

Decoding Fan and Societal Sentiment: ABSA of The Saudi Pro League's Recent Evolution

Dheya Ali Qasem Alraimi¹, Irving Vitra Paputungan²

^{1,2}Department of informatics, Faculty of Industrial Engineering, University of Islamic Indonesia, Yogyakarta, Indonesia

¹DheyaAli@outlook.com, ²irving@uui.ac.id,

Abstract

The Saudi Professional League (SPL) has attained global recognition through its recruitment of high-profile international players, yet this rise has intensified public scrutiny regarding incidents involving these athletes, such as Controversies surrounding sportsmanship, provocative celebrations, verbal altercations with spectators. This study analyzes (4,884) Arabic-language posts from (2021 to 2024), employing Aspect-Based Sentiment Analysis (ABSA) and the fine-tuned MARBERT model. The findings reveal a dominant negative sentiment (71.9%) across the dataset, with 'Player-Conduct' and 'Disciplinary-Action' emerging as the most frequently discussed aspects. Co-occurrence and correlation analyses indicate that negative sentiment is closely tied to perceptions of inadequate governance and cultural misalignment within the SPL, further intensifying public dissatisfaction. This research underscores the duality of high-profile players as drivers of global visibility and sources of domestic tension, particularly within culturally sensitive contexts. By addressing these challenges, the SPL can mitigate reputational risks while harmonizing its international ambitions with domestic expectations. This study advances Arabic Aspect-based sentiment analysis in the sports domain and provides actionable insights to enhance ethical governance, align with cultural sensitivities, and strengthen stakeholder engagement, thereby supporting the SPL's long-term credibility and growth.

Keywords: Saudi Professional League (SPL); Aspect-Based Sentiment Analysis (ABSA); MARBERT; Prominent International Athletes

1. Introduction

The Saudi Professional League (SPL) has experienced a surge in global attention, primarily due to its strategic recruitment of high-profile international players such as Cristiano Ronaldo [1], Malcom Filipe Silva, Sergej Milinković-Savić, and Éver Banega. While this strategic shift has elevated the league's visibility and appeal, it has also intensified public scrutiny regarding controversies involving these players. Incidents such as provocative goal celebrations, verbal confrontations with spectators, and perceived breaches of sportsmanship have sparked polarized public discourse. These controversies highlight the broader interplay between global competitiveness and cultural alignment, a tension observed in various professional sports organizations as they strive to integrate international players into culturally distinct contexts [2], in addition it underscores the tension between the SPL's ambitions for global competitiveness and its obligation to align with Saudi Arabia's deeply rooted cultural and religious values, which emphasize respect, accountability, and decorum [3].

Social media platforms, particularly X, have become central venues for public discourse surrounding these controversies. As noted by Stieglitz et al. [4], X captures

real-time public reactions, providing a dynamic dataset that reflects diverse societal sentiments. The platform's hashtags and threaded discussions offer unique opportunities to analyze how controversies are framed and debated online [5], [6]. However, Arabic social media text presents specific challenges for analysis due to its informal, context-dependent expressions and the diversity of dialects [7], [8].

As outlined by Nazir et al., [9]. Sentiment Analysis (SA) is a widely used method in research for automatically identifying and classifying the sentiments expressed in a text, typically categorizing them as positive, negative, or neutral. It is employed to assess the general sentiment of the entire text, helping to determine its overall emotional tone. According to Hoang et al., [10]. Aspect-Based Sentiment Analysis (ABSA) is a more advanced technique that goes beyond general sentiment by identifying specific aspects within the text and determining the sentiment expressed toward each of those aspects. And according to AlNasser et al., [11]. ABSA can be broken down into several sub-tasks, including Aspect Term Extraction (ATE), which identifies the key terms related to aspects within a text, and Aspect Term Polarity (ATP), which assigns sentiment to each identified aspect. Additional sub-tasks, such as Aspect Category Detection (ACD)

and Aspect Category Polarity (ACP), categorize and assign polarity to different aspects.

Advances in natural language processing (NLP) have introduced pre-trained transformer-based models that provide deep contextual embeddings, significantly enhancing ABSA's performance. (BERT) [12] laid the foundation for transformer-based NLP. Subsequent models such as (ArabicBERT) trained on Modern Standard Arabic (MSA), demonstrates strong performance on formal texts but struggles with dialectal and informal variations [13], (AraBERT) extended these capabilities by incorporating additional data and task achieving state-of-the-art results in several domains [14]. Tailoring these advancements to Arabic texts. However, these models underperform when handling dialectal and informal Arabic text prevalent on social media platforms like X [15], [16]. (MARBERT) addresses these challenges by leveraging extensive pretraining on both MSA and dialectal Arabic, including informal text from social media and has achieved state-of-the-art performance on multiple Arabic (NLP) tasks including sentiment analysis (SA) [17], [18], [19]. Furthermore, MARBERT's ability to handle complex morphological structures and dialectal diversity makes it uniquely suited for analyzing Arabic social media discourse [20]. Additionally, other transformer-based models like FAST-LCF-ATEPC a multilingual model. have adopted joint architectures for Aspect Term Extraction and Polarity Classification, enabling concurrent task completion, that reduces error propagation often associated with pipeline approaches. However, its domain-specific pretraining limits its generalizability to broader applications, such as analyzing sentiment in dynamic social media contexts [14]. Similarly, MTL-AraBERT introduced a multi-task learning approach to enhance performance in Arabic ABSA by sharing feature representations across ATE and ACD tasks. While this approach improved performance, it was tested primarily on structured datasets like hotel reviews, raising concerns about its applicability to unstructured and informal Arabic datasets [21].

Despite significant advancements in Aspect-Based Sentiment Analysis (ABSA), existing studies often rely on datasets from healthcare [11], education [14], and customer reviews [21]. These domains, while valuable for controlled evaluations, fail to capture the complexities of informal, dialectal Arabic prevalent on platforms like X, where linguistic variability and contextual ambiguity present unique challenges. Furthermore, existing research predominantly emphasizes general ABSA tasks, such as Aspect Term Extraction (ATE) and Aspect Polarity Classification (APC), with limited focus on unstructured, culturally sensitive contexts.

This gap is particularly evident in applications where public sentiment intersects with governance and cultural alignment. For instance, while MARBERT has

demonstrated robust performance in dialectal Arabic ABSA excelling in tasks such as Aspect Category Detection (ACD) and Aspect Category Polarity (ACP) [11], its application to culturally nuanced domains, such as sport domain, remains underexplored. Similarly, models like AraBERT and FAST-LCF-ATEPC, though effective in formal contexts, face challenges in adapting to the dynamic and informal nature of social media [21].

This study bridges these gaps by applying MARBERT-based ABSA leveraging its strengths in handling dialectal Arabic to analyze 4,884 Arabic posts spanning 2021 to 2024. These posts focus on controversies involving foreign players in the SPL, tied to public scrutiny, player conduct, cultural expectations, and governance practices. Moreover, this research contributes to Arabic ABSA by demonstrating MARBERT's capabilities in analyzing informal, dialect-rich Arabic text, bridging a critical gap in the literature while addressing practical challenges faced by the SPL in its global expansion.

The study aimed to answer the following questions:

1. How can Aspect-Based Sentiment Analysis (ABSA) uncover nuanced patterns of public sentiment in Arabic posts related to controversies involving foreign players in the Saudi Professional League (SPL)?
2. How do these sentiment patterns influence public perception of the league and contribute to broader discussions on sports ethics and institutional governance?
3. What reputational benefits and risks arise from the SPL's reliance on high-profile foreign players, and how can insights from this research inform strategies to enhance the league's global image and stakeholder engagement?

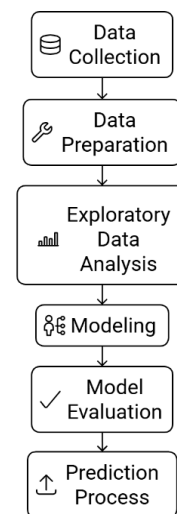


Figure 1. Research Methodology Workflow: A visual summary of the structured approach employed in the study, illustrating the logical progression through its key phases

2. Research Methods

The study employed a rigorous methodology structured to address the linguistic intricacies of Arabic and the socio-cultural nuances of the Saudi Professional League (SPL) context. The methodology is summarized in Figure 1, that provides a schematic representation of the entire research process. The steps in this methodology are detailed below.

2.1. Data Collection

The analysis commenced with data collection, wherein a curated dataset of 4,884 Arabic-language posts was compiled over a three-year period (2021–2024). X was selected as the primary data source due to its prominence as a platform for real-time public discourse, particularly in the Arab world [22]. Posts were manually curated over three months (May–August 2024), employing targeted hashtags such as (#حركة_غير_اخلاقية_رونالدو, #لجنة_الانضباط_والاخلاق) to ensure thematic relevance. The manual approach, rooted in thematic analysis methodologies, underscores the critical importance of contextual accuracy and conceptual precision, ensuring that identified themes authentically reflect the dataset’s intricacies [23]. The data collection process and its associated quality assurance measures are illustrated in Figure 2, This

diagram captures both the manual curation process and the subsequent steps to validate and refine the dataset. To ensure the dataset’s validity and reliability, a comprehensive Data Quality Assurance process was implemented, involving key steps such as language validation using the (langid.py¹) library, exclusion of incomplete or irrelevant posts, and the removal of duplicates through manual review. These measures addressed potential issues of noise and redundancy, ensuring that the dataset was linguistically consistent and thematically aligned with the study’s objectives. Additionally, to provide a clearer understanding of the dataset’s composition, Figure 3 presents a detailed breakdown of tweet distribution across key cases. This diagram highlights the volume of data associated with each foreign player and underscores the concentration of public discourse on specific incidents. Visualizing these patterns reinforces the dataset’s alignment with the study’s objectives and enhances its analytical depth. An illustrative sample of the dataset, including tweet translations and their thematic relevance, is provided in

Table 1, further demonstrating the structured approach to data collection and preparation.

Table 1. Example of dataset: A representative sample of the curated Arabic-language dataset, capturing the broad spectrum of public sentiment and discourse regarding controversies in the SPL

Text	Translated text	Data	Case
حركه غير أخلاقية من رونالدو صح انه بعض الجمهور ينرفز لكن طز في المباراة كلها انت في ارض السعودية احترم نفسك وهذه الحركات تسويها في بلادك	Ronaldo's unsportsmanlike conduct is unacceptable. Yes, fans can provoke at times, but you should dismiss the whole match. You are on Saudi soil, respect yourself, and save such actions for your home country	Feb 9, 2024	Cristiano Ronaldo
لجنة الانضباط خالفت لوائحها التي تنص (بحق اللجنة التدخل من تلقاء نفسها بحكم منصبها وصلحياته) في حالة انضباطية دون شكوى من أحد لكنها تجاهلت دورها وتركت مالكوم يسرح ويمرح دون عقوبة	The Disciplinary and Ethics Committee violated its own regulations, which state, 'The committee has the right to intervene on its own initiative by virtue of its position and powers,' in disciplinary cases without the need for a formal complaint. However, it neglected its role, allowing Malcom to roam freely without any punishment.	May 7, 2024	Malcom Filipe
كلنا مع الاسطورة وحركته تمثلنا جميعا تجاه الحكام واللجان والظلم ومضاغفة العقوبة ترا بسبب تهيبط الاهلي للامانة بانيجا لاعب شريف ويستحق الاحترام من الجميع	We all stand by the legend, and his gesture represents us all against the referees, the committees, and the injustices. Doubling the punishment is only because of Al-Ahli's relegation. To be fair, Banega is an honorable player who deserves respect from everyone.	Jun 30, 2022	Ever Banega
لقطة ليست من الناقل الرسمي قد تكون فوتوشوب خصوصا في تطور التكنولوجيا وان كانت صحيحة ف معناها في اوروبا العزيز وحب الانتصار	A shot that is not from the official channel may be photoshopped, especially in the development of technology, and if it is true, it means determination and love of victory in Europe.	Jun 12, 2022	Sergej Milinković-Savić

¹langid.py GitHub repository:
<https://github.com/saffsd/langid.py>



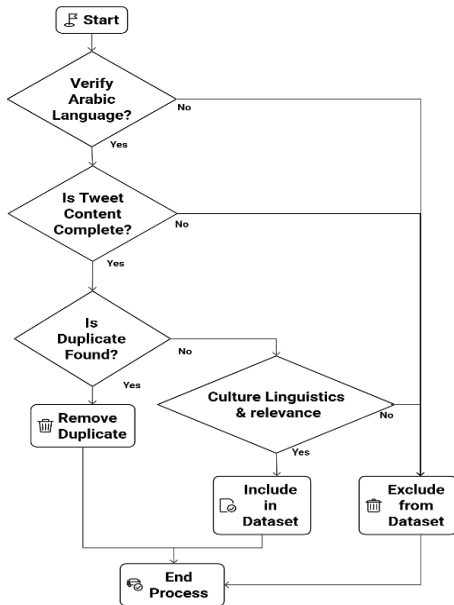


Figure 2. Data Collection Workflow: A systematic representation of the methodology employed to curate and validate the dataset, ensuring alignment with the study's thematic and analytical objectives

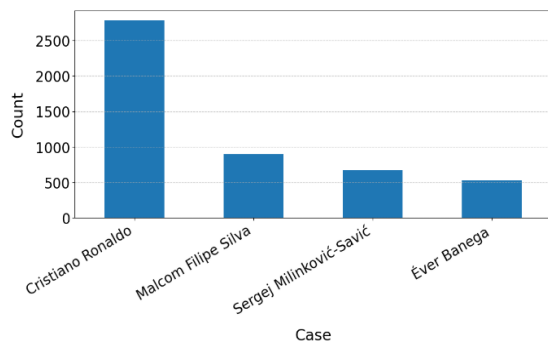


Figure 3. Data distribution: A representation of the dataset's composition, illustrating the relative frequency of player mentions and the focus of public discourse

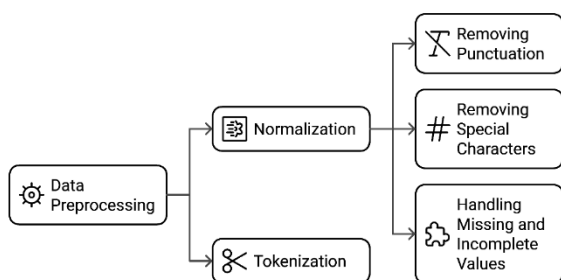


Figure 4. Data Preprocessing Workflow: A representation of the processes applied to prepare the dataset for analysis

2.2. Data Preprocessing

To prepare the dataset for analysis, a comprehensive preprocessing pipeline was implemented. Text normalization was performed to remove diacritics, punctuation, and special characters, ensuring textual uniformity while preserving critical linguistic features. Given the morphological complexity of Arabic, stemming and stop-word removal were eschewed to retain the semantic integrity of the text, a practice recommended by Abdul-Mageed et al., [24].

Tokenization was executed using MARBERT's Word-Piece tokenizer, which segmented text into sub-word units, enabling precise handling of both standard and dialectal Arabic expressions. The steps of this pipeline are illustrated in Figure 4, which outlines the preprocessing workflow. These preprocessing steps were essential to transform raw textual data into a structured format suitable for subsequent analytical tasks.

2.3. Human Annotation

To ensure the dataset was adequately prepared for model training, a rigorous human annotation process was undertaken following the pre-processing phase. The process aimed to construct a high-quality labeled subset that encapsulated the intricate nuances of the dataset. The workflow for this process is depicted in Figure 5, that systematically illustrates the sequential stages involved in annotating the data.

The aspects utilized for annotation were not arbitrarily assigned but were derived through a methodologically robust thematic analysis of the dataset. This analytical approach facilitated the identification of recurrent patterns and salient thematic constructs within the collected tweets, ensuring that the selected aspects were empirically substantiated and methodologically congruent with the overarching research questions. The thematic analysis adhered to an iterative paradigm, enabling an exhaustive examination of the dataset to discern and refine dominant themes. For instance, Player Conduct was identified as a pervasive thematic construct, reflecting public discourse surrounding ethical norms and professional decorum, while Disciplinary Actions illuminated critical discussions pertaining to governance and equitable enforcement. Additional aspects, including Cultural Differences, Audience Provocation, and Player, were similarly ascertained for their salience and relevance to the study's analytical objectives.

The insights garnered from the thematic analysis informed the development of a predefined list of aspects that structured the annotation process, this systematically curated list provided annotators with a coherent framework, ensuring thematic alignment and consistency throughout the labeling process. A representative subset of (1,000) posts was selected for manual annotation, conducted by two annotators who were native Arabic speakers proficient in both Modern Standard Arabic (MSA) and regional dialects. These annotators adhered to meticulously designed guidelines to ensure consistency in the categorization of sentiment (positive, negative, or neutral) and the accurate labeling of aspects, maintaining uniformity and analytical rigor across the dataset.

The integrity and reliability of the annotation process were quantitatively evaluated using Cohen's Kappa, a robust statistical measure of inter-annotator reliability [25]. The computed score of (0.966%) signified an

exceptionally high level of concordance between the annotators, underscoring the methodological precision and reliability of the process. Additionally, the percentage difference, a metric quantifying the proportion of discrepancies between annotators, was calculated at (3.10%), further corroborating the robustness of the annotations. This meticulously annotated dataset established a structured and thematically coherent foundation for subsequent analytical endeavors, ensuring the validity and relevance of the findings.

The annotation outcomes are further visualized in Figure 6, which highlights the frequency distribution of identified aspects, and Figure 7, which shows the proportion of consistent versus mixed sentiments within the dataset. An example of the human annotation process is provided in

Table 2, showcasing how the guidelines were applied to ensure uniformity and thematic alignment.

Table 2. Human Annotation Process Example: A sample of the annotated dataset, illustrating the application of the annotation process and categorization of sentiment and aspects.

Text	Translated text	Sentiment	Aspect
هذا كل مباراة يسوي حركاته القذرة	He does his dirty moves every game.	Negative	Player Conduct
من أصدرت العقوبة على اللاعب هذا ماذا عن حركة هذا اللاعب	Who issued the penalty for this player? What about this player's unethical behavior? We hope the rule applies to everyone.	Negative	disciplinary action, Player Conduct
اللاعب هذا لاعب كبير واختلاف الثقافات أمر طبيعي يمكن ما كان عارف انه هذا الشيء خطأ	This player is great, and cultural differences are natural, maybe he didn't know it was wrong.	Neutral	Cultural differences
الجمهور السعودي تعرف معنى الاحترام والتشجيع المثالي وليس لهم أي علاقة بتصرفات هؤلاء اللاعبين	Saudi fans understand respect and ideal support and have nothing to do with these players' behavior.	Positive	Audience Provocation
كريستيانو القدوة والمثال	Cristiano is the role model and example	Positive	Player

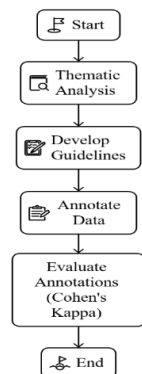


Figure 5. Human Annotation Process: A schematic representation of the methodological approach employed to annotate the dataset, ensuring rigorous thematic alignment and consistency

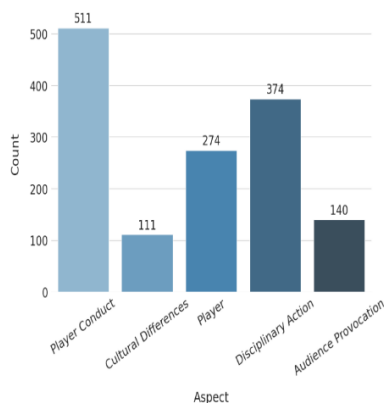


Figure 6. Aspect Frequency Identified: An illustration of the distribution of aspects annotated through the human annotation process

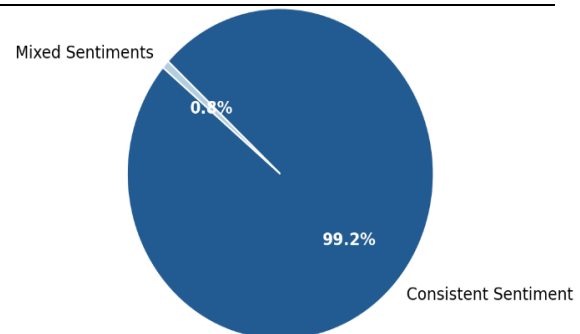


Figure 7. Proportion of Consistent vs. Mixed Sentiments: A representation of the distribution of consistent and mixed sentiment annotations within the dataset

2.4. Model Fine-Tuning

The fine-tuning process was conducted to optimize MARBERT for two primary tasks: Sentiment Analysis (SA) and Aspect Term Extraction (ATE). Techniques such as early stopping were employed to prevent overfitting and enhance the model's generalizability [26], with the stopping criterion defined as the absence of performance improvement over three consecutive epochs of validation loss. In line with best practices for model evaluation, the dataset was partitioned into training (70%), validation (15%), and test (15%) subsets, with random selection ensuring a representative distribution across sentiment categories and aspects. The fine-tuning was exclusively performed on the manually annotated subset of (1,000) posts, thus grounding the training process in rigorously labeled data to ensure high-quality model performance. After

the model was fine-tuned on this subset, the remaining unannotated data was processed during the inference phase, where the model applied the learned patterns to annotate the unannotated dataset. These processes, along with the subsequent inference phase, are comprehensively illustrated in Figure 8, which encapsulates the stages from task-specific training to generating predictions using the fine-tuned models.

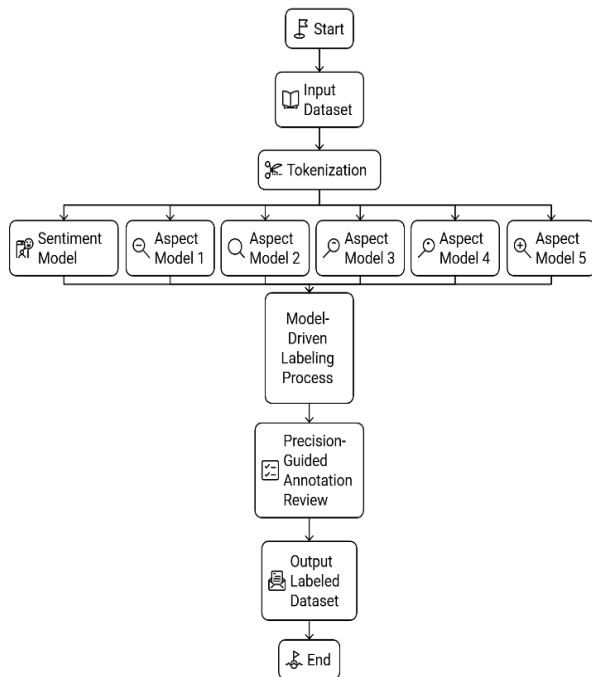


Figure 8. Fine-Tuning and Prediction Framework: A structured overview of the fine-tuning process and prediction pipeline, delineating the adaptation of MARBERT for sentiment analysis and aspect extraction

2.4.1 Sentiment Analysis (SA)

MARBERT was trained to classify posts into positive, negative, or neutral sentiment categories. The decision to assign one sentiment label per tweet was informed by the dataset’s observed tendency for monolithic sentiment expression, this characteristic, confirmed during manual annotation, demonstrated that individual posts predominantly conveyed a single dominant sentiment as illustrated in Figure 7. Fine-tuning was conducted on the annotated subset using iterative hyperparameter optimization to achieve optimal performance.

2.4.2 Aspect Term Extraction (ATE)

The focus was on identifying key aspects of public sentiment. The initial approach employed a multi-class classification model, which simultaneously predicted multiple aspects within each tweet. However, analysis of the dataset’s aspect distribution in Figure 6 revealed significant class imbalance, with certain aspects being heavily underrepresented. To address this limitation, separate models were fine-tuned for each aspect, allowing the parameters to adapt to the unique characteristics of individual classes. This approach was further validated in Table 3, that demonstrated the

improved performance of aspect-specific models compared to multi-class classification.

2.5. Model Evaluation

The final stage of the methodology involved evaluating MARBERT’s performance across both tasks. Standard metrics, including accuracy, precision, recall, and F1 score, were selected to ensure a comprehensive assessment of the model’s capabilities [27]. These metrics provided robust insights into the model’s effectiveness in both classification and extraction tasks, aligning with benchmarks from similar research in the field, the model performance results are illustrated in Table 3.

3. Results and Discussions

3.1. Results

This study’s analysis uncovered significant insights into public sentiment surrounding controversies in the Saudi Professional League (SPL), emphasizing the influence of governance, cultural sensitivities, and individual player dynamics. Public discourse exhibited a dominant negative sentiment, with (71.9%) of posts expressing dissatisfaction, (16.8%) neutral, and (11.4%) positive sentiment. As illustrated in Figure 9, this prevailing negativity underscores widespread discontent with key incidents involving foreign players, highlighting the league’s challenges in balancing global ambitions with local expectations.

The analysis of frequently discussed aspects identified Player-Conduct (2,432) instances and Disciplinary-Action (2,171) instances as the most prominent themes, both strongly associated with negative sentiment. Criticism of Player Conduct frequently reflects broader cultural sensitivities, as public disapproval often stems from actions perceived as misaligned with Saudi norms and values. These include provocative celebrations or verbal altercations, perceived as violations of cultural or ethical norms. While such incidents amplify dissatisfaction domestically, high-profile players like Cristiano Ronaldo also bring significant global visibility to the SPL, showcasing its competitiveness on an international stage. This duality underscores the league’s reputational dynamics, where the same players serve as both assets for global recognition and sources of domestic tension. Conversely, the Player aspect (879) instances indicate dissatisfaction directed toward individual players themselves, often tied to perceptions of underperformance, advancing age, or general disfavor. As depicted in Figure 10, these distinctions underline the multidimensional nature of public sentiment, where criticisms extend beyond conduct to encompass broader judgments about players’ reputations and capabilities. While Cultural-Differences (154) instances appeared less frequently overall, they often underpinned criticisms of Player Conduct, reflecting societal concerns about foreign players’ ability to integrate into Saudi cultural norms.

For instance, conduct that violated perceived cultural standards frequently amplified negative sentiment, as highlighted in co-occurrence patterns Figure 11, with governance critiques. Similarly, Audience-Provocation (319) instances captured tensions surrounding stadium interactions, highlighting the role of fan-player dynamics in influencing sentiment. These findings suggest that the SPL’s governance and disciplinary measures are closely scrutinized in the context of cultural expectations, making transparent governance practices critical for mitigating reputational risks while maintaining global ambitions

Player-specific analysis demonstrated disproportionate attention on Cristiano Ronaldo, that accounted for (1,424) instances of Player-Conduct and (1,051) instances of (Disciplinary-Action), with (75.6%) of sentiment expressed being negative. These figures suggest that Ronaldo’s conduct attracted heightened scrutiny, often tied to perceptions of unsportsmanlike conduct and cultural misalignment. In contrast, the Player aspect for Ronaldo (462) instances revealed dissatisfaction with his perceived inability to meet expectations, separate from his actions on the field. Comparatively, other players, such as Sergej Milinković-Savić and Malcom Filipe Silva, received less polarized sentiment, reflecting a more balanced public view of their performance and conduct. As illustrated in Figure 12.

Figure 11 highlights the Co-occurrence analysis highlighted significant interconnections between Player Conduct, Disciplinary Action, and Cultural Differences. Instances where players’ conduct was deemed inconsistent with cultural norms frequently overlapped with criticism of the league’s governance responses. These findings emphasize the interdependence of individual actions, institutional accountability, and cultural alignment in shaping public sentiment. Moreover, they reveal the reputational challenges and opportunities inherent in the SPL’s reliance on high-profile foreign players, as public sentiment plays a pivotal role in shaping the league’s domestic and global image.

The fine-tuned MARBERT model achieved strong performance in sentiment analysis, with an accuracy of 93.5% and an F1 score of 93.0%. For aspect term extraction, the model’s accuracy ranged from 80.0% to 90.0%, with F1 scores reaching 1%. For detailed performance metrics, refer to Table 3.

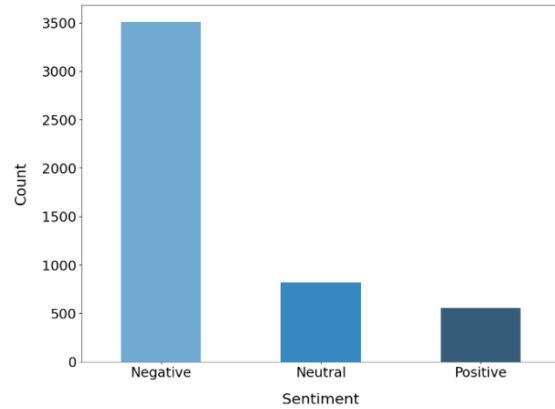


Figure 9. Sentiment Distribution: A visualization of sentiment classification, delineating the prevalence of negative, neutral, and positive sentiments expressed across the dataset

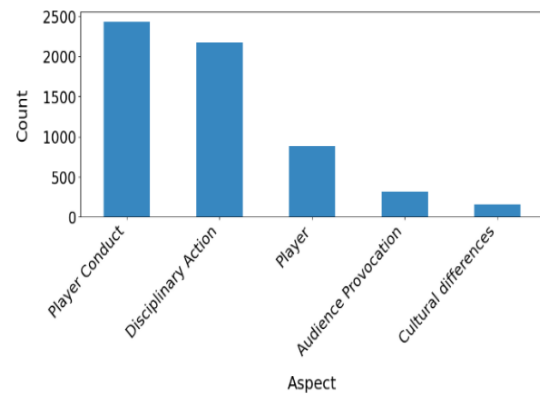


Figure 10. Aspect Frequency: A representation of the frequency distribution of aspects within the dataset.

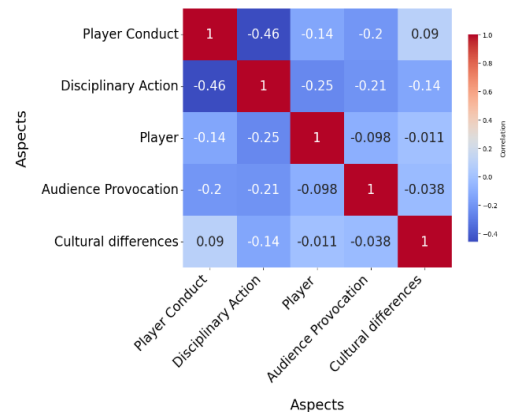


Figure 11. Aspect correlation matrix: A representation of the interrelationships among aspects, capturing the statistical correlations derived from the dataset

Table 3. Model Performance Results: An overview of model performance across Sentiment Analysis (SA) and Aspect Term Extraction (ATE) tasks.

Experiment	Task	Model	Accuracy	F1 Score	Recall	Precision
Experiment 1	Aspect Extraction	Multi-Class Model	0.862	0.871	0.871	0.878
	Sentiment Analysis	Sentiment Model	0.935	0.930	0.927	0.938
Experiment 2	Sentiment Analysis	Sentiment Model	0.935	0.930	0.927	0.938
		Aspect (1)	0.875	0.918	0.903	0.933



Aspect Extraction	Aspect (2)	0.850	0.870	0.952	0.800
	Aspect (3)	0.800	0.826	1.000	0.704
	Aspect (4)	0.850	0.786	0.688	0.917
	Aspect (5)	0.900	0.750	0.692	0.818

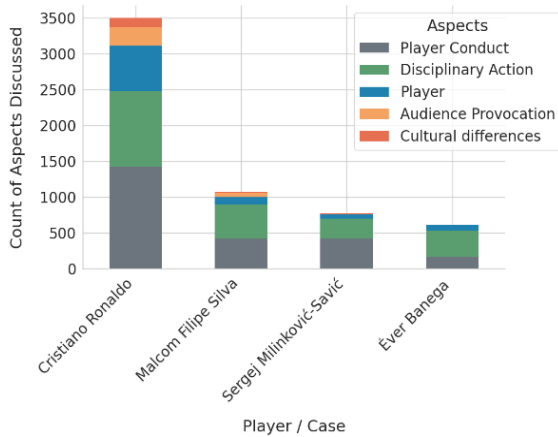


Figure 12. Aspect Distribution for Different Players: A representation of the interrelationships among aspects, capturing the statistical correlations within the dataset.

3.2. Discussions

The findings extend existing research on the SPL’s efforts to reconcile its global aspirations with domestic cultural sensitivities. Fauzul et al. emphasize the role of systemic cultural shifts within the SPL, including increased tolerance for foreign players and societal transformations such as the inclusion of women in stadiums. This study complements their analysis by illustrating persistent resistance to these shifts, as evidenced by the strong negative sentiment toward Player Conduct (75.6%) and Disciplinary Action (82%). Furthermore, the study adds nuance by illustrating how Cultural Differences function as an underlying factor shaping public perceptions, particularly when foreign players’ actions conflict with deeply held societal norms. These findings suggest that the SPL needs to continue evolving its governance strategies to address these tensions between global competitiveness and cultural alignment.

Schreyer et al., [28] document the economic benefits of high-profile players, noting Ronaldo’s impact on attendance at Al-Nassr home matches. However, this study nuances their conclusions by identifying a domestic backlash against Ronaldo’s conduct and perceived lack of alignment with local norms. The (75.6%) negative sentiment in Player Conduct discussions reflects broader societal discomfort, highlighting the cultural dissonance inherent in integrating globally celebrated players into a culturally conservative league. Additionally, negative sentiment in the Player aspect (462) instances underscores dissatisfaction with Ronaldo’s performance, extending beyond his behavior to broader critiques of his perceived decline

Mutz [29], highlights the SPL’s global reach, citing significant increases in search interest in regions such as Mexico and India. While this international recognition is noteworthy, the findings emphasize domestic challenges that risk undermining the league’s credibility. Cultural Differences (154) instances reveal how societal norms influence public sentiment, particularly when foreign players’ behavior is perceived as misaligned with Saudi cultural values. This cultural lens provides a critical context for understanding the interplay between international branding and local acceptance.

Furthermore, the findings raise questions about the impact of foreign players on domestic talent development. The influx of high-profile players has been celebrated for enhancing the league’s global profile, but its implications for local player opportunities and public perception warrant further investigation. This balance between global visibility and domestic growth aligns with Gryshuk’s [30] critique of sports diplomacy, that highlights the challenges of leveraging international players without alienating local stakeholders.

The reputational risks identified in this study underscore the importance of transparent governance frameworks and proactive cultural alignment strategies. The strong correlation between Player Conduct, Disciplinary Action, and Cultural Differences demonstrates the need for consistent disciplinary responses that respect cultural sensitivities while addressing public expectations. The SPL’s governance approach must continue to evolve, ensuring consistency and cultural alignment in its decision-making processes.

4. Conclusion

This study utilized a fine-tuned MARBERT model within the framework of Aspect-Based Sentiment Analysis (ABSA) to explore public sentiment surrounding controversies involving high-profile foreign players in the Saudi Professional League (SPL). The findings revealed a predominance of negative sentiment (71.9%), reflecting significant public dissatisfaction with governance-related issues and the behavioral dynamics of individual players. The analysis identified behavioral concerns and institutional responses as key drivers of this sentiment, underscoring the SPL’s critical challenges in addressing cultural and ethical expectations. These results provide insights into the nuanced patterns of public sentiment, addressing the first research of the study.

Further examination revealed the influence of societal norms, as reflected in aspects tied to cultural misalignment and audience interactions. These elements reinforced the need for the SPL to foster greater alignment between foreign players' conduct and domestic expectations. This addressing the study's second question, highlighting how sentiment patterns shape public perception of the league and inform broader discussions on governance and ethics.

The study also sheds light on the reputational advantages and risks associated with the SPL's reliance on high-profile foreign players. While these players boost the league's global visibility, they also increase scrutiny, particularly regarding their behavior and its alignment with Saudi cultural norms. These findings address the study's third question, emphasizing the duality of reputational risks and opportunities while offering actionable insights for improving the league's global image.

To address these challenges, the SPL must establish clear and transparent disciplinary protocols that ensure consistency and fairness, thus addressing public concerns about governance. Additionally, periodic independent reviews of disciplinary processes would enhance transparency and align the league's governance with global standards. Furthermore, cultural sensitivity and behavioral training for foreign players should be institutionalized, helping them adapt to societal expectations and mitigate negative public sentiment. Developing a robust framework for managing controversies involving high-profile players is also essential, ensuring swift and transparent responses to protect the league's reputation. Structured feedback mechanisms, such as surveys and forums, would further enable the SPL to engage fans effectively, fostering loyalty and satisfaction while incorporating their perspectives into policy reforms. The interconnected nature of these themes demonstrates the complex interplay between individual conduct, institutional accountability, and public perceptions. While high-profile players have elevated the SPL's global profile, they have also intensified scrutiny of its governance and cultural integration strategies. Unlike previous studies that focus primarily on economic outcomes or global visibility, this study provides a nuanced perspective on the cultural and ethical dimensions of public sentiment. By offering insights into how societal norms shape reactions to professional sports, this study contributes to a deeper understanding of the SPL's efforts to balance international appeal with local accountability. In summary, this study advances the discourse on public sentiment in sports by emphasizing the critical role of cultural alignment and governance in shaping perceptions. Addressing these challenges will enable the SPL to enhance its credibility and set new standards for professionalism and inclusivity in global sports management.

4.1. Suggestions for Future Research

Building upon the methodology applied in this study, future research should aim to expand the dataset by incorporating additional social media platforms and automating the data collection process. This will allow for a more comprehensive and timely analysis of public sentiment, providing a broader understanding of fan reactions across platforms. While Aspect Term Extraction (ATE) and Aspect Polarity Classification (APC) were handled separately in this research, integrating these processes into a unified framework could enhance the precision and efficiency of sentiment analysis, especially in regard to key aspects like player conduct and disciplinary actions. Such integration would provide a more granular view of sentiment at the aspect level. To further improve the accuracy of sentiment analysis, fine-tuning MARBERT to better handle dialectal Arabic and informal language is crucial, especially given the complexities of social media language. Additionally, expanding the scope of the research to include other sports leagues, such as the English Premier League or La Liga, would allow for cross-cultural comparisons, deepening the understanding of how sentiment dynamics vary across different sports contexts and regions

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