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Summary of WP Student Team

Enhancing Trust, Fairness, and Performance in the Sharing Economy

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Work project carried out under the supervision of:

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A Work Project, presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

Enhancing Trust, Fairness, and Performance in the Sharing Economy

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Abstract

This work project explores the factors shaping Airbnb host performance, visibility, and guest sentiment, focusing on algorithmic dynamics and predictive analytics. Using diverse datasets and Machine Learning models, it uncovers how Airbnb's recommendation system impacts trust, competitiveness, and guest engagement. Key findings reveal that review volume and host responsiveness drive performance, with smaller hosts facing challenges in visibility and pricing. Sentiment analysis highlights the outsized impact of negative reviews on reputations. The study identifies biases in Airbnb's algorithms, emphasizing the need for fairness, transparency, and user feedback to ensure equitable opportunities for all hosts in the sharing economy.

Keywords: Airbnb, Machine Learning, Guest Sentiment, Algorithmic Bias, Host Visibility, Sharing Economy, Recommendation Systems, Review Volume, Predictive Analytics, Trust Building

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1. Introduction

In its early years, Airbnb faced significant challenges, particularly concerning trust and safety amongst its target customers, as the idea of staying in a stranger's home was unfamiliar and often viewed with scepticism. To address these concerns, Airbnb introduced various measures to build trust, including a robust review system, secure payments, and a verification process for hosts and guests. The company continued to evolve over the next decade, transforming the travel and hospitality industry and challenging the traditional hotel business model, and is now considered one of the most recognizable brands in the world, with millions of hosts and guests using the platform across most countries in the world.

Despite Airbnb's large and huge success, new hosts face a key challenge which is predicting the occupancy rates when limited historical data is available. This research is essential because, while it examines static variables as traditional studies do, it also explores the use of Machine Learning (ML) to predict Airbnb listing performance by analysing review volume and patterns and providing a more dynamic and accurate approach to risk prediction. This perspective not only contributes to the academic understanding of digital feedback systems but also has real-world implications for Airbnb hosts and the platform itself. By developing ML models that predict occupancy based on the initial listing details, such as pricing, description quality, and host responsiveness, this study aims to provide tools for hosts to optimize their new listings proactively, leading to improved performance and higher occupancy rates.

Hosts can make targeted improvements by understanding patterns that lead to negative reviews or booking declines, preserving their reputation and improving guest experience. They can make strategic decisions on pricing, descriptions, and guest interactions right from the start, ensuring better performance in a competitive market. Additionally, this proactive approach ensures a higher standard of service and helps maintain user trust in the Airbnb ecosystem, aligning with Airbnb's interests by supplying the platform with tools to identify and intervene with at-risk listings, maintaining a consistent quality of service.

With the increasing dependence on AI, it's critical to examine the workings of the recommendation systems and the possible biases they may present. Another purpose of this study is to explore the differences in the visibility, review outcomes and competitiveness of hosts with different characteristics due to the recommendation system used by Airbnb.

While Newell and Marabelli (2015) and Eubanks (2018) provide valuable insights into the impacts of algorithmic bias, there remains a gap in understanding how specific characteristics of hosts, such as their newness to the platform, response rates and size, directly influence their visibility, review outcomes and competitiveness.

Another challenge with recommendation systems is the potential for unintended biases, particularly related to property type, geographic location, price per person, and host responsiveness metrics, creating unfair advantages for different type of hosts. Consequently, small-scale hosts often struggle to achieve sufficient visibility, making it difficult for them to compete effectively in the marketplace. Fairness in algorithmic visibility is essential to maintaining a diverse and competitive ecosystem, where small hosts have an equitable opportunity to succeed, as for example, a small host who struggles to gain visibility due to lower initial ratings and may face more difficulties in attracting guests, when comparing with larger hosts.

This thesis explores how effectively ML models predict Airbnb listing occupancy rates and review outcomes based on initial characteristics and review patterns, examine the extent to which recommendation systems shape host visibility and competitiveness, contribute to disparities in algorithmic decision-making and how transparency and user feedback mechanisms can increase fairness within these systems.

This work project employs a combination of advanced machine learning techniques to understand what influences success on Airbnb. Specifically, Linear Regression, Decision Tree, Random Forest, Ridge, and Lasso models are used to predict occupancy rates and analyse host visibility. To explore potential biases in Airbnb's recommendation system, Propensity Score Matching is applied. Additionally, a Random Forest classifier is used to identify listings at higher risk of receiving negative reviews. Together, these methods provide a well-rounded perspective on the various factors contributing to host visibility and competitiveness.

The main findings reveal that Airbnb's platform presents both opportunities and challenges for hosts. While the platform offers tools to increase visibility, systemic issues, such as algorithmic biases, create barriers for newer and smaller hosts, limiting their competitiveness. The applied machine learning models highlighted key factors influencing host success, including pricing strategies, listing quality, and responsiveness, while also revealing limitations like overfitting and difficulty in capturing subjective factors such as guest sentiment. Fairness and transparency in Airbnb's recommendation system is crucial for a balanced and inclusive platform, because without it, systemic biases could disadvantage smaller and new hosts, affecting trust and engagement. The findings highlight the need for transparency and proactive support mechanisms to build a fairer environment, allowing technological tools as predictive analytics to fully improve host performance and satisfaction.

2. Literature Review

Though academic interest in exploring the disruptive impacts of sharing economy platforms has grown recently, the implications of Airbnb on traditional industries and market structures are still being analysed. In a systematic literature review, Hati, Balqiah, Hananto and Yuliati (2021) explore how Airbnb has affected various stakeholders, including consumers, hosts, and the hospitality industry at large. Studies such as Zervas, Proserpio, and Byers (2017) demonstrate the significant disruption Airbnb has caused to traditional hotel markets, leading to changes in pricing and competitive strategies. In addition, Zach, Nicolau, and Sharma (2020) examine the broader implications of Airbnb as a disruptive innovation, showing how it has affected incumbent market value and forced traditional hospitality businesses to innovate or adapt to this new competitive landscape. This disruption has stimulated interest in emerging technologies that can help sharing economy platforms address challenges related to trust, transparency, and operational efficiency, areas that are critical to maintaining competitive advantage and user confidence.

However, challenges remain, particularly in data quality and availability. Chen et al. (2021) highlight that models require large, high-quality datasets for accurate predictions, which new hosts often lack. Model complexity and interpretability are additional issues; as Akter et al. (2021) explains, complex models can be hard for non-experts to understand, creating a “black box” problem where predictions lack transparency. Developing more interpretable models could aid wider adoption of these tools (Cheng et al., 2021).

Despite the referred challenges, machine learning models have emerged as powerful tools for boosting host performance and building guest confidence. Akter et al. (2021) and Kirkos (2022) showed the influence of pricing strategies, descriptions quality, responsiveness in guest decision-making. Machine learning models now assist in predicting listing success by analysing these characteristics, enabling hosts to make data-driven adjustments. Chen et al. (2021) and Heylighen (2016) highlight the effectiveness of these models in capturing user behaviour and adjusting to market shifts, helping hosts optimize their listings early on. Heylighen (2016) discusses how can these models predict market demand, allowing hosts to adjust their pricing and availability proactively. These tools can analyse user preferences, market conditions, and even the performance of competing listings to suggest actionable changes that improve occupancy rates. As noted by Balakrishnan et al. (2021), hosts who utilize these predictive technologies often experience greater success, as they can respond more effectively to shifts in demand and user expectations.

Among the many aspects that Machine Learning models analyse to improve host performance, pricing strategies stand out as a critical area for maximizing revenue and shaping guest perceptions and will be one of the focal points discussed in this paper.

Earlier, by Gibbs, Guttentag, Gretzel, Yao, and Morton (2019) examine how hosts adjust prices based on demand fluctuations, often complicating the competitive landscape for hotels that tend to rely on more static pricing models. Gutt and Herrmann (2015) found that frequent pricing changes can shape guest expectations, which can, in turn, influence review outcomes and future bookings. A fact is that the perceptions and reviews of the guests can be shaped by the price. Guests who perceive a price to be too high or too low might associate it with the quality of the experience. This aligns with consumer behaviour research, which shows that reviews are heavily influenced by guest expectations, and consequently, the price can play a role in moderating trust and reputation.

Trust is another fundamental component of the sharing economy, particularly for Airbnb where it significantly influences platform success. Several studies have explored how trust is recognised and maintained. One of those studies by Akhmedova, Vila-Brunet, and Mas-Machuca (2021) identified key antecedents of trust in sharing economy platforms, highlighting the importance of platform reliability and service provider behaviour. Pavlou and Dimoka (2006) highlight how the consistency of reviews over time either builds trust or leads to reputational damage, underscoring the platform’s reliance on peer-to-peer trust mechanisms. Luca (2016) suggests that a spike in negative reviews can significantly lower booking rates, as users heavily prioritize recent guest experiences, while, on the other side, Lee et al. (2019) found that positive reviews serve as social proof, building guest trust, especially when reviews highlight key aspects like cleanliness, location, and host responsiveness. Chen et al. (2021) further emphasizes that review quality and frequency help build a host's reputation, a vital factor in attracting new guests in competitive markets. Additionally, Airbnb's rating system plays a crucial role, where higher ratings increase visibility and trust, with higher-rated listings able to command higher prices (Balakrishnan et al., 2021). More than star ratings, research by Archak, Ghose, and Ipeirotis (2011) shows that the sentiment in reviews provides deeper insights and have more impact, as it captures specific emotional responses and complaints. The ease of communication with the host and listing accuracy foster cognitive trust, and consistent communication and transparency build guest confidence, encouraging repeat bookings and long-term success (Balakrishnan et al., 2021). Berger, Sorensen, and Rasmussen (2010) add that recent reviews are taken more into account by potential guests when evaluating a listing. Agapitou, Liana, Folinas, and Kostantoglou (2021) reinforce these findings, noting that customer preference for Airbnb is often driven by the personal and unique experiences captured in guest reviews. Besides the impact of reviews, Ert, Fleischer, and Magen (2016) studied the role of personal photos in influencing trust on Airbnb, finding that hosts with attractive photos tend to attract more guests, as these visual elements are linked to increased credibility. Airbnb algorithm considers three major factors: quality (to measure quality, the Airbnb algorithm assesses many listing characteristics, including photos, guest reviews, size, location, etc), popularity (booking requests, real bookings, number of listings in wish list), and price. So, it can be assumed that, for sure, reputation and trust play a critical role in this context. These studies underscore the importance of trust elements in driving guest actions; however, they do not address how AI-driven recommendation systems amplify or mitigate these trust dynamics.

While trust and reviews are central to consumer behaviour on Airbnb, the rapid advances of artificial intelligence and Machine Learning technologies has triggered a critical discourse about their implications for social equity and justice. These technologies, which are frequently seen as impartial and objective, have the unintended potential to reinforce social biases that already exist, leading to significant negative outcomes for marginalized groups.

According to Eubanks (2018), automated systems often mirror existing social biases, leading to outcomes that reinforce inequality rather than alleviate it, highlighting the tendency of algorithmic decision-making to replicate and exacerbate pre-existing social disparities. More than reinforcing the existing inequality, Chloudechova and Roth (2018) noted that these automated systems can also unintentionally both encode existing human biases and introduce new ones. The reason why this happens is because machine learning algorithms are typically trained on historical data, which inevitably includes human biases. Machine learning techniques are designed to fit the data, and consequently, it will naturally replicate any biases already present in the data creating a cycle of discrimination that is difficult to stop. As known, predictive algorithms are being used more and more in the public and corporate sectors, frequently with the guise of advancing impartiality and fairness. However, using algorithms exclusively might lead to "wrongful discriminatory decisions", including the categorization and data-mining techniques utilized, which can reflect biases held by humans (Cossette-Lefebvre and Maclure, 2023).

Algorithmic bias is not limited to problems with data, it also includes the creation and application of algorithms. According to Akter at al. (2022), past human biases, insufficient models, and unrepresentative datasets can all contribute to algorithmic bias in marketing models. These prejudices can result in unfair outcomes based on demographic characteristics like age, color and religion in addition to having an impact on how services are handled and provided. The author also referred that machine learning methods may be susceptible to data or sampling issues that can lead to biased predictions resulting in harmful or unfair consequences across different customer groups.

As trust and bias grow higher with the increasing prevalence of AI technologies, the need for a more equitable framework for developing these systems becomes critical. To attenuate the negative effects of algorithmic decision-making, it is important to understand how technology and social justice meet (Eubanks, 2018). It is still difficult to make sure that these technologies help vulnerable groups rather than undermine them, thus their development and application need continuous scrutiny and reform.

At the same time of the sharing economy evolution, platforms like Airbnb are progressively incorporating algorithmic systems that influence host behaviours and guest interactions, mirroring the more general concerns about bias that are addressed in the context of artificial intelligence. Even after the adoption of rules in 2016 to fight discrimination by Airbnb, according to Cheng and Foley (2016), Airbnb has faced significant pressure to address the digital discrimination practices of hosts who reject guests based on attributes such as race, generated by algorithms that penalize hosts for declining guest requests. This issue raises important consideration regarding the influence of algorithmic decision-making systems in visibility that differs for hosts with diverse features. Although algorithmic systems might offer users new options, they also presents significant challenges for Airbnb hosts. One of those challenges, explored by Zervas, Proserpio, and Byers (2017), is the phenomenon of consistently high ratings on Airbnb, noting that larger hosts often benefit from a positive reputation cycle, receiving consistently high ratings that further increase their visibility. This observation aligns with the findings of Liang, Choi, and Joppe (2018), who explored the relationship between satisfaction and trust in the Airbnb context, noting that trust mediates the effect of transaction-based satisfaction on repurchase intentions. Both studies imply that recommendation systems may support hosts who already have significant engagement and high ratings, creating a feedback loop that disadvantages smaller hosts with fewer reviews or ratings.

Li, Kim, and Srinivasan (2021) studied Airbnb's impact on local housing markets, finding that the platform's presence increases rental prices and decreases long-term rental availability, which may affect smaller hosts' market competitiveness, while not addressing how recommendation systems impact the competitiveness of small versus large hosts. The combination of insights from Zervas et al. (2017), Liang et al. (2018), and Li, Kim, and Srinivasan (2021) suggest that recommendations contribute to an asymmetrical playground by integrally supporting larger hosts who can benefit from greater marketing strategies and established reputations. This asymmetry ties closely to ongoing concerns about fairness in AI-driven systems and any of these studies did not explore if increased transparency in the recommendation systems could lead to fairer outcomes. Similarly, Ert et al. (2016) and Lampinen and Cheshire (2016) highlighted the role of trust but did not investigate transparency or feedback mechanisms as potential solutions for fairness. The findings from these studies suggest that while trust is well-understood as a critical factor, there is limited research on how AI transparency can influence trust and eventually contribute to fairer visibility outcomes for small-scale hosts or for new hosts and how integrating user feedback mechanisms into the recommendation system could help correct existing biases.

As noted by Benner (2016), there have been measures to decrease discrimination, but major structural changes are still necessary to promote equity. The absence of accountability and incentives on the platform to reduce discriminatory actions exacerbates this bias and highlights the systemic issues that our study aims to show.

This section aims to provide a comprehensive review of the dynamics of trust, visibility, and algorithmic management within the sharing economy, with a particular focus on Airbnb, offering a foundation for a deep exploration of the complex dynamics at play. By synthesizing these insights and focusing on their challenges, this study aims to contribute to the formulation of equitable and forward-thinking strategies that address these complexities while supporting the sustainability and inclusivity of the sharing economy.

Particularly, this study aims to address the following research questions:

1. *Can Machine Learning models predict which Airbnb listings are at high risk of receiving negative reviews based on review volume?*

   Negative sentiment in guest reviews often provides a more accurate and detailed indicator of potential booking declines compared to star ratings alone, as it highlights specific issues driving dissatisfaction. Accordingly, it is hypothesized that listings with a higher volume of reviews are more likely to attract a greater proportion of negative sentiment compared to those with fewer reviews.

2. *How accurately can Machine Learning models predict the likelihood of a new Airbnb listing achieving high occupancy rates based on initial listing characteristics, such as pricing strategy, description quality, and host responsiveness?*

   By addressing specific variables, this research aims to provide actionable insights for new hosts, equipping them with strategies to optimize their listings and improve their chances of success in a competitive market. This study contributes to the growing body of knowledge on the use of predictive models in the sharing economy, with a specific focus on the unique challenges faced by new Airbnb hosts. Based on that, it is predicted that Machine Learning models can predict high occupancy rates in new Airbnb listings, based on initial listing characteristics such as pricing strategy, description quality, and host responsiveness.

3. *To what extent does Airbnb's recommendation system contribute to disparities in visibility and review outcomes for hosts with different characteristics and how do these factors perpetuate biases in the platform's algorithmic decision-making?*

Based on the previous referred papers, it is known that Airbnb's AI recommendation system favours listings with characteristics that align with established platform norms (quick response rates, established reputation, higher prices, certain property types, or specific geographic locations), thereby disadvantaging hosts or listings that deviate from these norms due to external factors. This study aims to find the evidence that the hypothesis that these systematic biases disproportionately limit the visibility, booking opportunities, and review outcomes for new hosts and hosts with lower response rates.

4. *How do recommendation systems influence the visibility and competitiveness of small-scale hosts compared to larger hosts on Airbnb, and how can transparency and user feedback be incorporated to improve fairness in these systems?*

   Based again on the previous referred papers, it's evident that trust indicators, such as high ratings and positive reviews, play a central role in shaping guest perceptions and driving bookings on Airbnb. These indicators possibly create a positive feedback loop that benefits larger hosts with established reputations, allowing them to maintain higher visibility in recommendation systems. Given these, it is predicted that recommendation systems favour larger hosts over smaller ones.

3. Data Research & Methodology

3.1. Data Cleaning and Preprocessing

This study is grounded on two datasets obtained from Maven Analytics, offering a detailed look into Airbnb's operations. The first dataset focuses on listings, while the second provides guest reviews, allowing for a multifaceted exploration of how initial listing attributes influence performance metrics like occupancy rates and visibility.

The listings dataset is rich in detail, capturing essential information about properties and their hosts. Each property is uniquely identified by a listing ID, which serves as a key for tracking and analysis. Beyond basic identifiers, it includes information such as the name of the listing, often reflecting the host's attempt to highlight its unique qualities. Host-specific details, like the host’s ID and the date they joined Airbnb, offer insights into hosting experience, while variables such as the location of the host provide valuable context for regional analysis. Attributes like price, minimum and maximum nights required for booking, and the availability of amenities help paint a detailed picture of each property’s operational setup. Among these, the overall review score stands out as a crucial metric, summarizing guest satisfaction on a scale from 0 to 100 and serving as a proxy for the perceived quality of the listing.

The reviews dataset adds another layer of understanding by offering a snapshot of guest experiences. Each review is tied to a specific listing and includes details such as the review’s unique ID, the date it was written, and the reviewer’s own unique identifier. These elements not only allow for temporal analysis - highlighting trends over time - but also facilitate the exploration of guest behaviour and its potential influence on listing visibility.

Before diving into the analysis, it was essential to ensure the integrity and relevance of these datasets. This process began with handling missing values. Columns with a significant proportion of missing data, such as host_response_time and host_acceptance_rate, were excluded to avoid introducing bias. For variables where missing data was less prevalent, such as review_scores_rating, missing entries were filled using median imputation. This choice ensured that the data’s overall distribution remained stable and was not unduly influenced by extreme values. Categorical variables with minor gaps, like host_is_superhost and host_has_profile_pic, were filled using the most frequent category.

Irrelevant features were also removed at this stage. Columns such as listing_id, host_id, and district, which acted primarily as identifiers or provided redundant information, were excluded to streamline the dataset. Variables that were not directly tied to the research objectives, such as the listing's name or the host's precise location, were also set aside. This cleaning process reduced the dataset's complexity while preserving the information most relevant to predicting listing success.

Another crucial step involved addressing outliers in variables like price, minimum_nights, and maximum_nights, which exhibited significant skewness. These variables were log-transformed to normalize their distributions, making the data more manageable for analysis. After transformation, features like price displayed a more balanced range, which was essential for improving model performance. Box plots were used to confirm that the log-transformed variables had fewer extreme values, ensuring that the dataset was ready for reliable modelling.

Finally, to prepare the data for machine learning algorithms, categorical variables such as room_type and property_type were encoded using one-hot encoding, transforming them into numerical formats. Binary variables, like host_is_superhost, were mapped to 0s and 1s to maintain consistency. Numerical variables were scaled using MinMaxScaler to standardize their ranges, ensuring compatibility with distance-based models and improving overall model accuracy.

3.2. Modelling

With the data cleaned and prepared, the next phase involved developing and implementing predictive models to explore the factors influencing Airbnb listing performance. The primary focus was on understanding how initial attributes of a listing, such as pricing strategies, host responsiveness, and property characteristics, affect key outcomes like review scores, occupancy rates, and overall visibility.

To achieve this, three machine learning models were selected: Linear Regression, Random Forest, and Decision Tree. Each model was chosen for its ability to handle specific aspects of the research questions. Linear Regression served as a baseline, offering a straightforward approach to evaluate the relationships between features and target variables, while Random Forest and Decision Tree were employed to capture more complex, non-linear interactions within the data.

The modeling process began by splitting the dataset into training and testing sets, allocating 80% of the data for training and the remaining 20% for testing. This division ensured that the models could be evaluated on unseen data, providing a robust measure of their predictive performance. In addition, five-fold cross-validation was conducted during the training phase to further validate the models and reduce the risk of overfitting. This technique split the training data into five subsets, iteratively training on four while validating on the fifth, resulting in a comprehensive assessment of model generalizability.

Linear Regression was applied to the log-transformed features, including price, minimum nights, and maximum nights, along with additional predictors such as the number of amenities and host response rates. This model offered insights into the linear relationships between features and target outcomes, such as review scores and occupancy rates. While effective in explaining straightforward interactions, the limitations of this approach became evident when dealing with more nuanced or non-linear patterns in the data.

To address these complexities, Random Forest was introduced as an ensemble learning technique. This model constructs multiple decision trees during training, aggregating their predictions to enhance accuracy and robustness. Its ability to handle both categorical and numerical variables without requiring extensive preprocessing made it an ideal choice for this study. Random Forest proved particularly effective in capturing the interactions between features like years of hosting, room type, and review scores. By averaging the predictions from individual trees, it minimized overfitting and provided a more reliable estimate of listing performance.

The Decision Tree model, another essential component of the analysis, was employed to further investigate non-linear relationships. This model splits the data recursively based on feature values, creating a tree structure that highlights decision rules. While powerful for identifying patterns, Decision Trees are prone to overfitting, especially when applied to datasets with high variability. However, in this study, the model served as a valuable tool for visualizing the impact of individual features on the target outcomes.

Model performance was evaluated using metrics such as Root Mean Squared Error (RMSE) and the coefficient of determination (R^2), which provided a clear measure of each model's accuracy and explanatory power. Additionally, statistical tests, including paired t-tests and F-tests, were conducted to confirm the significance of the predictions and validate the models' reliability. The Random Forest model consistently outperformed the others, achieving the best balance between complexity and predictive accuracy, particularly when dealing with the multi-faceted nature of Airbnb listing dynamics.

The insights gained from these models underscored the importance of leveraging both linear and non-linear approaches to fully capture the factors driving Airbnb listing performance. By combining these techniques, the study not only validated the significance of initial listing attributes but also provided actionable recommendations for improving host strategies and enhancing guest experiences.

3.3. Model Evaluation

The evaluation phase was critical in determining how well the chosen models performed in predicting key outcomes such as occupancy rates, review scores, and visibility. This step involved assessing the models on the testing dataset and interpreting their results through a combination of statistical metrics and domain-relevant insights.

To measure predictive performance, metrics such as Root Mean Squared Error (RMSE) and the coefficient of determination (R^2) were used. RMSE provided a clear indication of the average error magnitude between predicted and actual values, while R^2 quantified how well the models explained the variance in the target variables. These metrics allowed for a direct comparison of the models' capabilities in addressing the research objectives.

The Linear Regression model, while simple and interpretable, showed limitations in capturing complex patterns, particularly when dealing with non-linear relationships. For instance, it struggled to account for interactions between variables like host responsiveness and pricing strategies, which often have compounding effects on review scores and visibility.

In contrast, the Random Forest model excelled in these scenarios. By aggregating predictions from multiple decision trees, it demonstrated a strong ability to handle the intricate relationships present in the data. The model's performance was especially notable in predicting visibility scores, where it achieved the lowest RMSE and the highest R^2 among the tested models. This finding highlighted the importance of ensemble methods in addressing the complexities of Airbnb's platform dynamics.

The Decision Tree model, while effective for exploratory purposes, exhibited higher variance in its predictions compared to Random Forest. Its sensitivity to outliers and tendency to overfit made it less suitable for generalized predictions, although it provided valuable insights into the relative importance of features.

To further validate the reliability of the models, statistical tests were conducted. Paired t-tests confirmed the significance of the predictions, demonstrating that the models performed well beyond random chance. F-tests were used to compare the explained variance of the models against residual variance, offering additional confirmation of their predictive power. Random

Forest consistently showed the strongest results, solidifying its position as the most effective model for the study's objectives.

Through these evaluations, it became clear that leveraging multiple models provided a more comprehensive understanding of Airbnb listing performance. While Linear Regression offered a foundational perspective, Random Forest's ability to capture non-linearities and feature interactions proved indispensable. Together, these models contributed to a nuanced understanding of the factors driving success on the Airbnb platform, aligning with the overarching goal of providing actionable insights for hosts and enhancing guest experiences.

3.4. Integration and Additional Analyses

After completing the individual modeling phases, the study focused on integrating the findings and performing additional analyses to address potential gaps and explore further dimensions of Airbnb's platform dynamics. This step aimed to combine insights from all contributors and extend the analysis to provide a more comprehensive view of the factors influencing listing success.

The integration process began by consolidating the results from different models and analyses. For instance, features identified as significant predictors across multiple methodologies, such as host response rate, pricing, and years of hosting, were reevaluated in a unified framework. This approach ensured that the insights were not only robust but also aligned with the overarching objectives of the study.

To explore the potential biases within Airbnb's recommendation algorithm, additional statistical analyses were conducted. Propensity Score Matching (PSM) was employed to create comparable groups of hosts with varying levels of experience and responsiveness. This method allowed the study to quantify differences in visibility scores and booking performance, while controlling for confounding variables such as property type and pricing strategies. The results confirmed that experienced hosts and those with high response rates consistently outperformed their counterparts, suggesting systemic advantages built into the platform's algorithms.

In addition to PSM, feature importance analysis using permutation methods was applied to identify the variables that had the most significant impact on model predictions. This analysis revealed that variables related to host performance, such as response time and review volume, played a critical role in determining visibility and guest satisfaction. Property-specific characteristics, including the availability of essential amenities and proximity to popular locations, were also highlighted as key contributors.

To further understand the variability in performance between small and large-scale hosts, the data was segmented by host size. This segmentation revealed notable differences in how features influenced visibility and booking outcomes. Large-scale hosts, with multiple properties and structured operations, benefited from more consistent performance across metrics like review scores and occupancy rates. In contrast, small hosts exhibited greater variability, with performance heavily dependent on factors such as pricing and responsiveness. This disparity underscored the challenges faced by small-scale hosts in achieving and maintaining competitive visibility on the platform.

Finally, the study revisited outlier cases that displayed unusually high or low performance metrics. These cases provided valuable qualitative insights into the limitations of predictive modeling and the unique dynamics of Airbnb's marketplace. For example, listings with extremely high prices but low occupancy rates highlighted the importance of balancing affordability with perceived value, while properties with consistently poor review scores pointed to the long-term impact of negative guest experiences on visibility.

4. Introduction to Individual Parts

This part of the study takes a closer look at some of the most critical factors shaping success on Airbnb. It starts by exploring how the volume and sentiment of reviews impact listing performance. While a higher number of reviews can enhance trust and credibility, it also brings increased scrutiny, which may lead to a higher likelihood of negative feedback.

The focus then shifts to the importance of initial listing characteristics, such as pricing strategies and host responsiveness, in predicting the success of new Airbnb hosts. With little to no historical data to rely on, the findings highlight how strategic adjustments can help new hosts stand out in a competitive market.

Next, the study examines the biases inherent in Airbnb's recommendation system, revealing how the platform often favours more experienced hosts and those with faster response times, creating challenges for newcomers. The analysis calls attention to the need for fairer algorithmic practices that provide equal opportunities for all hosts.

Finally, the research looks at the disparities between small-scale and large-scale hosts. Larger hosts tend to dominate the visibility due to their ability to optimize key factors, leaving smaller hosts at a disadvantage. The study evaluates how increased transparency and user feedback mechanisms could help level the playing field, fostering a more equitable environment.

Taken together, these perspectives offer valuable insights into the inner workings of Airbnb's ecosystem, highlighting the ways to make the platform more inclusive and fairer for all types of hosts.

5. Discussion

To address the challenges highlighted in the findings, a multi-faceted approach is required to ensure that Airbnb's platform fosters fairness, inclusivity, and performance optimization for all hosts.

Firstly, a critical step is reforming the design of Airbnb's recommendation algorithm to enhance equity. The current system often disproportionately favours larger and more established hosts due to their historical data advantage. By incorporating a fairness index, the platform could account for factors such as geographic diversity, property type, and the potential of smaller hosts, ensuring a more balanced distribution of visibility. Additionally, providing hosts with transparent insights into how their listings are ranked can empower them to make more informed adjustments. A detailed dashboard could also work, highlighting key performance metrics such as responsiveness, review volume, and pricing alignment that would allow for hosts to have a better understanding of how to optimize their listings.

Support programs specifically targeting new hosts would also play a pivotal role in levelling the playing field. New hosts often lack the historical performance data that the algorithm inside the platform values, making it challenging for them to achieve visibility and occupancy. A possible solution would be for Airbnb to introduce mentorship initiatives where experienced hosts guide newcomers on optimizing their listings. On the other hand, personalized onboarding tools that leverage predictive analytics could simulate potential booking outcomes, leading to new hosts being able to adjust their listings' price, description, and even potential guest interactions. These tools would provide a vital safety net for those just starting on the platform.

Integrating dynamic feedback mechanisms into the platform could enhance the platform's responsiveness and equity. Real-time guest feedback loops would allow for hosts to address potential issues before they escalate into negative reviews, fostering a collaborative and solution-oriented environment. There is also the possibility of extending these feedback systems to periodic host surveys and focus groups, which would allow for Airbnb to improve its algorithms and address recurring host concerns. This dynamic exchange would build trust among users and ensure the platform evolves to meet the needs and wants of its diverse host and guest base.

Expanding access to dynamic pricing and performance analytics is another essential step. As of today, smaller hosts still end up struggling to keep pace with market fluctuations and competitor strategies. By allowing everyone to access advanced pricing tools, Airbnb can enable hosts to adjust their pricing dynamically based on real-time demand and competition. Integrating these tools with automated alerts and actionable recommendations would make the decision-making process much simpler for hosts, reducing the risk of underperformance or overbooking and ensuring their competitiveness in a crowded marketplace.

Finally, fostering partnerships with academic institutions and independent researchers to conduct long-term trend analyses would ensure continuous refinement of the platform. Sharing anonymized datasets with researchers could uncover deeper insights into trends affecting host performance and guest satisfaction. These collaborations would not only enhance the platform's algorithms but also inform future policy changes, ensuring Airbnb remains at the forefront of innovation in the sharing economy.

6. Limitations

The findings indicate that ML can indeed be a powerful tool in predicting high-risk listings, but with certain limitations that should be acknowledged. By addressing class imbalance through up sampling and conducting rigorous cross-validation, the study sought to avoid common pitfalls like overfitting. The model performed well on the up sampled dataset, showing reliable accuracy in identifying high-risk listings. However, when tested on the original dataset, the predictive power showed some limitations, suggesting that the nuances of real-world data can challenge the robustness of even well-calibrated models.

Although the model successfully identified significant risk indicators, it also showed that some variables, such as host response rate and categorical factors, had lower impact that anticipated and certain variables, as price, proved less reliable as direct predictors, suggesting that human behaviour in the Airbnb ecosystem might be more variable and harder to quantify. The complexity of guest satisfaction reflects a broader challenge in using ML for prediction in contexts where subjective guest experiences and emotional responses play a key role.

Data quality and availability remain a challenge, especially for new Airbnb listings with limited historical data, which can affect predictive accuracy. Hosts should be aware of this when attempting to predict outcomes with minimal inputs. Additionally, the overfitting issue in the Decision Tree model underscores the importance of careful model selection for datasets with concentrated values. Simpler models, such as Linear Regression, were more adept at managing this skewed distribution, highlighting that less complex models are sometimes better suited for accurate predictions. The reliance on specific models, means the findings are influenced by the assumptions and capabilities of these models, which may restrict their overall applicability

The model's relatively low R-squared value indicates that other factors may impact review scores. Also, the dataset's focus on specific cities limits the generalizability of the findings across different contexts. Additionally, while associations between host characteristics and review scores are observed, this study does not establish a strong causality, and other external factors may also contribute to the observed relationships. The results indicate that various factors, particularly those related to host performance and property attributes, impact review scores within the Airbnb platform, thereby reinforcing the need for careful consideration of these elements in the analysis of algorithmic bias.

Besides that, the concepts of transparency and fairness are subjective, and the variables used to define these concepts in the models may lead to circular reasoning, as the models predict transparency and fairness are based on the same variables that define these metrics, creating a risk of overfitting and limiting the generalizability of the results.

The identified limitations in this research also point to the potential for future improvement, while the research question was effectively addressed, future work could focus on refining the model to better handle the inherent complexities of Airbnb data. Expanding the dataset to include more diverse regions or incorporating additional contextual factors could improve model accuracy. Moreover, refining feature engineering, such as better capturing the sentiment behind reviews or considering the impact of external factors like local events, could improve predictive power.

Airbnb's recommendation system could benefit from integrating responsiveness and description quality, increasing visibility for listings with high potential for success. Future research could increase model accuracy by incorporating external data sources, such as local demand, tourism trends, or regional economic indicators. Furthermore, while this study focused on quantifiable characteristics, future research might explore behavioural factors within the sharing economy, examining how personal interactions between hosts and guests affect listing success. Additionally, as emerging technologies, such as IoT and blockchain, continue to advance, future research could investigate how these technologies could boost transparency, trust, and efficiency within the sharing economy. Advanced techniques could be used as well, such as deep learning, to better capture non-linear relationships and mitigate overfitting, and then examine how transparency and fairness can be more objectively defined beyond the variables currently used.

7. Conclusion

The collective findings across the individual analyses shed light on both the opportunities and challenges presented by Airbnb’s platform. On the one hand, the platform empowers hosts with tools to maximize visibility and optimize their listings for competitive advantage. On the other hand, systemic issues such as algorithmic biases, the disproportionate impact of negative reviews, and inequities in listing visibility disproportionately disadvantage new and smaller hosts. These issues underscore the need for a more balanced platform design that fosters inclusivity and fairness while maintaining operational efficiency.

The analyses revealed that smaller hosts often face challenges stemming from limited historical data, which directly impacts their visibility within Airbnb’s recommendation system. This issue is compounded by the platform’s heavy reliance on prior performance metrics, which often favours larger and more established hosts. Similarly, the overemphasis on recent reviews and responsiveness metrics perpetuates disparities, creating a feedback loop where smaller hosts struggle to gain traction even when offering quality services. These findings point to an urgent need for interventions to level the playing field for all hosts, irrespective of scale or amount of time on the platform.

Machine learning models that were employed across our studies have shown significant potential in predicting critical outcomes, such as the likelihood of receiving negative reviews or achieving high occupancy rates. These tools have allowed for the extraction of valuable insights into the most important drivers of host success, which include pricing strategies, quality of description of the listing, and responsiveness. However, they have also highlighted the limitations of existing systems, such as overfitting in certain models and challenges in addressing subjective factors like guest sentiment. These limitations emphasize the need for more sophisticated and interpretable algorithms that balance technical robustness with user-centric design principles.

Fairness in AI-driven recommendation systems plays a crucial role in creating a balanced and inclusive platform. A system designed with fairness at its core not only supports individual hosts but also strengthens the platform by encouraging diverse and high-quality offerings that appeal to a much broader audience. Systemic biases, if left unaddressed, could alienate smaller and newer hosts, potentially jeopardizing trust and engagement with the platform, and impacting Airbnb's long-term sustainability. Transparency and proactive support mechanisms within the platform are key strategies to build trust and ensure that both host and guests feel valued and supported.

The research concludes that while technological tools such as predictive analytics and dynamic pricing models can significantly enhance host performance, their full potential can only be realized within a framework that prioritizes equity and user satisfaction.

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9. Appendix

Table 1. VIF Score per Feature Selected for Training

Feature	VIF
const	345.348
is_new_host	1.014545
host_response_rate	1.012580
amenities_dummies	1.246095
latitude	1.492450
longitude	1.170584
accomodates	2.124327
bedrooms	2.078440
review_scores_accuracy	3.186405
review_scores_cleanliness	2.354049
review_scores_checkin	2.400055
review_scores_communication	2.711072
review_scores_locaton	1.575616
review_scores_value	2.871181
log_price	1.540765
log_minimum_nights	1.056076
log_maximum_nights	1.055168
log_jost_total_listings_count	1.148721

Table 2. OLS Results

Dep. Variable	review_scores_rating	**R-squared:**	0.761
Model:	OLS	**Adj. R-squared:**	0.761
Method:	Least Squares	**F-statistic:**	2.33E+04
No. Observations:	124170	**Prob (F-statistic):**	0.0001
Df Residuals:	124170	**Log-Likelihood:**	-3.47E+05
Df Model:	17	**AIC:**	6.93E+05
Covariance Type:	nonrobust	**BIC:**	6.93E+05

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-2.515	0.208	-12.089	0.000	-2.923	-2.107
is_new_host	-0.8666	0.056	-15.341	0.000	-0.977	-0.756
host_response_rate	0.6195	0.072	8.652	0.000	0.479	0.760
amenities_dummies	0.343	0.025	13.725	0.000	0.294	0.392
latitude	-0.0039	0.000	-9.037	0.000	-0.005	-0.003
longitude	0.0012	0.000	-7.015	0.000	-0.002	-0.001
accomodates	0.0232	0.007	3.386	0.001	0.010	0.037
bedrooms	0.0008	0.014	0.057	0.954	-0.027	0.029
review_scores_accuracy	2.7173	0.023	117.443	0.000	2.672	2.763
review_scores_cleanliness	2.0468	0.018	115.995	0.000	2.012	2.081
review_scores_checkin	0.6495	0.025	26.141	0.000	0.601	0.698
review_scores_communication	1.9182	0.025	77.425	0.000	1.870	1.967
review_scores_location	0.3525	0.021	16.938	0.000	0.312	0.393
review_scores_value	2.2595	0.020	111.156	0.000	2.220	2.299
log_price	0.1365	0.011	12.702	0.000	0.225	0.158
log_minimum_nights	0.0832	0.013	6.506	0.000	0.058	0.108
log_maximum_nights	-0.0378	0.007	-5.198	0.000	-0.052	-0.024
log_host_total_listings_count	-0.2547	0.009	-28.82	0.000	-0.271	-0.238

Table 3. Random Forest Classifier

Classification Report:

	precision	recall	f1-score	support
High	0.93	0.96	0.95	30973
Low	0.85	0.69	0.76	766
Medium	0.72	0.60	0.66	5512
accuracy			0.91	37251
macro svg	0.83	0.75	0.79	37251
weighted avg	0.90	0.91	0.90	37251

Feature Importance
review_scores_accuracy: 0.15630145449218116
review_scores_value: 0.12838478084167926
review_scores_cleanliness: 0.12004140849074277
review_scores_communication: 0.08303873326425201
latitude: 0.07946981663569158
longitude: 0.07857949781897465
log_price: 0.07484673198304469
review_scores_checkin: 0.0558549713018356
log_host_total_listings_count: 0.05018334137665839
accommodates: 0.03156814324791481
log_maximum_nights: 0.03132290005598477
log_minimum_nights: 0.029964417201813597
host_response_rate: 0.02693802986937645
review_scores_location: 0.02575292428102502
bedrooms: 0.01412567706595879
amenities_dummies: 0.010132217303288829
is_new_host: 0.0034949547695776397

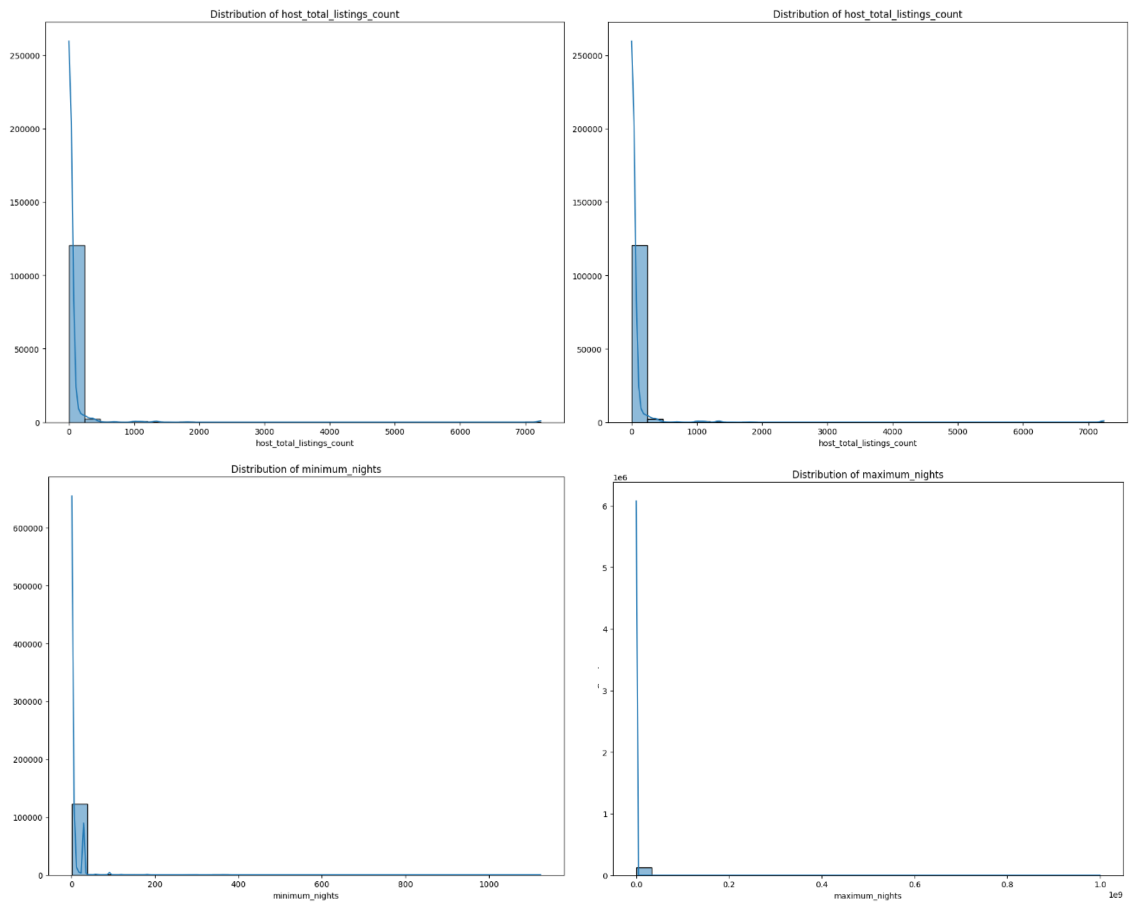

Figure 1. Distribution of Numerical Variables

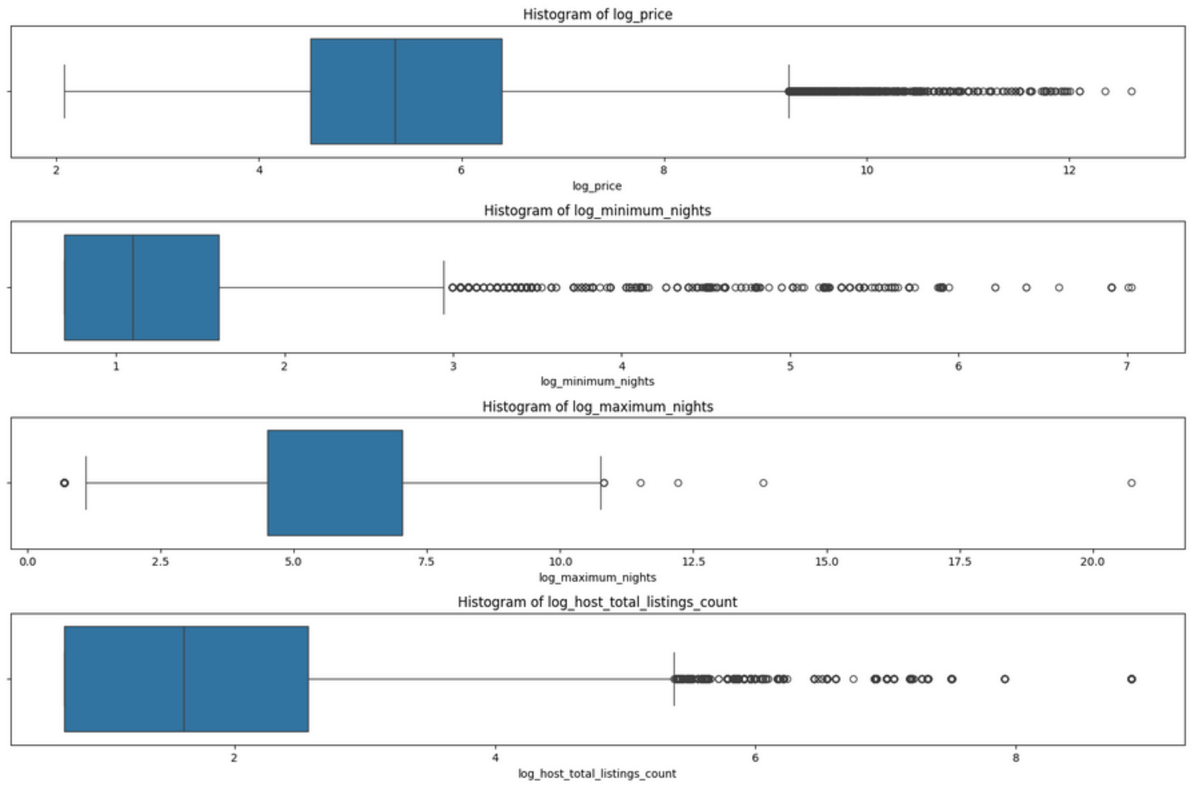

Figure 2. Outliers Detection - Histogram of Numerical Variables

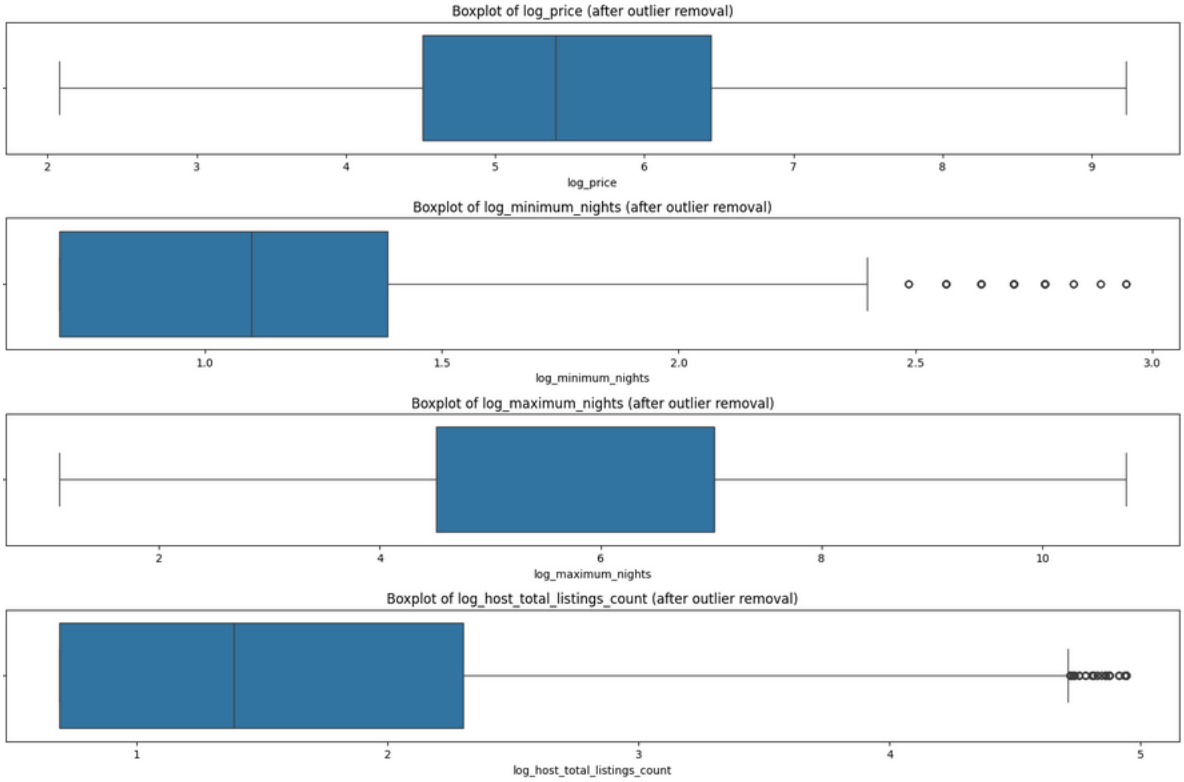

Figure 3. Outliers Removal - Histogram of Numerical Variables after Outlier Removal

A Work Project, presented as part of the requirements for the Award of a Master's degree in Business Analytics from the Nova School of Business and Economics.

ALGORITHMIC BIAS IN SHARING ECONOMY: EXAMINING VISIBILITY DISPARITIES IN AIRBNB'S RECOMMENDATION SYSTEM

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December 2024

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ALGORITHMIC BIAS IN SHARING ECONOMY: EXAMINING VISIBILITY DISPARITIES IN AIRBNB'S RECOMMENDATION SYSTEM

Joaquim Cortes

December 2024

ABSTRACT

Through Artificial Intelligence and Machine Learning, recommendation systems are revolutionizing consumer behavior by allowing a more personalized user experience. Despite all the advantages, there is a need to look deep at the threats it may cause. Previous studies show, in a general way, that recommendation systems can represent and empathizing existing biases in the society, and even creating new ones. However, little is known about what kind of specific characteristics make users affected by the platform. Focusing on Airbnb's platform, this research investigates the influence of host experience and response rate in visibility, powered by the recommendation systems. Findings show that new hosts has less visibility than experienced hosts, and that hosts with lower response rates has less visibility than hosts with higher response rates, suggesting existing biases in the recommendation system. This study contributes to the expanding academic dialogue on the role of AI and recommendation systems in shaping the tourism and hospitality sector. The findings signal the need for a more equitable and transparent algorithmic practices in the sharing economy.

1. Introduction

The sharing economy has revolutionized consumer behavior by allowing people to transact with each other in a variety of industries on a peer-to-peer basis. Airbnb is leading this change by using artificial intelligence (AI) extensively to improve user experience and operation efficiency in addition to making accommodations easier to find. But as we know, this helpfulness of AI has some challenges. As highlighted by Newell and Marabelli (2015), the tourism and hospitality sector have been impacted by the datafication process that innovated business strategies by creating new opportunities, and growth for numerous organizations. Algorithms are being used to aggregate and analyze data, enhancing the decision-making process. This advancement transcends basic analytics, effectively replacing certain tasks traditionally performed by human beings, particularly those typically handled by middle managers (Jarrahi & Sutherland, 2019).

With the increasing dependence on AI, it's critical to examine the workings of these recommendation systems and the possible bias they may present. The purpose of this study is to explore the differences in visibility and review outcomes of hosts with different characteristics due to the recommendation system used by Airbnb.

The data used to train AI systems and the innate design decisions made by the model developers are two common sources of algorithmic bias in these systems. O'Neil (2016) highlight that biases in algorithmic decision-making can lead to systemic inequalities within the sharing economy, and Eubanks (2018) confirm this hypothesis highlighting the impact of these biases in Airbnb, suggesting that socioeconomic position, geography, and professional reputation have a substantial impact on hosts' exposure and success.

Previous research has extensively examined the implications of algorithmic bias in various sectors, particularly in the context of the sharing economy. Studies by Newell and Marabelli (2015) and Eubanks (2018) have highlighted how algorithmic decision-making can exacerbate existing inequalities, revealing that factors such as socioeconomic status, geographical location, and host experience play significant roles in determining visibility and success on platforms like Airbnb. Additionally, research by Jarrahi and Sutherland (2019) emphasized the shifting dynamics in job roles due to the increasing reliance on AI, suggesting that traditional managerial functions are being transformed. However, while these studies provide valuable insights into the impacts of algorithmic bias, there remains a gap in understanding how specific characteristics of hosts—such as their experience in the platform and response rates—directly influence their visibility and review outcomes.

This study aims to confirm the hypothesis that Airbnb's AI recommendation system gives preference to hosts and listings that fit in with the established platform standards, disadvantaging those that deviate from the platform criteria due to external factors. It will specifically show that hosts with less experience and with lower response rates are affected by the Airbnb's recommendation system. This study examines the biases within Airbnb's recommendation algorithm, focusing on how algorithmic disparities may restrict opportunities for these typo of hosts. It underscores the need for equitable AI practices that account for the varied characteristics of hosts and listings, with particular attention to disparities in visibility and opportunity between new and experienced hosts, as well as those with differing response rates. By analyzing these factors, I demonstrate the presence of bias in Airbnb's algorithmic processes.

2. Literature Review

The rapid advances of artificial intelligence and machine learning technologies has triggered a critical discourse about their implications for social equity and justice. These technologies, which are frequently seen as impartial and objective, have the unintended potential to reinforce social biases that already exist, leading to significant negative outcomes for marginalized groups.

According to Eubanks (2018), automated systems frequently replicate pre-existing social biases, resulting in outcomes that perpetuate inequality instead of reducing it., highlighting the tendency of algorithmic decision-making to replicate and exacerbate pre-existing social disparities. More than reinforcing the existing inequality, Chloudechova and Roth (2018) noted that these automated systems can also unintentionally both encode existing human biases and introduce new ones. The reason why this happens is because machine learning algorithms are typically trained on historical data, which inevitably includes human biases. Machine learning techniques are design to fit the data, and consequently, it will naturally replicate any biases already present in the data creating a cycle of discrimination that is difficult to stop. Furthermore, predictive algorithms are being used more and more in the public and corporate sectors, frequently with the guise of advancing impartiality and fairness. However, using algorithms exclusively might lead to "wrongful discriminatory decisions" due to several factors, including the categorization and data-mining techniques utilized, which can reflect biases held by humans (Cossette-Lefebvre and Maclure, 2023). Further difficulties arise from the opaque nature of these algorithms, which goes against democratic ideals that demand accountability and transparency in decision-making procedures.
Algorithmic bias is not limited to problems with data, it also includes the creation and application of algorithms. According to Akter at al. (2022), past human biases, insufficient models, and unrepresentative datasets can all contribute to algorithmic bias in marketing models.

These prejudices can result in unfair outcomes based on demographic characteristics like age, color and religion in addition to having an impact on how services are handled and provided. The author also referred that machine learning methods may be susceptible to data or sampling issues that can lead to biased predictions resulting in harmful or unfair consequences across different customer groups.

As the stakes of fairness and bias grow higher with the increasing prevalence of AI technologies, the need for a more equitable framework for developing these systems becomes critical. To attenuate the negative effects of algorithmic decision-making, it is important to understand how technology and social justice meet (Eubanks, 2018). It is still difficult to make sure that these technologies help vulnerable groups rather than undermine them, thus their development and application need a continuous scrutiny and reform.

At the same time of the sharing economy evolution, platforms like Airbnb are progressively incorporating algorithmic systems that influence host behaviors and guest interactions, mirroring the more general concerns about bias that are addressed in the context of artificial intelligence. Even after the adoption of rules in 2016 to fight discrimination by Airbnb, according to Cheng and Foley (2016), Airbnb has faced significant pressure to address the digital discrimination practices of hosts who reject guests based on attributes such as race, generated by algorithms that penalize hosts for declining guest requests.

This issue raises important consideration regarding the influence of algorithmic decision-making systems in visibility that differ for hosts with diverse features. Although algorithmic systems might offer users new options, as we saw before, it also presents significant challenges for Airbnb hosts. Cheng and Foley (2019) indicated that the practices of Airbnb hosts are being shaped by algorithmic management through penalties and rewards administered via both the platform itself and potential Airbnb guests. Cheng and Foley (2019) also mentioned that, in circumstances where Airbnb host perceive that the algorithm might not be fair enough, this algorithmic management may cause anxiety in some hosts.With Airbnb, hosts may choose which guests to accept or reject based on personal attributes such as race and religion. This reflects the real life discriminatory patterns that we see in society, as we saw in before. Cheng and Foley (2018) define digital discrimination as the “range of circumstances in which a person or group is treated less favorably than another person or group based on their background and/or certain personal characteristics with regards to Internet”. This discrimination is facilitated by the design of Airbnb’s platform that allows hosts to assess the digital profiles of potential guests, reinforcing biases that exist in society.

Airbnb algorithm considers three major factors: quality (to measure quality, the Airbnb algorithm assesses many listing characteristics to evaluate quality, including photos, guest reviews, size, location, etc), popularity (booking requests, real bookings, number of listings in wish list), and price. So, reputation and trust play a critical role in this context. Ert et al. (2016) in his study found that the more trustworthy the host is perceived to be from the profile photo, the higher the listing price and the likelihood of being selected. And this is confirmed by the Airbnb itself, that refers in their site that the algorithm evaluates many factors to determine how to order the search results, some having more impact than others. It says also that there are ways for the hosts to influence the search results, by increasing the availability, adjusting prices ad making discounts, photos with high quality, and others.

Further evidence from Zhang et al. (2022) underscores the critical role of host reputation in mitigating discrimination. They found that elements such as the number and quality of reviews significantly impact how hosts are perceived and their overall success on the platform. This reinforces the notion that, much like algorithmic systems in general, Airbnb’s recommendation system perpetuates existing inequalities, disadvantaging those who may already be marginalized in society. Such findings highlight the urgency of my research question, which aims to uncover the underlying algorithmic biases that favor certain host characteristics over others.

As noted by Benner (2016), there have been measures to lessen discrimination, but major structural changes are still necessary to promote equity. According to Edelman and Luca (2014), prejudice may unintentionally be made easier by Airbnb's algorithmic design. They contend that although biases may be lessened by the internet, services like Airbnb may have the reverse impact by facilitating host discrimination based on characteristics that are readily apparent. The absence of accountability and incentives on the platform to reduce discriminatory actions exacerbates this bias and highlights the systemic issues that my study aims to show.

Afterall, my research question is *"To what extent does Airbnb's recommendation system contribute to disparities in visibility and review outcomes for hosts with different characteristics and how do these factors perpetuate biases in the platform's algorithmic decision-making?"*

This study aims to find evidence for the hypothesis that systematic biases in Airbnb's recommendation system disproportionately limit the visibility, booking opportunities, and review outcomes for new hosts and hosts with lower response rates. This hypothesis is grounded in prior research and theorical arguments which suggest that recommendation systems favours users with characteristics that align with established platform norms (quick response rates, established reputation, higher prices, certain property types, or specific geographic locations), thereby disadvantaging hosts or listings that deviate from these norms due to external factors.

Hypothesis 1: New Hosts are disadvantaged in Airbnb's recommendation system compared to experienced hosts.

Theorical Argument 1: New hosts don't have any historical data with feedback, such as reviews and ratings, which are core inputs into the platform's algorithm for determining visibility and credibility.

Hypothesis 2: Hosts with lower response rates are disadvantaged in Airbnb's recommendation system compared to hosts with higher response rates.

Theorical Argument 2: Response rate is one of the key performance metrics used by Airbnb to evaluate host reliability. As noted by Wu and Li (2021), quick responsiveness signals attentiveness and reliability, which are highly valued by guests. Hosts with lower response rates may face penalties in visibility as the algorithm prioritizes listings from hosts perceived as more reliable. This penalization may affect hosts who face external constraints, such as work schedules, making it harder for them to compete with consistently responsive hosts.

3. Data Research and Methodology

3.1. Sampling Data

My research utilizes a dataset extracted from Maven Analytics website, which contains Airbnb listings across several countries, including France, Brazil, Unite States of America, Japan, Italy, between others. The dataset encompasses a wide range of variables that capture the essential characteristics of each listing, including the host demographics, host characteristics, property characteristics, guest reviews, and more.

This dataset comprises 279712 listings and includes various features such as listing ID, host ID, host response time, host response rate, host acceptance rate, prices, and other features that provide a comprehensive overview of the listings, enabling a detailed analysis of potential biases in Airbnb's recommendation system. The geographical distribution of the listings is diverse, allowing for a comparative analysis across different socio-economic contexts.

3.2. Data Preprocessing

Prior to analysis, the dataset underwent a thorough preprocessing phase to ensure data integrity and reliability. Some missing values – form review_scores variables with the median values – were substituted by the median. This approach is chosen because the median is robust to outliers and provides a reasonable estimate for imputation without skewing the data distribution. Columns such as host_response_time and host_acceptance_rate are removed entirely from the dataset due to their high proportion of missing values (46%). Including these variables in the analysis will introduce significant bias, as the missing data can not be reliably imputed without making strong assumptions. The decision to exclude these columns ensures that the model remains robust and free from inaccuracies that could arise from biased imputations. Another variable with a high percentage of missing values is host_response_rate. But, since this variable is central to my hypothesis, it is essential to remain it in the dataset. So, to ensure the validity of the analysis, all rows with missing values for this variable are removed. This approach allowed for the creation of a dataset that is unbiased with respect to this key variable, ensuring that any relationships observed between host_response_rate and the target outcomes are based on complete and reliable data.

To address skewness (Figure 2. Distribution of Numerical Variables) in several numerical variables, log transformations are applied to the variables price, minimum_nights, maximum_nights, and host_total_listings_count. The log transformation was chosen to handle potential zero values while normalizing these variables, making their distributions closer to normal. In order to achieve the dataset's quality, I identify the outliers in key numerical variables and remove using the interquartile range (IQR) method. This approach ensures that extreme values which could disproportionately influence the analysis are excluded. Observations of the variables log_price, log_maximum_nights, log_minimum_nights, and log_host_total_listings_count falling outside the range of $[Q_1 - 1.5 \times IQR, Q_3 - 1.5 \times IQR]$

(Figure 4. Outliers Removal - Histogram of Numerical Variables after Outlier Removal) were removed.

The dataset is adjusted accordingly, reducing it to 105421 rows, which remains a strong sample for analysis.

In order to confirm the hypothesis that Airbnb's AI recommendation system favor listings with characteristics that align with established platform norms (quick response rates, established reputations, higher prices, certain property types, or specific geographic locations), first I define review scores rating as a proxy for visibility. The choice of review scores rating is due to their significant influence on how listings are ranked and presented to potential guests on the Airbnb platform. Higher review scores generally correlate with increased visibility, as the algorithm tends to prioritize listings that exhibit better guest feedback. So, I identify two variables that have impact on review scores and so, have an indirect impact on visibility.

Also, I create some new variables, such as “is_new_host” (where I considered new hosts those that entered in the platform in less than one year), “popular_neighbourhood” and “amenities” (classifies the essential amenities as 1 - wifi, heating, kitchen, essentials - and the listings where is missing at least one of the essentials as 0).

3.3. Model Development

3.3.1. Propensity Score Matching

To identify the potential biases in the recommendation system, Propensity Score Matching (PSM) was employed to create comparable groups of new and experienced hosts and hosts with high and low response rates, identifying the differences of the probability of visibility between these groups. The propensity score equation can be represented as:

$$Propensity\ Score = P(T = 1|X) = \frac{e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots+\beta_n X_n}}{1 + e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots+\beta_n X_n}}$$

where T is the treatment variables (host experience and host response rate), $X_1, X_2, X_3, \dots, X_n$ are the covariates, β_0 is the intercept, and the β' s are the coefficients estimated from the logistic regression. To pair hosts with similar propensity scores from the treatment and control groups, I applied the nearest neighbor matching method. After matching, the model computed the average review scores for both groups. The goal of this procedure was to reduce selection bias by matching hosts with the same characteristics but with different levels of experience or response rates. This method allows a more accurate comparison of the probability of visibility between these groups while controlling for confounding variables

3.3.2. Ordinary Least Squares Regression

To explore the impact of host response rate and experience on review scores, I conducted an Ordinary Least Squares regression, modeling review_scores_rating as the dependent variable. The independent variables included host response rate, host experience (indicated by whether the host is new and the total number of listings), log-transformed price, property type, and additional controls such as review-specific metrics (accuracy, cleanliness, communication, location, value), amenities, and geographic details (latitude and longitude). The regression equation its represented by:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \varepsilon$$

$$review\_scors\_rating = \beta_0 + \beta_1 . is\_new\_host + \beta_2 . host\_response\_rate + \beta_3 . amenities\_dummies + \beta_4 . latitude + \beta_5 . longitude + \beta_6 . accomodates + \beta_7 . bedrooms + \beta_8 . review\_scores\_accuracy + \beta_9 . review\_scores\_cleanliness + \beta_{10} . review\_scores\_checkin + \beta_{11} . review\_scores\_communication + \beta_{12} . review\_scores\_value + \beta_{13} . \log\_price + \beta_{14} . \log\_minimum\_nights + \beta_{15} . log\_maximum\_night + \beta_{16} . log\_host\_total\_listings\_count + \varepsilon$$

where y representes the dependent variable, β_0 is the intercept, $\beta_1, \beta_2, \beta_3, \dots, \beta_n$ are the coefficients of the independent variables, and $X_1, X_2, X_3, \dots, X_n$ are the independent variables included in the model. By including these variables, the regression analysis quantified their individual effects on review scores while controlling for confounding factors, isolating the linear relationships between predictors and review scores.

3.3.3. Random Forest Classifier

To complement the linear analysis, I utilized a Random Forest Classifier to capture non-linear relationships and interactions among variables, to predict review score categories – high, medium, low. This model is represented by:

$$\hat{y} = f(X_1, X_2, X_3, \dots, X_n)$$

$$review\_scores\_rating = f(is\_new\_host,\ host\_response\_rate,\ amenities\_dummies,\ latitude,\ longitude,\ accomodates,\ bedrooms,\ review\_scores\_accuracy,\ review\_scores\_cleanliness,\ review\_scores\_checkin,\ review\_scores\_communication,\ review\_scores\_value,\ \log\_price,\ \log\_minimum\_nights,\ log\_maximum\_night,\ log\_host\_total\_listings\_count)$$

Where $\hat{y}$ represents the predicted category (high, medium, low), f is the non-linear function, and $X_1, X_2, X_3, \dots, X_n$ are the independent variables included in the model (the same variables included in the OLS model).

Through an ensemble of decision trees, each one providing a classification, the Random Forest aggregates the results through majority voting or averaging, capturing complex, non-linear relationships and interactions between variables and reducing the risk of overfitting.

Model performance was assessed using various metrics, including accuracy, precision, recall, and F1-score for classification models. The results of the OLS regression were interpreted in the context of their practical significance and implications for host visibility within the Airbnb platform.

3.4. Variables Selection

The quality of the dataset is a crucial factor to consider when building a model. The normalization step of numerical variables is an essential step for improving reliability of subsequent statistical analyses by ensuring that variables are on a comparable scale and mitigating the influence of extreme values. For this, I used the min-max scaling, coupled with log transformations applied to the variables price, host_total_listings_count, minimum_nights and maximum_nights, significantly enhancing the distribution of critical features within the dataset.

Another important factor that I consider is the Variance Inflation Factor (VIF), with the goal to avoid the issue of redundant features, which may arise when variables are highly correlated. The assessment of multicollinearity revealed, as we can see in Table 1., low variance inflation factors (VIF) among the independent variables, indicating minimal excessive correlation among them, improving the robustness of the model, as it suggests that the estimation of individual effects on the dependent variable can be executed with a higher degree of confidence. The Variance Inflation Factor is represented by the following equation:

$$VIF = \frac{1}{1 - R_j^2}$$

where R_j^2 is the coefficient of determination from a regression of the feature X_j on all other features in the dataset.

The correlation analysis revealed different degrees of correlation between some independent factors and the dependent variable, review score ratings. Specifically, a positive correlation was observed between host response rate and review scores, thereby supporting the hypothesis that higher responsiveness is rewarded by the recommendation system.

4. Insights & Discussion

4.1. Performance Measure

4.1.1. Propensity Score Matching

Through the Propensity Score Matching, it was determined that new hosts consistently received lower average review scores compared to experienced hosts, after controlling for all the other factors, and the same for hosts with low and high response rates. The PSM analysis indicates that the new hosts have review scores ratings that are, on average, 1,5% lower than experienced hosts, and that hosts with low response rates have review scores rating, on average, 1,3% lower than hosts with high response rates.

Table 1. Propensity Score Matching (PSM) Results

Feature	Classification	PSM
Response Rate	High Response Rate (>85%)	0.9438
	Low Response Rate (>85%)	0.9283
Is New Host	Yes (<1 year experience)	0.9291
	No (>1 year experience)	0.9422

4.1.2. Ordinary Least Squares Regression

The Ordinary Least Squares regression analysis, results in Appendix (*Table 4. OLS Results*), also provided important information about the relationship between review_scores_rating and the independent variables. The strong model fit (R-squared of 0.761) indicates that 76,1% of the variation in review scores is explained by the model. Also, the high F-statistic (2.33E+04) and a p-value of 0.00 confirm the overall significance of the predictors.

The significant coefficients provide robust evidence supporting the hypothesis that Airbnb's recommendation system is biased, favoring experienced hosts and properties with certain desirable features.

When examining the features individually, the results indicate that the coefficient for host_response_rate is 0.6195, with a significant p-value (near 0). This suggest a positive relationship between the percentage of inquiries a host responds to and higher review scores. Specifically, for every unit increase in response rate, there is an increase of approximately 0.6195 in review scores, holding all other factors constant. Additionally, the coefficient for is_new_host is -0.8793, which is also associated with a significant p-value.

4.1.3. Random Forest Classifier

The random forest classifier used in this investigation showed a noteworthy accuracy in classifying review scores into distinct categories. The model achieved an overall accuracy of approximately 91%, indicating its effectiveness in identifying the relative performance of listings. Because the greatest part of review scores are concentrated between 80% and 100%, it was noted that the model performed better in identifying high review scores (with an accuracy of 93%) than medium review scores (with a precision of 72%) and lower review scores (with a precision of 85%), suggesting that while the model is adept at recognize listings that performed well in terms of guest reviews, it may not be as effective in identifying those that do not.

Table 2. Random Forest Classifier: Precision, Recall, F-1 Score, Accuracy

Classification Report:				
	precision	**recall**	**f1-score**	**support**
High	0.93	0.96	0.95	30973
Low	0.85	0.69	0.76	766
Medium	0.72	0.60	0.66	5512
accuracy			0.91	37251
macro svg	0.83	0.75	0.79	37251
weighted avg	0.90	0.91	0.90	37251

Feature importance analysis using permutation highlighted the dominant role of variables such as review_scores_accuracy, review_scores_value, and review_scores_cleanliness in predicting review scores, aligning with the emphasis placed on these attributes by guests when evaluating their stays. However, variables central to the hypothesis, such as is_new_host and host_response_rate, show lower importance in the model. While these features appear to have a limited direct impact on review scores, their significance may manifest through indirect effects on host visibility and guest engagement,

Overall, the results indicate that various factors, particularly those related to host performance and property attributes, impact review scores within the Airbnb platform, thereby reinforcing the need for careful consideration of these elements in the analysis of algorithmic bias.

4.2.Discussion

The results align with the hypothesis that Airbnb's recommendation system may favor established hosts and characteristics that align with the platform's priorities, thereby influencing existing disparities. Also, beyond the known factors that we have seen already, and that were already confirm by other authors, the results confirm the hypothesis that the factors "New Host" and "Response Rate" have an impact in hosts visibility, by impacting the review rate scores.

4.2.1. Hypothesis 1

The analysis reveals a consistent pattern where new hosts have less opportunities. These hosts can be affected due to several reasons, for example: a new hosts often face a steep learning curve as they adapt to the platform, they may not fully understand the nuances of guest expectations or how to present their listings attractively. Also, as I mentioned before, Airbnb's algorithm considers three major factors: quality, popularity, and price. Without historical feedback data, such as reviews or ratings, new hosts lack the established credibility and popularity that help experienced hosts achieve higher visibility in search results. This limited exposure can make it more difficult for new hosts to gain bookings and improve their standing on the platform. While *Table 1. Propensity Score Matching (PSM) Results* shows that new hosts receive review scores that are, on average, 2.4% lower than those of experienced hosts, the magnitude of this difference is relatively modest. However, even small disparities can compound over time, further disadvantaging new hosts as they try to build their reputation and visibility on the platform.

4.2.2. Hypothesis 2

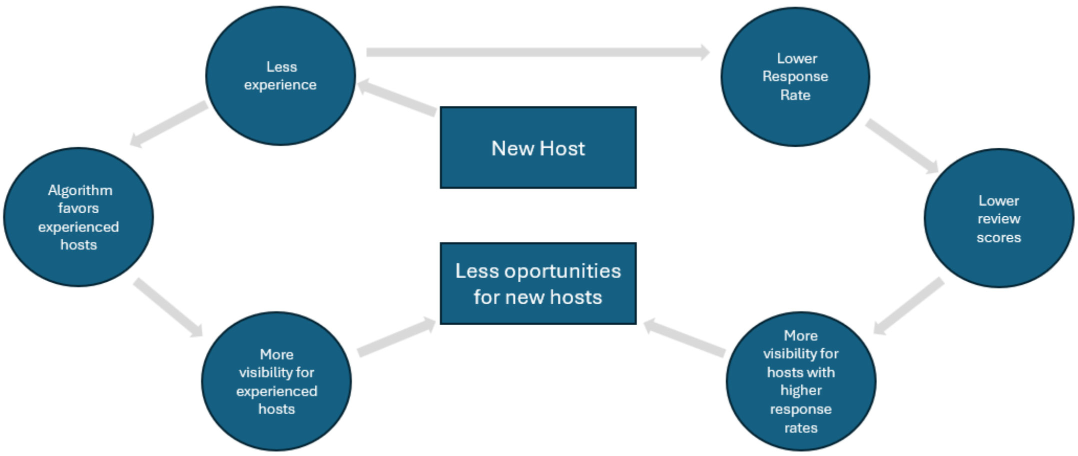
Similarly, the hypothesis is also confirmed by the positive relationship identified between host response rates and review scores. There are several reasons for this to happen: higher response rate may be a signal to potential guests that a host is attentive and reliable, therefore allowing for a better overall experience and increasing the likelihood of favorable reviews; a lower number of responses may result in misunderstandings or unresolved concerns, negatively affecting the overall experience and leading to unfavorable reviews; The results indicate that for every unit increase in response rate, review scores increase by approximately 0.62 points, holding other factors constant. While this impact may seem modest, it demonstrates the importance of responsiveness in shaping guest perceptions. Hosts with lower response rates, often due to time or resource constraints, are at a disadvantage, which can create a feedback loop. As lower response rates lead to lower review scores, these hosts may experience reduced visibility and booking opportunities, making it harder for them to compete effectively on the platform.

While it is evident that hosts with lower response rates typically receive lower review scores—a relationship that is indeed valid—the concept of algorithmic bias highlights how the system can exacerbate this issue. If an algorithm disproportionately rewards hosts with higher response rates, it creates a feedback loop that further penalizes hosts who have inability to maintain a high number of responses.

4.2.3. Hypothesis 1 and 2

It is also interesting to investigate the relationship between these two factors – new host and response rate, and how the "new host" factor can be double penalized (figure 1). Beyond the tested hypothesis that new hosts are penalized because Airbnb's algorithm favors more experienced hosts, the findings suggest that new hosts may also be indirectly penalized through their response rates. Due to limited experience and familiarity with the platform, new hosts often can have a lower response rate, which can lead to delays in communication. This lower responsiveness negatively impacts their overall review scores and places them at a disadvantage within an algorithm that prioritizes higher response rates. As a result, new hosts face a dual disadvantage; they are penalized for their inexperience and for their inability to respond quickly to inquiries. This creates a compounding effect that further limits their visibility and opportunities for bookings, reinforcing systemic barriers within the platform.

Figure 1. Algorithmic Cycle – New Host Feedback Loop Double Effect



Already confirmed by Zhang, Y., & Wang, L. (2022) that analyzed the impact of host pricing strategies in visibility, emphasizing the significance of this variable in a listing's attractiveness and competitiveness, the results of the OLS Model also reflect the relevance of price for the algorithm. With a coefficient of 0.1365, the model reinforces this hypothesis demonstrating that economic factors play an important role in determining host visibility. Hosts who are unable to adjust their prices competitively are disadvantaged, echoing the findings of previous studies that highlight how algorithmic systems perpetuate inequalities based on host characteristics.

4.3.Limitations

I should note some limitations. First, the dataset's focus on specific cities limits the generalizability of the findings across different contexts. Secondly, while median imputation is a reasonable choice of handling missing data, it assumes that the missing values are randomly distributed and do not systematically differ from the observed values, which poses the possibility of creating biases in the model. Thirdly, the lack of review date information in the dataset restricts the scope of the analysis. As a result, the model compares review scores between hosts who have been on the platform for less than one year and those who have been active for longer. If review date information were available, it would allow for a more detailed comparison by analyzing review scores received during each host's first year on the platform versus subsequent years. This would provide deeper insights into the relationship between host experience and review outcomes. Finally, another possible limitation of my study is the use of review_scores_rating as a proxy for visibility. In one hand, based on my literature review, it is valid to assume that higher review scores lead to increase visibility in the platform's recommendation system. On the other hand, this variable is not a direct measure, which can also lead to some bias in the results interpretation.

5. Conclusion and Recommendation for Actions

This study gives crucial light into possible bias present in Airbnb recommendation system, suggesting that the platform favors established hosts and characteristics that align with its interests. While the results are not 100% conclusive, they indicate that new hosts and hosts with low response rate are at some point disadvantaged by the algorithm, impacting their visibility and overall review scores. This study also reveals a positive correlation between host response rate and review scores, underscoring the importance of engagement in shaping guest perceptions and experiences. This means that hosts with lower response rates are placed at a disadvantage, leading to a cycle of less visibility.

It is essential for Airbnb to mitigate these systemic barriers, implementing measures that support with lower visibility due to external reasons. This could include educational resources for all hosts, covering topics such as effective communication, guest expectations, pricing strategies; introduction of features that highlight listings in underrepresented areas or those that provide unique experiences, regardless of the host's experience level, among others. By addressing these issues, Airbnb can foster a more equitable environment that not only benefits individual hosts but also enriches the overall guest experience.

Concluding, this research emphasizes the urgent need for ongoing scrutiny and reform of algorithmic practices within the sharing economy. By implementing solutions to solve the approached issues, Airbnb can work toward a more inclusive platform that provides equal opportunities for all hosts, ultimately contributing to a more just and equitable sharing economy.

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Appendix

Table 3. VIF Score per feature selected for training.

Feature	VIF
const	345.348
is_new_host	1.014545
host_response_rate	1.012580
amenities_dummies	1.246095
latitude	1.492450
longitude	1.170584
accomodates	2.124327
bedrooms	2.078440
review_scores_accuracy	3.186405
review_scores_cleanliness	2.354049
review_scores_checkin	2.400055
review_scores_communication	2.711072
review_scores_locaton	1.575616
review_scores_value	2.871181
log_price	1.540765
log_minimum_nights	1.056076
log_maximum_nights	1.055168
log_jost_total_listings_count	1.148721

Table 4. OLS Results

Dep. Variable	review_scores_rating	**R-squared:**	0.761
Model:	OLS	**Adj. R-squared:**	0.761
Method:	Least Squares	**F-statistic:**	2.33E+04
No. Observations:	124170	**Prob (F-statistic):**	0.0001
			-
Df Residuals:	124170	**Log-Likelihood:**	3.47E+05
Df Model:	17	**AIC:**	6.93E+05
Covariance Type:	nonrobust	**BIC:**	6.93E+05

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	-2.515	0.208	-12.089	0.000	-2.923	-2.107
is_new_host	-0.8666	0.056	-15.341	0.000	-0.977	-0.756
host_response_rate	0.6195	0.072	8.652	0.000	0.479	0.760
amenities_dummies	0.343	0.025	13.725	0.000	0.294	0.392
latitude	-0.0039	0.000	-9.037	0.000	-0.005	-0.003
longitude	0.0012	0.000	-7.015	0.000	-0.002	-0.001
accomodates	0.0232	0.007	3.386	0.001	0.010	0.037
bedrooms	0.0008	0.014	0.057	0.954	-0.027	0.029
review_scores_accuracy	2.7173	0.023	117.443	0.000	2.672	2.763
review_scores_cleanliness	2.0468	0.018	115.995	0.000	2.012	2.081
review_scores_checkin	0.6495	0.025	26.141	0.000	0.601	0.698
review_scores_communication	1.9182	0.025	77.425	0.000	1.870	1.967
review_scores_location	0.3525	0.021	16.938	0.000	0.312	0.393
review_scores_value	2.2595	0.020	111.156	0.000	2.220	2.299
log_price	0.1365	0.011	12.702	0.000	0.225	0.158
log_minimum_nights	0.0832	0.013	6.506	0.000	0.058	0.108
log_maximum_nights	-0.0378	0.007	-5.198	0.000	-0.052	-0.024
log_host_total_listings_count	-0.2547	0.009	-28.82	0.000	-0.271	-0.238

Table 5. Random Forest Classifier

Classification Report:

	precision	recall	f1-score	support
High	0.93	0.96	0.95	30973
Low	0.85	0.69	0.76	766
Medium	0.72	0.60	0.66	5512
accuracy			0.91	37251
macro svg	0.83	0.75	0.79	37251
weighted avg	0.90	0.91	0.90	37251

Feature Importance
review_scores_accuracy: 0.15630145449218116
review_scores_value: 0.12838478084167926
review_scores_cleanliness: 0.12004140849074277
review_scores_communication: 0.08303873326425201
latitude: 0.07946981663569158
longitude: 0.07857949781897465
log_price: 0.07484673198304469
review_scores_checkin: 0.0558549713018356
log_host_total_listings_count: 0.05018334137665839
accommodates: 0.03156814324791481
log_maximum_nights: 0.03132290005598477
log_minimum_nights: 0.029964417201813597
host_response_rate: 0.02693802986937645
review_scores_location: 0.02575292428102502
bedrooms: 0.01412567706595879
amenities_dummies: 0.010132217303288829
is_new_host: 0.0034949547695776397

Figure 2. Distribution of Numerical Variables

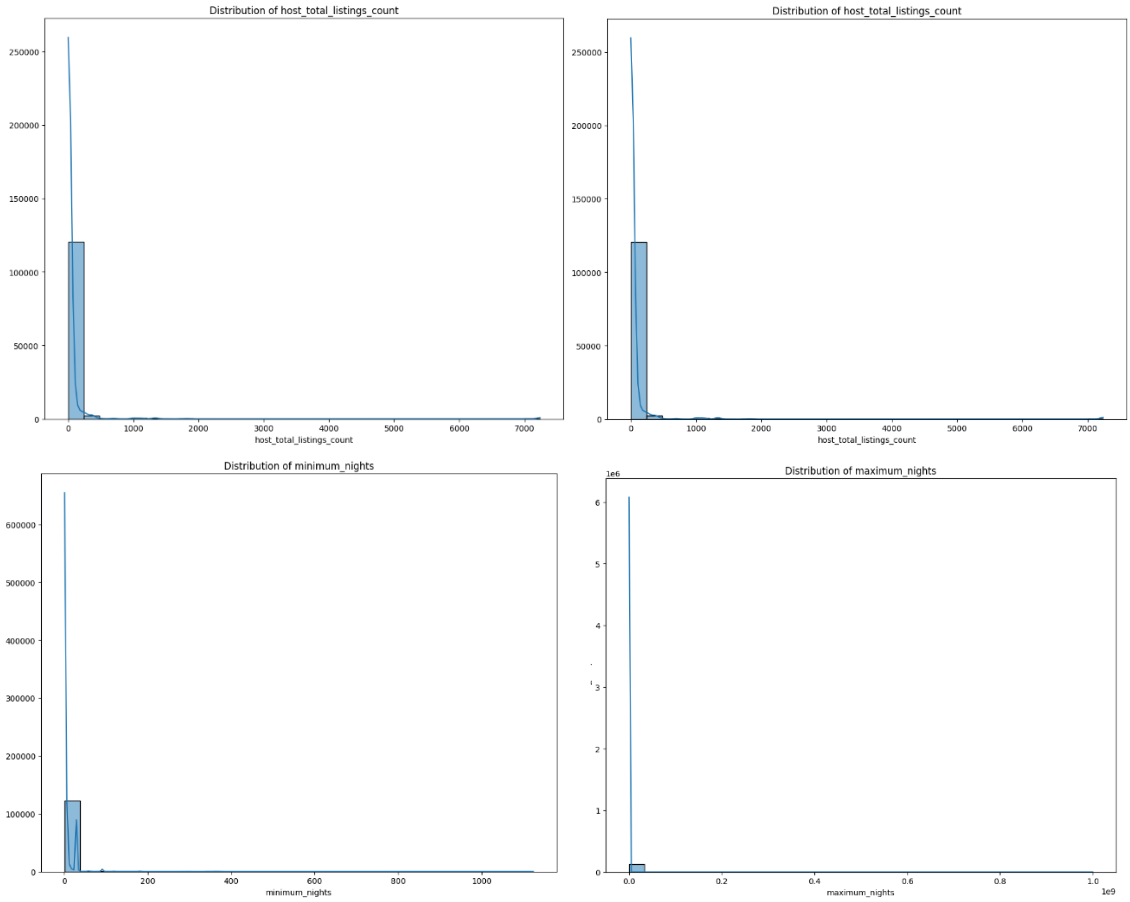

Figure 3. Outliers Detection - Histogram of Numerical Variables

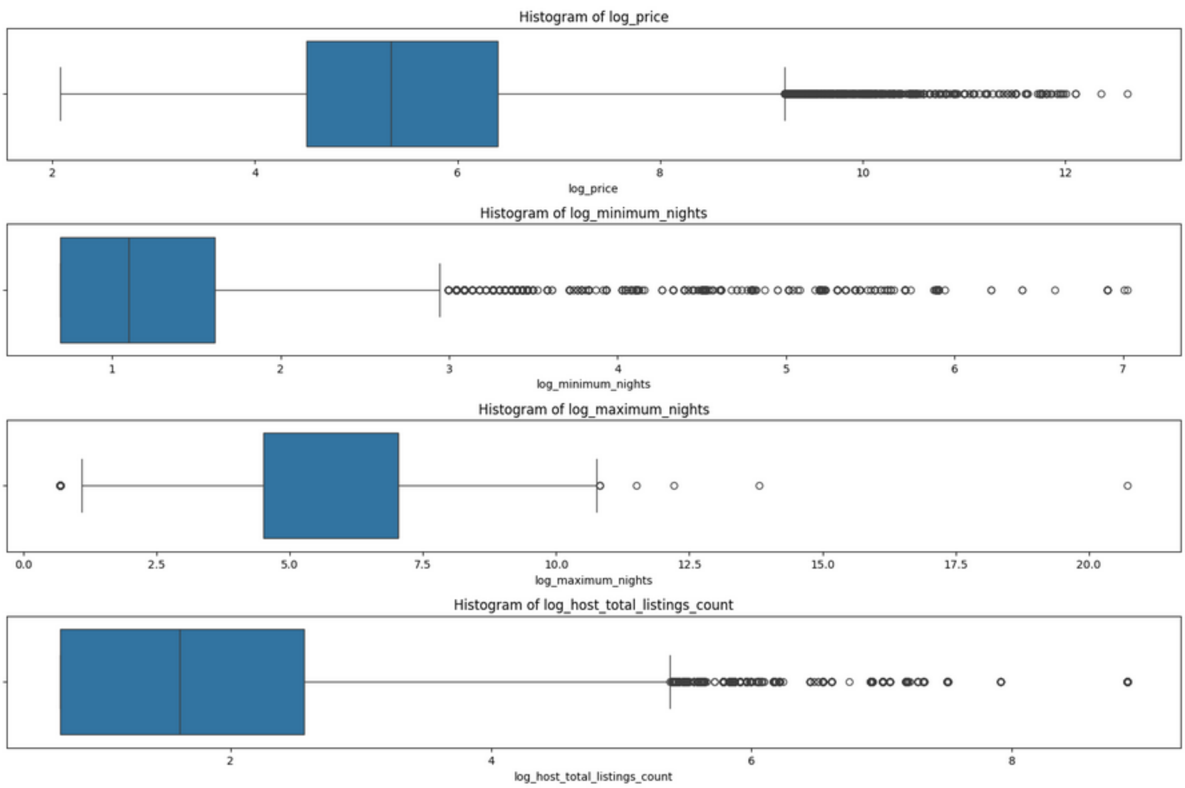

Figure 4. Outliers Removal - Histogram of Numerical Variables after Outlier Removal