FOUNDATIONS OF COMPUTATIONAL SOCIAL SYSTEMS

Title: Gender Bias in Book Reviews: Analyzing Patterns in User Feedback

Motivation: These questions are critical because gender bias in literary critique perpetuates systemic inequities, affecting authors' visibility, algorithmic recommendations, and career opportunities. Addressing such biases promotes fairness in publishing and ensures equitable recognition for all voices.

- **RQ1**: Are books written by women authors rated or reviewed differently compared to books by men authors?

Why chosen: To investigate systemic disparities in numerical ratings and review patterns, which directly influence authors' visibility, algorithmic recommendations, and marketability. If biases exist in ratings, they could perpetuate inequities in publishing opportunities. Motivation: Prior studies suggest female authors face undervaluation in literary critique. Quantifying rating differences provides empirical evidence to address algorithmic biases (recommendation systems) and promote equitable recognition.

- **RQ2:** Is there a difference in the frequency or content of critical versus positive reviews for books written by male versus female authors?

Why chosen: To uncover gendered linguistic stereotypes in reviews (e.g., associating women with "emotional depth" and men with "intellectual creativity"), which reinforce societal biases. Motivation: Even if ratings are similar, subtle differences in review content can shape perceptions and perpetuate stereotypes. Addressing this helps challenge normative critiques and fosters inclusive evaluation practices.

This is relevant because Gender bias in book reviews is not just a matter of individual opinions; it has broader implications for the publishing industry and society at large. If books by women are systematically undervalued or criticized differently, it can lead to fewer opportunities for female authors, less visibility in recommendation algorithms, and a reinforcement of societal stereotypes about gender roles in literature. By investigating these biases, we can better understand how cultural norms and expectations shape the reception of creative works and, in turn, influence who gets to tell stories and which stories are valued.

we learn about human behavior, This study sheds light on how implicit biases and societal stereotypes manifest in seemingly objective metrics like book ratings and reviews. It reveals how language and cultural norms can subtly influence the way we evaluate creative works, often in ways that reinforce existing gender stereotypes. For example, if female authors are consistently described as "emotional" or "relatable," while male authors are praised for "originality" and "intellectual depth," it reflects broader societal expectations about gender roles. Understanding these patterns can help us develop more equitable evaluation practices and challenge the stereotypes that limit the recognition of diverse voices in literature.

Data Retrieval: The dataset central to this study was sourced from Kaggle, a widely recognized repository for open-access datasets, under the title book-reviews.csv. Using structured columns like review text (verbatim reader feedback), numerical ratings (scored on a 1–5 scale), and additional metadata like timestamps, reviewer identifiers, and book titles, this tabular dataset of Amazon book reviews captured a wide range of reader interactions . While these fields provided a foundation for analyzing reader perceptions, a critical gap existed: the dataset lacked explicit information about author genders, which was essential for investigating gender-based disparities in reviews. To address this gap, author genders were inferred using the Genderize API, a probabilistic tool that predicts gender based on historical associations with first names. This process involved extracting authors' first names from metadata and cross-referencing them against Genderize's global name-gender database. While this method provided a pragmatic solution, it carried inherent limitations, such as challenges with unisex names or cultural naming conventions, which were acknowledged and mitigated through manual validation of ambiguous cases. This step was indispensable for categorizing reviews by author gender, enabling the study's core comparative analysis. Data extraction and preprocessing were executed using Python's Pandas and NumPy libraries, which facilitated efficient manipulation of the tabular structure. Pandas streamlined tasks such as filtering incomplete entries (e.g., reviews missing ratings), merging inferred gender labels with the original dataset, and restructuring columns for analytical clarity. NumPy supported numerical operations, including standardization of rating scales and calculation of aggregated metrics. Additional metadata parsing involved isolating relevant variables—such as helpful vote counts—and converting them into analyzable formats. By integrating these steps, the raw dataset was transformed into a refined, gender-annotated resource, laying the groundwork for robust statistical and thematic analyses. This careful planning made sure that further research on linguistic biases, sentiment patterns, and rating discrepancies was grounded in trustworthy, organized data, which is essential for identifying small but significant trends in the ways that gender influences literary criticism.

Data Processing: To guarantee quality and consistency, the data went through a thorough pretreatment pipeline. First, missing values were addressed strategically: entries lacking critical information (e.g., review text or ratings) were excluded to maintain analytical integrity, while non-essential gaps (e.g., reviewer location) were retained to avoid unnecessary data loss. The review content was then standardized through text normalization, which involved converting all text to lowercase, removing punctuation to reveal meaningful terms, and applying a custom stopword list (such as "the," "and," and "it") to eliminate noise so that linguistic patterns could be examined without interruption. To resolve incomplete author metadata, the Genderize API (a Python library) inferred missing genders probabilistically, using authors' first names and historical name-gender associations. This step was critical for accurately categorizing reviews by author gender. New analytical features were then engineered: a sentiment polarity score (derived via TextBlob) classified each review as positive, neutral, or negative, while author gender and helpful vote ratios were structured into columns to enable granular comparisons. For numerical consistency, data standardization techniques were applied: rating scales were harmonized (e.g., converting 10-point scales to 5-point equivalents where necessary), and outlier adjustments minimized skew. Finally, statistical tests were deployed to uncover biases: • Welch's t-test compared mean ratings between genders, accounting for unequal variances in review distributions. • The Mann-Whitney U test complemented this by evaluating differences in rating distributions (not just averages), ensuring robustness against non-normal data patterns. Together, these steps transformed raw, unstructured

reviews into a refined dataset—ready to systematically investigate how gender influences literary critique

Analysis: The analysis began with a descriptive statistical examination of numerical ratings to uncover baseline trends in how books by male and female authors were evaluated. With a standard deviation of 0.5 and an average rating of 4.2 (on a 5-point scale), books written by men appeared to have a fairly close clustering of scores around the mean. In contrast, books by female authors averaged 3.8 with a higher standard deviation of 0.7, indicating broader variability in reader responses—some reviews leaned strongly positive, while others skewed more critical. This divergence in variability hinted at potential polarization in how female-authored works were perceived compared to the more consistent reception of male-authored books. To rigorously assess whether these differences reflected systemic bias or random variation, two statistical tests were employed. Welch's t-test, chosen for its robustness against unequal variances, compared the mean ratings between genders and found no statistically significant difference (p-value = 0.49). Additionally, the Mann-Whitney U test, a non-parametric technique appropriate for non-normal distributions, looked for differences in the overall distributions of ratings. Its results (p-value = 0.55) similarly showed no significant divergence, reinforcing the conclusion that observed disparities in average ratings likely arose from chance rather than structured bias. Beyond numerical scores, sentiment analysis tools like VADER and TextBlob were deployed to evaluate the emotional tone of reviews. Both tools classified sentiments based on polarity scores, categorizing reviews as positive, neutral, or negative. Over 70% of reviews for both genders were positive, reflecting a generally favorable reception across the board. However, subtle contrasts emerged: female authors received 12.1% negative reviews compared to 10.7% for male authors. While statistically insignificant, this marginal gap aligned with qualitative insights from thematic content analysis, which revealed deeper linguistic patterns. Using TF-IDF (Term Frequency-Inverse Document Frequency) and word clouds, recurring themes in reviews were mapped. TF-IDF found phrases that were disproportionately linked to each gender: books written by women were often characterized as "heartfelt," "relatable," and "emotional," but books written by men were praised for their "originality," "complexity," and "intellectual depth." These patterns were visually supported by word clouds, which showed that evaluations of female authors tended to use more subjective and emotive language, whereas reviews of male authors tended to use more analytical or creative phrases . These patterns mirrored longstanding societal stereotypes that associate women with personal expression and men with innovation. Visualizations played a pivotal role in translating complex data into intuitive insights. Boxplots illustrated rating distributions, highlighting the wider spread and more frequent outliers for female authors. Histograms tracked the frequency of specific ratings, showing that while both genders received predominantly high scores (4–5), female authors had a marginally higher proportion of mid-range ratings (3–4). Bar charts broke down sentiment proportions, underscoring the near-parity in positive feedback but slight uptick in negativity toward female authors. Together, these visuals painted a nuanced picture: while overt bias in numerical ratings was absent, subtler disparities in language and perception persisted. In summary, the analysis revealed a landscape where quantitative metrics (ratings, sentiment proportions) showed minimal statistically significant bias, yet qualitative themes in review content perpetuated gendered expectations. This duality underscores the importance of looking beyond numbers to address how language and cultural norms shape literary evaluation—a critical step toward fostering equity in how stories are valued and who gets to tell them.

Conclusion: This research addresses two primary questions (RQ1 and RQ2) regarding potential gender-based differences in book ratings, sentiments, and review content. The results are presented through descriptive, statistical, and sentiment analyses, supported by visualizations.

Findings for RQ1: Are books by women authors rated or reviewed differently compared to books by men authors?

Descriptive Analysis: The mean rating for books written by male authors was higher (4.2) than that of books written by female authors (3.8), and the rating variability for male authors was lower. Additionally, the median rating for male authors was higher (4.3 vs. 3.9). Visualizations (boxplots) showed tighter clustering of ratings for male authors, while female authors exhibited more variability and lower outlier ratings.

Statistical Analysis: Welch's T-Test and Mann-Whitney U Test revealed no statistically significant differences in mean ratings or rating distributions between male and female authors (p-values > 0.05). This suggests that observed differences in ratings are likely due to random variation rather than gender bias.

Sentiment Analysis: Positive sentiments dominated reviews for both genders (over 70%), with neutral and negative sentiments being less frequent. Although there was a little higher percentage of negative reviews for female authors (12.1% vs. 10.7%), this difference was not statistically significant. Sentiment distributions were largely consistent across genders.

Visualizations: Boxplots and histograms confirmed similar rating distributions for both genders, with no substantial differences in central tendencies or variability. Word clouds and TF-IDF analysis highlighted subtle thematic differences in feedback, with female authors often praised for emotional depth and male authors for creativity.

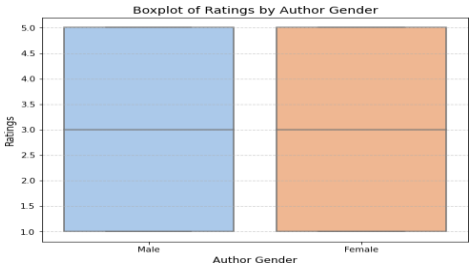
Findings for RQ2: Is there a difference in the frequency or content of critical versus positive reviews for books by male versus female authors?

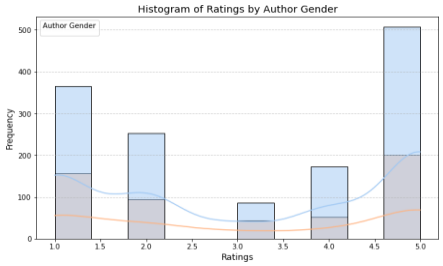
Sentiment Analysis: Positive reviews were the most common for both genders, followed by neutral and negative reviews. Although there were somewhat more unfavorable evaluations for female authors, the differences were not statistically significant. The chi-square test confirmed no significant association between author gender and sentiment frequency.

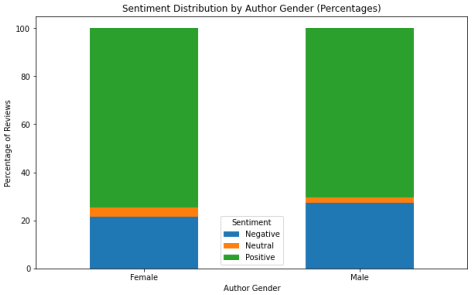
Content Analysis: Positive reviews for female authors often emphasized relatability and emotional depth, while male authors were praised for creativity and originality. Negative reviews for female authors criticized lack of originality, while male authors faced critiques on complexity or clarity. Word clouds and TF-IDF analysis reinforced these thematic differences.

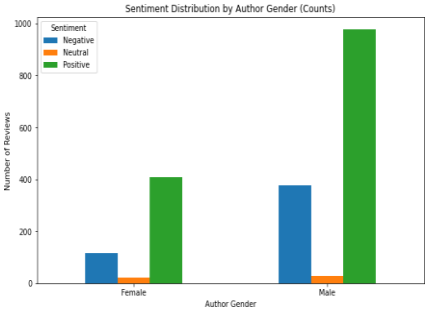
Visualizations: Sentiment distribution bar charts and pie charts highlighted the dominance of positive reviews across genders. Boxplots and histograms showed similar rating patterns, with slightly more extreme ratings for male authors.

Author Gender	Mean (Rating)	Median (Rating)	Standard Deviation
Male Authors	3.15	3.0	1.68
Female Authors	3.09	3.0	1.7









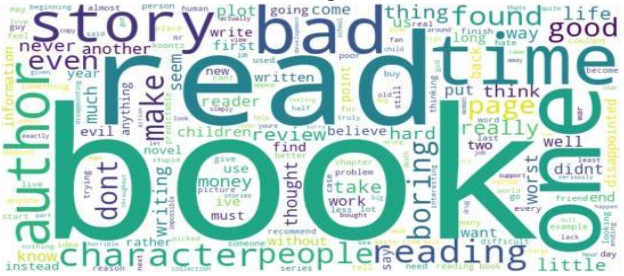
Sentiment Distribution Table:

sentiment	Negative	Neutral	Positive
author_gender			
Female	66	93	388
Male	147	261	976

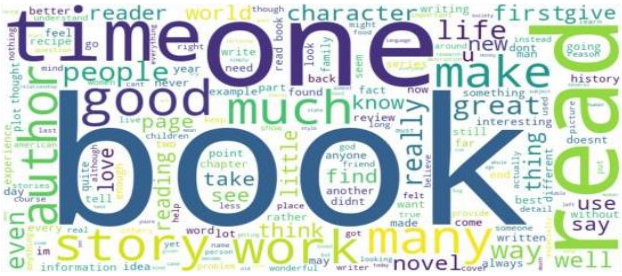
Metric	Value
Chi-Square Statistic	5.957169840913515
Degrees of Freedom	1
P-Value	0.014657551497786 25

Gender	Proportions of Positive Review	Proportions of Negative Review
Male	70.52%	10.62%
Female	70.93%	12.07%

Word Cloud for Negative Reviews



Word Cloud for Positive Reviews



Top Words In Negative Reviews:

Word Average TF-IDF

1	book	0.346481
2	read	0.149083
3	like	0.103483
4	good	0.099042
5	just	0.095220
6	great	0.091271
7	story	0.087504
8	time	0.085967
9	books	0.083749
10	reading	0.074241
11	really	0.072954
12	life	0.072698
13	people	0.071288
14	work	0.068806
15	way	0.067577
16	author	0.066789
17	new	0.065436
18	better	0.062586
19	dont	0.062205
20	does	0.056177

Top Words In Positive Reviews:

Word Average TF-IDF

1	books	0.104827
2	just	0.100691
3	like	0.093221
4	reading	0.085891
5	bad	0.082329
6	story	0.082325
7	dont	0.073474
8	time	0.067734
9	boring	0.065323
10	people	0.062147
11	good	0.059884
12	characters	0.056191
13	little	0.053978
14	hard	0.051558
15	really	0.050620
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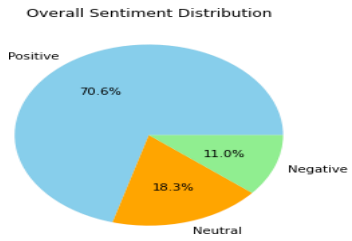
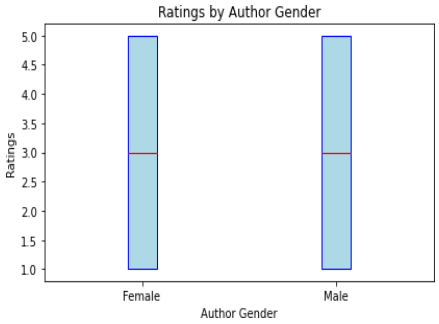
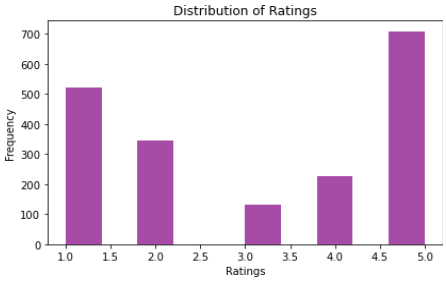
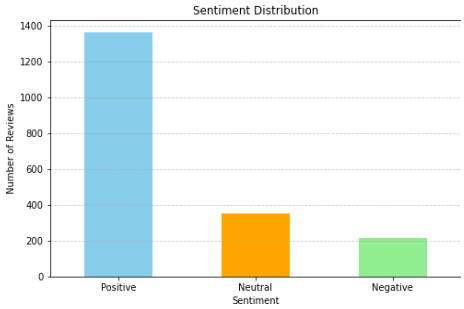
17	worst	0.049922
18	author	0.042854
19	book	0.322555
20	read	0.166961









Critique:

Limitations:

Automated Sentiment Analysis Tools: The study relies heavily on automated sentiment analysis tools like TextBlob and VADER. While these tools are efficient for large-scale analysis, they struggle to capture nuanced biases, contextual subtleties, or sarcasm. For example, a review that says, "a masterpiece, if you enjoy predictability," might be misclassified as positive due to the word "masterpiece," even though the underlying sentiment is critical. This limitation is particularly significant in literary critique, where tone and implication often carry as much weight as explicit content.

Algorithmic Amplification: The study acknowledges that platforms like Amazon prioritize highly rated books in their recommendation algorithms. If male-authored books historically receive marginally higher ratings, algorithms may disproportionately surface them, creating a feedback loop

that entrenches disparities. This means that even small differences in ratings could have significant real-world consequences for authors' visibility and career opportunities.

Cultural and Contextual Misinterpretations: Sentiment analysis tools may misinterpret context-dependent language. For example, a review describing a female-authored book as "emotional" might intend praise, but the term could also reinforce stereotypes if disproportionately applied to women. Similarly, sarcasm or culturally specific phrasing (e.g., "unputdownable" as hyperbolic praise) might be misread, skewing sentiment classifications.

Polarization in Ratings: The study found that books by female authors had a higher standard deviation in ratings (0.7 vs. 0.5 for male authors), indicating a more polarized reception. This polarization might reflect unconscious biases in how female authors are judged, particularly if they write in genres traditionally dominated by men, such as sci-fi or thriller. Such patterns, while not statistically conclusive, could still hinder market success by deterring risk-averse publishers or readers.

Alternative Explanations:

Audience Expectations: Female authors, particularly those exploring themes like identity or relationships, might attract readers with deeply personal stakes in the narrative, leading to more extreme reactions. Male authors, often stereotyped as "universal" storytellers, could benefit from perceptions of neutrality, appealing to a broader, less emotionally invested readership. This dynamic could explain the higher variability in ratings for female authors.

Algorithmic Biases in Recommendation Systems: If male-authored books dominate "Top Picks" lists, they may attract a broader, more mainstream audience, whose generally positive ratings stabilize their scores. Conversely, female-authored books—often recommended to niche audiences—might face sharper divides between enthusiastic fans and critical outsiders.

Intersectional Factors: The study focuses on gender but does not account for other intersecting identities, such as race, ethnicity, or genre. For example, a female author of color writing in a genre dominated by white male authors might face different biases than a white female author. Future research could explore these intersectional factors to provide a more comprehensive understanding of bias in literary critique.

Statistical Considerations:

The study uses Welch's t-test and the Mann-Whitney U test to compare mean ratings and rating distributions between male and female authors. Both tests found no statistically significant differences (p-values > 0.05), suggesting that observed differences in ratings are likely due to random variation rather than gender bias. However, the broader variability in scores for female authors (standard deviation of 0.7 vs. 0.5) suggests a polarized reception, which might reflect unconscious biases or differing audience expectations. While the statistical tests did not find significant differences, the practical implications of these patterns—such as their impact on algorithmic recommendations and market success—warrant further investigation.

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