced a benchmark to assess the sports-related capabilities of LLMs, revealing that while these models have a good grasp of basic sports knowledge, they struggle with advanced tasks like scenario-based reasoning and contextual comprehension. These findings highlight the current gaps in LLM functionality when applied to nuanced sports contexts.

Live sports commentary, especially in fast-paced games like football, presents another challenge for LLMs. The need for accurate and timely event descriptions is difficult due to the rapid nature of gameplay. Nonetheless, adaptive language models offer a promising solution for delivering near real-time commentary during matches, addressing this challenge to some extent (Cook and Karakuş, 2024).

In professional sports, LLMs have shown utility in tactical analysis. For example, TacticalGPT has been used in professional football as a tactical analyst, providing contextually relevant and precise insights that support coaching strategies and enhance team performance (Caron and Müller, 2023).

Racket sports like tennis and badminton, which require players to manage variables like speed, angles, and force without direct physical interaction with opponents, present unique analytical challenges. Traditional video analysis methods are labor-intensive, but LLM applications offer efficient alternatives by creating high-level video comprehension frameworks, enabling more streamlined and accurate analysis (Zhang et al., 2025).

In strategic consulting, LLMs have also shown potential. Robinson (2023) examined their applications in Major League Baseball (MLB), assessing both their contributions and limitations in generating actionable insights for teams.

Another area where LLMs demonstrate significant potential is in automating sports reporting. Compiling game details, including player statistics, scores, and match outcomes, can be time-consuming. In badminton, for instance, LLMs have been successfully used to automate report preparation, reducing the workload of sports journalists (Chiang et al., 2024).

Finally, predictive analytics is a critical application of LLMs in sports, particularly in outcome prediction. In basketball, where the dynamic nature of the game and numerous influencing factors complicates forecasting, LLMs have shown promise in improving prediction accuracy, benefiting areas such as coaching strategies and sports gambling (Sprint, 2024).

Cricket and LLMs

A study by Bhatnagar (2024) delves into the creation of a fantasy cricket league, allowing participants to build teams based on the real-world performances of international players. This research uses advanced multi-agent systems for dynamic team management and player selection based on performance data, showcasing a sophisticated application of artificial intelligence (AI) and data analytics in sports. The study offers valuable insights into how such technologies can enhance the fan experience and engagement in cricket.

In sports media, one major challenge is creating engaging video content that captures key moments in fast-paced games like cricket. A study by Sattar et al. (2023) addresses this by reducing the labor and time needed to generate highlight reels of cricket matches. By using LLMs, the study proposes a method to automatically identify pivotal moments and streamline the video highlight generation process. This advancement in automation not only saves time but also improves the efficiency and accuracy of content production, which is crucial for media outlets in the digital age.

Similarly, writing narratives and articles about cricket matches is a time-consuming task for sports journalists. Sarkar et al. (2024) suggest using LLMs to automate the creation of cricket narratives that mimic the expertise and insight of seasoned sports writers. This approach could transform cricket journalism by reducing the

manual effort needed to produce high-quality articles while maintaining the depth of analysis and expertise that fans expect. The potential for LLMs to replicate journalistic styles and adapt to the nuances of cricket commentary marks an important development in the future of sports reporting.
Question and Answer (QA) systems, which have gained prominence in AI research, are increasingly used in sports to facilitate knowledge exchange, learning, and problem-solving. In cricket, QA systems can be vital tools for fans to share knowledge and engage more deeply with the sport. Tatawat and Ghosh (2023) highlight the use of LLMs to deploy advanced QA systems capable of processing both simple and complex free-text questions. These systems not only improve the accuracy of answers but also enhance the user experience by providing insightful and contextually relevant responses. This research emphasizes the role of QA systems in facilitating fan interaction with the game and its intricacies.

While AI and machine learning have been extensively applied in cricket, the integration of LLMs in the sport is still relatively unexplored (Jayalath, 2018; Manage et al., 2021; Wickramasinghe, 2020; Wickramasinghe, 2022). Most research focuses on machine learning techniques for performance analysis, predictive modeling, and video analytics. However, using LLMs for cricket-related tasks such as journalism, fan engagement, and content generation is a novel and emerging field. This gap in the literature presents an exciting opportunity for future research, particularly in exploring how LLMs can revolutionize sports media, fan interaction, and data-driven insights in cricket.

Research questions

A structured framework can effectively test the factual accuracy of an LLM's responses, its ability to process and contextualize cricket data, and its depth of knowledge regarding player performance and series dynamics. This framework includes three key components:

1. *Summarization of Series Outcome*: This component evaluates whether the LLM can accurately summarize and provide concise results of a Test or ODI series, including the overall outcome (e.g., which nation won and by what margin). It tests the model's ability to synthesize and accurately relay sports outcomes.
2. *Identification of Top Batsmen*: This check if the LLM can identify the top three batsmen from the series, based on the number of runs they scored in the series. It measures the model's capability to recognize key individual performances from the series.
3. *Identification of Top Bowlers*: Similar to the batsmen query, this tests the LLM's ability to discern the top three bowlers from the series.

The outcomes of these evaluations will highlight the strengths and potential limitations of LLMs in the domain of cricket analytics.

MATERIAL AND METHODS

This study aims to evaluate the accuracy of three well-known LLM applications ChatGPT, Linear, and Co-Pilot in providing cricket-related information. Specifically, it examines how knowledgeable these applications are about recent ODI series and their ability to generate accurate responses. The evaluation focuses on three key queries related to cricket matches played during the 2024 calendar year.

LLM applications

The three LLM applications chosen for this study are ChatGPT, Linear, and Co-Pilot. These models were selected because they are well-known for their natural language processing capabilities and are widely used for text generation and information retrieval.

Research queries

To measure the knowledge and accuracy of the LLM applications, the following three queries were formulated:

1. What is the outcome of the ABC Test/ODI series between countries X and Y in 2024?
2. Who are the top three batsmen, and what are their total runs scored in the ABC Test/ODI series between countries X and Y in 2024?
3. Who are the top three bowlers, and what are their total wickets taken in the ABC Test/ODI series between countries X and Y in 2024?

These queries were designed to capture key aspects of the cricket series, such as the overall result of the tournament, player performances (top batsmen and bowlers), and statistical details.

Data collection

The actual match data for comparison was collected from the official Cricinfo website (https://www.espncricinfo.com), including comprehensive reports, player statistics, and tournament results. These sources provided the ground truth for evaluating the responses generated by the LLMs. The data covered both Test and ODI cricket series that took place in 2024, focusing on the specific series between countries X and Y.

Evaluation criteria

The accuracy of the responses generated by each LLM was assessed by comparing their answers with the actual results of the cricket series. The following criteria were used to measure the accuracy of each application:

1. *Tournament Outcome*: The LLM must correctly identify the outcome of the series, including the scores of both teams.
2. *Top Batsmen*: The LLM must correctly identify the top three batsmen, along with their names and total runs scored in the series.
3. *Top Bowlers*: The LLM must correctly identify the top three bowlers, along with their names and total wickets taken in the series.

Each correct response was awarded one point, with a maximum possible score of 14 points (1 point for each correct query component across all three queries). The final score reflects the model's ability to accurately summarize the key details of the cricket series.

Comparison and analysis

The answers provided by ChatGPT, Linear, and Co-Pilot were compared to the actual data to determine the accuracy of each model. For each query, the responses were evaluated based on whether they correctly summarized the match outcome, identified the top three batsmen and bowlers, and provided the corresponding statistics. The total number of correct responses was calculated for each application, and the results were analyzed to quantify the overall accuracy.

RESULTS

Table 1 presents the actual summary of the bilateral Test series that took place in 2024, while Table 2 shows the summaries generated by the three LLMs: ChatGPT, Linear, and Co-Pilot. For the bilateral ODIs, Tables 3 and 4 provide the actual summaries and the summaries generated by the LLM applications.

Table 1. Summary of the test Cricket tournaments took place during 2024 and their results.

S/N	Series/Tournament	Team 1	Team 2	Winner	Top scorers	Top Bowlers	Margin
1	Freedom Trophy	6	SA	Draw	D Elgar 201 V Kohli 172 K Rahul 113	J Bumrah 12 N Burger11 K Rabada 11	1-1 (2)
2	Benaud-Qadir Trophy	AUS	PAK	AUS	M Marsh 344 D Warner 299 U Khawaja 220	P Cummins 19 A Jamal 18 N Lyon 13	3-0 (3)
3	The Frank Worrell Trophy	WI	AUS	Draw	U Khawaja 139 K McKenzie 138 S Smith 120	J Hazlewood 14 S Joseph 13 K Roach 8	1-1 (2)
4	Afghanistan in Sri Lanka	SL	AFG	SL	R Shah 145 A Mathews 141 I Zadran 114	P Jayasooriya 8 A Fernando 6 V Fernando 4	1-0 (1)
5	Tangiwai Shield	NZ	SA	NZ	K Williamson 403 R Ravindra 301 D Bedingham 268	W O'Rourke 9 N Brand 8 D Piedt 8	2-0 (2)
6	Afghanistan v Ireland	IRL	AFG	IRL	H Shahidi 75 L Tucker 73 P Stirling 66	M Adair 8 Z Rehman 6 C Young 5	1-0 (1)
7	Anthony de Mello Trophy	IND	ENG	IND	Y Jaiswal 712 S Gill 452 Z Crawley 407	R Ashwin 26 T Hartley 22 J Bumrah 19	4-1 (5)
8	Australia in New Zealand	AUS	NZ	AUS	C Green 238 R Ravindra 145 A Carey 125	M Henry 17 N Lyon 13 J Hazlewood 10	2-0 (2)
9	Sri Lanka in Bangladesh	SL	BAN	SL	K Mendis 367 D de Silva 281 M Haque 175	L Kumara 11 V Fernando 10 K Rajitha 8	2-0 (2)
10	Zimbabwe in Ireland	IRL	ZIM	IRL	P Masvaure 86 A McBrine 83 P Moor 79	A McBrine 7 B Muzarabani 5 B McCarthy 4	1-0 (1)
11	Botham-Richards Trophy	ENG	WI	ENG	J Root 291 O Pope 239 K Hodge 216	G Atkinson 22 J Seales 13 C Woakes 11	3-0 (3)
12	Sir Vivian Richards Trophy	SA	WI	SA	T de Zorzi 163 T Stubbs 138 J Holder 121	K Maharaj 13 J Seales 12 J Marrican 8	1-0 (2)
13	Bangladesh in Pakistan	BAN	PAK	BAN	M Rizwan 294 M Rahim 216 L Das 194	M Hasan 10 K Shahzad 9 H Mahmud 8	2-0 (2)
14	Sri Lanka in England	ENG	SL	ENG	J Root 375 J Smith 280 K Mendis 267	A Fernand0 17 C Woakes 13 G Atkinson 12	2-1 (3)
15	New Zealand in Sri Lanka	SL	NZ	SRI	K Mendis 309 D Chandimal 207 Ku Mendis 179	P Jayasooriya 18 N Peiris 9 W O'Rourke 8	2-0 (2)
16	Bangladesh in India	IND	BAN	IND	Y Jaiswal 189 S Gill 164 R Pant 161	J Bumrah 11 R Ashwin 11 R Jadeja 9	2-0 (2)
17	England in Pakistan	PAK	ENG	PAK	H Brook 373 J Root 352 S Shakeel 280	N Ali 20 S Khan 19 J Leach 16	2-1 (3)
18	South Africa in Bangladesh	SA	BAN	SA	T de Zorzi 248 T Stubbs 159 W Mulder 159	K Rabada 14 K Maharaj 13 T Islam 13	2-0 (2)
19	New Zealand in India	NZ	IND	NZ	R Pant 261 R Ravindra 256 W Young 244	W Sundar 16 R Jadeja 16 A Patel 15	3-0 (3)
20	Bangladesh in West Indies	BAN	WI	Draw	J Ali 176 M Hasan 146 A Athanze 139	T Ahmed 11 J Seales 10 K Roach 9	1-1 (2)
21	Sri Lanka in South Africa	SA	SL	SA	T Bavuma 327 T Stubbs 189 D Chandimal 156	M Jansen 14 P Jayasuriya 10 K Maharaj 9	2-0 (2)

22	Crowe-Thorpe Trophy	ENG	NZ	ENG	K Williamson 395 H Brook 350 J Bethell 260	B Carse 18 M Henry 15 G Atkinson 12	2-1 (3)

Table 2. Findings for the test cricket using ChatGPT, Liner, and Co-Pilot. (Team #1's score is first).

S/N	ChatGPT			Liner			Co-Pilot		
	Series Results	Top 3 scorers	Top 3 bowlers	Series Results	Top 3 scorers	Top 3 bowlers	Series Results	Top 3 scorers	Top 3 bowlers
1	1-1 (TT)	D Elgar 201 (TT) V Kohli 172 (TT) K Rahul 113 (TT)	J Bumrah 12 (TT) N Burger 11 (TT) K Rabada 11 (TT)	1-1 (TT)	D Elgar 201 (TT) V Kohli 172 (TT) K Rahul 113 (TT)	J Bumrah 12 (TT) N Burger 11 (TT) KL Rabada 11 (TT)	1-1 (TT)	D Elgar 201 (TT) V Kohli 172 (TT) KL Rahul 113 (TT)	J Bumrah 12 (TT) N Burger 11 (TT) K Rabada 11 (TT)
2	2-0 (FT)	M Marsh 344 (TT) B Azam 297 (FF) S Smith 289 (FF)	P Cummins 19 (TT) N Lyon 15 (FF) S Afridi 12 (FF)	3-0 (TT)	M Marsh 344 (TT) D Warner 299 (TT) U Khawaja XX (TF)	P Cummins 19 (TT) A Jamal 18 (TT) XX YY (FF)	3-0 (TT)	M Marsh 344 (TT) D Warner 299 (TT) U Khawaja 220 (TT)	P Cummins 19 (TT) A Jamal 18 (TT) N Lyon 13 (TT)
3	1-1 (TT)	U Khawaja 139 (TT) Labuschange 130 (FF) S Smith 125 (TF)	P Cummins 12 (FF) N Lyon 10 (FF) M Starc 8 (FT)	1-0 (TF)	J Hazlewood 158 (FF) S Joseph 132 (FF) K Roach 120 (FF)	J Hazlewood 14 (TT) S Joseph 13 (TT) K Roach 11 (TF)	1-1 (TT)	U Khawaja 139 (TT) K McKenzie 138 (TT) S Smith 120 (TT)	J Hazlewood 14 (TT) S Joseph 13 (TT) K Roach 8 (TT)
4	1-0 (TT)	R Shah 145 (TT) A Mathews 141 (TT) I Zadran 114 (TT)	P Jayasooriya 8 (TT) A Fernando 6 (TT) V Fernando 4 (TT)	1-0 (TT)	R Shah 145 (TT) A Mathews 141 (TT) I Zadran 114 (TT)	Jayasooriya 9 (TF) A Fernando 6 (TT) N Zadran 6 (FF)	1-0 (TT)	A Mathews 141 (FF) R Shah 91 (FF) Karunaratne 77(FF)	Jayasooriya 8 (TT) N Haq 4 (FT) V Fernando 4 (TT)
5	1-0 (FT)	K Williamson 403 (TT) R Ravindra 301 (TT) D Bedingham 268 (TT)	W O'Rourke 9 (TT) N Brand 8 (TT) D Piedt 8 (TT)	2-1 (TF)	K Williamson 403 (TT) T Latham 332 (FF) D Elgar 252 (FF)	W O'Rourke 9 (TT) K Maharaj 8 (FT) T Southee7 (FF)	2-0 (TT)	K Williamson 403 (TT) R Ravindra 301 (TT) Bedingham 268 (TT)	W O'Rourke 9 (TT) N Brand 8 (TT) D Piedt 8 (TT)
6	1-0 (TT)	A Balbirnie 142 (FF) H Shahidi 75 (FF) C Campher 68 (FF)	M Adair 8 (TT) Z Rehman 6 (TT) N Zardran 5 (FT)	0-1 (FF)	H Shahidi 179 (TF) C Camper 129 (FF) R Gurbaz 83 (FF)	G Naib 5 (FF) S Ahmad 4 (FF) M Adair 4 (FF)	1-0 (TT)	H Shahidi 75 (TT) L Tucker 73 (TT) P Stirling 66 (TT)	M Adair 8 (TT) Z-Rehman 6 (TT) C Young 5 (TT)
7	4-1 (TT)	Y Jaiswal 712 (TT) S Gill 452 (TT) J Root 432 (FF)	R Ashwin 25 (TF) T Hartley 7 (TF) J Bumrah 6 (TF)	4-1 (TT)	M Marsh 344 (FF) S Joseph 132 (FF) K Roach 120 (FF)	P Cummins 19 (FF) A Jamal 18 (FF) Other Bowler XX (FF)	4-1 (TT)	Y Jaiswal 712 (TT) S Gill 452 (TT) Z Crawley 407 (TT)	R Ashwin 26 (TT) T Hartley 22 (TT) J Bumrah 19 (TT)
8	2-0 (TT)	C Green 238 (TT) R Ravindra 145 (TT) A Carey 125 (TT)	M Henry 17 (TT) N Lyon 13 (TT) P Cummins 13 (FF)	2-1 (TF)	T Head (FF) K Williamson (FF) Labuschangne (FF)	P Cummins 15 (FF) T Southee 15 (FF) J Hazlewood 12 (TF)	2-1 (TF)	S Smith 402 (FF) K Williamson 350 (FF) Labuschangne 310 (FF)	P Cummins 18 (FF) T Boult 15 (FF) M Starc 14 (FF)
9	2-0 (TT)	K Mendis 367 (TT) D de Silva 281 (TT) M Haque 175 (TT)	L Kumara 11 (TT) V Fernando 10 (TT) K Ahmed 7 (FF)	2-0 (TT)	M Marsh 344 (FF) S Joseph 132 (FF) K Roach 120(FF)	P Cummins 19 (FF) A Jamal 18 (FF) O Bowler XX (FF)	2-0 (TT)	K Mendis 367 (TT) D de Silva 281 (TT) M Haque 175 (TT)	L Kumara 11 (TT) V Fernando 10 (TT) K Ahmed 7 (FF)

10	1-0 (TT)	P Masvaure 86 (TT) A McBrine 83 (TT) P Moor 79 (TT)	A McBrine 7 (TT) B Muzarabani 5 (TT) R Ngarava 4 (FT)	1-0 (TT)	H Tector 158 (FF) S Williams 134 (FF) M Adair 67 (FF)	G Hume 6 (FF) J Little 4 (FF) B Muzarabani 3 (FF)	1-0 (TT)	P Stirling 210 (FF) C Ervine 185 (FF) H Tector 160 (FF)	M Adair 12 (FF) B Muzarabani 10 (TF) A McBrine (FF)
11	2-0 (FT)	J Root 291 (TT) O Pope 239 (TT) K Hodge 216 (TT)	G Atkinson 22 (TT) J Seales 13 (TF) C Woakes 11 (TF)	2-1 (FF)	J Root 400 (TF) K Brathwaite 280 (FF) J Blackwood 210 (FF)	G Atkinson 22 (TT) M Wood 15 (FF) K Roach 12 (FF)	3-0 (TT)	J Root 291 (TT) O Pope 239 (TT) K Hodge 216 (TT)	G Atkinson 22 (TT) J Seales 13 (TF) C Woakes 11 (TF)
12	2-0 (FT)	T de Zorzi 163 (TT) T Stubbs 138 (TT) J Holder 121 (TT)	K Rabada 14 (FF) K Maharaj 10 (TF) J Seales 8 (FF)	2-0 (FT)	D Elgar 226 (FF) K Brathwaite 180 (FF) K Verreynne 158 (FF)	K Maharaj 14 (TF) G Coetzee 10 (FF) A Joseph 8 (FF)	1-0 (TT)	T de Zorzi 163 (TT) T Stubbs 138 (TT) J Holder 121 (TT)	K Maharaj 13 (TT) J Seales 12 (TT) J Marrican 8 (TT)
13	2-0 (TT)	M Rizwan 294 (TT) M Rahim 216 (TT) L Das 194 (TT)	M Hasan 12 (TF) S Hasan 10 (FF) H Mahmud 9 (TF)	0-2 (FF)	B Azam 320 (FF) T Iqbal 228 (FF) M Haque 211 (FF)	S Afridi 12 (FF) N Shah 10 (FF) T Ahmed 8 (FF)	2-0 (TT)	M Rizwan 294 (TT) M Rahim 216 (TT) L Das 194 (TT)	M Hasan 10 (TT) K Shahzad 9 (TT) H Mahmud 8 (TT)
14	2-1 (TT)	J Root 375 (TT) J Smith 280 (TT) K Mendis 267 (TT)	G Atkinson 18 (FF) C Woakes 15 (TF) P Jayasooriya 12 (FF)	2-1 (TT)	J Root 395 (TF) D Chandimal 278 (FF) Ku Mendis 257 (FF)	M Wood 18 (FF) J Anderson 15 (FF) D Chameera 12 (FF)	2-1 (TT)	J Root 375 (TT) J Smith 280 (TT) K Mendis 267 (TT)	A Fernand0 17 (TT) C Woakes 13 (TT) G Atkinson 12 (TT)
15	2-0 (TT)	K Mendis 309 (TT) D Chandimal 207 (TT) Ku Mendis 179 (TT)	P Jayasuriya 18 (TT) N Peiris 9 (TT) A Fernando 8 (TT)	2-0 (TT)	K Williamson (FF) R Mendis 218 (FF) T Latham 210 (FF)	K Jamieson 17 (FF) T Boult 9 (FF) P Jayasuriya 9 (FF)	2-0 (TT)	K Mendis 309 (TT) D Chandimal 207 (TT) Ku Mendis 179 (TT)	P Jayasuriya 18 (TT) N Peiris 9 (TT) A Fernando 8 (TT)
16	2-0 (TT)	Y Jaiswal 189 (TT) S Gill 164 (TT) R Pant 161 (TT)	J Bumrah 11 (TT) R Ashwin 11 (TT) R Jadeja 9 (TT)	2-0 (TT)	V Kohli 192 (FF) M Rahim 145 (FF) S Gill 140 (FF)	J Bumrah 11 (TT) R Ashwin 9 (TF) S Islam 6 *TT)	2-0 (TT)	Y Jaiswal 189 (TT) S Gill 164 (TT) R Pant 161 (TT)	J Bumrah 11 (TT) R Ashwin 11 (TT) R Jadeja 9 (TT)
17	2-1 (TT)	H Brook 373 (TT) J Root 352 (TT) S Shakeel 280 (TT)	N Ali 20 (TT) S Khan 19 (TT) J Leach 16 (TT)	2-1 (FF)	J Root 285 (FF) B Azam 290 (FF) H Brook 275 (FF)	M Wood 18 (FF) S Afridi 12 (FF) S Khan 10 (FF)	2-1 (TT)	H Brook 373 (TT) J Root 352 (TT) S Shakeel 280 (TT)	N Ali 20 (TT) S Khan 19 (TT) J Leach 16 (TT)
18	2-0 (TT)	T de Zorzi 248 (TT) T Stubbs 159 (TT) W Mulder 159 (TT)	K Rabada 14 (TT) K Maharaj 13 (TT) T Islam 13 (TT)	2-0 (TT)	D Elgar 289 (FF) M Rahim 220 (FF) T de Zorzi 182 (FF)	K Rabada 15 (FF) K Maharaj 10 (TF) S Islam 8 (TF)	2-0 (TT)	T de Zorzi 248 (TT) T Stubbs 159 (TT) W Mulder 159 (TT)	K Rabada 14 (TT) K Maharaj 13 (TT) T Islam 13 (TT)
19	3-0 (TT)	R Pant 261 (TT) R Ravindra 256 (TT) W Young 244 (TT)	W Sundar 16 (TT) R Jadeja 16 (TT) A Patel 15 (TT)	0-2 (FF)	V Kholi 304 (FF) D Conway 259 (FF) S Gill 215 (FF)	J Bumrah 13 (FF) R Ashwin 10 (FF) T Southee 8 (FF)	3-0 (TT)	R Pant 261 (TT) R Ravindra 256 (TT) W Young 244 (TT)	W Sundar 16 (TT) R Jadeja 16 (TT) A Patel 15 (TT)

20	1-1 (TT)	J Ali 176 (TT) M Hasan 146 (TT) A Athanze 139 (TT)	T Ahmed 11 (TT) J Seales 10 (TT) K Roach 9 (TT)	0-2 (FF)	S Hope 361 (FF) M Rahim 225 (FF) K Roach 176 (FF)	K Roach 111 (FT) J Seales 10 (TT) S Islam 7 (FF)	1-1 (TT)	J Ali 176 (TT) M Hasan 146 (TT) A Athanze 139 (TT)	T Ahmed 11 (TT) J Seales 10 (TT) K Roach 9 (TT)
21	2-0 (TT)	T Bavuma 327 (TT) T Stubbs 189 (TT) D Chandimal 156 (TT)	M Jansen 14 (TT) P Jayasuriya 10 (TT) K Maharaj 5 (TF)	2-0 (TT)	D Elgar 336 (FF) Ku Mendis 205 (FF) T Bavuma 198 (FF)	K Rabada 14 (FF) K Maharaj 9 (FF) D Chameera 5 (FF)	2-0 (TT)	T Bavuma 327 (TT) T Stubbs 189 (TT) D Chandimal 156 (TT)	M Jansen 14 (TT) P Jayasuriya 10 (TT) K Maharaj 9(TT)
22	2-1 (TT)	K Williamson 395 (TT) H Brook 350 (TT) J Bethell 260 (TT)	B Carse 18 (TT) M Henry 15 (TT) G Atkinson 12 (TT)	2-1 (TT)	J Root 385 (FF) T Latham 327 (FF) B Stokes 290(FF)	M Wood 18 (FF) S Afridi 14 (FF) M Henry 12 (FF)	2-1 (TT)	K Williamson 395 (TT) H Brook 350 (TT) J Bethell 260 (TT)	B Carse 18 (TT) M Henry 15 (TT) G Atkinson 12 (TT)

Table 3. Summary of the ODI Cricket tournaments took place during 2024 and their results.

S/N	Series/Tournament	Team 1	Team 2	Winner	Top scorers	Top Bowlers	Margin
1	Zimbabwe in Sri Lanka ODI Series	SRI	WI	SRI	Ku Mendis 129 J Liyanahge 119 C Asalanka 101	R Ngarava 8 W Hasaranga 7 M Theekshana 5	2-0 (3)
2	West Indies in Australia ODI Series	AUS	WI	AUS	K Carty 138 C Green 110 J Inglis 109	X Bartlett 8 S Abbott 6 G Motie 4	3-0 (3)
3	Canada in Nepal ODI Series	NEP	CAN	NEP	A Sah 162 B Sharki 141 N Dhaliwal 102	R Paudel 6 K Malla 5 I Sohi 4	3-0 (3)
4	Afghanistan in Sri Lanka ODI Series	SRI	AFG	SRI	P Nissanka 346 A Omarzai 206 A Fernando 184	P Madushan 8 A Fernando 4 W Hasaranga 4	3-0 (3)
5	Afghanistan v Ireland ODI Series (in United Arab Emirates)	AFG	IRL	AFG	R Gurbaz 172 H Tector 141 H Shahidi 119	M Nabi 5 F Farooqi 5 N Kharote 4	2-0 (3)
6	Sri Lanka in Bangladesh ODI Series	BAN	SRI	BAN	J Liyanage 177 N Hossain 163 P Nissanka 151	T Ahmed 8 W Hasaranga 6 L Kumara 5	2-1 (3)
7	India in Sri Lanka ODI Series	SRI	IND	SRI (2-0)	R Sharma 157 A Fernando 137 D Wellalage 108	J Vandersay 8 D Wellalage 7 C Asalanka 6	2-0 (3)
8	Afghanistan v South Africa ODI Series (in United Arab Emirates)	AFG	SA	AFG	R Gurbaz 194 A Omarzai 113 A Markram 91	R Khan 7 F Farooqi 4 N Kharote 4	2-1 (3)
9	Australia in England ODI Series	AUS	ENG	AUS	H Brook 312 B Duckett 305 T Head 248	M Potts 8 A Zampa 8 B Carse 8	3-2 (5)
10	Ireland v South Africa ODI Series (in United Arab Emirates)	SA	IRL	SA	T Stubbs 211 R Rickelton 135 K Verreynne 105	L Williams 11 C Young 7 M Adair 6	2-1 (3)
11	West Indies in Sri Lanka ODI Series	SRI	WI	SRI	S Rutherford 204 C Asalanka 145 N Madushka 107	W Hasaranga 6 G Motie 4 A Fernando 4	2-1 (3)
12	England in West Indies ODI Series	WI	ENG	WI	K Carty 218 L Livingstone 178 P Salt 151	M Forde 8 A Joseph 4 G Motie 4	2-1 (3)
13	Pakistan in Australia ODI Series	PAK	AUS	PAK	S Ayub 125 A Shafique 113 B Azam 80	H Rauf 10 S Afridi 8 N Shah 5	2-1 (3)
14	Afghanistan v Bangladesh ODI Series (in United Arab Emirates)	AFG	BAN	AFG	M Nabib 135 N Shanto 123 M Hasan 116	A Ghazanfar 8 M Rahman 8 A Omarzai 5	2-1 (3)

15	New Zealand in Sri Lanka ODI Series	SRI	NZ	SRI	Ku Mendis 217 W Young 130 A Fernando 105	M Theekshana 5 M Bracewell 5 J Vandersay 4	2-0 (3)
16	Pakistan in Zimbabwe ODI Series	PAK	ZIM	PAK	S Ayub 155 K Ghulam 120 A Shafique 83	A Ahmed 6 S Agha 6 F Akram 5	2-1 (3)
17	Bangladesh in West Indies ODI Series	WI	BAN	WI	M Mahmudullah 196 S Rutherford 167 K Carty 161	J Seales 5 A Joseph 4 R Shepherd 4	3-0 (3)
18	Afghanistan in Zimbabwe ODI Series	AFG	ZIM	AFG	S Atal 156 A Malik 113 S Williams 76	A Ghazanfar 9 A Omarzai 6 N Zadran 3	2-0 (3)
19	Pakistan in South Africa ODI Series	PAK	SA	PAK	H Klaasen 264 S Ayub 235 S Agha 163	S Afridi 7 M Jansen 6 K Rabada 5	3-0 (3)

Table 4. Findings for the ODI cricket using ChatGPT, Liner, and Co-Pilot.

	ChatGPT			Liner			Co-Pilot		
S/N	Series Results	Top 3 scorers	Top 3 bowlers	Series Results	Top 3 scorers	Top 3 bowlers	Series Results	Top 3 scorers	Top 3 bowlers
1	2-0 (TT)	Ku Mendis 129 (TT) J Liyanage 1 19 (TT) C Asalanka 101 (TT)	R Ngarava 8 (TT) W Hasaranga 7 (TT) M Theekshana 5 (TT)	2-1 (TF)	Ku Mendis 211 (TF) S Raza 190 (FF) D Gunathilaka (FF)	M Theekshana 8 (FT) W Hasaranga 7 (TT) R Ngarava 6 (FF)	2-0 (TT)	Ku Mendis 129 (TT) J Liyanage 119 (TT) C Asalanka 101 (TT)	R Ngarava 8 (TT) W Hasaranga 7 (TT) M Theekshana 5 (TT)
2	3-0 (TT)	K Carty 138 (TT) C Green 110 (TT) J Inglis 109 (TT)	A Joseph 6 (FF) J Hazlewood 5 (FF) P Cummins 4 (FF)	3-0 (TT)	M Labuschangne (FF) S Home 157 (FF) D Warner 175 (FF)	J Hazleewood 8 (FF) A Zampa 7 (FF) O Thomas 4 (FF)	3-0 (TT)	K Carty 138 (TT) C Green 110 (TT) J Inglis 109 (TT)	X Bartlett 8 (TT) S Abbott 6 (TT) G Motie 4 (TT)
3	3-0 (TT)	A Sah 162 (TT) B Sharki 141 (TT) N Dhaliwal 102 (TT)	R Paudel 6 (TT) I Sohi 4 (FF) S Kami 3 (FF)	3-0 (TT)	A Sah 162 (TT) R Paudel 130 (FF) N Dhaliwal 102 (TT)	R Paudel 6 (TT) I Sohi 4 (FF) U Bhagwan (FF)	3-0 (TT)	A Sah 162 (TT) B Sharki 141 (TT) N Dhaliwal 102 (TT)	R Paudel 6 (TT) K Malla 5 (TT) I Sohi 4 (TT)
4	2-1 (FF)	I Zadran 174 (FF) P Nissanka 132 (FF) D Karunaratne (FF)	W Hasaranga 6 (FF) D Chameera 6 (FF) F Ahmad 4 (FF)	3-0 (TT)	Ku Mendis 236 (FF) R Gurbaz 185 (FF) D Shanaka 184 (FF)	M Theekshana 8 (FT) H Silva 7 (FF) F Farooqi 5 (FF)	3-0 (TT)	P Nissanka 346 (TT) A Omarzai 206 (TT) A Fernando 184 (TT)	P Madushan 8 (TT) A Fernando 4 (TT) W Hasaranga 4 (TT)
5	2-0 (TT)	R Gurbaz 172 (TT) H Tector 141 (TT) H Shahidi 75 (TF)	M Nabi 5 (TT) F Farooqi 5 (TT) T Woerkom 4 (FT)	2-0 (TT)	R Gurbaz 223 (TF) H Tector 195 (TF) H Shahidi 184 (TF)	M Nabi 8 (TF) A Farooqi 7(TF) J Little 5 (FF)	2-0 (TT)	R Gurbaz 172 (TT) H Tector 141(TT) H Shahidi 119 (TT)	M Nabi 5 (TT) F Farooqi 5 (TT) N Kharote 4 (TT)
6	2-1(TT)	K Mendis 367 (FF) D de Silva 281 (FF) M Haque 175 (FF)	N Thushara 5 (FF) T Ahmed 4 (FF) R Hossain 3 (FF)	2-1 (TT)	Ku Mendis 218 (FF) S Hasan 185 (FF) T Iqbal 177 (FF)	M THeekshana 9 (FF) W Hasaranga 7 (TF) M Rahman 6 (FF)	2-1 (TT)	J Liyanage 177 (TT) N Hossain 163 (TT) P Nissanka 151 (TT)	T Ahmed 8 (TT) W Hasaranga 6 (TT) L Kumara 5 (TT)
7	2-0 (TT)	R Sharma 157 (TT) A Fernando 137 (TT) D Wellalage 108 (TT)	J Vandersay 8 (TT) W Sundar 5 (FF) D Wellalage 5 (FF)	3-0 (FF)	V Kohli 301 (FF) S Gill 263 (FF) Ku Mendis 215 (FF)	M Siraj 10 (FF) K Yadav 7 (FT) M	2-0 (TT)	R Sharma 157 (TT) A Fernando 137 (TT) D Wellalage 108 (TT)	J Vandersay 8 (TT) D Wellalage 7 (TT) C Asalanka 6 (TT)

						Theekshana 6 (FT)			
8	2-1(TT)	R Gurbaz 194 (TT) A Omarzai 113 (TT) A Markram 91 (TT)	R Khan 7 (FT) Mohammad 4 (FT) L Ngidi 4 (FT)	3-0 (FF)	Q de Kock 290 (FF) R Gurbaz 180 (FF) A Markram 150 (TF)	L Ngidi 10 (FF) T Shamsi 7 (FF) F Farooqi 5 (FF)	2-1 (TT)	R Gurbaz 194 (TT) A Omarzai 113 (TT) A Markram 91 (TT)	R Khan 7 (TT) F Farooqi 4 (TT) N Kharote 4 (TT)
9	3-2 (TT)	H Brook 312 (TT) B Duckett 305 (TT) T Head 248 (TT)	M Potts 8 (TT) A Zampa 8 (TT) B Carse 8 (TT)	2-1 (FF)	D Warner 243 (FF) J Butler 207 (FF) M Labuschangne 220 (FF)	J Hazlewood 8 (FT) A Zampa 7 (TF) M Wood 6 (FF)	3-2 (TT)	H Brook 312 (TT) B Duckett 305 (TT) T Head 248 (TT)	M Potts 8 (TT) A Zampa 8 (TT) B Carse 8 (TT)
10	2-1 (TT)	T Stubbs 191 (TF) R Rickelton 91 (TF) K Verreynne 88 (FF)	L Williams 4 (TF) M Asair 4 (FF) C Young 3 (FF)	3-0 (FF)	Q de Kock 290 (FF) H Tector 190 (FF) R Dussen 225 (FF)	K Rabada 10 (FF) L Ngidi 8 (FF) J Litte 5 (FF)	2-1 (TT)	T Stubbs 211 (TT) R Rickelton 135 (TT) K Verreynne 105 (TT)	L Williams 11 (TT) C Young 7 (TT) M Adair 6 (TT)
11	2-1 (TT)	S Rutherford 204 (TT) C Asalanka 145 (TT) N Madushka 107 (TT)	W Hasaranga 6 (TT) G Motie 4 (TT) A Fernando 4 (TT)	2-1 (TT)	Ku Mendis 250 (FF) S Hope 230 (FF) D Karunaratne 215 (FF)	W Hasaranga 9 (TF) M Siraj 6 (FF) M Theekshana 5 (FF)	2-1 (TT)	E Lewis 204 (FF) C Asalanka 145 (TT) N Madushka 107 (TT)	M Theekshana 6 (FT) G Motie 4 (TT) A Fernando 4 (FT)
12	2-1 (TT)	K Carty 218 (TT) L Livingstone 178 (TT) P Salt 151 (TT)	M Forde 8 (TT) A Joseph 4 (TT) A Rashid 3 (FF)	2-1 (TT)	J Root 275 (FF) B Stokes 215 (FF) S Hope 210 (FF)	M Wood 9 (FF) J Holder 7 (FF) A Rashid 6 (FF)	2-1 (TT)	B King 202 (TF) L Livingstone 178 (TT) P Salt 154 (FF)	G Motie 8 (FT) R Topley 6 (FF) A Hosein 5 (FF)
13	2-1 (FF)	S Ayub 125 (TT) A Shafique 113 (TT) B Azam 80 (TT)	H Rauf 10 (TT) S Afridi 8 (TT) N Shah 6 (TF)	2-1 (TT)	D Warner 270 (FF) B Azam 235 (FF) T Head 215 (FF)	J Hazlewood 9 (FF) S Afridi 6 (FF) A Zampa 5 (FF)	2-1 (FF)	S Ayub 125 (TT) A Shafique 113 (TT) B Azam 80 (TT)	H Rauf 10 (TT) S Afridi 8 (TT) N Shah 5 (TT)
14	2-1 (TT)	M Nabib 135 (TT) N Shanto 123 (TT) M Hasan 116 (TT)	A Ghazanfar 8 (F) A Omarzai 5 (TT) T Ahmed 5 (FF)	2-1 (TT)	R Gurbaz 230 (FF) M Rahim 190 (FF) H Shahidi 175 (FF)	M Nabi 8 (FT) S Hasan 6 (FF) F Farooqi 5 (FT)	2-1 (TT)	R Gurbaz 189 (FF) N Shanto 172 (TF) I Zadran 145 (FF)	R Khan 9 (FF) S Hasan 7 (FF) M Rahaman 6 (FF)
15	2-0 (TT)	Ku Mendis 217 (TT) W Young 130 (TT) A Fernando 105 (TT)	M Theekshana 3 (TF) M Bracewell 5 (TT) J Vandersay 4 (TT)	2-1 (TF)	Ku Mendis 245 (TF) D Conway 210 (FF) D Shanaka 180 (FF)	W Hasaranga 9 (FF) T Southee 7 (FF) M Theekshana 6 (FF)	2-0 (TT)	Ku Mendis 217 (TT) P Nissanka 145 (FF) H Nicholls 92 (FF)	M Shiraz 6 (FF) M Santer 5 (FT) M Theekshana 4 (FF)
16	2-1 (TT)	S Ayub 155 (TT) K Ghulam 120 (TT) A Shafique 83 (TT)	A Ahmed 6 (FF) S Agha 6 (FF) F Akram 5 (TT)	3-0 (FF)	K Ghulam 240 (FF) S Ayub 215 (FF) C Ervine 190 (FF)	H Rauf 9 (FF) A Ahmed 6 (TT) B Muzarbani 5 (FT)	2-1 (TT)	S Ayub 155 (TT) K Ghulam 120 (TT) A Shafique 83 (TT)	A Ahmed 6 (TT) S Agha 6 (TT) F Akram 5 (TT)
17	3-0 (TT)	M Mahmudullah 196 (TT) S Rutherford 167 (TT)	J Seales 5 (TT) R Hossain 4 (FT)	2-1 (FF)	S Hasan 235 (FF) T Iqbal 210 (FF) B King 190 (FF)	M Siraj 8 (FF) A Joseph 6 (TF) S Hasan 5 (FF)	3-0 (TT)	M Mahmudullah 196 (TT) S Rutherford 167 (TT)	J Seales 5 (TF) N Rana 6 (FF)

		A Jangoo 104 (FF)	R Shepherd X (TF)					K Carty 161 (TT)	M Miraz 5 (FF)
18	3-0 (FT)	S Atal 156 (TT) A Malik 113 (TT) S Williams 76 (TT)	A Ghazanfar 9 (TT) A Omarzai 6 (TT) N Zadran 3 (TT)	3-0 (FT)	R Khan 240 (FF) R Gurbaz 225 (FF) S Raza 190 (FF)	M Nabi 9 (FT) F Farooqi 6 (FT) B Muzarabani (FF)	2-0 (TT)	S Atal 156 (TT) A Malik 113 (TT) S Williams 76 (TT)	A Ghazanfar 9 (TT) A Omarzai 6 (TT) N Zadran 3 (TT)
19	3-0 (TT)	H Klaasen 264 (TT) S Ayub 235 (TT) S Agha 163 (TT)	S Afridi 7 (TT) M Jansen 6 (TT) K Rabada 5 (TT)	2-1 (FF)	B Azam 275 (FF) H Klaasen 230 (FF) M Rizwan 210 (FF)	S Afridi 9 (TF) K Rabada 7 (FF) M Nabi 5 (FT)	3-0 (TT)	H Klaasen 264 (TT) S Ayub 235 (TT) S Agha 163 (TT)	S Afridi 7 (TT) M Jansen 6 (TT) A Ahmed 5 (FF)

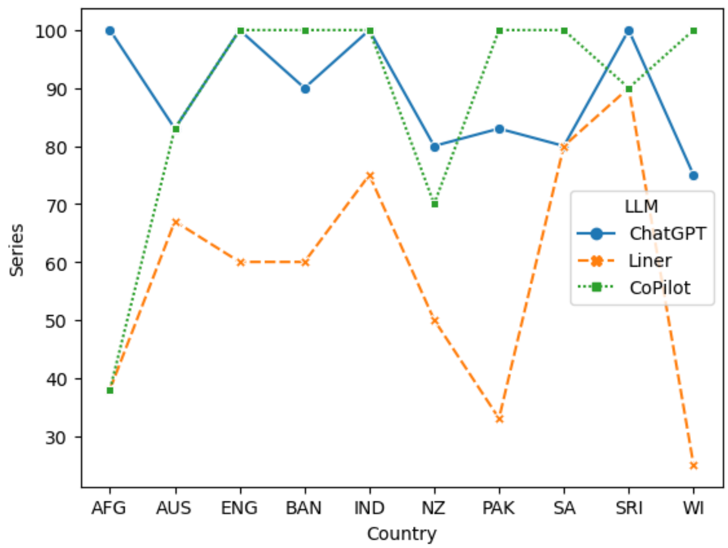

Figure 1. Accuracy of test series results by each LLMs.

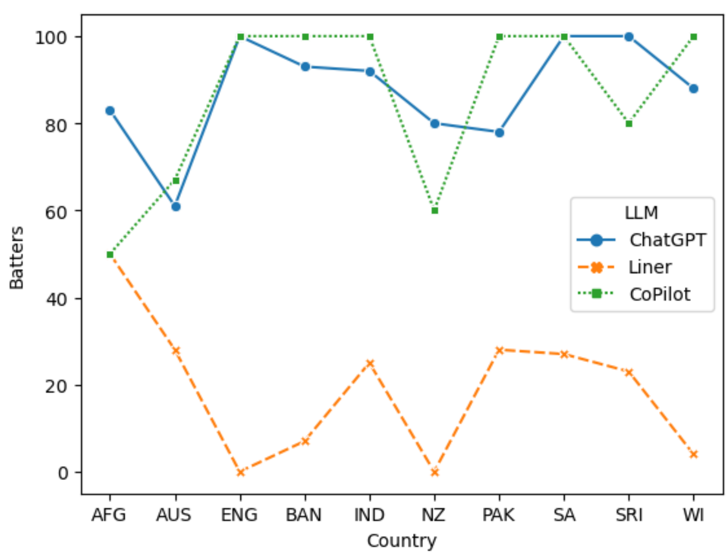

Figure 2. Accuracy of top three batters and their scores in test series by each LLM.

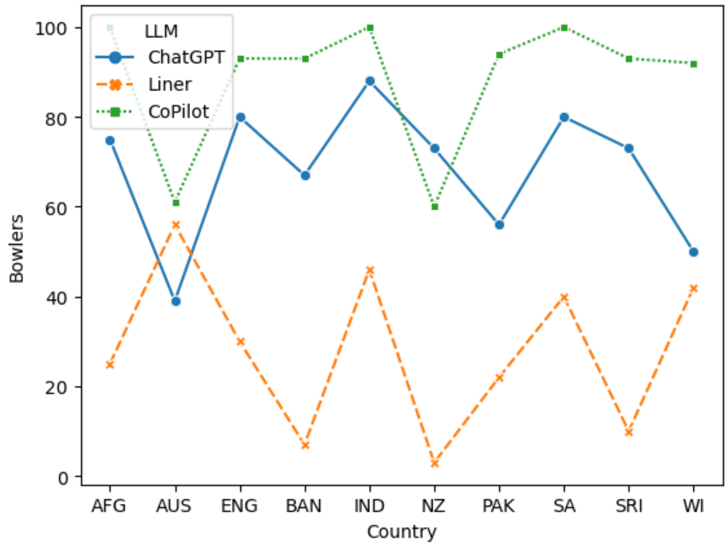

Figure 3. Accuracy of top three bowlers and the number of wickets in test series by each LLM.

Figures 1, 2, and 3 illustrate the accuracy of each LLM in generating overall results, identifying the top three batsmen, and the top three bowlers for the bilateral Test series that took place in 2024. Table 5 summarizes these results for the bilateral ODI series held during 2024.

Table 5. Accuracy of the ODI series by each LLM.

Team	% of Accuracy with ChatGPT			% of Accuracy with Liner			% Accuracy with Co-Pilot		
	Series	Batters	Bowlers	Series	Batters	Bowlers	Series	Batters	Bowlers
AFG	88	60	47	75	3	27	100	63	60
AUS	67	94	89	67	22	22	100	100	100
BAN	100	89	28	67	0	17	100	72	39
ENG	100	92	75	100	25	17	100	75	58
IND	100	100	33	100	67	33	100	100	100
NZ	100	100	83	50	0	0	100	33	17
PAK	67	100	72	33	0	28	100	100	89
SA	100	33	33	67	0	22	100	100	100
SRI	83	100	50	58	14	17	100	83	81
WI	100	93	60	20	7	20	100	90	67
Overall	87	83	56	55	9	21	100	88	78

DISCUSSION

The overall performance of various large language models in summarizing bilateral Test series results, identifying top batters with their scores, and listing top bowlers with their wickets reveals significant differences in accuracy across tasks. ChatGPT achieved accuracies of 91%, 92%, and 72% for these tasks, respectively. Liner, however, performed significantly worse, recording accuracies of 66%, 16%, and 26%. In contrast, Co-Pilot demonstrated strong overall performance, with accuracies of 95%, 86%, and 87%, establishing itself as the most reliable model.

When summarizing series results, ChatGPT showed perfect accuracy (100%) for games involving Afghanistan, Bangladesh, India, and Sri Lanka but dropped to its lowest accuracy of 75% for West Indies games. Liner's highest accuracy of 90% was recorded for Sri Lanka games, though it struggled significantly with West Indies games, achieving only 25% accuracy. Co-Pilot excelled in this category, achieving 100% accuracy for games involving Bangladesh, India, England, and West Indies, although it performed relatively poorly for Afghanistan games, with an accuracy of 38%.

For identifying the top three batters and their scores, ChatGPT performed best with 100% accuracy for games involving Bangladesh, South Africa, and Sri Lanka. However, its lowest performance was recorded for Australia games. Liner achieved a maximum accuracy of 50% for Australia games but struggled with Bangladesh games, recording 0% accuracy. Co-Pilot maintained its lead by achieving 100% accuracy for games involving Bangladesh, England, India, Pakistan, South Africa, and West Indies, although its performance dropped to 50% for Afghanistan games.

In summarizing the top three bowlers and their wickets, ChatGPT achieved its highest accuracy of 80% for India games but dropped to its lowest accuracy of 39% for Australia games. Liner recorded its best accuracy of 56% for Australia games but struggled significantly with New Zealand games, achieving only 3% accuracy. Co-Pilot outperformed both models, achieving 100% accuracy for games involving Afghanistan, India, and South Africa, with its lowest performance being 60% for New Zealand games. Figures 1, 2, and 3 provide a detailed illustration of these findings, which highlight Co-Pilot's consistent superiority across tasks and teams. While ChatGPT showed strong performance in several areas, its accuracy varied notably. Liner, on the other hand, faced significant challenges in summarizing player contributions.

The overall performance of the three LLMs when generating accurate information related to ODI games, ChatGPT achieved accuracies of 87%,83%, and 56% for these tasks, respectively. Similar to the test games, Liner performed significantly worse, recording accuracies of 55%, 9%, and 21%. In contrast, Co-Pilot demonstrated strong overall performance, with accuracies of 100%, 88%, and 78%, establishing itself as the most reliable model.

When generating results for bilateral ODI series, ChatGPT demonstrated perfect accuracy (100%) for games involving Bangladesh, England, India, New Zealand, South Africa, and West Indies but struggled with games involving Australia and Pakistan. Liner achieved 100% accuracy for games played by England and India but recorded a low accuracy of 20% for West Indies games. Co-Pilot remained consistent, achieving 100% accuracy for all teams in this task.

In summarizing top three batters and their scores during bilateral ODI series, ChatGPT performed best with 100% accuracy for games involving India, New Zealand, and Pakistan but dropped to 33% accuracy for South Africa games. Liner's best performance was with India games, achieving 67% accuracy, but it failed to provide accurate results for games involving Bangladesh, New Zealand, Pakistan, and South Africa, where it recorded 0% accuracy. Co-Pilot excelled again, achieving 100% accuracy for games involving India, Pakistan, and South Africa but dropped to 33% accuracy for New Zealand games.

For identifying the top bowlers and their wickets during the ODI series, ChatGPT achieved its highest accuracy of 89% for Australia games but struggled with Bangladesh games, where its accuracy was only 28%. Liner's performance was notably poor, with a maximum accuracy of 33% for India games and 0% for New Zealand games. Co-Pilot outperformed both models in this task, achieving 100% accuracy for games involving Australia, India, and South Africa and a minimum accuracy of 17% for New Zealand games. Additional details can be found in Table 5, which further supports Co-Pilot's overall superiority in generating cricket-related data.

CONCLUSION

Based on the findings, Co-Pilot consistently outperformed the other models, demonstrating high accuracy in generating information about the bilateral Test and ODI series in 2024. This included the series results (number of games each team won), the top three batsmen, and the top three bowlers who performed well. Co-Pilot excelled across all tasks, particularly in generating ODI data. While ChatGPT showed notable strengths in certain areas, its accuracy varied significantly depending on the task and teams involved. Liner, however, exhibited lower overall performance, struggling especially with tasks requiring detailed information about players and their contributions.

Co-Pilot showed exceptional reliability in generating accurate cricket data for ODI games played by Australia, India, and South Africa. For Test series data, it accurately generated information for games involving both India and South Africa. This highlights Co-Pilot's potential as a robust tool for summarizing cricket-related information with high accuracy.

Despite advancements in LLM applications, it is important to exercise caution when using them. These tools occasionally generate unrelated or incorrect information, a phenomenon known as "*hallucination*." This study observed such occurrences with cricket-related queries, such as suggesting player names from one team that belong to another. These inaccuracies underscore the need for critical evaluation of outputs from LLM tools.

This study acknowledges several limitations. Firstly, only three LLM tools were evaluated, despite the availability of numerous other applications. Secondly, the scope was limited to bilateral Test and ODI cricket matches. Lastly, the analysis focused exclusively on cricket data from the year 2024. Future research aims to expand the study across these dimensions by including more tools, exploring different formats of cricket, and analysing data from a broader time frame.

SUPPORTING AGENCIES

No funding agencies were reported by the author.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author.

REFERENCES

Bandulasiri, A., Brown, T., & Wickramasinghe, I. (2016). Factors affecting the result of matches in the one day format of cricket. Operations Research and Decisions, 26(4), 21-32.

Bhatnagar, M. (2024). FanCric: Multi-agentic framework for crafting fantasy 11 cricket teams. arXiv preprint arXiv:2410.01307.

Caron, M., & Müller, O. (2023). TacticalGPT: Uncovering the potential of LLMs for predicting tactical decisions in professional football. In StatsBomb Conference (pp. 1-11).

Chiang, S. H., Chao, L. W., Wang, K. D., Wang, C. C., & Peng, W. C. (2024). BADGE: BADminton report generation and evaluation with LLM. arXiv preprint arXiv:2406.18116.

Connor, M., & O'Neill, M. (2023). Large language models in sport science & medicine: Opportunities, risks, and considerations. arXiv preprint arXiv:2305.03851.

Cook, A., & Karakuş, O. (2024). LLM-Commentator: Novel fine-tuning strategies of large language models for automatic commentary generation using football event data. Knowledge-Based Systems, 300, 112219. https://doi.org/10.1016/j.knosys.2024.112219

Haemmerli, J., Sveikata, L., Nouri, A., May, A., Egervari, K., Freyschlag, C., ... et al. (2023). ChatGPT in glioma patient adjuvant therapy decision-making: Ready to assume the role of a doctor in the tumor board? bioRxiv. https://doi.org/10.1101/2023.03.19.23287452

Jayalath, K. P. (2018). A machine learning approach to analyze ODI cricket predictors. Journal of Sports Analytics, 4(1), 73-84. https://doi.org/10.3233/JSA-17175

Lewis, M., Liu, Y., Goyal, N., Ghazvininejad, M., Mohamed, A., Levy, O., Stoyanov, V., & Zettlemoyer, L. (2019). BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. https://doi.org/10.18653/v1/2020.acl-main.703

Manage, A. B., Kafle, R. C., & Wijekularathna, D. K. (2021). Classification of all-rounders in limited-over cricket-a machine learning approach. Journal of Sports Analytics, 6(4), 295-306. https://doi.org/10.3233/JSA-200467

Mehdi, Y. (2023). Confirmed: The new Bing runs on OpenAI's GPT-4. Microsoft Bing Blogs.

Mitchell, E., Lee, Y., Khazatsky, A., Manning, C. D., & Finn, C. (2023). DetectGPT: Zero-shot machine-generated text detection using probability curvature. arXiv preprint arXiv:2301.11305.

Naveed, H., Khan, A. U., Qiu, S., Saqib, M., Anwar, S., Usman, M., Barnes, N., & Mian, A. (2023). A comprehensive overview of large language models. arXiv preprint arXiv:2307.06435.

Olena, K. (2024). Application of LLMs for a chatbot system in the logistics industry.

Qiu, Y. (2024). The impact of LLM hallucinations on motor skill learning: A case study in badminton. https://doi.org/10.1109/ACCESS.2024.3444783

Robinson, D. (2023). Evaluating the potential of AI in sports consulting: Investigating ChatGPT-4's ability to consult an MLB team.

Romero, A. (2021). GPT-3: A complete overview. Medium. Retrieved from [Accessed 2025, March 14]: https://towardsdatascience.com/gpt-3-a-complete-overview-190232eb25fd

Sarkar, S., Yashwanth, T. S., & Giri, A. (2024, July). Advancing cricket narratives: AI-enhanced advanced journaling in the IPL using language models. In 2024 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT) (pp. 1-6). IEEE. https://doi.org/10.1109/CONECCT62155.2024.10677234

Sattar, H., Umar, M. S., Ijaz, E., & Arshad, M. U. (2023, December). Multi-modal architecture for cricket highlights generation: Using computer vision and large language models. In 2023 17th International Conference on Open Source Systems and Technologies (ICOSST) (pp. 1-6). IEEE. https://doi.org/10.1109/ICOSST60641.2023.10414235

Sprint, G. (2024). Social networks and large language models for Division I basketball game winner prediction. IEEE Access. https://doi.org/10.1109/ACCESS.2024.3403490

Tatawat, S., & Ghosh, K. (2023, December). CricGPT: A GPT-aided question-answering system for cricket. In Proceedings of the 15th Annual Meeting of the Forum for Information Retrieval Evaluation (pp. 44-50). https://doi.org/10.1145/3632754.3632757

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., & Polosukhin, I. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30.

Wickramasinghe, I. (2022). Applications of machine learning in cricket: A systematic review. Machine Learning with Applications, 10, 100435. https://doi.org/10.1016/j.mlwa.2022.100435

Wickramasinghe, I. P. (2014). Predicting the performance of batsmen in test cricket. https://doi.org/10.14198/jhse.2014.94.01

Wickramasinghe, I. (2020). Classification of all-rounders in the game of ODI cricket: Machine learning approach. Athens Journal of Sports, 7(1), 21-34. https://doi.org/10.30958/ajspo.7-1-2

Xia, H., Yang, Z., Wang, Y., Tracy, R., Zhao, Y., Huang, D., ... & Shen, W. (2024). SportQA: A benchmark for sports understanding in large language models. arXiv preprint arXiv:2402.15862. https://doi.org/10.18653/v1/2024.naacl-long.283

Yosinski, J., Clune, J., Bengio, Y., & Lipson, H. (2014). How transferable are features in deep neural networks? Advances in Neural Information Processing Systems, 27.

Zhang, J., Han, D., Han, S., Li, H., Lam, W. K., & Zhang, M. (2025). ChatMatch: Exploring the potential of hybrid vision-language deep learning approach for the intelligent analysis and inference of racket sports. Computer Speech & Language, 89, 101694. https://doi.org/10.1016/j.csl.2024.101694