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Algorithmic Gatekeeping and Gendered Visibility: The Role of AI in Shaping Media Narratives of Women's Football in India

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Abstract

This study investigates algorithmic gatekeeping and gendered visibility in the digital media representation of women's football in India through a comprehensive mixed-method computational audit framework. The research integrates survey responses (200), media and social platform records (1000), official web data (500) and manually annotated samples (500) collected from YouTube, news portals and official websites. Combining manual content analysis, statistical modelling and machine learning the study evaluates gender inference accuracy, visibility disparities, ranking parity, recommendation gap, engagement dynamics, media framing and algorithmic fairness across men and women's football content. Women's content recorded an average visibility score of 70.382 compared with 75.049 for men's content, yielding a parity ratio of .938. Further analysis shows ranking parity gap was 2.147, while gendered inference achieved 50% accuracy with 50% misclassification. Visibility prediction reached 93.6% versus 60% leakage, demonstrating unequal algorithmic amplification and validating a robust proposed AI-XAI framework for assessing sports media visibility fairness.

Keywords: Algorithmic gatekeeping; women's football; gendered visibility; artificial intelligence; sports media; visibility prediction; fairness audit; media framing; Indian Women's League; machine learning.

INTRODUCTION

Today, the nature of news and social media space is becoming increasingly algorithmic, with automated systems that select, rank, and boost content, effectively serving as so-called gatekeepers to the flow of sports stories across online platforms (Fosch-Villaronga et al., 2021; Gillespie, 2014). In practice, these AI-based ranking and recommendation systems are more than just tools for personalizing feeds; they organize attention on a mass scale, forming feedback loops where prior consumption signals teach these models to continue favoring similar content, further concentrating the benefits of visibility on already dominant actors and narratives (Gillespie, 2014).

An emerging policy and research discourse demonstrates that these systems are able to internalize and reproduce gendered structures based on their training data and design decisions, thereby directly impacting how athletic achievements are viewed, positioned as authoritative, and commercialized (Mittelstadt, 2019; Bucher, 2018). In the case of women's football, the power of visibility is not merely

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conceptual; media coverage is closely associated with participation opportunities, sponsorship, and career longevity. However, algorithmic curation is capable of skewing that exposure by assuming relevance based on previous (male-normative) consumption patterns and learning from historically biased corpora, thereby producing androcentric images of athleticism, competence, and power (Couldry & Mejias, 2019; Crawford, 2023).

Platform ecosystem studies and generative AI research continue to report homocentric role allocations and the aestheticization of women, which highlight representational harm as a product of the same tools that have come to mediate sports storytelling (Crawford, 2023; Blodgett et al., 2020). These dynamics are particularly important in India, where women's football has evident momentum but remains structurally underrepresented. The All India Football Federation has indicated a 138 percent increase in women player registration in less than two years, reflecting strong grassroots growth and institutional development through programs such as the IWL-2 pathway (Hanim, 2025; Mitchell et al., 2019).

Simultaneously, research and coverage also point to differences in the season duration, organization, and regular media coverage between the Indian Women's League (IWL) and men's football, which contributes to discouraging the formation of regular audiences and reducing algorithmic relevance of women's football coverage (Van Dijck et al., 2018; Andrejevic, 2019). Football news reports in Indian media also indicate a biased set of attention effects that, when processed into ranking systems, can further influence the algorithmic spread of attention to matches of women, player profiles, and tactical analysis (Carlson, 2018). Commercial and governance reactions are emerging. Solutions such as strategic co-branding across men's and women's football properties aim to align scheduling, cross-promote stories, and build a unified content inventory that provides platforms with more consistent touchpoints for women's football (Zuboff, 2023).

Media and sponsorship statistics worldwide indicate that women's football is on a strong upward trajectory, with fanbases expected to elevate it into the top five sports by 2030, offering India an opportunity to capitalize on algorithm-aware distribution frameworks to transform increased participation into sustained digital engagement (Criado-Perez, 2020). However, realizing this potential requires addressing the opacity of ranking criteria on platforms and the gendered priors embedded in AI-mediated news systems (Fosch-Villaronga et al., 2021; Bucher, 2018).

Currently, existing literature on algorithmic profiling and gender inference primarily focuses on targeted advertising or generic social media personalization (D'ignazio & Klein, 2023; Mehrabi et al., 2021). However, there is a clear lack of sport-specific evidence that (a) compares self-reported gender identity with algorithmically inferred identity among creators and athletes in women's football, and (b) quantifies the impact of such mismatches on digital visibility (e.g., ranking position, impressions) and participation (engagement, monetization, leads) (Jobin et al., 2019). Recent artificial intelligence studies using feature-importance analysis and cross-validated classification further demonstrate the value of examining the variables that influence algorithmic outcomes, rather than relying only on aggregate model-accuracy measures. This analytical orientation is relevant to digital sports-media research because the identification of visibility- and ranking-related predictors can support a more interpretable assessment of algorithmic fairness [51].

The present study treats the problem of Algorithmic Gatekeeping and Gendered Visibility as an intersectional issue of computational design, feminist media critique, and platform governance. It poses the question of how ranking, recommendation, and moderation systems mediate the discoverability and framing of women's football in India; how imbalances in legacy media systems are translated into algorithmic advantage or disadvantage; and how policy, product, and editorial interventions can reduce representational harm while increasing equitable reach (van Boven et al., 2022; Zuboff, 2023). The study aims to move beyond descriptive accounts of underrepresentation toward a diagnostic understanding of how algorithmic infrastructures learn, reproduce, and can be re-tuned to elevate women's football narratives within Indian media ecologies.

The study aims to evaluate the accuracy of gender inference for creators, athletes, and content items (posts, thumbnails, captions) (Carlson, 2018); to examine the relationship between inferred identity and algorithmic outcomes, including ranking position, recommendation frequency, predicted audience segmentation, and engagement velocity (Barocas et al.,

2019); to assess fairness and inclusiveness in the distribution of sports media content in digital environments (Gbekevi, 2021).

The analytical framework is grounded in feminist data studies and critical algorithm auditing, operationalized at the outcome level (exposure and ranking parity) rather than focusing solely on input-level bias removal (Braun et al., 2019; Lombard et al., 2010).

LITERATURE REVIEW

Research on algorithmic gatekeeping shows that visibility is produced through selection, ordering and recommendation rather than through content availability alone. Gillespie's account of the relevance of algorithms and later work on platform power explain how apparently technical ranking rules become institutional decisions about what is discoverable (Gillespie, 2014; Bucher, 2018; Van Dijck et al., 2018; Gillespie, 2018). In news and social-media settings, these systems learn from prior clicks, interactions and publishing routines; consequently, historically dominant content can receive a cumulative advantage even when a platform does not explicitly encode gender as a ranking rule (Andrejevic, 2019; Carlson, 2018; DeVito, 2017).

Gender-focused scholarship adds a second strand. Feminist data studies treat datasets, labels and performance metrics as socially situated rather than neutral (Criado-Perez, 2020; D'ignazio & Klein, 2023). Work on automatic gender recognition demonstrates that inferred categories can misgender users and compress non-binary identities into administratively convenient labels (Fosch-Villaronga et al., 2021; Keyes, 2018). Fairness research therefore recommends examining both measurement error and downstream allocation, including exposure, ranking and opportunity outcomes (Mehrabi et al., 2021; Barocas et al., 2019; Barocas & Selbst, 2016; Selbst et al., 2019; Dwork et al., 2012; Hardt et al., 2016). This is particularly relevant when inferred identity is used for audience segmentation or recommendation without an explicit, consent-based self-identification mechanism.

A third strand concerns women's sport and digital media. Recent studies describe expanding participation and fandom alongside persistent inequalities in the regularity, prominence and commercial treatment of women's sport (Hanim, 2025; Westerbeek, 2025; Ventaja-Cruz et al., 2024; Ayhan, 2025; Garnica-Caparrós & Memmert, 2021). However, most studies examine representation, audience response or platform culture separately. Fewer studies combine identity-inference validity, content framing, visibility metrics, ranking outcomes and leakage-aware prediction in one sport-specific audit. Table 13 presents the literature synthesis and shows how the present study connects these previously separated strands in the Indian women's-football context.

THEORETICAL FRAMEWORK

The study is guided by an integrated sociotechnical framework combining algorithmic gatekeeping, platformization, feminist data studies and outcome-oriented algorithmic fairness. Algorithmic gatekeeping specifies the mechanism: platforms select, rank and repeatedly recommend content, thereby allocating scarce audience attention (Gillespie, 2014; Gillespie, 2018; Van Dalen, 2023). Platformization locates that mechanism within an ecosystem of publishers, federations, sponsors and users whose prior behaviour supplies the engagement signals from which future relevance is inferred (Bucher, 2018; Van Dijck et al., 2018). Feminist data studies identify how gender categories, missing values and historical visibility patterns enter this process as power-laden representations rather than objective facts (Criado-Perez, 2020; D'ignazio & Klein, 2023). Fairness theory provides the evaluative layer through exposure parity, ranking parity and error analysis (Barocas et al., 2019; Selbst et al., 2019; Dwork et al., 2012; Hardt et al., 2016).

The framework follows a four-stage pathway. First, institutional and editorial conditions shape the volume, timing, metadata and framing of football content. Second, platform systems infer user or creator attributes and classify content. Third, ranking and recommendation models combine those classifications with engagement, source and contextual signals. Fourth, the resulting placement generates observable visibility, interaction and commercial opportunity. Feedback occurs when observed engagement is reused as a future ranking input, potentially converting an initial visibility difference into cumulative advantage or disadvantage.

Within this framework, content volume is a necessary but insufficient indicator of inclusion. Fairness is evaluated jointly through the exposure parity ratio, visibility differential, ranking parity gap, engagement gap, recommendation gap and gender-inference error.

The framework also separates explanatory prediction from transportable prediction: a full model containing rank and engagement can explain observed visibility, whereas the non-leakage model tests how much can be predicted without variables that are already close to the visibility outcome. This distinction prevents high predictive accuracy from being interpreted automatically as evidence of a generalizable or fair system.

Proposition 1. When historical attention signals privilege men's football, women's content can receive lower visibility and weaker placement even when its engagement is comparable.

Proposition 2. Gender-inference errors can create upstream measurement bias that distorts segmentation and downstream allocation.

Proposition 3. Performance-oriented framing alone will not ensure parity when platform ranking and source-level signals dominate discoverability.

Proposition 4. A valid fairness audit must assess volume, exposure quality, ranking quality and model sensitivity together rather than treating any single metric as conclusive.

METHODS

Research Design

To investigate algorithmic gatekeeping and gendered visibility in the digital media representation of women's football in India, a mixed-methods computational audit design was used. The design involved a mix of survey identity and perception data, public media/social content auditing, manual media-frame annotation, statistical testing and machine-learning modelling. This was chosen because algorithmic visibility is not just about whether content exists or not: it is also about ranking position, how often content is recommended, user or creator engagement on the platform, how content is framed and even what kind of creator or user is inferred from the content. The methodological framework was designed around three study objectives. The first assessed the accuracy of gender inference by comparing the platform-inferred gender categories with the gender as reported by the user. Second, it explored how inferred identity correlates with algorithmic measures like visibility score, engagement rate, search rank, and recommendation frequency. Third, it examined how fair and inclusive was the distribution of sports-media content, with visibility and ranking outcomes contrasted between men's football content, women's football content and across women's football narrative categories. The entire methodological procedure is illustrated in Figure 1.

Study Context

The research was on the Digital media of Indian women football. The context covered Indian Women League, IWL-2, Women’s national football team of India also known as Blue Tigresses and content related to AIFF about women football. The Indian Women's League and IWL 2 form the backbone of the study context, considered under the umbrella of All India Football Federation in Women's Football. Three main categories of digital sources were considered: YouTube, News/Web sources, and Official Web sources. The official federation content has been sourced from AIFF's digital streams and the media has been analyzed using Indian sports-media and news outlets. The Indian Football official YouTube channel was added as it serves as a significant public-facing video platform, showcasing Indian football highlights, match coverage and videos related to the Indian Football Federation. To gauge the extent to which women's football information was given comparable visibility, location and engagement impact the men's football content was employed as a comparison category.

Dataset Construction

The dataset was created based on three interrelated component data sets: a survey data set, a media/social content data set and a manually coded media-frame data set. These elements enabled the study to link identity and perception of users with visibility outcomes on the platform and framing of the narrative in the content. 2.3.1 Survey Dataset The survey sample comprised 200 responses from stakeholders related to sports-media consumption and visibility of women's football. Respondent groups comprised athletes, fans, sports content producers, journalists/media workers, coach/football staffs, and students/research participants. The primary variables collected in the survey were self-reported gender, platform-inferred gender, main platform used, perceived visibility gap, ranking fairness score, inclusiveness score and open-ended feedback on women's football visibility. The survey component was utilized primarily for Objective 1, and for qualitative support of Objective 3. To

calculate the accuracy of gender inference and the error rate for Objective 1, the self-reported gender was considered as the reference gender, and the inferred gender was considered as the inferred gender. The open-ended comments were then subjected to a thematic analysis, revealing the concerns of low visibility, algorithmic bias, tactical-analysis gaps, cross-promotion, and inclusiveness.

Media/Social Content Dataset

The media/social dataset contained 1 thousand football related Digital Content Items. From the YouTube, News/Web sources and Official Web sources. There were 543 YouTube items, 336 News/Web and 121 Official Web items. Regarding sport/content gender, 853 football items related to women and 147 football items related to men were included. This allowed for a comparison of women's football content with men's football content with regard to visibility, ranking, engagement and recommendation indicators. The primary variables of the media/social data were: platform, source/channel, type of content, title/caption, sport/content gender, engagement rate, search-rank position, visibility score, and recommendation frequency. The public source discovery and verification was carried out with the help of the official and media owners of the Indian Women's League, Women's Football and Indian Football Reporting. The official AIFF Indian Women's League page, AIFF women's football page, Indian Football YouTube page, and the Indian Women's League coverage by the Olympics were found to be the key points from which the football-media context and content categories were traced.

Manual Annotation Dataset

There were 500 media items in the manual annotation data set. The primary frame, secondary frame, tone, gendered-language indicator, performance-focus score, aesthetic-focus score, visibility-quality score, and algorithmic gatekeeping signal were coded for each item. The primary aim of this data set was to explore if women's football material was primarily represented in terms of performance and competition, lifestyle and aesthetic representation, achievement narrative, governance and/or commercial visibility, inspirational story or marginalizing language. Both descriptive media-frame analysis and training of machine learning models were supported by the annotation process. The manually labelled subset was then used to train frame classification on the larger media/social data-set by means of supervised learning. This enabled us to integrate fine-grained content analysis with scalable computational classification into this study.

Dataset Source Links and Traceability

The public content audit was conducted with the help of football-media sources that cover football, containing listings or searchable records of Indian women's football, Indian Women's League activities, AIFF activities and Indian football video/media. The main source categories were:

I. AIFF Indian Women's League competition source: for official competition context (for IWL).
II. AIFF women's football source: for women's football, IWL 2, Blue Tigresses and women's football from the federation.
III. AIFF official website: Federation level football structure and official competition references.
IV. Indian Football YouTube channel: For public football video content and platform visibility auditing.
V. Olympics Indian Women's League coverage: applied to the scheduling and public media verification of IWL-related coverage.
VI. Indian women archers senior national team source: used for Indian women archers senior national team context and coverage related to Blue Tigresses.

These sources were used in the construction of the media audit frame, source channel categorization, search terms and content-verification process.

Data Pre-processing and Integration

To ensure that the data would be appropriate for the statistical analysis and machine learning modelling, data pre-processing was performed. Initial standardization was performed to ensure the consistency of column names across the various datasets: survey data, media/social data and annotation data. The numeric variables: engagement rate, visibility score, search rank, recommendation frequency, performance-focus score, aesthetic-focus score, and visibility-quality score were transformed to numeric data. Missing values were screened to determine variables that were not suitable for formula calculations (e.g., followers/subscribers and missing view counts). The common media_id field was used to combine the

media/social and manual annotation datasets. This matching resulted in a master dataset of 1000 media/social records, with 500 records having manual annotation information on it. Text data (e.g. titles, captions) was preprocessed by converting to lower case, removing unwanted symbols and regularizing spaces for natural language processing. Core audit metrics were then broken down to derive variables such as total interactions, engagement proxy, visibility differential, ranking parity gap, recommendation gap, misclassification rate, and framing bias score.

Core Metrics

A small, but dense, set of core metrics were employed to measure visibility, engagement, ranking, frequency of recommendation, inference of identity and framing bias. These metrics were chosen to reflect algorithmic results and representational trends within sports-media product.

As lower search rank values mean better placement, a positive parity gap in ranking means that the average placement for women's football content is worse. Likewise, a negative visibility differential shows that women's football content is less visible than men's football content.

Objective-wise Analysis Methods

Objective 1: Gender-Inference Accuracy

Objective 1 study assessed gender-inference accuracy by comparing the self-reported gender with gender inferred from the platform. The confusion matrix, accuracy, weighted precision, weighted recall, weighted F1-score, and misclassification rate were used to analyze the data. Misclassification rate was defined as the number of wrong identities inferred/total number of identities checked. Further role-wise and platform-wise mismatch analyses were performed to test if there were differences in inference errors by respondent type or by type of primary platform used.

Objective 2: Inferred Identity and Algorithmic Outcomes

In order to investigate how inferred identity is related to algorithmic outcomes, descriptive statistics, correlation analysis, ANOVA, Kruskal-Wallis testing, OLS regression and visibility prediction modelling were employed in the study for Objective 2. Visibility score, search-rank position, engagement rate, recommendation frequency and total interaction indicators were the key outcome variables. Group comparisons were performed between the football content for women and men as well as the visibility, rank, engagement and recommendations frequency to test whether there was any difference between sport/content gender categories.

Using correlation analysis, the relationship between visibility score, engagement rate, search rank, recommendation frequency, and total interactions were explored in terms of strength and direction. Group level differences were compared using ANOVA and Kruskal-Wallis tests. Predictor analysis of visibility score was conducted using OLS regression and machine-learning models were used to classify content into high and low visibility.

Objective 3: Fairness and Inclusiveness

The fairness and inclusiveness for Objective 3 was measured through the following indicators: exposure parity ratio, visibility differential, ranking parity gap, engagement gap, recommendation gap and group-wise fairness audit. The fairness audit analyzed the visibility and ranking results for men's football content, women's football content, tactical/performance women's content, commercial women's content, governance women's content, inspirational women's content, marginalizing women's content and achievement-oriented women's content.

Perceived visibility gap, ranking fairness score and inclusiveness score were also analyzed to determine indicators of fairness and inclusiveness based on the survey. A descriptive analysis was performed of these indicators, while comparisons were made between the different sports cent roles of respondents to determine if there were any differences between the groups regarding perceptions of digital sports-media fairness.

Media Narrative and Text Analysis

The media narrative analysis integrated sentiment analysis, topic modelling, gendered-language analysis, and the comparison between the performance and aesthetic framing. Sentiment analysis was used to categorize the text by title/caption-level language into positive, neutral, and negative categories. To find major clusters of content in the media/social dataset, TF-IDF vectorization and Non-negative Matrix Factorization were performed on it.

The frames were classified according to seven categories of narrative: tactical/performance,

lifestyle/aesthetic, achievement, governance, commercial, inspirational and marginalizing. These categories were chosen as they encompass sport-performance representation, as well as gendered media narratives. Gendered-language analysis was conducted regarding the presence of explicit, unclear or absent gendered language. The scores from the performance-focus and aesthetic-focus were compared to determine the framing bias score.

Qualitative Thematic Analysis

Thematic coding was completed with the assistance of the keywords in the open-ended survey responses. Thematic categories were created based on the recurring issues that were seen in the answers and on the objectives of the study. The main themes were low visibility, tactical-analysis gap, algorithmic bias, women's football growth, cross promotion needed, monetisation/sponsorship and fairness and inclusion.

The qualitative analysis was used to support and contextualize the quantitative findings. The visibility differential, ranking parity gap and media-frame results were then compared with the responses regarding low visibility and weak tactical analysis, for example. This facilitated a linkage of numerical audit findings with perceptions of visibility on platforms and representation in sports-media.

Machine-Learning Implementation

Model 1: Media Frame Classifier

The first machine-learning model categorised media contents according to the narrative frames. Cleaned title/caption text was used as the input feature with TF-IDF for Logistic Regression and Linear Support Vector Machine, which were implemented as baseline classifiers. The frame types were tactical/performance, lifestyle/aesthetic, achievement, governance, commercial, inspirational, and marginalizing. Accuracy, precision, recall, F1-score and confusion matrix were used to evaluate model performance.

To this end, the transformer-based BERT/RoBERTa model was proposed as an extension to be implemented in the future for fine-grained frame classification. This extension can be used to enhance students' semantic understanding of short sports media text, particularly where there is overlap in the frames of performance, achievement, governance and inspirational stories.

Model 2: Visibility Prediction Model

The second model was the one that predicted whether a content item was a high-visibility or low-visibility item. The median visibility score was used as the classification value to produce the target variable. The full visibility prediction model was implemented using Logistic Regression, Random Forest and XGBoost. Platform, sport/content gender, source/channel, content type, content frame, engagement rate, search rank, recommendation frequency, posting time, title length and total interaction indicators were among the feature sets.

Two versions of the visibility prediction model were estimated. All the platform, engagement, ranking, recommendation and content-context variables were included in the full model. To get a more conservative estimate that focuses only on content and contextual features, a second non-leakage model excluded search rank, engagement rate, total interactions, and recommendation frequency. This two-model approach enabled this study to differentiate between explanatory visibility prediction and content/context-only prediction.

Model 3: Fairness Audit

The third model was not a predictive classifier model but a fairness audit model. It examined the visibility, ranking, engagement and recommendation outcomes of key content groups, including men's football content, women's football content, tactical/performance women's content, commercial women's content, governance women's content, inspirational women's content, marginalising women's content and achievement-oriented women's content.

The fairness audit was conducted to assess if the visibility and ranking outcomes of women's football were comparable to men's football, and if there were any differential amplification or weakening of particular frames on women's football. This model was designed to determine the presence or absence of algorithmic gatekeeping, the placement of the weaker ranking, the reduction of visibility score and the differentiated amplification of the algorithmic gatekeeping phenomenon based on each of the narrative categories.

STATISTICAL EXPLORATORY DATA ANALYSIS AND INFERENTIAL STRATEGY

Exploratory data analysis was performed separately for the survey, media/social and manually annotated components before the integrated models were interpreted. The 1,000-item media/social dataset comprised 543 YouTube records (54.3%), 336 News/Web records (33.6%) and 121 Official Web records (12.1%). Women's football accounted for 853 records (85.3%) and men's football for 147 (14.7%). The 500 matched manual annotations represented 50.0% of the media/social records. Figure 15 visualizes these composition checks, while Table 14 reports the principal derived proportions and comparison indicators.

For the survey, only 48 of 200 responses (24.0%) contained both self-reported and platform-inferred gender and were therefore eligible for the inference-accuracy analysis. Twenty-four of those paired cases were classified correctly and 24 were mismatched. In the manual annotation subset, performance/competition represented 386 of 500 records (77.2%), whereas general sports news represented 21.6% and commercial media 1.2%. Positive and neutral tones together accounted for 86.2% of annotations; explicit gendered language was present in 8.2%. In the larger media/social text analysis, 74.1% of records were neutral, 24.8% positive and 1.1% negative.

Because the gender-content groups were unequal in size, mean comparisons were evaluated using both one-way ANOVA and the rank-based Kruskal-Wallis test. Both tests supported differences in visibility (ANOVA $p = 0.00071$; Kruskal $p = 0.00092$), search rank ($p = 0.00001$ and $p < 0.00001$) and recommendation frequency (both $p < 0.00001$), but not engagement rate ($p = 0.30321$ and $p = 0.28560$). Relative to the men's mean, women's visibility was 6.2% lower, the numerical search-rank value was 38.6% higher (and therefore worse), engagement was 4.1% lower and recommendation frequency was 4.7% higher. These relative contrasts are descriptive and do not replace effect sizes or confidence intervals.

The correlation matrix showed that visibility was strongly associated with engagement ($r = 0.787$), moderately and inversely associated with search rank ($r = -0.595$), and moderately associated with total interactions ($r = 0.487$). Recommendation frequency had little linear association with visibility ($r = -0.012$). The OLS model explained 97.3% of observed variance (adjusted $R2 = 0.972$), but the prediction sensitivity analysis provides the more conservative interpretation: Logistic Regression accuracy declined from 0.936 in the full model to 0.600 in the non-leakage model, a reduction of 33.6 percentage points. Accordingly, the full-model result should be read as explanatory performance within this audit rather than as stand-alone evidence of out-of-sample generalizability.

RESULTS

Dataset Profile

The final data set made up of three components: survey responses, media/social content records, and manually annotated media items. The survey included 200 responses from various stakeholder groups related to football consumption and women's football visibility. Media/social data set comprised 1000 football related data items gathered from YouTube, News/Web and Official Web sources. Manual annotation data set contained 500 media items coded, and matched with the media/social data set by the common media identifier.

Table 2 shows the characteristics of the data set and the platforms involved. The largest category was YouTube, followed by News/Web and Official Web sources. The women's football content was the largest group, with men's football content selected as a comparison group for the visibility, ranking, engagement and fairness analysis, based on the sport/content gender.

Gender-Inference Accuracy Results

The first objective of the study was to look at gender-inference accuracy which is the accuracy in the comparison between self-reported gender and platform-inferred gender. Based on the total number of survey cases, 48 cases had valid information for both self-reported and inferred gender. Of these valid cases, 24 were correctly matched and 24 were mismatched, resulting in a gender-inference accuracy of 50.0% and a misclassification rate of 50.0%.

Table 3 shows that the weighted precision was 0.535, the weighted recall was 0.500 and the weighted F1-score was 0.516. The results of these suggest that the reliability of the inferred gender categories with the valid checked subset was limited. A role-wise analysis revealed that the greatest mismatch was with student/research participants and a platform-wise analysis revealed that the greatest mismatch was on Instagram.

The confusion matrix also showed that mismatches could not be restricted to one category. Misery was present in all categories—female, male, non-binary and 'prefer not to say'. This discovery indicates that, if used to algorithmically rank, segment audiences and/or recommend sports media, care should be given when using labels that are inferred from a user's race, ethnicity, and/or gender.

Manual Media-Framing Results

A manual annotation was carried out on 500 media items, focused on content framing, tone, presence of gendered language, and a performance versus aesthetics emphasis. Table 4 is a composite of the main framing distribution, tone distribution, gendered-language coding, and key framing-score results.

The most prevalent primary frame was performance/competition with 386 annotated items. In total 108 items of general sports news and 6 items of commercial media were used. The majority of the content was positive or neutral with only 6 negative items on tone analysis. 369 items had no gendered language; 90 items had unclear gendered language and 41 items had clear gendered language. The average score for performance-focus was 2.670, and the average for aesthetic-focus was 0.234. The mean of the framing-bias score was -2.436, which means that the data set was more performance-oriented than aesthetic-oriented.

The framing results indicate that the most frequent representational problem in the data set is not the prevalence of aesthetic and/or lifestyle framing. Rather, the data set was predominantly driven by performance. But that did not necessarily mean equal visibility for women's football and better rankings for the content.

Core Visibility and Fairness Results

Core visibility and fairness results are shown in Table 5. The mean visibility score of the men's football content was 75.049, while the score of the women's football content was 70.382. This resulted in a “visibility difference” of -4.667 which suggested that women's football content was less visible on average than men's football content. The exposure parity ratio was less than full parity, with a value of 0.938.

The results from the ranking were also similar. The mean rank for the men's football content was 5.565 and for women's football content was 7.712. The positive ranking parity gap of 2.147 suggests that women's football content on average had lower search/audit placements. The engagement gap was less than 0.149, whereas the recommendation gap was positive at 0.532, suggesting that there was a slight presence of women's football content in repeat engagement frequency.

Based on these results, it is revealed that the football content for women was not entirely lacking in the media/platform environment. Instead, it was evident in the form of reduced visibility scores and sub-optimal ranking.

Statistical Testing Results

The differences between the amount of football content seen by men versus women were statistically tested for significance for visibility, rank, engagement and recommendation frequency. The tests employed were both ANOVA and Kruskal-Wallis since group comparisons and non-parametric confirmation were required.

The effect of sex on the visibility score of women's football content in comparison to men's football content was statistically significant as seen in Table 6. The difference in search-rank was also statistically significant suggesting that women football content was not as well placed as search-ranks. The difference in the engagement rate was not statistically significant and was small. The significant difference was found in the frequency of recommendation, in which women's football content seemed to be repeated more in the repeated frequency of audit.

The statistical outcomes indicate that it was not engagement but visibility and ranking that was the primary distinction. However, in the case of women's football, while the frequency of recommendation was marginally increased, the average visibility was lower, and the placement was also lower.

Correlation and Regression Results

Correlation analysis was performed to investigate potential relationships among the visibility score, engagement rate, search rank, total number of interactions, and recommendation frequency. The results in Table 7 indicated a strong positive relationship between visibility score and engagement rate, and a moderate positive relationship between the variables of visibility score and total interactions. The negative correlation between visibility score and search rank was to be expected as a lower rank value was

expected to be a higher placement. There was little correlation between recommendation frequency and visibility score.

The adjusted R2 value of the corrected OLS regression model for visibility score was high (0.972) and explained a high proportion of the variance in the visibility score. The strongest positive predictor was the engagement rate and search rank was a strong negative predictor. As seen in the regression results, there was a strong relationship between higher engagement and better placement in the ranking, and higher visibility.

Regression and correlation results support the notion that visibility is linked to the relationship between ranking and engagement. Recommendation frequency was not the only factor to describe the quality of visibility, meaning that if a website recommends something repeatedly, this does not mean that it has a good ranking and high visibility.

Media Narrative and Topic Modelling Results

Sentiment, topic distribution and general frame categories were analyzed using media narrative analysis. Table 8 indicates that major proportion of content was neutral followed by positive content. There was limited negative sentiment. Five predominant content clusters were found by topic modelling using TF-IFIDF and Non-negative Matrix Factorization techniques: East Bengal FC and coverage on the club, IWL 2025-26 and fixture coverage, AFC Women's Asian Cup coverage, Indian Women League coverage, live match or Sesa FA related coverage.

After frame extension, the broad frame distribution revealed that the most prominent frame was performance competition (768 media/social items). There were 220 items of general sports news and 12 items of commercial media.The showers of the story line suggest that women's football coverage was mostly neutral positive, and performance based. Hence, the primary sign of algorithmic gatekeeping was not necessarily unfavorably negative media tone but lesser visibility and ranking results.

Qualitative Thematic Results

Open-ended survey answers were coded to find common perceptions about women's football visibility and algorithmic media distribution. The major themes and the frequency are shown in Table 9. Low visibility was the most common response with 92 responses. The top gaps identified in the 66 responses were tactical-analysis gap, growth of women's football, algorithmic bias, and cross-promotion needs.

The qualitative results confirmed the quantitative results. Low visibility and Poor tactical play and important aspects to address. These themes are related to what was found in the ranking difference between men's and women's football content and the differential in visibility.

Machine-Learning Results

The machine-learning step comprised of three models: (1) media frame classifier, (2) visibility prediction model, and (3) fairness audit model. The aim of this phase was to determine if there was validity in a computational classification of content frames, if high and low visibility could be predicted, and if there were measurable differences in the fairness of these classifications between content groups.

Model 1: Media Frame Classifier

Model 1 segmented media content into seven classes of narrative frame. The results of the seven-class frame distribution and the model performance are shown in Table 10. Tactical/performance was the biggest frame category, with governance and commercial content as the next two. Logistic Regression and Linear SVM were tested as baseline classifiers. The accuracy of linear SVM was 0.424 and weighted F1-score 0.438 which was better.

The moderate performance of the frame classifier shows that seven-class media framing is a classification task which is more difficult than the broad frame separation. There is some overlap between governance, achievement, inspirational and tactical/performance frames that may have limited classification.

Model 2: Visibility Prediction Model

Model 2 simply determined if a content item was a high-visibility or low-visibility one. The median of the visibility scores was determined as the classification threshold. The full visibility model was implemented using Logistic Regression, XGBoost and Random Forest. Another non-leakage model was also tested without the variables of search rank, engagement rate, total interactions, and recommendation frequency.

Table 11 indicates that the accuracy of the whole Logistic Regression model is 0.936, precision is 0.936, recall is 0.936, F1-score is 0.936 and ROC-AUC is 0.989 which is the best overall result. XGBoost gave also good performance

followed by random forest. In the non-leakage setting, Logistic Regression was able to reach an accuracy of 0.600 and an F1-score of 0.609, while Random Forest produced an accuracy of 0.588 and an F1-score of 0.596.

The comparison between the full model and non-leakage model indicates that the ranking and engagement dynamics have a strong influence on the visibility. Content and contextual variables contributed for moderate prediction power, whereas outcome-related visibility signals contributed significantly to the level of classification.

Model 3: Fairness Audit

Model 3 investigated whether gender and content-frame groups differed in terms of fairness. Table 12 shows the visibility, ranking and engagement proxy values of men's football content, women's football content and the major women's football content categories. The mean visibility score of men's football content was higher than women's football content as a whole, and the content had a better mean rank than overall women's football content. Tactical/performance content was more visible in women's football than commercial and achievement oriented women's content. The least average rank went to achievement-oriented women's football content, with commercial women's content also being relatively low on visibility and ranking.

The fairness audit highlights that the lack of visibility inequality was due to the absence of women's football content. Rather, the inequality emerged as a result of reduced quality of ranking and decreased mean visibility for both narrative categories, as well as unequal amplification between the two.

Summary of Key Findings

The findings reveal algorithmic differences in visibility and gendered distribution of media content in Indian football. Gender-inference accuracy was 50.0%, which meant that there was a high level of mismatch in the valid checked identity cases. The mean visibility of women's football content was lower than the men's football content and the search/audit ranking was also lower. There was not a significant difference in engagement between women's and men's football content and women's content had a slightly higher rate of recommendations.

Overall, media tone was neutral-positive and performance framing was the majority of the data. This indicates that the problem wasn't necessarily bad representation or high aesthetic flair, but less visibility and less ranking placement. The accuracy of the full visibility prediction model was 93.6% and the conservative non-leakage model was 60.0%. The fairness audit also revealed that women's football material on routine and achievement was still less well ranked and displayed. The overall findings suggest that algorithmic gatekeeping is primarily a process of rank, and not a total ban on accessing the digital media environment based on the quality and visibility score.

DISCUSSION

The study results indicate that the presence or absence of content is not the only issue with algorithmic gatekeeping in Indian women's football. Women's football content was significantly represented in the data, but was not as visible as men's football content and was not as highly ranked for search/auditing. This means that the visibility inequality is manifested not at the level of outright exclusion, but in quality ranking, discoverability and amplification at platform level. The visibility differential of -4.667 and exposure parity ratio of 0.938 indicate that women's football was not as visible as men's football on average and the ranking parity gap of 2.147 confirm that it was ranked lower on average. The gender-inference results also point to a significant issue with AI systems in media. Gender inference achieved an accuracy of 50.0%, and a misclassification rate of 50.0%. This means that gender categories that platforms infer from users' activity might not necessarily reflect what the user is or who the creator is. Inferred categories in recommendation, targeting or audience segmentation can add additional distortion in visibilities. A high level of mismatch between groups of respondents and platforms points to the need for caution in algorithmic identity inference in sports-media analytics.

The results of the engagement provide helpful contrast. The engagement in women's football was slightly lower than men's football but this was small and not significant. That is, reduced visibility does not necessarily imply that audience response is less strong. Rather, there are notable differences in rank and visibility implying that the ordering of platforms, search listings and recommendation logic may have a greater influence. The recommendation gap was positive for women's football, with women's content slightly more likely to be found in the repeated audit

records. But just because you saw something repeatedly doesn't mean it was ranked as number one or the visibility was the same.

The media-framing results also give helpful clarification. The set did not show any lifestyle or aesthetic frames. Performance/competition framing was the strongest category and the mean framing-bias score was negative, meaning that the content was more performance than aesthetic oriented. This is significant as it calls into question the notion of women's sport being predominantly portrayed as appearance or lifestyle stories. The more important issue in this study was that there was still no visibility of the women's football content equal to the men's football content even if it was of a performative nature. The interpretation is supported by machine-learning results. When the full visibility prediction model was examined, variables of ranking, engagement, platform, source, and content were found to show high degree of visibility prediction performance. Moderate performance was found for the non-leakage model, however, indicating that visibility outcomes are not just attributable to the content features. This reinforces the conclusion that there is a great deal of influence on discoverability at the algorithmic and platform level.

In conclusion, the study reveals that the visibility of women's football in India is a multi-layer process that includes gender inference, ranking placement, engagement signals, media framing, and platform distribution. The most important thing that the study brings to the table is that it takes the discussion of underrepresentation beyond the abstract and presents the measurable evidence of algorithmic visibility inequality. The results indicate that to make women's football more visible, there is a need not only for more content creation, but also for more effective ranking practices, cross-promotions, transparent recommender systems, and platform responsibility.

THEORETICAL IMPLICATIONS

The findings extend algorithmic-gatekeeping theory by showing that exclusion can operate through allocation quality rather than through the complete absence of content. Women's football formed the majority of the audited corpus, yet its mean visibility and ranking remained weaker. This separates representational presence from algorithmic prominence and indicates that volume-based measures alone can conceal a second-order visibility disadvantage.

The combination of comparable engagement, performance-oriented framing and lower visibility also qualifies demand-side explanations. If women's content were disadvantaged mainly because audiences were uninterested or because coverage was predominantly aesthetic, the observed pattern would be expected to differ. Instead, the results are more consistent with a sociotechnical account in which ranking position, source context and accumulated engagement signals jointly mediate discoverability. The study therefore links feminist media analysis to platform-level allocation mechanisms rather than treating representation and computation as separate domains.

A further implication concerns measurement. The 50.0% inference accuracy among valid paired cases indicates that gender categories can be unreliable inputs before any recommendation decision is made. Fairness analysis must therefore examine label validity as well as outcome parity. Finally, the marked performance reduction in the non-leakage model demonstrates why fairness scholarship should distinguish explanation of an observed platform outcome from prediction using genuinely antecedent features. High accuracy produced by outcome-adjacent variables may describe the existing allocation process without providing a fair or transferable decision rule.

PRACTICAL IMPLICATIONS

For digital platforms, the results support routine, position-weighted exposure audits by sport/content gender and narrative frame. Dashboards should report not only recommendation counts but also average rank, first-page exposure, visibility parity and uncertainty over time. Inferred gender should not be used as a silent proxy where voluntary self-identification is unavailable; users and creators should be able to inspect, correct or opt out of such attributes. Ranking teams should test parity before and after model updates and investigate sources or features that repeatedly produce large group differences.

For AIFF, leagues, clubs and sports-media organizations, a consistent publication calendar, standardized metadata, searchable player and match terminology, and coordinated cross-promotion can strengthen the signals available to search and recommender systems. The relatively weak performance of achievement and commercial categories suggests a need to connect these stories with match context, tactical analysis and official source

links rather than publishing them as isolated items. Regular tactical and player-development coverage can also address the survey's identified analytical-content gap.

For sponsors and advertisers, raw impression or recommendation volume should be supplemented by placement quality, verified engagement and gender-parity indicators. Contracts and campaign evaluations can include minimum prominence standards and disaggregated reporting for men's and women's properties. For researchers and auditors, search terms, audit accounts, timestamps, geographic settings and ranking positions should be archived so that results can be reproduced and compared across events, seasons and platform changes.

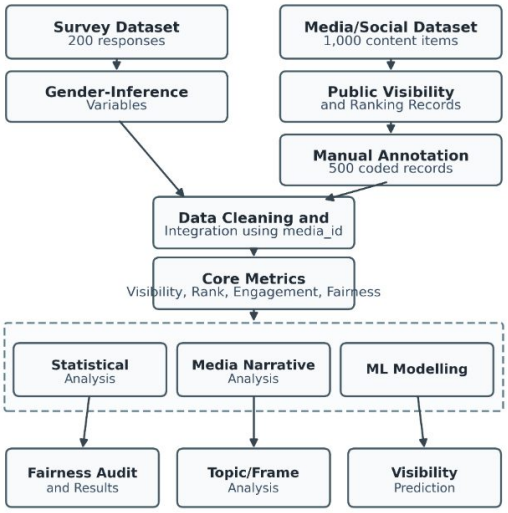


Figure 1. Proposed mixed-method computational audit workflow for algorithmic gatekeeping and gendered visibility analysis

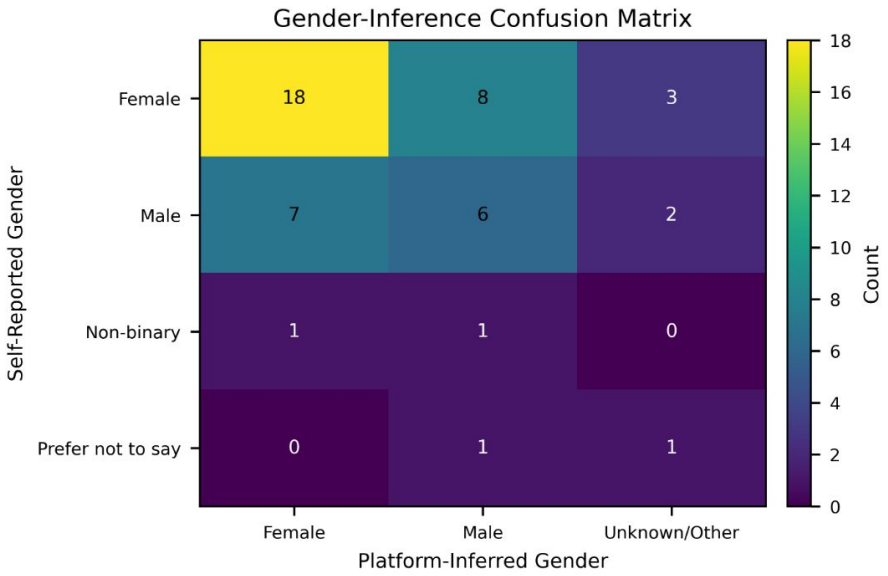


Figure 2. Gender-Inference Confusion Matrix

CONCLUSION

This study explored the algorithmic gatekeeping and gendered visibility in digital media representations of women's football in India. The study included a mixed-method computational audit involving survey responses, media/social content analysis, manual annotation, statistical testing, and machine-learning models. The results indicated that women's football content was not non-existent on digital platforms, but did have lower average visibility and search/audit ranking than men's football content. The visibility differential of -4.667 and the ranking parity gap of 2.147 signal that the main disparity is not one of content available, but rather discoverability and ranking quality.

The misclassification rate was also high (50.0%) for the gender-inference analysis, indicating that platform-inferred genders and identities might not be suitable for

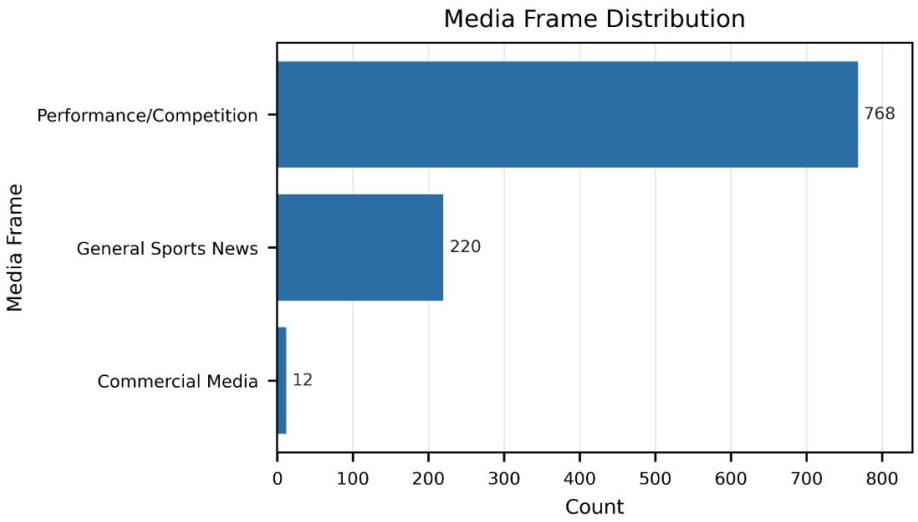


Figure 3. Media Frame Distribution

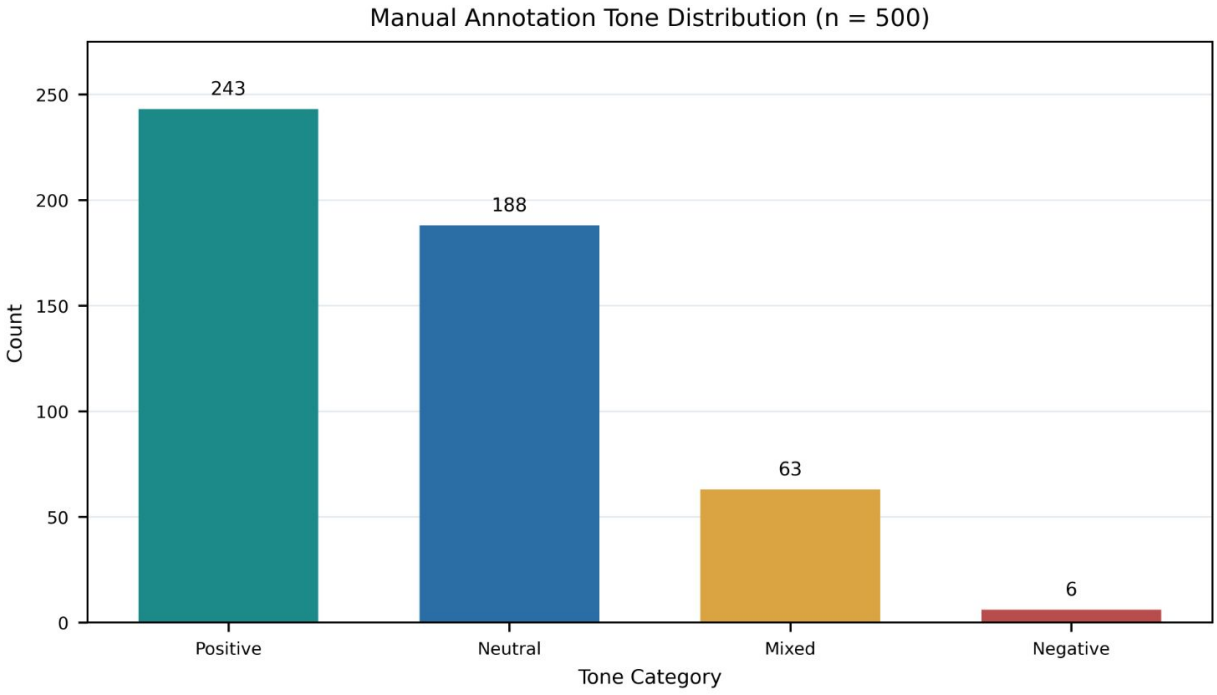


Figure 4. Tone Distribution

Table 1. Core Metrics Used in the Study

Metric	Formula / Meaning
Engagement Rate	(likes + comments + shares) / followers × 100
Engagement Proxy	Available engagement-rate percentage recorded in the dataset
View Engagement	(likes + comments) / views × 100
Visibility Differential	Women's mean visibility − Men's mean visibility
Exposure Parity Ratio	Women's mean visibility / Men's mean visibility
Ranking Parity Gap	Women's mean rank − Men's mean rank
Recommendation Gap	Women's mean recommendation frequency − Men's mean recommendation frequency
Misclassification Rate	Incorrect inferred identity / Total checked identities
Framing Bias Score	Aesthetic-focus score − Performance-focus score

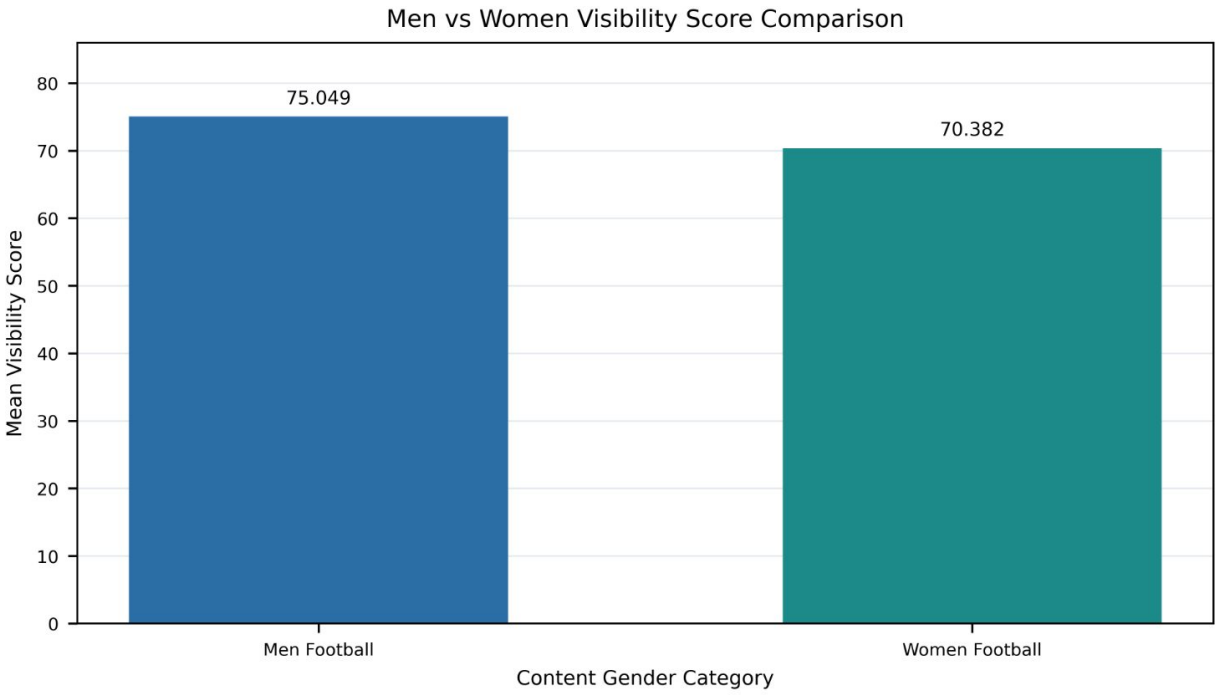


Figure 5. Men vs Women Visibility Score Comparison.

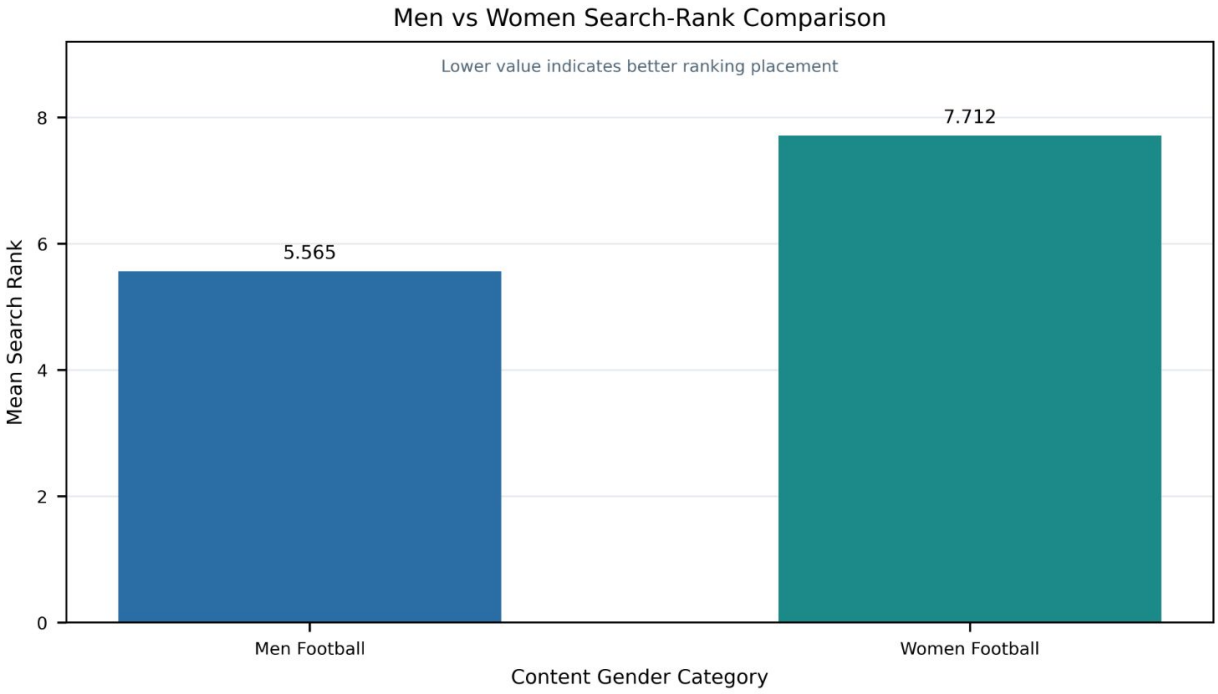


Figure 6. Men vs Women Search-Rank Comparison

Table 2. Dataset Profile and Platform Composition

Component / Category	Count
Survey responses	200
Media/social items	1,000
Manual annotations	500
Matched annotation records	500
YouTube items	543

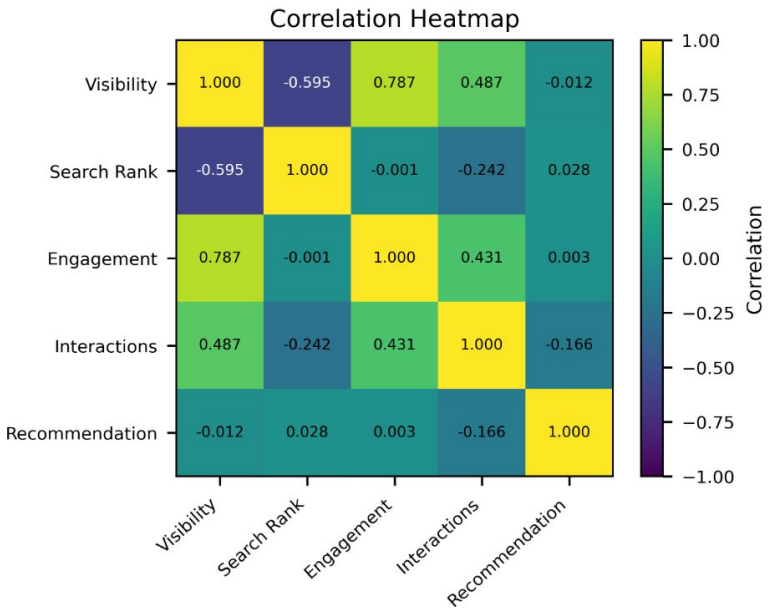


Figure 7. Correlation Heatmap

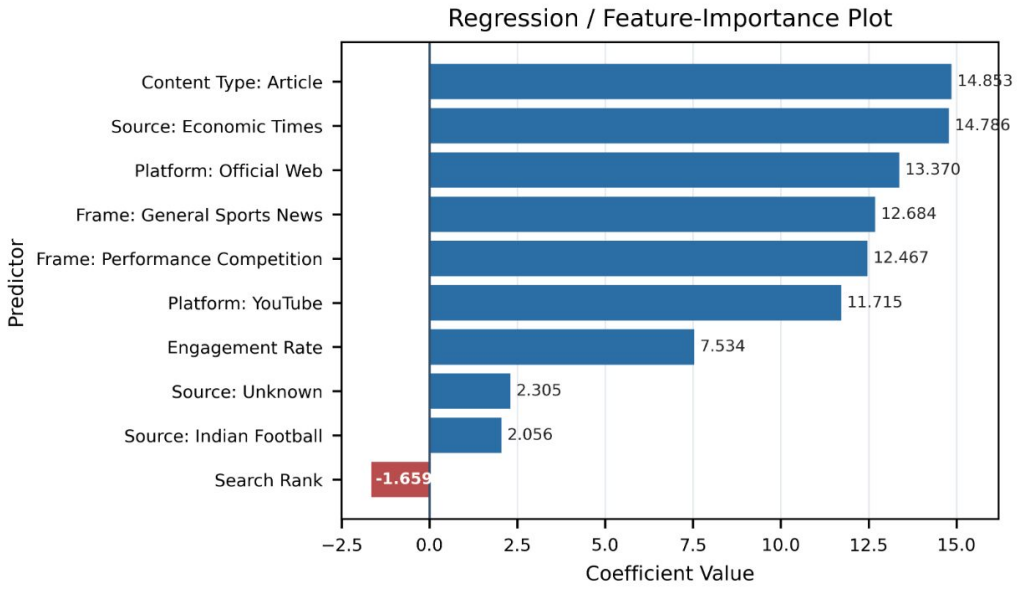


Figure 8. Regression or Feature-Importance Plot

Table 3. Gender-Inference Accuracy and Misclassification Results

Measure	Result
Valid checked identities	48
Correct matches	24
Mismatches	24
Accuracy	50.0%
Weighted precision	0.535
Weighted recall	0.500
Weighted F1-score	0.516
Misclassification rate	50.0%
Highest role-wise mismatch	Student/Research participant: 100.0%

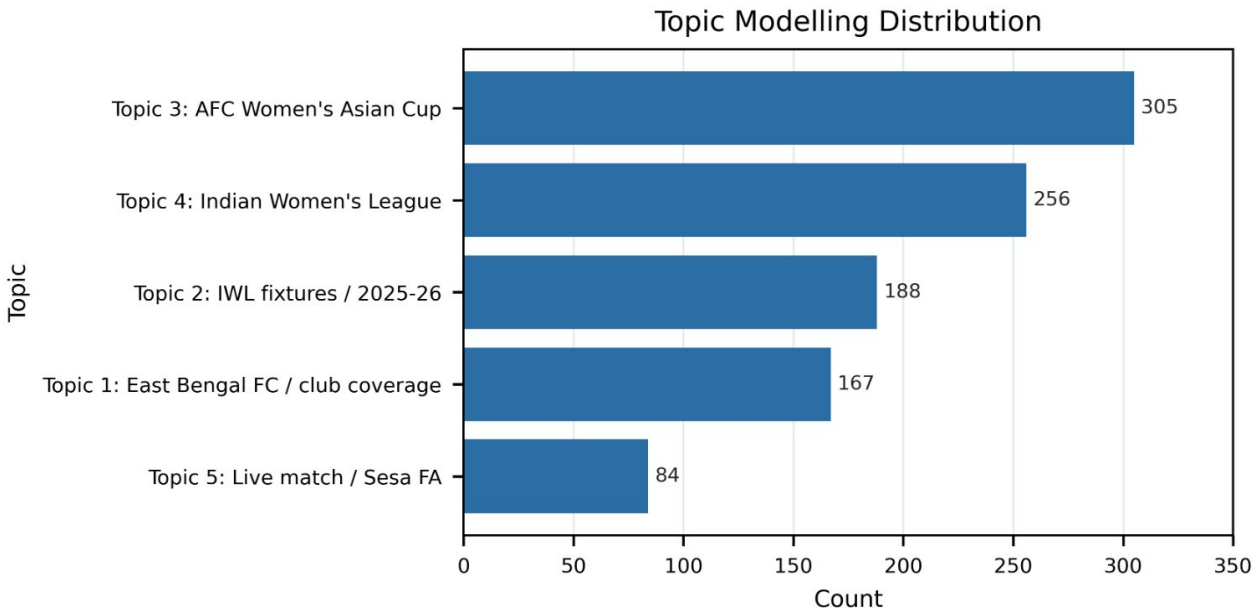


Figure 9. Topic Modelling Distribution

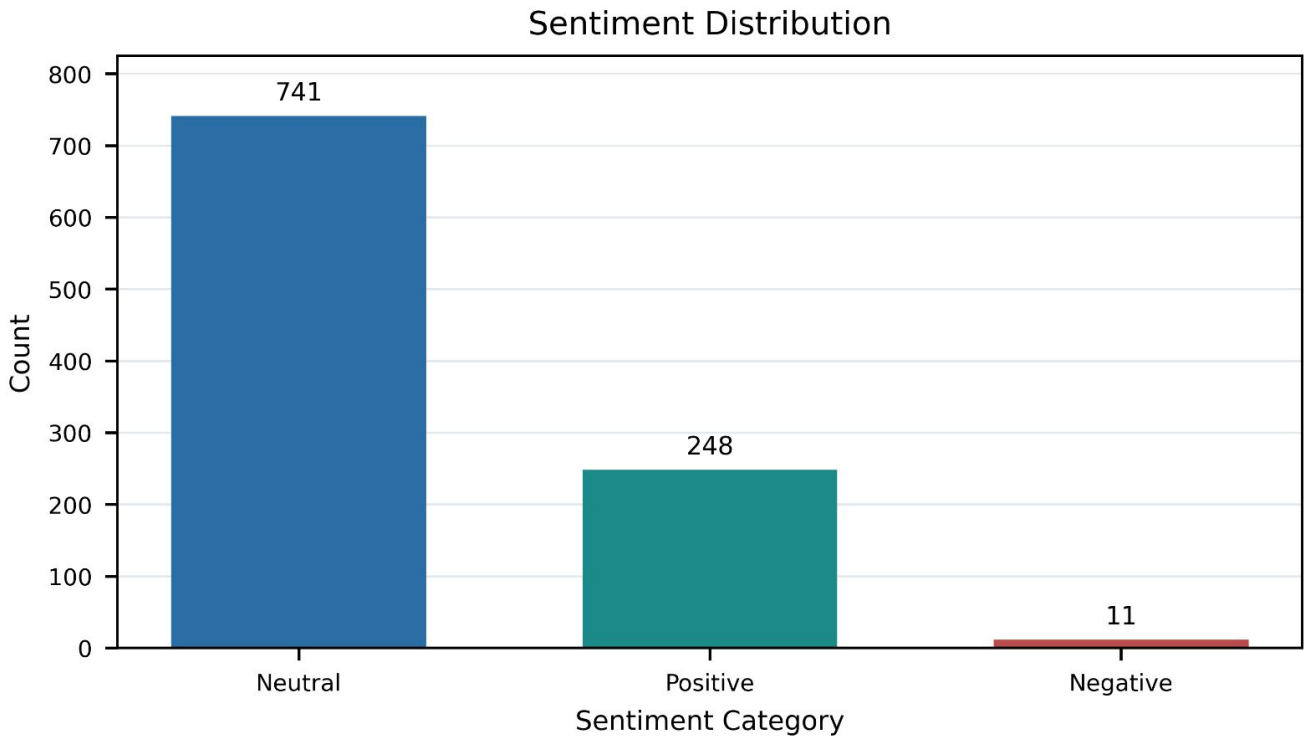


Figure 10. Sentiment Distribution

Table 4. Manual Framing, Tone and Gendered-Language Results

Category	Main Result
Dominant primary frame	Performance/competition: 386
General sports news	108
Commercial media	6
Positive tone	243

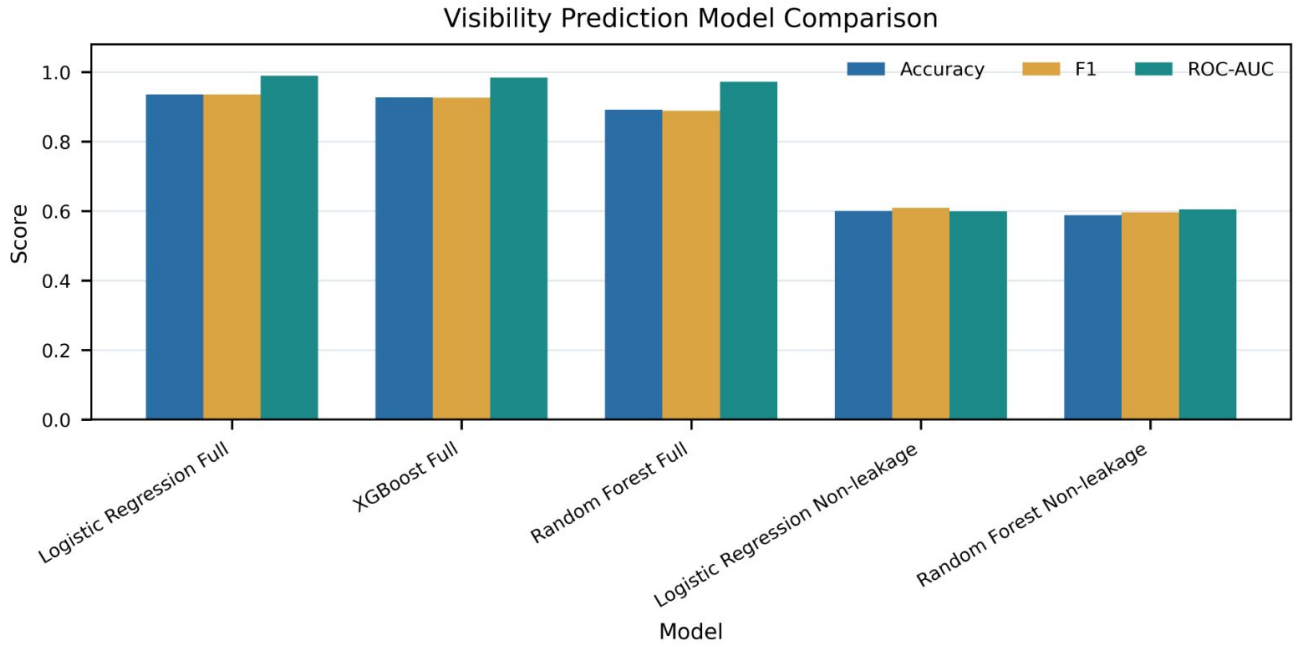


Figure 11. Visibility Prediction Model Comparison

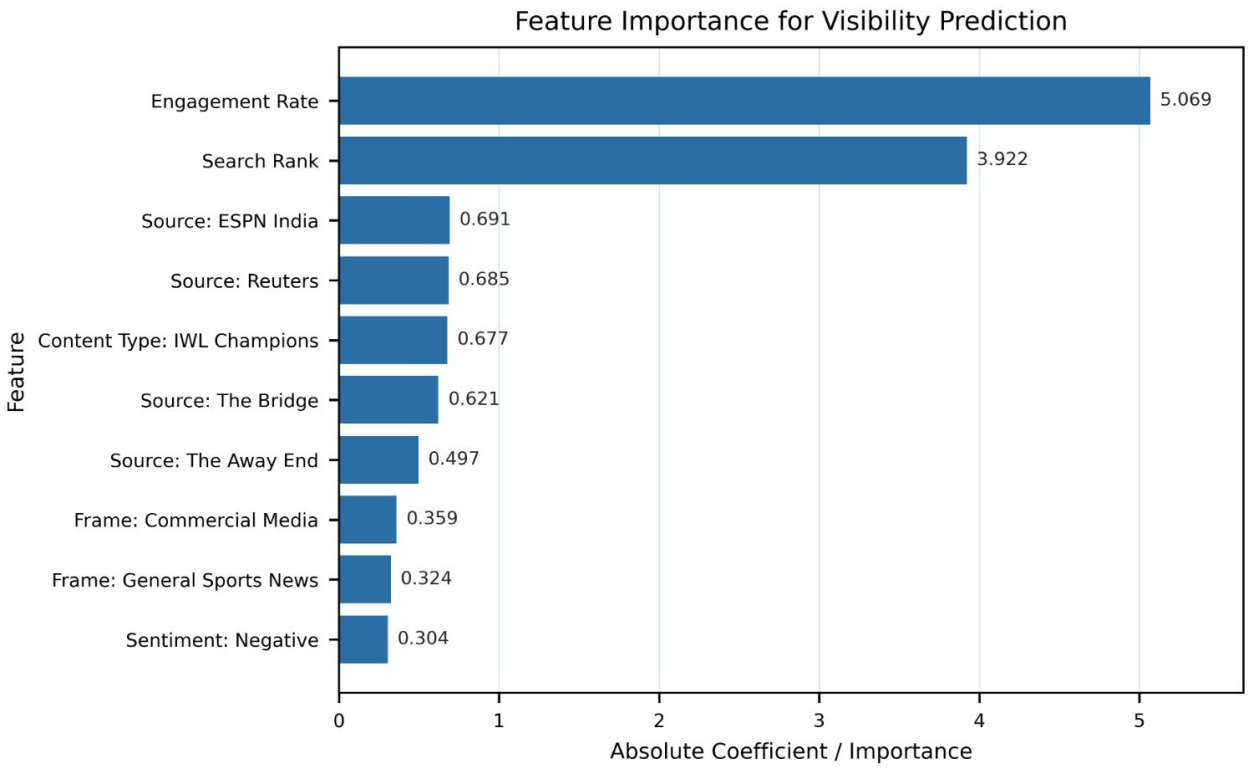


Figure 12. Feature Importance for Visibility Prediction

Table 5. Core Visibility, Ranking and Fairness Metrics

Metric	Result	Interpretation
Men's mean visibility	75.049	Higher than women's
Women's mean visibility	70.382	Lower than men's
Visibility differential	-4.667	Women's visibility lower

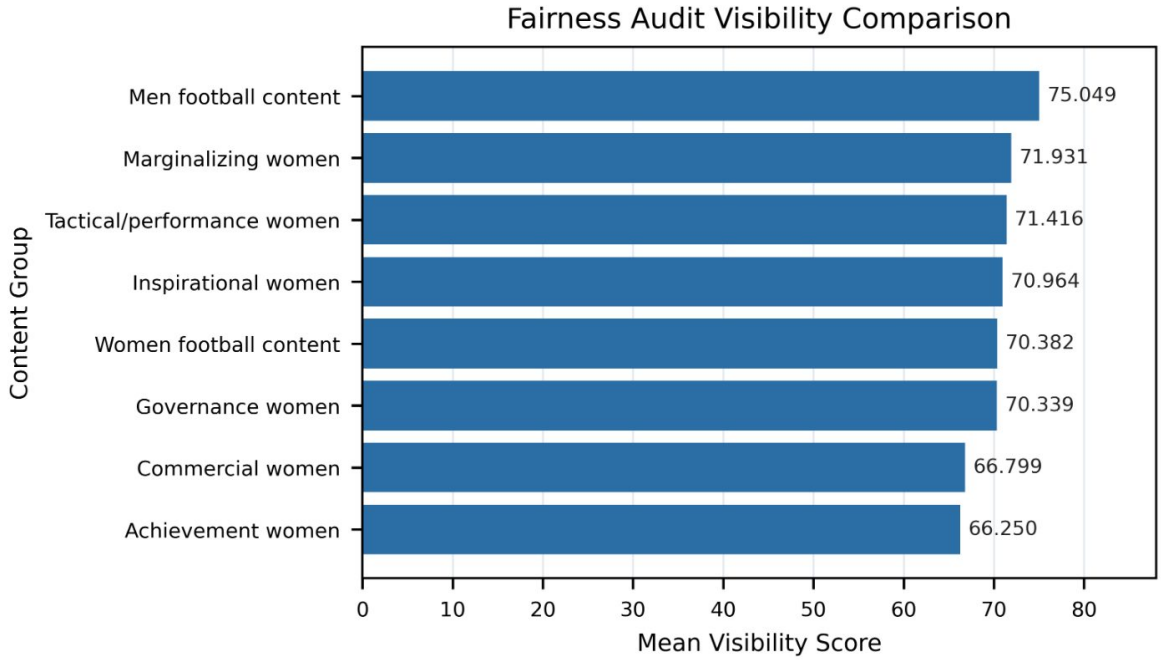


Figure 13. Fairness Audit Visibility Comparison

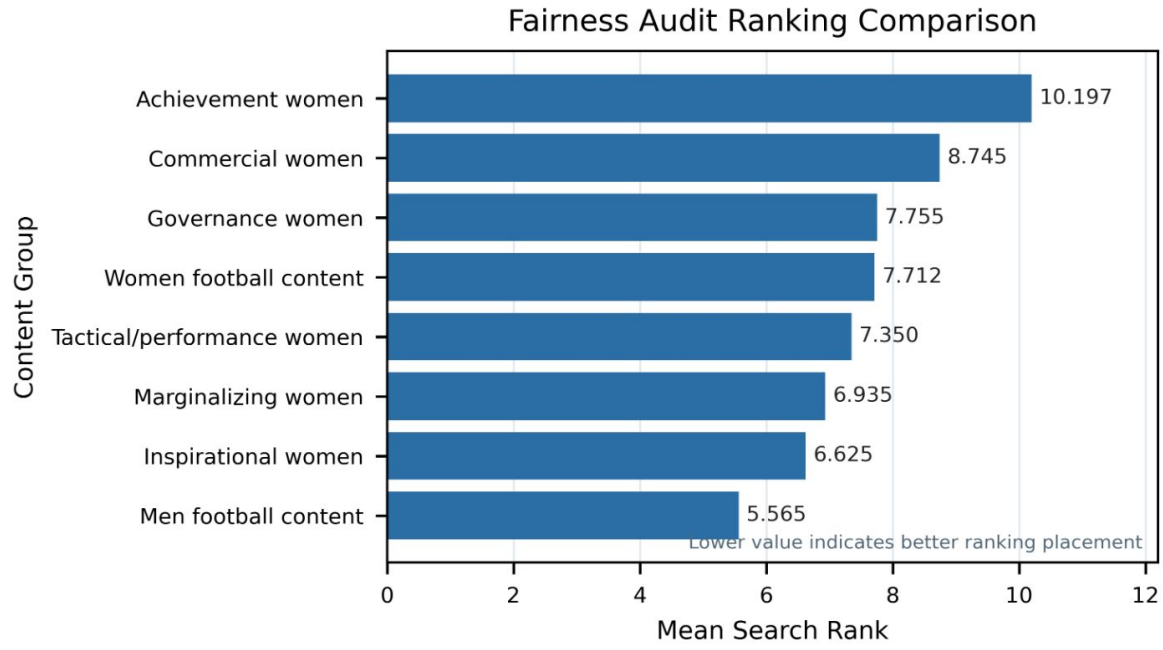


Figure 14. Fairness Audit Ranking Comparison

Table 6. Statistical Comparison of Men's and Women's Football Content

Metric	Women Mean	Men Mean	Difference	ANOVA p-value	Kruskal p-value	Result
Visibility score	70.382	75.049	-4.667	0.00071	0.00092	Significant
Search rank	7.712	5.565	2.147	0.00001	<0.00001	Significant
Engagement rate	3.514	3.663	-0.149	0.30321	0.28560	Not significant

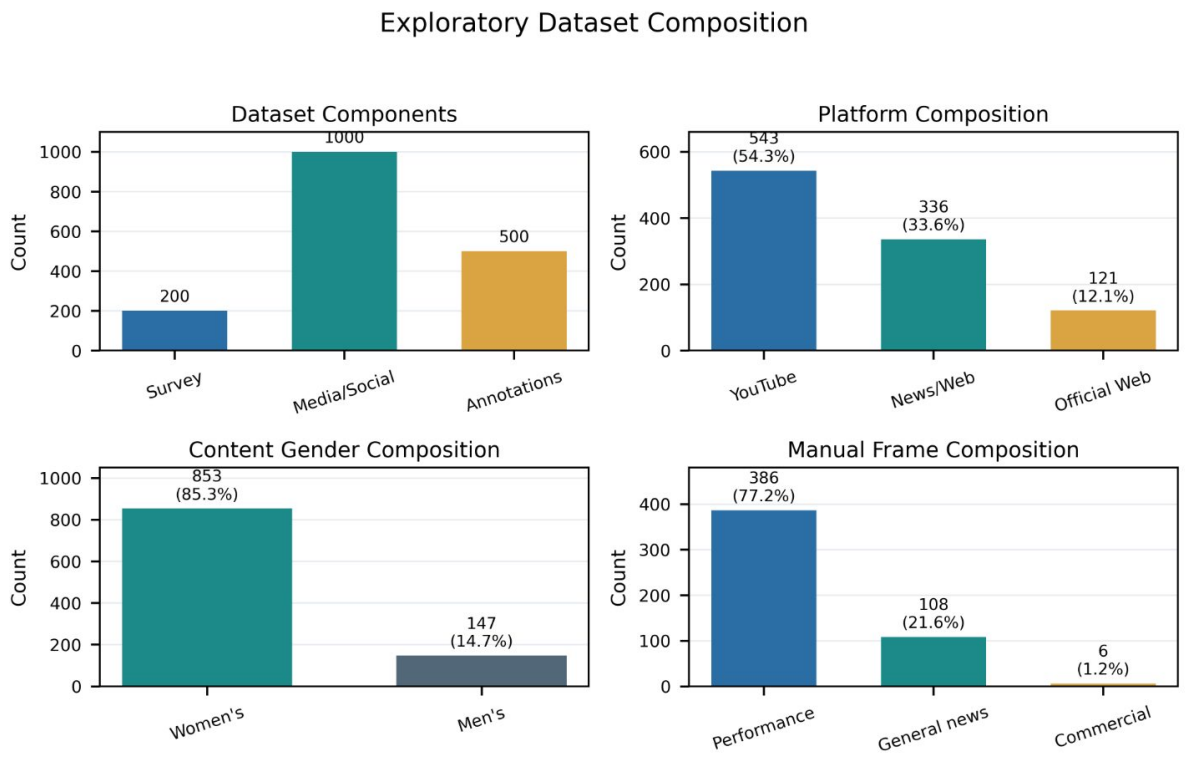


Figure 15. Exploratory dataset composition across study components, platforms, content gender and manual frames

Table 7. Correlation and Regression Summary

Analysis	Result
Visibility × Engagement correlation	0.787
Visibility × Search rank correlation	-0.595
Visibility × Total interactions correlation	0.487
Visibility × Recommendation frequency correlation	-0.012
OLS regression R^2	0.973
Adjusted R^2	0.972
Observations	1,000
Strong positive predictor	Engagement rate
Strong negative predictor	Search rank

Table 8. Sentiment and Topic Modelling Results

Analysis	Main Result
Neutral sentiment	741
Positive sentiment	248
Negative sentiment	11
Topic 1	East Bengal FC / club-specific coverage
Topic 2	IWL 2025–26 and fixture coverage
Topic 3	AFC Women’s Asian Cup
Topic 4	Indian Women’s League coverage
Topic 5	Live match / Sesa FA coverage
Dominant broad frame	Performance competition: 768
General sports news	220

Table 9. Open-Response Thematic Results

Theme	Frequency	Percentage
Low visibility	92	46.0%
Tactical-analysis gap	66	33.0%
Women's football growth	65	32.5%
Algorithmic bias	47	23.5%
Cross-promotion needed	29	14.5%

Table 10. Media Frame Classification Results

Model / Frame Result	Value
Tactical/performance frame	237
Governance frame	126
Commercial frame	79
Marginalizing frame	25
Achievement frame	24
Inspirational frame	9
Logistic Regression accuracy	0.408
Logistic Regression weighted F1	0.425
Linear SVM accuracy	0.424
Linear SVM weighted F1	0.438
Best model	Linear SVM

Table 11. Visibility Prediction Model Performance

Model	Accuracy	Precision	Recall	F1	ROC-AUC
Logistic Regression full model	0.936	0.936	0.936	0.936	0.989
XGBoost full model	0.928	0.942	0.912	0.927	0.984
Random Forest full model	0.892	0.915	0.864	0.889	0.972
Logistic Regression non-leakage	0.600	0.595	0.624	0.609	0.599
Random Forest non-leakage	0.588	0.585	0.608	0.596	0.605

Table 12. Fairness Audit Across Content Groups

Group	Items	Mean Visibility	Mean Rank	Engagement Proxy
Men football content	147	75.049	5.565	3.663
Women football content	853	70.382	7.712	3.514
Tactical/performance women content	371	71.416	7.350	3.562
Commercial women content	94	66.799	8.745	3.285
Governance women content	139	70.339	7.755	3.527
Inspirational women content	24	70.964	6.625	3.375
Marginalizing women content	154	71.931	6.935	3.545
Achievement women content	71	66.250	10.197	3.524

Table 13. Tabular Synthesis of Literature and Its Relevance to the Present Study

Evidence base	Theoretical/empirical strand	Central contribution	Key limitation	Relevance to this study
Gillespie (Gillespie, 2014; Gillespie, 2018); Van Dalen (Van Dalen, 2023)	Algorithmic gatekeeping	Ranking and recommendation allocate public attention.	Limited sport- and gender-specific outcome testing.	Defines visibility and rank as gatekeeping outcomes.
Bucher (Bucher, 2018); Van Dijck et al. (Van Dijck et al., 2018); Andrejevic (Andrejevic, 2019)	Platform power	Platform rules and feedback loops shape discoverability.	Often conceptual; limited paired audit data.	Explains cumulative advantage from prior engagement signals.
Criado-Perez (Criado-Perez, 2020); D'Ignazio and Klein (D'ignazio & Klein, 2023)	Feminist data studies	Data categories and missingness reproduce structural power.	Does not by itself specify sport-ranking metrics.	Supports analysis of labels, visibility and institutional context.
Fosch-Villaronga et al. (Fosch-Villaronga et al., 2021); Keyes (Keyes, 2018)	Gender inference	Automatic inference can misgender and erase non-binary identities.	Predominantly generic social/HCI contexts.	Motivates self-reported versus inferred-gender validation.
Mehrabi et al. (Mehrabi et al., 2021); Barocas et al. (Barocas et al., 2019); Hardt et al. (Hardt et al., 2016)	Algorithmic fairness	Fairness requires measurable error and allocation criteria.	No single metric captures sociotechnical fairness.	Supports joint exposure, rank, engagement and error audit.
DeVito (DeVito, 2017); Sandvig et al. (Sandvig et al., 2014)	Platform auditing	Observable outcomes can reveal systematic platform differences.	Audits cannot expose proprietary causal mechanisms.	Justifies repeated query, ranking and recommendation measures.
Hanim (Hanim, 2025); Westerbeek (Westerbeek, 2025); Ventaja-Cruz et al. (Ventaja-Cruz et al., 2024); Ayhan (Ayhan, 2025)	Women's sport media	Participation and fandom grow while media prominence remains uneven.	Limited computational evidence for Indian women's football.	Locates the audit in an underexamined national sport context.
Mitchell et al. (Mitchell et al., 2019); Deck et al. (Deck et al., 2024)	Explainability and governance	Model reporting and feature-level interpretation improve accountability.	Explanations do not guarantee fairness or causality.	Supports full/non-leakage comparison and transparent reporting.

Table 14. Statistical EDA and Derived Dataset Indicators

Indicator	Reported value	Reference base	Derived statistic	Interpretation
Valid gender-inference pairs	48	200 survey responses	24.0%	Only paired cases enter accuracy analysis.
Matched manual annotations	500	1,000 media items	50.0%	Half of media records have manual coding.
YouTube share	543	1,000 media items	54.3%	Largest platform/source category.
Women's football share	853	1,000 media items	85.3%	Group sizes are unequal; dual tests are appropriate.
Performance/competition frame	386	500 annotations	77.2%	Manual coding is predominantly performance-oriented.
Positive plus neutral tone	431	500 annotations	86.2%	Negative/mixed tone is not the dominant pattern.
Gendered language present	41	500 annotations	8.2%	Explicit gendered wording is relatively infrequent.
Neutral sentiment	741	1,000 media items	74.1%	Text sentiment is predominantly neutral.
Visibility contrast	70.382 vs 75.049	Women vs men	-4.667 (-6.2%)	Women's mean visibility is lower.
Search-rank contrast	7.712 vs 5.565	Women vs men	+2.147 (+38.6%)	Higher rank value indicates weaker placement.
Engagement contrast	3.514 vs 3.663	Women vs men	-0.149 (-4.1%)	Difference is not statistically significant.
Recommendation contrast	11.858 vs 11.327	Women vs men	+0.532 (+4.7%)	More frequent recommendation does not ensure prominence.
LR accuracy sensitivity	0.936 vs 0.600	Full vs non-leakage	-0.336 points	Outcome-adjacent variables drive much of full-model accuracy.

Note. Percentages and relative contrasts in Table 14 were derived only from counts and means already reported in Tables 2-12; no unreported row-level values were imputed.

sports-media recommendation and audience segmentation. The content analysis of the media texts revealed a largely performance-focused, neutral-positive tone for the coverage of women's football. So the primary issue wasn't over-the-top aesthetic framing, but unequal algorithmic amplification. The full visibility prediction model was well performing, but the non-leakage model revealed that content/context variables on their own account only for a moderate level of visibility. This validates that the dynamics of ranking and engagement do matter significantly for the outcomes of visibility.

Table 8. Sentiment and Topic Modelling Results *(continued)*

Analysis	Main Result
Commercial media	12

Table 6. Statistical Comparison of Men's and Women's Football Content *(continued)*

Metric	Women Mean	Men Mean	Difference	ANOVA p-value	Kruskal p-value	Result
Recommendation frequency	11.858	11.327	0.532	<0.00001	<0.00001	Significant

Table 5. Core Visibility, Ranking and Fairness Metrics *(continued)*

Metric	Result	Interpretation
Exposure parity ratio	0.938	Below full parity
Men's mean rank	5.565	Better placement
Women's mean rank	7.712	Weaker placement
Ranking parity gap	2.147	Women ranked lower
Engagement gap	-0.149	Small lower engagement
Recommendation gap	0.532	Women appeared slightly more repeatedly

Table 4. Manual Framing, Tone and Gendered-Language Results *(continued)*

Category	Main Result
Neutral tone	188
Mixed tone	63
Negative tone	6
Gendered language absent	369
Gendered language unclear	90
Gendered language present	41
Mean performance-focus score	2.670
Mean aesthetic-focus score	0.234
Mean framing-bias score	-2.436

Table 3. Gender-Inference Accuracy and Misclassification Results *(continued)*

Measure	Result
Highest platform-wise mismatch	Instagram: 66.67%

Table 2. Dataset Profile and Platform Composition *(continued)*

Component / Category	Count
News/Web items	336
Official Web items	121
Women's football content	853
Men's football content	147

FUTURE WORK AND SCOPE

Future research should move from a cross-sectional audit to repeated, platform-specific measurement across complete IWL seasons, international tournaments and ordinary non-event periods. Larger, consent-based identity samples are needed to evaluate gender inference across women, men, non-binary

participants and people who prefer not to disclose gender. Stratified sampling by platform, source, content type and season would permit uncertainty intervals, effect-size estimation and clearer separation of platform effects from corpus composition.

The analytical scope can be expanded through multilingual text models for English, Hindi and regional-language coverage; multimodal analysis of thumbnails, photographs, video and transcripts; and transformer-based frame classification with external validation. Controlled audit accounts or ethically designed synthetic-user experiments could test how identical content is ranked under different interaction histories. Longitudinal change-point analysis could then identify whether visibility shifts follow major matches, policy changes or recommendation-system updates.

A subsequent intervention study should evaluate practical remedies such as synchronized cross-promotion, metadata templates, prominence floors and position-weighted parity monitoring. Pre-registered audit queries, archived result pages, data statements, model cards and versioned code would improve reproducibility. Where access permits, causal or quasi-experimental designs should estimate the effect of ranking position on engagement rather than treating the two as contemporaneous predictors, and all models should be reported with leakage checks, calibration, confidence intervals and out-of-period validation.

LIMITATIONS

First, the media corpus was constructed for an Indian women's-football audit and was not a probability sample of all football content. Women's records substantially outnumbered men's records (853 versus 147), and platform representation was also uneven. The estimates therefore describe the audited corpus and should not be generalized automatically to every Indian user, search query or platform. Results may also vary with location, personalization, login status, time of collection and platform updates.

Second, only 48 survey responses contained a valid self-reported/inferred-gender pair. The 50.0% accuracy estimate is important as a diagnostic signal but has limited precision and cannot characterize every identity category or platform. The confusion matrix also groups some inferred outcomes as Unknown/Other, which restricts category-specific interpretation. A larger consent-based matched sample is required before making population-level claims about platform gender inference.

Third, visibility score, search rank and recommendation frequency are observational proxies for algorithmic allocation. They do not reveal proprietary model logic and cannot by themselves establish intentional discrimination or a causal effect of gender. Missing or inconsistent follower and view fields further limited the use of uniform engagement denominators. The manual annotation results are also subject to coding judgement; because an independent intercoder-agreement coefficient is not reported, fine-grained frame comparisons should be interpreted cautiously.

Fourth, ANOVA and Kruskal-Wallis p-values establish evidence of group differences but the available summary data do not provide standard deviations, confidence intervals or standardized effect sizes. Multiple outcomes were tested, and no multiple-comparison adjustment is reported. The full visibility model includes rank and engagement variables that are closely related to the target, which inflates explanatory performance; the lower non-leakage result is the more appropriate benchmark for prospective use. These limitations do not negate the observed disparities, but they constrain causal, population and deployment claims.

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