ABSTRACT
The use of datasets that contain incorrect data could have several severe consequences. In recent years, large datasets that consist of online user generated contents have been leveraged by scholars to study social phenomena, test hypotheses, and develop predictive models. The collection of such large datasets, however, remains a challenge for researchers. Many use existing datasets that have been collected and verified by other scholars. Others use open datasets that are available online for direct download. By using an open dataset, scholars are able to avoid the often tedious data collection phase and focus instead on their research inquiries. While many of these datasets are verified and reliable, some are not, and therefore may have data quality issues. Inside Airbnb is a website that collects data of places and their reviews as posted by users of Airbnb.com. Visitors can effortlessly download data collected by Inside Airbnb for several locations around the globe. While the dataset is widely used in academic research, no thorough investigation of the dataset and its validity has been conducted. This paper analyzes the dataset and explains one major data quality issue that was discovered. The primary contribution of this evidence-based work is its documentation of incorrect data added to the dataset. Findings suggest that this issue is attributed to systemic errors in the data collection process. Additionally, this paper explains why reproducibility is a problem when two different releases of the dataset are compared.

1. INTRODUCTION
It is undoubtedly imperative to use valid data in research. If scholarly work is based on invalid data, discoveries reached using such data may also be invalid. Similarly, an operationalized predictive model that is developed based on a dataset with data quality issues could produce results that are problematic. Data quality is defined as “agreement between the data views presented by an information system and that same data in the real world” [1]. In recent years, the rise of computational social science and the increased accessibility of advanced computational resources have motivated scholars from a variety of disciplines to utilize computational methods in their research [2], [3]. These advances have also motivated researchers to utilize large open datasets. Open data refer to datasets collected and made freely available online for use by governments, organizations, researchers, or any interested individual [4]. These datasets are usually hosted by online repositories such as the UC Irvine Machine Learning Repository [5] or made available through dedicated websites. Examples for the latter include Pushshift, which hosts data extracted from Reddit [6] and Inside Airbnb (IA). IA, as the name implies, hosts data collected from Airbnb [7]. Scientists studying several emergent topics, such as disinformation in online platforms [8], [9] and the sharing economy [10], [11], often utilize these open datasets.

The sharing economy is commonly defined as the process in which individuals offer their underutilized resources for use by others. Platforms in the sharing economy include Uber and Airbnb. The sharing economy and its platforms have been studied by scholars from several academic disciplines [12]–[17]. Based on a search in the “Web of Science” database for
“Uber” and then “Airbnb,” there seems to be more research papers published on the latter. One likely reason is the availability of a large open dataset that includes places, their reviews, and their locations for Airbnb listings, as collected by the IA website [7]. InsideAirbnb.com is a website that was started by an activist who wanted to “dispute Airbnb’s claim that 87% of the hosts rent out the place in which they live” [18]. The website offers direct download for data reportedly collected from Airbnb’s website. Visitors can effortlessly download data of places and their reviews from locations such as Los Angeles, New York City, and London. The data for each location includes the date of data compilation. IA collects new data for each location periodically, and a new data for each location replaces all existing ones for the same location. Datasets from IA have enabled scholars to study several relevant topics such as trust in the sharing economy [19], [20], pricing issues and impacts of the sharing economy [21], [22], and textual contents of reviews extracted from the platform [11], [23].

Despite the popularity of IA, the website only provides minimal information on the data collection process that was implemented to extract data from Airbnb. According to a page on IA’s website [24], the data is collected using python scripts. These scripts included ones that have been “copied and pasted” [24] from other online resources. One such resource is a script available on Github [25]. Tom Lee, the person who is responsible for this script, indicated that he no longer maintains the project. He also included a disclaimer that he does not guarantee the quality of the data. Additionally, he documented changes that Airbnb implemented on the layout of their website and explained how these changes negatively affected the web scraper’s performance. IA did not provide information on any possible effects these changes had on the performance of their scrapers. However, they noted that some of the reviews in their data might be “spam” added by Airbnb [24]. Websites that are not friendly to scrapers often implement methods to prevent or deceive the scripts [26]. IA stated that these spam reviews were insignificant in terms of size. Nevertheless, no detailed descriptions or examples were provided on the reviews or the process of their discovery. This lack of clarity regarding the quality of the data raises concerns regarding the use of data from IA.

While the IA dataset is widely used in academic research, no independent researchers have provided an evaluation of the dataset and its validity. Additionally, few authors have provided justifications for their use of an open dataset that has not been verified or properly documented. Several authors have stated that they verified the data by selecting a small sample and confirming that the data exist on Airbnb’s website [20], [27], [28]. In one of the papers, the sample used for verification contained only 10 entries [27]. Therefore, it is possible that the sample size was too small for any issues to be discovered. Another justification provided by authors was that the data have been used in other academic papers [22], [23], [29]. The rationale is that the dataset is deemed creditable since other authors have used it in their research. However, most of the papers that used IA did not provide justification for their use of an unverified open dataset collected by a third party. Acknowledgements of potential issues in the IA’s datasets were stated in one paper [30]. In this paper, the authors noted possible data quality issues with information collected using the previously mentioned Github project [25], which IA used in their data collection. The authors compared the number of listings collected using the Github project to the number of listings collected by IA. They stated that inconsistencies in the numbers were discovered. This suggests that data quality issues may indeed exist.

Delving into this matter more deeply, this paper addresses potential data quality issues and challenges the validity of the IA dataset by providing documentation of incorrect data. To determine the significance of the discovered issue, all the listings from two locations are analyzed using automated methods, and the reviews for each location are examined. The results suggest that the use of unverified open datasets can be problematic, although the discoveries presented in this paper are not significant enough to challenge all published research that uses the IA dataset. Additionally, findings in this paper indicate that the incorrect data happen due to a new feature implemented by Airbnb. Thus, unless changes are made, it is likely that the consequences of this issue would only become more severe. The main contributions of this work are as follows:

- An explanation of a data quality issue in the IA dataset that results in the addition of incorrect data. These instances of incorrect data increase the number of reviews linked to each listing in IA. In some rare cases, the number of incorrect reviews linked to a listing are higher than the number of actual and correct reviews.
- A demonstration of how an unverified dataset collected by a third party has been used in academic papers even though it has never been verified, documented, or inspected for data quality issues.
- Evidence on reproducibility issues when the IA dataset is used. These reproducibility issues happen due to IA periodically releasing new versions of listings and reviews. While this is not an issue in the IA dataset itself, it becomes problematic when authors using IA do not specify the release used.

The rest of the paper is organized as follows: Section 2 introduces related works; Section 3 describes and summarizes the dataset and explains the process to evaluate the issue discovered in the dataset; Section 4 provides all of the details regarding the discovered incorrect data and their significance in addition to explaining the reproducibility issue; Section 5 presents a short discussion; and Section 6 offers a conclusion.
2. RELATED WORK

A. Issues in Open Datasets

Similar research has discovered data quality issues in unverified open datasets. Reddit is a popular website where users can submit posts and comments in communities of interest. Pushshift is a website unaffiliated with Reddit that collects Reddit’s data and makes them freely available for download. Similar to data from IA, data by Pushshift have been used extensively in research, even though they have never been independently verified by researchers. Gaffney and Matias [31] investigated the dataset and discovered evidence of missing data. Put differently, there were data available on Reddit that were not found in Pushshift’s dataset. The authors concluded their paper by summarizing the risks to research validity when the dataset is used in publications. These include risks to machine learning models, research that compares communities, and research that analyzes specific users. Their work, similar to the work presented in this paper, demonstrates how large open datasets not thoroughly evaluated for validity have been widely used in academic research while containing previously undiscovered data quality issues. Consequently, individuals responsible for the Pushshift dataset have recently provided detailed documentations for their work, including the data collection process, in a paper [6].

B. Data Quality Issues and Methods

Several researchers have described numerous data quality issues and challenges when big open datasets are used [4][32]. One paper lists issues to validity that are likely to happen when researchers use a data dump that they did not collect [33]. The authors explained how such data that have not been “crafted for research” could present issues. The IA dataset investigated in this paper meets this description. In another paper, the authors discussed challenges associated with data quality when validating big data [34]. “Lack of validation” during data collection was specified as a factor that could cause data quality issues. Dimensions and classification of data quality issues were proposed in another paper [35]. The authors stated that “incorrect data” happens when a value for an entity “does not conform to the real entity.” They also described the negative consequences of poor data quality in organizations. In another paper, information quality was referenced as a potential issue in open data [36].

In yet another paper, the authors studied “automatic veracity assessment of open source data” by surveying 107 published papers [37]. The authors provided several existing definitions for “veracity” when used in this context but acknowledged the lack of academic consensus on one definition. However, they provided a list of concepts often used when the term is mentioned. These terms include “truth, trust, uncertainty, credibility, reliability, noisy, anomalous, imprecise, and quality.” The authors discovered that insufficient details regarding certain datasets may present challenges to researchers attempting to reproduce results obtained by other scholars. In business, data quality increases firms’ ability to find useful information from data and improves firms’ “decision quality” [38]. In light of these urgent problems, several authors have proposed automated methods and processes to discover data quality issues [39], [40]. One method relied on the discovery of poor data that may lead to errors in tests and, as a result, may lead to the inability to reproduce results [41]. Another paper discussed data quality issues in repurposed datasets, that is, datasets that are available but contain minimal meta-data or descriptions [42]. The authors proposed “LANG” as an approach to aid the discovery of data quality issues in repurposed datasets.

C. Large Open Datasets

In several disciplines, significant efforts have been made to develop large datasets that are available for researchers and practitioners to download and then use to develop applications, test hypotheses, and solve challenging research questions. For example, ImageNet [43] is a large open dataset of images and their classes. It has helped accelerate research in several research areas, such as image classification, neural networks, and object detection. Some open datasets have been used significantly in social science research, and possibly paved the way for computational social science. An example of such datasets is the “reality mining” dataset [44]. These two datasets provide evidence that 1) large open datasets may require significant work to develop and thoroughly evaluate, and 2) they may have a major impact and contribute to advancing multiple fields.

D. Data Quality and IS Research

Several recent works have discussed data quality in Information Systems (IS) research [45], [46]. Marsden and Pingry [47] focused on quality issues related to numerical data used in IS. The authors defined numerical data as data collected using one of the following methods “interviews, surveys, field experiments, quasi-experiments, controlled laboratory experiments, empirically observed, and third party fee-for-service data.” The authors stated that IS research needs to devote additional resources to addressing data quality issues. They also suggested that published IS papers should detail their data collection process. Finally, the authors suggested seven questions that should be asked about datasets used in IS research: what, when, where, how, who, which, and why. For example, authors described the “when” issue of data collection and how it may affect replicability. Leary explored how “when” and “where” a technology is studied may affect the type of data collected [48]. Put differently, data collected about a technology at a certain time may change when compared with the same data collected at a different time. The present paper takes this into account by comparing two releases of IA.

Moreover, Vial extended Marsden and Pingry’s numerical data issues to Digital Trace Data (DTD), which he defined as...
“digital records of activities and events that are produced, stored and retrieved using information technologies.” [49]. The author discussed how such datasets are increasingly utilized in IS research and explained how Marsden and Pingry’s seven questions are applied to DTD’s datasets. Similarly, Dong explained the questions in the contexts of simulation research in IS [50]. Likewise, Lee-post and Pakath investigated data quality issues in “secondary” data sources, that is, open or public datasets that are available for others to use [51]. The authors stated that such datasets could “contain unaddressed quality issues that merit further attention” and that “establishing quality with secondary data is a more difficult task as one usually is doing this post hoc.” Finally, the authors provided a list of guidelines for journals publishing research that relies on secondary data. They assert that the provider of the dataset “must be credible” and the author should clearly state the particular individuals responsible for the data collection. The paper also discussed minimum thresholds of data quality for datasets, a topic also discussed in other papers [52], [53].

3. INVESTIGATING INSIDE AIRBNB DATASET

The objective of investigating the IA dataset is to identify any data quality issues, which may have impacted the findings of peer-reviewed academic papers that used this dataset without evaluating it for validity or reliability. The presence of a single error could then be used as evidence that there are indeed issues in the dataset, and thus further investigation of the dataset is needed. Therefore, this work does not attempt to classify all the data quality problems in the dataset. Instead, its objective is to identify a single issue and explain its significance. This section provides information about the structure of data from IA. Moreover, it explains details about features in Airbnb that are attributed to indirectly adding incorrect data to the IA dataset. This section also includes a brief description of the issue of incorrect data discovered, the dataset used to inspect this issue, and the evaluation process completed to determine the significance of the issue.

A. Background

| Column     | Description                  |
|------------|------------------------------|
| Listing id | The listing ID of the review |
| ID         | The ID of the review         |
| Date       | The date of the review       |
| Reviewer id| The ID of the reviewer       |
| Comment    | Textual content of the review|

Inside Airbnb provides several downloadable files for each available location. The available file downloads for a selected location includes “listings.csv.gz,” and “reviews.csv.gz.” The “reviews.csv.gz” includes all reviews from the location selected (such as Los Angeles or Rome). Each review is linked to one listing. A listing could, for example, be a room, house, or an apartment. Several columns that provide more information about the reviews are available. These columns, which are listed and defined in Table 1, include the listing ID, the date the review was written, and the actual textual content of the review. In Airbnb, each listing has a unique listing ID [54]. The data in the files “listings” and “reviews” are linked using this listing ID. This enables the access of additional information about a listing, such as the name and response rate for the host of the listing, the neighborhood and location (latitude and longitude) of the listing, and the URL of the listing.

In November of 2016, Airbnb introduced Airbnb Experiences [55]. It is an attempt by the company to expand its offerings by providing two options for users: 1) places for stays such as rooms, apartments, and houses, and 2) activities and excursions users can book, such as cooking classes, guided city tours, and hiking trips. The structure of URLs for places is http://airbnb.com/rooms/

http://airbnb.com/experiences/

In the December 5th release of the IA dataset for the Los Angeles area, no column exists to indicate that a listing in the table is for a “place” or an “experience.” Additionally, based on information from IA’s website, there does not seem to be a current option that allows visitors to download information extracted from Airbnb’s website about experiences. Upon exploring a representative sample of the data in the downloaded “listings” file, all the listings seem to be of the “place” type. In Airbnb, while it is not possible for two places to have the same listing ID, it is possible to have a “place” and an “experience” with the same listing id. In Figure 1, two listings are displayed. The first is for an “experience” in Tokyo, Japan where users can book a class to learn to play the game “Go,” while the second is for a house in Burbank (which is in the Los Angeles, CA, USA area) that is available for rent. Both the house and the class have the same ID “344.” In IA’s “reviews.csv.gz” file for the Los Angeles area, all the reviews written by guests who have stayed in the house with the listing ID “344” are available and accurately linked to the listing. However, instances of incorrect data were discovered when it was observed that the reviews for the “Go” class in Tokyo with the listing ID “344” were also added as reviews linked to the house in Los Angeles. This signals a data quality issue that requires additional exploration. The details of this issue are presented in Section 4.A.
FIGURE 1. Two listings with the same listing id “344.” First is for an “experience” in Tokyo and the other is for a “place,” in this case, a house in Los Angeles.

B. Dataset
To investigate data quality issues in data collected by IA, two locations are selected for examination. The datasets for each location are accessed and downloaded directly from IA. The locations selected are Los Angeles, CA, USA and Ashville, NC, USA. The purpose of the selection of two locations (and thus two sets of files to process for each location) is to determine if issues discovered are not unique to a single location. According to IA, the Los Angeles dataset was compiled on December 5th, 2019 while the Ashville dataset was compiled on November 28th, 2019. For additional comparison and to study the issue of reproducibility when two different releases of the data from the same location are used, an earlier version of the data from Los Angeles is also tested. The earlier data from Los Angeles will be referred to as Los Angeles 1 (LA1) while the second will be referred to as Los Angeles 2 (LA2). In summary, LA1 and LA2 will be used to assess the issue of reproducibility when two releases of data from the same location are used. Further, LA2 and Ashville will be used to explore the issue of incorrect data and its significance, which is the primary focus of this paper. Table 2 shows summary statistics for the three locations. The statistics are based on processing the csv files in “reviews.csv.gz” for each of the three sets. There is an observable decrease in the number of listings and reviews for data from LA1 to LA2. A possible explanation is Airbnb’s policy of removing places from the platform if their hosts decide to delete the listings. However, this is only one possible explanation and further investigation is needed for confirmation.

C. Evaluation Process
To investigate the issue of incorrect reviews found in IA, the files with the reviews from LA2 and Ashville are analyzed. The process starts by collecting all the listing IDs. Then, for each listing ID, the standard webpage for an Airbnb’s experience (http://airbnb.com/experiences/“listing_id_for_experience”) is visited. The objective of this step is to see if the ID of the listing is also used as an ID for an experience in Airbnb. This check is completed using a web scraper. The scraper loops over all the available listing IDs and determines whether they are also used as IDs for experiences. As of January 2020, the “robots.txt” page in Airbnb does not state that they disallow the access of the /experiences/* pages using scripts. For each ID that is classified as one that exists as an experience, the reviews for the experience are examined. The objective of this step is to find if at least one review for the experience has been added to the IA dataset. Initially, the objective was to process and compare all the reviews for the place and then the experience with the same ID. However, the “robots.txt” page explicitly states that Airbnb disallows the processing of reviews for a place. This evaluation results in two lists: 1) listing IDs from IA that match both a location and an experience and 2) listing IDs in IA that have at least one review of an experience that was incorrectly added to the listing.

TABLE 2
SUMMARY STATISTICS FOR THE THREE LOCATIONS ANALYZED. DATES FOR Compilation dates are in 2019

| Location       | Number of unique listings | Number of reviews | Max number of reviews per listing | Average number of reviews per listing | Compilation date (according to IA) |
|----------------|---------------------------|-------------------|----------------------------------|---------------------------------------|-----------------------------------|
| Los Angeles 1  | 35,959                    | 1,427,153         | 813                              | 39.6                                  | July 8th                          |
| Los Angeles 2  | 32,029                    | 1,368,997         | 813                              | 42.7                                  | Dec 5th                           |
| Ashville       | 2,263                     | 170,973           | 907                              | 75.5                                  | Nov 28th                          |

FIGURE 2. A flow chart of the process to determine: 1) the IDs that exist as experiences and 2) the IDs in IA with at least one incorrect review.
4. RESULTS

A. Issue #1: Incorrect data
The incorrect data issue refers to reviews that were incorrectly added to listings in IA. For example, Figure 3 shows five reviews linked to a listing with the listing ID “344.” The first and third reviews were both present and found to be accurate when the webpage for the respective listing was visited. However, this was not the case for the second and fourth reviews. Additionally, the first review was clearly written by a person documenting their stay in a house in Los Angeles while the second review was written by a person reviewing a “Go” learning class in Tokyo. Based on viewing the webpage for the class in January of 2020, only two reviews were written for the experience. In the IA dataset for LA2, both reviews appeared as reviews for the house in Los Angeles with the same listing ID (false positive). Moreover, all the reviews for the stay with the same listing ID were also present in the IA dataset (true positive). Therefore, it is possible that an issue in the data collection code written by IA is causing the collection of all the reviews with the specified listing ID regardless of the type of listing (“place” or “experience”). However, due to restrictions employed by Airbnb on the collection of reviews from places, it is not possible to document in this paper if this is indeed the case for all listings. Nevertheless, manual inspections of listings support this hypothesis.

Following the process explained in Section 3.C, all the listing IDs in LA2 and Ashville were processed. For each listing, the webpage for the experience with the same listing ID was accessed using an automated script. The script determined if an experience existed with the same listing ID. To reduce the possibility of issues in the web scraper, a browser window was automatically opened by the script every time a new listing ID was tested. The objective of this step is to monitor the scraper’s activity. Additionally, all the IDs identified as ones that exist as experiences were assessed for accuracy. This was completed by visiting the URLs of the experiences. All but one ID was found to be accurate. This one ID could be of an experience that has since been deleted. One limitation of the scraper is that it is unable to identify if certain IDs were formerly employed as IDs for experiences. Thus, it is possible that the list of IDs that exists as both a place and an experience is larger than reported in this paper.

The result of this process is a list of 103 listing IDs that exist as both a listing ID for a stay and an experience in LA2, and a list of only five IDs for Ashville. For the 103 listings, at least one review for the experience with the same listing ID as a location was added to the IA dataset for 50 of the IDs. Put differently, 50 of the listings in the IA dataset for LA2 included reviews that were added incorrectly. Some of these reviews were from experiences that include boat rides in India, a yoga class in Australia, and a city tour in Prague.

The low number of IDs with incorrect data suggests that while the issue requires attention, it may not currently be severe enough to affect published papers using the IA dataset. The number of unique listings in LA2 is 32,029, and the percentage of IDs with incorrect data is only 0.15%. This low percentage could be due to the overall low number of available experiences. In other words, as more experience and their reviews are added to Airbnb, the number of incorrect data in IA is likely to increase.

| Review | Reported Location | Actual Location |
|--------|-------------------|-----------------|
| We really enjoyed our tour with Sara! She knows the history of her country and her city, and she also knows plenty of interesting little stories about art, religion and culture. Alla & Francois | A house in Topanga Canyon (Los Angeles) | Prague, Czech Republic |

A wonderful excursion with a wonderful local host. Giuseppe was kind, informative, flexible with our schedule and went above and beyond throughout our tour. Highly recommend.

TABLE 3
EXAMPLES OF INCORRECT REVIEWS AS WELL AS REPORTED LOCATIONS (BY IA) AND ACTUAL LOCATIONS (AS FOUND IN THIS PAPER)

FIGURE 3. Example of how reviews in the dataset for the listing ID “343” are actually from two different listings. The ones on top are from the listing of the “place” type with the ID “343” while the ones on the bottom are from the listing for the “experience” with the listing ID “343.”
Listing IDs in Airbnb are numerical and in IA the IDs are ordered ascendingly. While no confirmed information was found, it seems that Airbnb creates a new listing ID for new places or experiences by simply adding one to the latest created ID. To further examine the low number of IDs that included incorrect reviews in IA, four classes of IDs were created. The first class included the first 500 IDs in LA2, the second class included the second 500 IDs in LA2, the third class included the third 500 IDs, and the fourth class included the final 500 IDs. Based on matching the IDs that exist as both a place and an experience within these categories, it was found that the first 500 listings included 47 listings, the second 34, the third 22, and the rest of the listings included zero matches. Figure 4 illustrates this decreasing trend. All the results for each sample are in Table 4. Due to the small number of problematic IDs for Ashville, no segmentation of the data was conducted. It should be noted that an examination of the latest release of the Los Angeles data from IA (compiled on May 8th, 2020) indicates that the inaccurate data issue still exists.

While further exploration is needed, these results suggest the following:

- The low number of incorrect data in IA is indirectly related to the overall low number of experiences available in Airbnb. This is supported by the fact that all IDs that exist as experiences are in the first 1,500 IDs of the 32,029 unique listings.
- For the first 500 listings in LA2, incorrect reviews where found for 31 of the listings. Put differently, 6.2% of the listings include at least one incorrectly added review. This is a significant difference from the 0.15% reported earlier for the entire set. Therefore, the effects of this discovered issue could be severe if this subset of the data (the first 500 IDs) is selected.

The statistical significance of the primary discovery remains a crucial question. The answer depends on how many records of incorrect data were used and for what purpose. For example, if only the first 500 listings were used in a study, the effects could be of statistical significance. Alternatively, if the entire dataset for a set location is used, for example all the reviews from Los Angeles, it is possible that the incorrect data issue will have no effects. Therefore, additional work is needed prior to providing measurable results on the effects of these findings. To do this, researchers might test the effects of incorrect data on several tasks as well as on multiple samples of the dataset.

B. Issue #2: Differences in Releases and Reproducibility Issues

While the primary focus of this paper is to highlight the issue of incorrect data in the IA dataset, another objective is to explain a separate matter for concern when using the dataset. This issue is one of reproducibility. It is imperative that results from one experiment can be reproduced in another. Such replicability is not always possible, however, in studies involving IA that do not specify the version or release used. Since IA releases a new version of the dataset for each location almost every month, the new version replaces an existing release. These updates throw into question the ability for one scholar using the latest release to reproduce results obtained by another researcher who used an older version of the dataset but did not specify the version used. To explore this problem further, two releases for the reviews and listings from the Los Angeles area were analyzed (LA1 and LA2). The compilation dates as indicated by IA were July 8th, 2019 and December 5th, 2019. By only comparing the sizes of the two releases, changes in the number of unique listings and number of reviews were observed.

The number of unique listings decreased from 35,959 to 32,029. Thus, 10% of the unique listings in the earlier release were no longer available in the newer release. An attempt to access the webpages of a small random sample of removed listings was made. Results suggest that these listings no longer exist on Airbnb’s website, hence it does not seem that there is an issue in the data collection process. However, further exploration is needed. For reviews, the number changed from 1,427,153 reviews to 1,368,997 reviews. This suggests that the newer version includes 58,156 less reviews. Alternatively, 4% of the reviews in LA1 were not available in LA2. To compare

![FIGURE 4. The number of IDs that exist as both a “room” and an “experience” for the four classes of IDs.](image-url)

| Dataset | Sample               | Listings that Exist as Experiences | Listings With at Least One Incorrect Review |
|---------|----------------------|-----------------------------------|-------------------------------------------|
| LA2     | All                  | 103 (0.32%)                       | 50 (0.15%)                                |
| LA2     | First 500 listings   | 47 (9.4%)                         | 31 (6.2%)                                 |
| LA2     | Second 500 listings  | 33 (6.6%)                         | 13 (2.6%)                                 |
| LA2     | Third 500 listings   | 23 (4.6%)                         | 6 (1.1%)                                  |
| LA2     | Rest (listings 1501-)| 0                                 | 0                                          |
| Ashville| All                  | 5 (0.22%)                         | 3 (1.3%)                                  |

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if the change is of statistical significance, Welch's t-test was computed by comparing the number of reviews per listing in the two releases. The null hypothesis in this case is that two releases have an identical average number of reviews per listing. The result of the test was statistically significant (p value < 0.05) and thus the null hypothesis was rejected.

While further examination is needed, this result suggests that significant changes are observed when the number of reviews in two releases of the dataset are compared. However, this does not necessarily indicate that these significant changes are a result of data quality issues in the dataset itself. For this reason, one recommendation for scholars employing the IA dataset in their research is to state the version used in their work in order to avoid potential reproducibility issues. Moreover, during this task it was observed that the mean number of reviews per listing increased from 39.6 reviews per listing to 42.7 reviews per listing. A possible explanation for this increase is that as “experiences” are becoming more popular in the platform, more incorrect reviews of “experiences” are being added to the dataset.

5. DISCUSSION

A. Options for Collecting Large Datasets

This work highlights the issue of data collection faced by some researchers when they conduct research relying on large online user-generated datasets. Social data scavenging refers to a method of data collection that relies on collecting information from online contents posted by users who are unaware that their data is being collected. With this method, users are uninformed that their participation in an online platform is being utilized in data collection [56]. For researchers and practitioners who want to use such data in their work, there are several options: directly downloading the dataset from the platform, developing scripts that access the data using APIs or web scrapers, and allocating resources to manually collect the data.

The most direct method to access these datasets is to download them directly from the online platforms. For example, Twitter has a service where interested individuals can pay to download an exported dataset based on specified search criteria. According to one paper, Airbnb is not cooperative about sharing their data and thus obtaining full and verified data directly from the platform is difficult [57]. In some cases, researchers might have the option to use an API provided by the service. For Airbnb, an API was provided near the end of 2017. In one paper where the API was used, the authors described how rate limits were an obstacle [58]. Additionally, as of February of 2020, Airbnb indicated they no longer accept requests to access the API [59]. Therefore, relying on APIs is not always an option and presents its own set of difficulties. Another option for data collection is for researchers to develop their own web scrapers, a technique used in one paper to collect data from Airbnb [14]. However, the use of web scrapers presents a set of ethical concerns for researchers, in addition to the challenge of dealing with prevention mechanisms commonly employed by websites [26]. The “/robots.txt” page in Airbnb indicates that the platform disallows access to reviews for a specific listing of the “place” type. Moreover, it is worth noting that using either APIs or web scrapers requires knowledge of a programming language. Thus, these two options require skills that many social scientists interested in “big data research” may not have. A fourth option is to employ manual methods for collection, which entail using crowdsourcing platforms to hire a large number of workers who collect and annotate datasets. However, this option is tedious and may require vast resources.

In summary, these options present several challenges, largely because they require resources that are difficult to obtain. For these reasons, open datasets are an appealing option, as they enable scientists to focus on their inquiries and avoid the often lengthy data collection process. To limit the potential for data quality issues, online platforms should consider providing samples of their data, similar to what Yelp does with its Yelp open dataset [60].

B. IA’s Quality and IS Research

It is worth recalling the work of Marsden and Pingry [47], which proposed seven questions that should be asked before using numerical datasets in IS research. Although their definition for numerical datasets does include open source datasets obtained freely, it can be argued that their seventh type, defined as “third party fee-for-service data – purchased (possibly constructed) for specific research,” is loosely applicable to IA’s dataset, because this dataset is collected by a third party. Although IA is not for-profit and not necessarily developed for research, it would still benefit from being subjected to Marsden and Pingry’s seven questions. Therefore, this section provides answers to these seven questions based on 1) what IA provides as answers and 2) what authors generally indicate when they use the dataset. Table 5 includes these responses.
TABLE 5
Answers Based on What IA and Researchers Provide

| Questions from [47] | IA | Researchers using IA |
|---------------------|----|----------------------|
| “What provides an explanation of exactly what is captured in the data.” | While IA provides an explanation of the dataset, their explanation is limited and lacks detailed descriptions on potential flaws in the dataset. Researchers often provide a short description of the dataset but fail to provide a full and detailed explanation. |
| “When refers to the time at which the data is collected.” | IA provides the “compilation date” that indicates the date the dataset for a particular location was collected. Researchers often do not mention the compilation dates for the IA sets used in their work. |
| “Where refers to the location (virtual or real) of the data collection.” | IA includes the locations of the data; more specifically, the cities where the listings and reviews originated. Researchers often do specify the cities used. |
| “How describes the precise process(es) of data collection.” | IA does not provide an explanation, but rather shares general information. Only a few researchers included information on IA’s data collection methods or their limitations. |
| “Who details the individual(s) involved in the data collection.” | IA shares information about the person responsible for starting the project. Researchers cite IA but do not include details about individuals involved in their potential biases and activism. |
| “Which details instruments or artifacts used in collecting the data.” | IA only shares vague information about the source code used to collect the data. Researchers do not specify the methods IA used to collect the data. |
| “Why provides the set of reasons or goals for collecting the data.” | IA provides their reason for collecting the data. Researchers do not provide that IA started as a project to track the potential negative impacts of Airbnb. |

6. CONCLUSION

In this paper, evidence of a data quality issue in a popular open dataset widely used in research was described. More specifically, this work explained the issue of incorrect data that adds wrong reviews to listings in the Inside Airbnb dataset. For some listings, the majority of reviews in IA were incorrect as they were written for an “experience” with the same listing ID. To demonstrate that this is not the only concern when this dataset is used, the question of reproducible findings was explored. As discussed in Section 4.2, statistically significant changes were observed when two releases of IA for the same location were compared. An immediate address for this discovery is for scientists to indicate the exact release date used when an open dataset with periodical releases is employed in their research.

This work can be extended in several ways. One is to explore the history of non-verified open datasets used in research. The objective of this exploration is to investigate how such datasets initially gain interest and credibility. Based on a search in Google Scholar, it is likely that one of the first documented uses for IA in academic papers is from a student paper completed by two undergraduates. Thus, one hypothesis is that open datasets are initially utilized in papers that are not peer-reviewed or published in reputable outlets. Then, after these papers are cited in several papers, the dataset is noticed by others who assume the validity of the dataset since it has already been used in papers. As stated earlier, several authors used other researchers’ use of the data as a justification for their own employment of the dataset. Another possible extension is to explore other issues present in the IA or similar open datasets.

The potential impacts of this work include: 1) an increased awareness on the importance of a responsible data science that prioritizes data quality and research rigor, 2) a change in how open datasets that have not been independently verified are perceived, and 3) a motivator for individuals responsible for the IA dataset to investigate the issue discovered and remedy it along with other potential issues. While no other problems were discovered, it is not guaranteed that the dataset is free from errors if the issues explained here are addressed. Therefore, it is possible that issues exist in the dataset even after the issues discussed in this paper are fixed. It is worth restating the central role that the IA dataset has played in cutting-edge research on the sharing economy. By using this dataset, scientists have made claims about several topics such as tourism management, urban planning, and the economics of the sharing economy. These issues might not have been explored if the researchers could not readily download and process this open dataset. Thus, as IA continues to enable innovative research, it is essential that the dataset be scrutinized so that it offers scientists valid and reliable datasets.

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