Examining the landscape of the Sharing Economy, in Particular through Airbnb: A Literature Review

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Abstract

In this systematic literature review, I present the latest research on the sharing economy since 2017, focusing on Airbnb. From the 19 papers I have investigated, 4 key themes have emerged: Urban Geography, Equality Diversity and Inclusion (EDI), Experiences and Reviews, and Trust. To gain an insight into the latest research in the sharing economy, I compare the key contributions, methodologies, strengths and weaknesses of the papers in each theme, identifying overlaps and differences.

1 Introduction

1.1 Overview

A phenomenon born in the age of the internet, the sharing economy is a peer-to-peer collaborative economic model, based on individuals sharing underutilised assets with others, typically through a community-based computer-mediated online platform. The sharing economy shifts the consumer value from ownership to access, making services in communities available to more people while reducing overconsumption, pollution and inequality [1]. Short-term peer-to-peer transactions allow users to share their assets such as their car on ride-sharing platforms Uber and Bolt, their skills and time completing tasks on Fiverr and TaskRabbit, and more. A key player in the sharing economy, Airbnb has revolutionised the hospitality market by allowing users to rent out full properties, or individual rooms to guests interested in staying.

The modern sharing economy is relevant to computer science because it relies upon digital platforms to match providers to consumers and handle transactions, as such computer scientists are responsible for ensuring that their design and implementation results in fair treatment for all users. Additionally, the digital records left behind by these transactions can be analysed using computational methodologies to observe users' behaviour, understand how the platform evolves, and determine where improvements can be made.

1.2 Methodology and Themes

Papers were selected from 2017 onwards since [2], a systematic literature review, covered papers on the sharing economy published before 2017. Papers were primarily found using Google Scholar, searching for keywords such as "Sharing Economy", "Airbnb", "Geography", "HCI", "Diversity", "Trust" and more. Computational aspects were required, generally analysis methods, and required sound methods for collecting data, quantitative or qualitative.

From considering the literature, the papers were divided into the following 4 key themes for analysis and comparison:

Urban Geography
Equality, diversity, and inclusion
Experiences and reviews
Trust

2 Key Themes

2.1 Urban Geography

Urban Geography plays a key role in the sharing economy by dictating where people live and work, and how they move around. By analysing the impact of geography, biases, cultural differences and inequalities can be identified, and steps can be taken to reduce or eliminate their effect.

Papers [3] and [4] investigate Airbnb's penetration and urban geography in cities. Secondary data scraped from Airbnb's website is made available by `insideairbnb.com`, and used in these and other papers' investigations. Paper [3] focuses on 8 US cities while [4] investigates 19 cities globally. [3] Employs multivariate linear regression to explain spatial penetration using tracts' geographic, social and economic values and 4 different models are tested to explore predicting Airbnb penetration: Support Vector Machines, logistic regression, random forest and Naive Bayes. [4] Uses different methods: host penetration was computed with the Gini coefficient of the number of guest reviews in a city; adoption with the VADER NLP algorithm and GSDMM to analyse review sentiment. Paper [3]'s use of 4 different machine learning models facilitated useful comparison, and [4] stood out thanks it its wide multi-cultural scale. [3]'s results cannot be generalised outside the US, in particular in developing nations, especially as cities investigated were primarily Airbnb early adopters. [4] Suffered from difficulties in analysing reviews common with other papers, requiring the purging of non-English reviews, as well as those too short or long for VADER to analyse accurately (shorter than 5-8 words, exceeding 175 words).

Paper [5] investigated how Chicago's urban geography affected human behaviour on 2 platforms other than Airbnb: TaskRabbit and UberX. Mixed effect logistic modelling regression was applied to indicate a TaskRabbit worker's willingness to take on a task in a given area, and Spatial Durbin modelling was introduced to computing literature, to investigate the effect neighbouring tracts have on a given tract, in terms of waiting time for Uber rides. While Spatial Durbin modelling provided compelling evidence, the TaskRabbit investigation relied on self-reported qualitative data, potentially leading to inaccurate reporting.

Papers [6], [7] and [8] considered the links between gentrification and Airbnb.

[6] Considered using Airbnb data to measure gentrification in real-time, rather than relying on infrequently collected census data. New York, Los Angeles and London-based Airbnb properties were considered, with review sentiment scores computed with VADER, and property gentrification scores computed from property information. Linear and Out-of-sample Random Forest regression were then used to predict gentrification scores with Airbnb data, with these models having greater accuracy than the baseline model (RMSE: 9.23 to 13.95 vs 13.36 to 18.05). Models that used both property and review data performed better than those which used one or the other. While providing a repeatable method for nowcasting gentrification, causality cannot be established, and the models were only suitable for large cities with extensive tourism.

[7] Analysed the spatiotemporal distribution patterns of Airbnb properties in the Dublin metropolitan area (DMA), also to determine if Airbnb data could be used to identify gentrification. Emerging Hotspot Analysis was used to find different trends in locations over time, and Self-Adjusted DBSCAN to identify clusters of high Airbnb density. Airbnb property distribution was found to be uneven, and Airbnb monopolised the short-term rental market. Unfortunately, the paper could not conclusively determine what came first, gentrification or Airbnb, and did not incorporate official housing market data to evaluate gentrification.

[8] Investigated how Airbnb and the wider sharing economy contribute to gentrification in Beijing, including data during the COVID-19 pandemic (until December 2020). Housing transaction records and Airbnb listings were analysed. Multiple linear regression and ArcGIS were used to quantify the impact of COVID-19 on Airbnb's resilience regarding gentrification, and difference-in-difference models were fit to determine whether new practices were stimulated that related to Airbnb. Key findings included that more Airbnb listings survived in ungentrified and gentrifying neighbourhoods than in gentrified and regentrifying. The paper provided useful insight into the impact of the COVID-19 pandemic on Airbnb, in a non-western context, however, despite studying neighbourhood-level indicators such as distance to metro services or tourist facilities, neighbourhood-level demographic data such as socioeconomic status (SES) was not considered.

2.2 Equality, Diversity and Inclusion

Maintaining equality, diversity and inclusion (EDI) in the sharing economy is essential to its success, ensuring that the sharing economy is open to all.

All four papers analysed how the race of guests or hosts affects their interaction with the sharing economy, with papers [9], [10] and [11] also considering age and gender. Listings and review data were collected from `insideairbnb.com`. [9] And [10] investigated homophily of host/guest pairings to identify offline biases as a result of race, age and gender; with [10] succeeding [9], applying the same method it had developed but focusing on a single city - London, rather than the 5 cities considered in [9]. Various software solutions were used to extract the host/guests' race, gender and age from profile pictures. [9] Employed Betaface software to extract the ethnicity, and Sightcorp for age, while [10] used the Clarifai API for ethnicity and Microsoft Azure Face API for gender and age estimation. Both papers then used the same bi-partite graph network shuffling method to compute the preferential attachments between different ethnicity, gender and age groups. In both papers, it was found that group pairings of different racial groups were under-expressed, eg: White host and black guest. [9] Demonstrated a valuable repeatable and scalable method, as shown applied in [10]. Key limitations were that only White, Black and Asian races could be classified, excluding hosts and guests of other races, and in [9], 4/5 cities were majority White, potentially resulting in increased observed homophily and avoidance.

[11] Performed 2 studies, the first in 24 cities internationally, and the second in 16 US cities, investigating possible significant price differences between the prices charged by White, and non-White hosts (Black and Asian). The researchers chose Face++ to identify race, age and gender, and multilevel regression was applied to compute the differences in impacts on the listing price due to the aforementioned races, room type, location, reviews and more. The paper's strengths included more control variables than other studies, a large number of cities (35), extensive regression analysis, and compelling outcomes of racial price disparity by city, its main weakness being that all cities considered in study 1 are majority White. The inclusion of more non-White majority cities such as in South America, Asia or Africa may have yielded different results.

[12] Performed a large-scale real-world experiment to investigate how the presence and sentiment of reviews affected the rate at which hosts accepted booking requests from accounts with White and African-American-sounding names (as a proxy for the guest's race). The authors made requests to Airbnb hosts in 5 US cities to test the acceptance rates of accounts with positive, non-positive and blank reviews. Linear and logistic regression were used to compute the statistical significance of the results. A clear discrepancy in acceptance rates between races was identified, however the use of White and African-American names could have been substituted with profile pictures identical other than the race of the guest, as typically African-American names could be associated with lower SES, reducing acceptance rates.

2.3 Experiences and Reviews

Reviews and ratings form a fundamental aspect of sharing economy platforms, assuring that services were provided as described. The experience of users matters, in particular in the case of Airbnb, where experiences may vary from host to host.

Papers [13], [14] and [15] investigated the topics discussed in reviews posted by guests: [13] to understand topics that improve customer experience, [14] to identify the dominant aspects of emotions in reviews, and [15] to compare the topics between Airbnb and the traditional hotel industry.

Although various methodologies were used to analyse the reviews, Latent Dirichlet Allocation (LDA) was the most common, used in these 3 papers. [14] Used listing and review data in Los Angeles, applying Latent Aspect Rating Analysis (LARA) to identify the weighted importance of different aspects of Airbnb experiences: communication, location, value, experience and service. LDA with an extended bootstrapping algorithm was then used to extract the keywords maximally related to these aspects. Paper [13] also applied LDA to extract topics for a single city, New York. LDA with Gibbs Sampling extracted 43 topics, each with its top 50 relevant keywords. Hierarchical ward clustering was then applied to reveal underlying conceptual relationships between topics. [15] Used LIWC to calculate an authenticity score for reviews in 7 US cities, then identified the most relevant topics with LDA. The papers used sensible mixed-methods processes to develop similar topic and keyword lists. By focusing on developed and richly diverse New

York City, [13] was able to produce a topic list with more topics than [15], with more keywords per topic than previous investigations (50 rather than 10). [13] and [14] were limited in their generalisability, only considering reviews in 1 city each, New York and Los Angeles. [15] Used Linguistic Inquiry and Word Count (LIWC), a relatively simple tool that makes use of word counting and a general-purpose dictionary for review analysis, unlike more modern text analysis technologies.

[16] Investigated review rating inflation on Airbnb, compared to TripAdvisor, a holiday review website. The authors performed a global-scale analysis of the distribution of overall listing ratings for Airbnb and TripAdvisor, plotting the results on a histogram, and then used linear regression and Kendall rank coefficients to compare review ratings for locations cross-listed on both platforms. A clear discrepancy between the platforms' review scaling was found, with 14% more properties rated 4.5 stars on Airbnb than TripAdvisor, however, the authors could not explain why.

Paper [17] aimed to determine whether Airbnb has become a primarily business transactional platform, rather than a social one. A coding scheme was developed from thematic analysis of 100 reviews, verified via crowdsourcing, from which with natural language processing techniques and hierarchical clustering techniques, a reusable dictionary of topics was created, which was later used in paper [6].

A key difficulty in investigating reviews is that non-English reviews have to be excluded, as well as reviews shorter than 5 words or exceeding 175 words. Papers [17], [13] and [4] (Urban Geography) discussed experiencing this difficulty, reducing the number of reviews available for analysis that may have included significant details.

2.4 Trust

The sharing economy relies on trust when connecting unknown providers and consumers, in Airbnb's case hosts and guests, to ensure the safety of and a positive experience for all parties. The papers below consider mechanisms on sharing economy platforms to understand the key components that promote trust.

All papers relied on qualitative surveys of individuals from varying backgrounds to identify trust topics or answer questions regarding mechanisms that increase trust.

Paper [18] explored how self-disclosed content in an Airbnb host's profile affects their trustworthiness perceived by potential guests, and if this affects whether guests chose to stay with them. The authors identified 9 key topics to develop a novel coding scheme for Airbnb host profile self-disclosure, after which crowdsourcing on Amazon Mechanical Turk (AMT) was applied to annotate sentences to identify the associated topic. A trustworthiness scale was also developed, with workers rating their confidence in a profile on it, and stating whether they would stay with the host. Host type was found to influence profile disclosures, and perceived trustworthiness predicted choice for shorter profiles.

[19] Was largely similar to [18], also investigating host profile self-presentation and perceived trust among prospective guests. A similar topic investigation was performed, and a survey that evaluated the trustworthiness of host profiles, and willingness to stay. Partial Least Squares modelling was applied in papers [19], [20] and [21] to compute the weighting scores for each survey question.

[20] Performed a survey that investigated sharing economy mechanisms that developed trust attachment for guests. Survey participants were required to have been Airbnb guests in the US and South Korea in the preceding 2 years, providing firsthand behavioural data. They were surveyed on their experience using the website and staying with hosts. Website security and privacy had the most significant impact on users trusting Airbnb, and the frequency of interaction with hosts impacted user-host trust.

[21] Considered how the implementation of Blockchain technologies could improve trust on a sharing economy website. Survey participants were introduced to `slock.it`, a Blockchain-based P2P sharing platform, and answered questions regarding their experience and understanding of the increased trust factors from Blockchain technology. Users valued the increased trust resulting from Blockchain technology on the platform, allowing for a shift from trusting individual users to better-trusting platforms as a whole.

The common weakness among all papers was that qualitative survey-based analysis methods were used. Crowdsourcing survey answers can yield lower-value data if survey participants have little incentive to read profiles and make considered decisions. Furthermore, survey results may not reflect real-world behaviour driven by external needs; users may accept a higher level of risk to ensure they have accommodation or service at busy periods, or for a cheaper price - yet these factors cannot be considered in a simulated experiment.

3 Discussion and Future work

In this literature review, I considered 19 papers across 4 key themes, that investigated the sharing economy.

The majority of papers considered in this literature review made use of quantitative analysis methods. Quantitative studies require less human interaction in the analysis application, allowing for greater scalability, especially useful in analysing large-scale sharing economy platforms with data that spans the globe. Some papers such as [17] and [18] employed crowd workers to annotate data for creating dictionaries; the subjective choices made by many crowd-workers could then be combined to perform larger-scale automated analyses. 4 out of 19 papers base some or all of their findings on surveys, performing qualitative analysis of the subject: [5], [20] and [19] and [21]. Qualitative methods, while generally more costly and time-consuming, allow authors to understand the causation of observed effects by asking participants directly, rather than identifying correlation and speculating on causes in the case of quantitative studies.

A variety of analysis algorithms and modelling techniques were applied in the reviewed papers. The techniques used in each paper are shown in Table 1. The majority of papers employ mixed-method modelling approaches, combining different analysis methods in the same or separate studies.

A common limitation across many (but not all) papers, was that investigations took place in developed Western countries, missing out on investigating the current development of Airbnb and other sharing economy platforms in less developed countries. By focusing on the West, where greater concentrations of sharing economy participants operate, data can be collected and analysed in a setting more familiar to the generally Western authors, but trends found may not generalise in other regions with different cultures and modus operandi. The map in Figure 1 shows the countries investigated in the 19 papers analysed, and highlights a clear bias towards the US, Europe and South America, with no countries in Africa, the Middle East or South Asia considered.

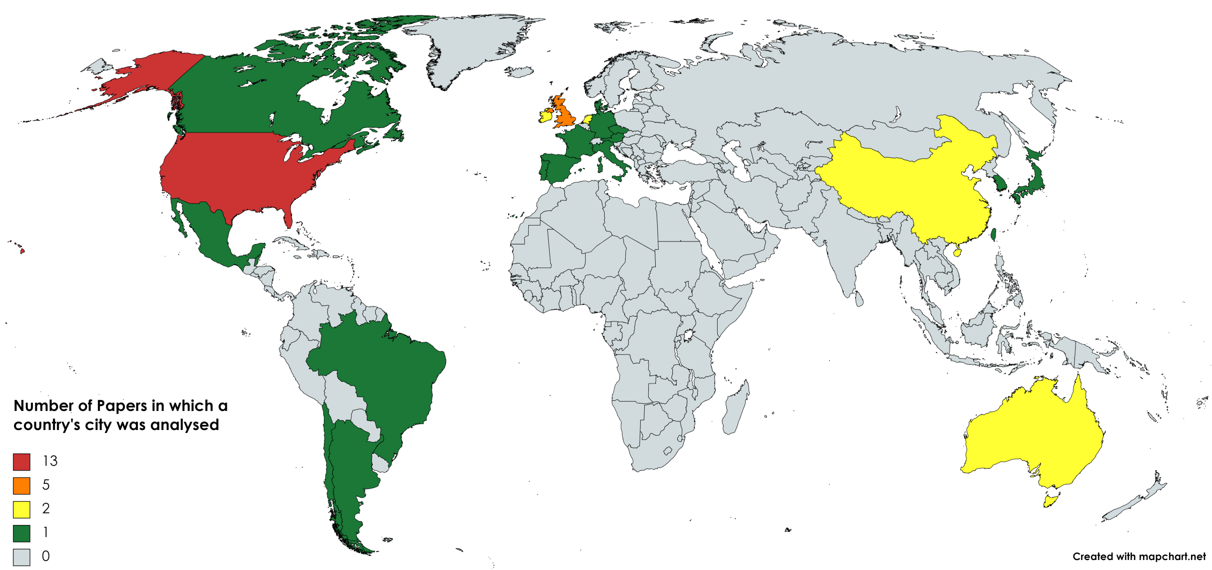

Figure 1: Highlighted countries containing cities that were investigated in the 19 papers analysed.

Themes	Paper	Platform	Algorithmic Methods
Urban Geography	[3]	Airbnb	Linear Regression, Multivariate Linear Regression, Multilevel Regression, Naive Bayes, Random Forest, Support Vector Machines
	[4]	Airbnb	Gibbs Sampling Dirichlet Multinomial Model (GSDMM), Valence Aware Dictionary for Sentiment Reasoning (VADER)
	[5]	TaskRabbit, Uberx	Latent Dirichlet Allocation (LDA), Spatial Durbin Modelling
	[6]	Airbnb	LDA, VADER, Linear Regression, Random Forest
	[7]	Airbnb	Emerging hotspot analysis, Space Time Cube, ArcGIS Pro, Mann Kendall test
	[8]	Airbnb	Multiple linear regression, ArcGIS Pro, Heterogeneous difference-in-difference (DID) models
EDI	[9]	Airbnb	Kendall Rank Correlation, Sightcorp, Betaface, Bipartite Graph Random Shuffling Network
	[10]	Airbnb	VADER, Microsoft Azure Face API, Bipartite Graph Random Shuffling Network
	[11]	Airbnb	Logistic Regression, Face++
	[12]	Airbnb	Linear Probability Modelling, Logit Modelling, Logistic Regression
Experiences & Reviews	[13]	Airbnb	LDA, Hierarchical ward clustering
	[14]	Airbnb	Latent Aspect Rating Analysis (LARA), LDA, GSDMM
	[15]	Airbnb	Linear Regression, LDA, Linguistic Inquiry and Word Count (LIWC), Python NTLK
	[16]	Airbnb, TripAdvisor	Linear Regression, Kendall Rank Correlation
	[17]	Airbnb	Hierarchical Clustering, NLP application
Trust	[18]	Airbnb	Linear Regression
	[19]	Airbnb	KH Coder, Stanford POS tagger, Hierarchical cluster analyses, Partial Least Squares Modelling (PLS)
	[20]	Airbnb	PLS
	[21]	Slock.it	PLS

Table 1: Table summarising platforms and methodologies

When analysing review sentiment with VADER, the requirement that reviews be of a certain length and written in English limited the number of reviews available for analysis in some cities such as Beijing in [4] to less than 10%. This impacted the ability to study the sharing economy in developing countries where English may not be the primary language used by guests writing reviews.

Finally, studies that considered race were generally limited to White, Black and Asian people, due to these being the categories that classification models could most accurately identify. This resulted in the exclusion of many other ethnic groups, such as those of Middle Eastern or Latino descent, and does not provide the required nuance to analyse the effect of ethnicity outside of the 3 aforementioned groups.

Future investigations should attempt to remedy the general weaknesses which I have highlighted, considering a wider variety of cities, particularly in Africa, South Asia, the Middle East and Oceania, with a clear focus on rapidly developing nations and cities taking advantage of sharing economy platforms.

The capacity to analyse non-English reviews should be sought, either using translation tools that translate both meaning and sentiment, or with sentiment analysis models that can evaluate non-English text. Investigation into the sharing economy in more rural areas should also be considered, as sharing economy studies are generally centred in cities where the greatest concentration of participants live.

The latest or future ethnicity classification models may have a greater capacity to more accurately identify race, allowing for study in greater detail how sharing economy participants of different races experience the platform. Finally, more emerging technologies such as Blockchain and AI will be applied to the sharing economy, therefore their impacts and challenges should be studied.

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