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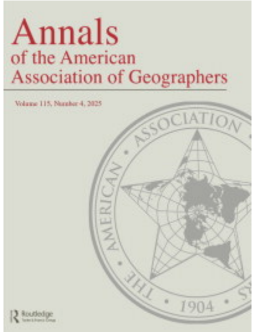

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Diagnosing Spatial and Temporal Biases of OSM Contributors: Identifying Differences Between Gender and Age from an Online Survey

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Citizen science projects are open and available to anyone to contribute data. The literature concerning volunteered geographic information, however, has demonstrated significant demographic participation biases across time and space. Understanding the significance and impacts of these biases is challenging due to privacy concerns, which lead to the (pseudo-)anonymity of contributors. Using a sample of 265 users, this article statistically analyzes edits to the crowdsourced mapping platform OpenStreetMap to examine the impact of gender and age on spatial and temporal contribution patterns. We find that men aged in the others group (i.e., below twenty-five or over fifty-four) made more contributions during the week and on weekends than those in the economically active age group (i.e., ages twenty-five through fifty-four). Using the Kruskal–Wallis test to compare temporal contributions between gender groups, the economically active group showed a significant gender difference on both weekdays and weekends, as well as the hours of the day, with men making more contributions than women regardless of age category. Men in the others group made the most contributions overall. Calculating the Simpson Index of Diversity for user edits reveals that women have more limited spatial interests (i.e., they contribute to fewer countries) than their male counterparts, suggesting particular spatial preferences by gender. *Key Words: demographic bias, gender, OpenStreetMap (OSM), Simpson Index of Diversity (SID), survey.*

Geographic crowdsourcing has provided us with a freely available collection of geospatial data for a wide range of applications. OpenStreetMap (OSM), a peer-produced editable map of the world, is arguably the most successful example, with more than 8 million registered users (Bertolotto, McArdle, and Schoen-Phelan 2020). Crowdsourcing offers the potential to create vast data sets and flexibility in when and how the crowd makes contributions (Stamm and Eklund 2017). This effectively saves a huge amount in costs and time in carrying out experiments (Geldmann et al. 2016; Gauvin et al. 2020).

Although crowdsourcing platforms are technically inclusive for anyone with access to the Internet, current literature has revealed that "the crowd" tend to exhibit some degree of skewness and homogeneity (Stephens 2013; Leszczynski and Elwood 2015; Gardner et al. 2020). These tend to be young, technically enabled men (Stephens 2013; Gardner and Mooney 2018; Gardner et al. 2020), but they are also those with higher incomes, more time to volunteer, and fluency in English (Brown, Kelly, and Whitall 2014; Basiri, Haklay, and Gardner 2018; Haworth et al. 2018; Young et al. 2021). The lack of reflection on who the crowd is can violate the principles of sound research (Geldmann et al. 2016), and the data collected, which often tend to be temporarily inconsistent and spatially unbalanced, can inevitably lead to erroneous results and false conclusions (Callaghan et al. 2019).

To date, citizen science research that examines bias is composed of two groups: (1) the bias between demographic or socioeconomic characteristics (Stephens 2013; Leszczynski and Elwood 2015; Das, Hecht, and Gergle 2019; Gardner et al. 2020),

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and (2) the bias of spatial or temporal patterns (Geldmann et al. 2016; Callaghan et al. 2019). There are limitations, however. First, previous studies have failed to consider the demographic subgroups during analysis, even though these subgroups have different distributions in comparison with the overall group (Tilley and Houston 2016; Das, Hecht, and Gergle 2019). For example, bicycle activities were disproportionately distributed among men and those under the age of fifty-five, yet this disparity narrowed throughout the early pandemic (Fischer, Nelson, and Winters 2022). Simply collapsing the information characteristics might not only hold back dynamic interactions between indicators but also limit the perception of delivering evidence-based insights to real-world implications (Gauvin et al. 2020). If there is no consideration of how demographic groups contribute differently it would be difficult to design more inclusive crowdsourcing platforms (Mulder et al. 2016; Basiri et al. 2019; Bailur and Sharif 2020).

Second, few studies mentioned how spatially and temporally unbalanced results are associated with contributors' behaviors. Ecological studies have observed that crowdsourced data, particularly bird watching, contains patchy distribution data across space and time (Geldmann et al. 2016; Muñoz et al. 2020). This is mainly because the majority of reporters work voluntarily, the data are reliant on the observers' ease of access to the bird-watching sites (Callaghan et al. 2019), or perhaps dependent on their skills (Brabham 2012). Recent studies using the Strava fitness app, which allows consenting users to report their commuting or exercise behaviors, have found that cycling activities are more frequent on weekends compared to weekdays (Lin and Fan 2020), and that the dominant users of Strava are men between the ages of twenty-five and fifty-four (Alattar, Cottrill, and Beecroft 2021; Livingston et al. 2021). Additionally, mobility studies also encounter challenges with data sparsity, making it difficult to infer patterns, as the data are derived either from mobile cell towers or through voluntary app usage. Although Fischer, Nelson, and Winters (2022) discovered that the representativeness of Strava increased to around 7 percent of the cycling population in two Canadian cities during the early years of the pandemic, findings from other cities were still known to be dominated by men in the twenty-five to fifty-four age group (Alattar, Cottrill, and Beecroft 2021; Livingston et al. 2021).

Addressing the gaps, this study examines how demographic differences in spatial and temporal biases affect contributions to citizen science projects. Building on Gardner et al. (2020), we use data from OSM. Here, we ask the following research questions: (1) Do temporal OSM contributions differ by gender, age, or both? (2) How do these demographic characteristics affect the spatial distributions of OSM contributions?

The remainder of this article is structured as follows (see Figure 1). We first review the literature associated with participation biases and the spatial and temporal differences between groups. We then describe the methodology by introducing the data collection and cleaning procedure and introduce the nonparametric statistical analysis. We explore OSM contributions between demographic groups temporally, considering both days of the week and times of the day. We then employ the Kruskal–Wallis test to unravel the statistical difference of OSM contributions by demographic groups. We measure the spatial bias of contributions using the Simpson Index of Diversity (SID). Finally, we discuss these findings, draw a conclusion, and outline future work.

Related Works

Identification of Contributors' Participation Bias in Crowdsourced Geospatial Data

The unevenness of participation has been a focus in the literature concerning geographic crowdsourcing. To date, only a small, privileged population have used and contributed to crowdsourced platforms (Sui and DeLyser 2012; Haworth, Whittaker, and Bruce 2016). These people are likely men dwelling in the northern hemisphere, communicating in English, who have sufficient time for volunteering. Haklay (2016) also added that the majority of crowdsourcing has been done by those in high-paid jobs and without child-care responsibilities outside their paid work.

The primary focus of early work on participation biases in geographic crowdsourcing platforms was characterizing contributors by their geodemographics, including gender, age, country of origin, native language, income, time availability, and the availability of social and technical support (Huynh, Doherty, and Sharpe 2010; Sui and DeLyser 2012; Stephens 2013; Brown, Kelly, and Whitall 2014; Haworth

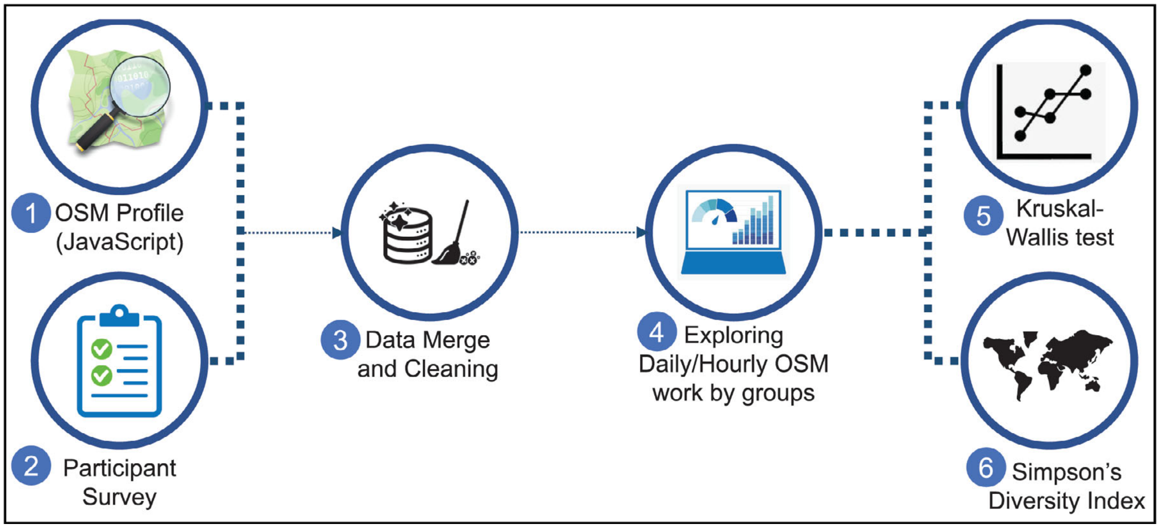

Figure 1. Overview of the analytical process. The Kruskal–Wallis test examines the temporal biases of the study participants, whereas SID looks at the spatial biases of the participants. *Note:* OSM = OpenStreetMap.

et al. 2018; Das, Hecht, and Gergle 2019; Gardner et al. 2020; Young et al. 2021). Among these, gender has been the most cited indicator, as reducing gender biases is not only the basis of human rights, but balanced gender perspectives also help represent the distribution of the population (Schmidt and Klettner 2013; Stephens 2013; Das, Hecht, and Gergle 2019; Garrote, Gutiérrez-Pérez, and Díez-Herrero 2019; Gardner et al. 2020).

Understanding of gender has increasingly been influenced by social constructionism, although the meaning of the latter term has also taken various forms (Brickell 2006). Lorber (1994) characterized gender as both a "social institution" and "individual status." As a social institution, gender functions as a point of difference between individuals by defining roles and expectations based on societal norms (e.g., what men or women should do). As an individual status, gender is seen as a point of similarity, reflecting personal identity and self-expression (e.g., women can be warriors and heroes while men cry). The relationship between space and gender has been of particular interest to geographers and other scholars. Studies have examined how gender influences the use and perception of various spaces, from gyms (Johansson 1996) and beaches (Löw 2006), to public places more generally (Ranade 2007). These studies highlight the power relations negotiated through the navigation of gendered spaces. More recently, the role of gender in online spaces has also emerged as a key topic of research (Armentor-Cota 2011).

The concept of nonbinary gender identification has also become increasingly prominent (Richards et al. 2016; Yeadon-Lee 2016), although there is notable evidence that different understandings of gender have existed throughout human history (for an overview, see Vincent and Manzano 2017). Although the inclusion of a "prefer not to say" category in data collection (as is the case for the data employed here) is an imperfect substitute for a full range of response options allowing for nonbinary gender identities, it does provide an option for respondents to opt out of binary gender classification.

Studies by Lam et al. (2011) and Cohen (2011) have found that Wikipedia contributions are skewed toward male users, and there are good reasons to believe that gender relations might play a role in shaping capacity to contribute to other crowdsourcing activities. Comparatively, women appear to have less leisure time (Craig and Mullan 2013), have more caring responsibilities (Ferrant, Pesando, and Nowacka 2014; Petrongolo and Ronchi 2020), and undertake more housework (Braun et al. 2008).

More recent studies focused on gender biases in geographic crowdsourcing can be categorized according to two trends. First, studies that have identified distinctive patterns in modal filters by gender observed that female participants tend to spend more time on tagging locations, whereas their male counterparts are focused more on spatial accuracy in map volunteering (Huynh, Doherty, and Sharpe 2010; Stephens 2013). A second strand has focused on differences in thematic interests by gender. Das, Hecht, and Gergle (2019) found that women contributed in higher percentages to urbanized and multiethnic areas compared to men. The authors also found that women edit feminized areas such as child care and hospice, whereas men show a greater interest in masculinized areas such as spaces of sexual services (e.g., brothels). Both the authors and Stephens (2013) point out this as a self-focus biased problem (i.e., only retrieving data from those on whom we want to focus).

In common, both groups of studies discuss the gendered disparity in contributed content. What is missing from this literature, however, is a focus on the impact of age on contribution patterns, in addition to how volumes of contributions vary temporally or spatially. Studies have found that men and women have different preferences for time investments throughout their lifetime (Rubalcava, Teruel, and Thomas 2009). Accordingly, age specification can be useful as to whether interactions between gender and age can provide more findings than the individual indicators themselves (Haklay 2016; Alattar, Cottrill, and Beecroft 2021). Understanding the gendered temporal patterns and their spatial preferences is imperative as contributors' daily volunteering routines and preferences can reveal habits and interests that affect their future contributed content (Basiri et al. 2019). Understanding participation biases can assist app designers and software engineers to create more inclusive crowdsourcing platforms between demographic groups (Basiri et al. 2019; Bailur and Sharif 2020). If the platform allows participants an open space to share opinions, submit ideas, and provide feedback, then these participants feel more engaged and included, which will lead to reliable and creative results (Aroyo et al. 2019; Temiz 2021).

Geographic Crowdsourcing on Spatial and Temporal Bias

Crowdsourcing studies that compare temporal patterns between users show a remarkable variation across platforms. Li, Goodchild, and Xu (2013) compared the temporal activity patterns between Twitter, and Flickr over a six-week period in residential areas in California. The study discovered that Flickr users were more active during weekends due to the association with daylight hours, whereas Twitter showed less difference during weekdays and weekends but variation in the hourly patterns, with volumes of messages peaking at 1:00 p.m. to 2:00 p.m. and 8:00 p.m. to 9:00 p.m., and troughing between 4:00 a.m. and 5:00 a.m. Bahrehdar, Adams, and Purves (2020) also identified that dominant updates in Flickr were made during weekends as people take more photos during their leisure activities, which tend to be outside standard office hours. This pattern was also observed in other leisure activities. Based on 525,849 uploads, Cooper (2014) found that distinctively more participants contributed on Saturdays than on any other day.

Variations in contribution patterns to mapping platforms have also been observed over the days of the week. Mocnik, Mobasheri, and Zipf (2018), for example, used an open-source data mining infrastructure to gather semantic information on OSM between 2013 and 2016, revealing that fewer contributions were made during weekends. A surprisingly high level of activity was seen during festive periods such as the Christmas holidays and large events such as the 2016 Summer Olympics, however. Other OSM studies have consistently demonstrated weekday activity to be starkly higher than on weekends and productivity during the five weekdays was higher than at weekends (Yang, Fan, and Jing 2016; Anderson, Sarkar, and Palen 2019). Recent studies of Strava, using annual data or specified recreational cycling behaviors, have found that activities were concentrated on weekends, holidays, and in warmer seasons (Sun et al. 2017; Dadashova et al. 2020; Ferster et al. 2021). The lack of demographic information, however, disallows further breakdown of OSM activities by gender and age groups.

In terms of spatial biases in geographic crowdsourcing, the scale has ranged from national (Li, Goodchild, and Xu 2013; Bright, De Sabbata, and Lee 2018) to street scale (Sun and Mobasheri 2017; Alattar, Cottrill, and Beecroft 2021; Livingston et al. 2021). At the regional scale, Bright, De Sabbata, and Lee (2018) observed a correlation between the volume of contribution and high socioeconomic levels; that is, wealthier areas and those with high levels of education tend to have higher volumes of volunteered contributions than socioeconomically deprived areas. At a nation-wide scale, Li, Goodchild, and Xu (2013) examined the geotags of Flickr and Twitter across the United States and discovered that the majority of uploads were concentrated in urban areas, particularly on or near roads. This was due to people's active use during walking, driving, and in fuel stations or hotels. Although a wider geographical scale can characterize the distribution of activities, using the aggregation of data can cause an ecological fallacy problem (i.e., an error in attributing the characteristics of a population to an individual).

At the street scale, there has been ample research on cycling using Strava data. The themes of the current literature include route choices (Alattar, Cottrill, and Beecroft 2021), predicting cycling volumes (Livingston et al. 2021), and associating cycling with air pollution exposure (Sun and Mobasheri 2017). Despite user bias, the findings of these studies have increased our understanding of cyclists' spatial preferences, indicating that most cycling activities were reported near rivers and major cycling routes. In areas such as Glasgow (UK), which has complex terrain surrounding the city, users preferred less hilly routes (Alattar, Cottrill, and Beecroft 2021; Livingston et al. 2021). Other open-source platforms, such as Flickr, exhibit less spatial variation because the geotags guide the users to add the name of the buildings or iconic places when posting online, regardless of the exact location (Bahrehdar, Adams, and Purves 2020).

Methods

Data Collection

We collected two sets of data: (1) from the OSM user survey conducted by Gardner et al. (2020), users' OSM ID, and demographic information; and (2) using users' OSM ID, their OSM activity data retrieved from the open-source Web page "How Did You Contribute to OpenStreetMap" (HDYCOSM; Neis 2021). Participants' demographic data comprised their gender, age, and country of residence (Gardner et al. 2020). The OSM user data comprised total mapping days since registration and the number of changesets per day and hour. Among the respondents ($N = 284$), we excluded those who did not have a valid OSM ID (last checked in September 2021). This gave us a final selection of 265 users: 35 women (13 percent), 227 men (86 percent), and 3 who preferred not to say (1 percent). Compared to the estimated female participation rate of 3 percent to 4 percent in OSM (Schmidt and Klettner 2013; Das, Hecht, and Gergle 2019), the female respondents in this study suggest an oversampling of female contributors.[1] Participants were grouped by gender and age (see Tables 1 and 2).

Users' age data were originally categorized into five-year intervals. Here, we aggregated the age groups by the economically active (ages twenty-five to fifty-four) and the others (younger than twenty-five, older than fifty-five) according to the OECD employment rate by age group (OECD 2022).[2]

To better understand the temporal contribution between demographic groups, we initially compared the OSM contributions by the days of the week between gender and age groups, then compared the hours of the day, namely core (9:00 a.m. to 4:00 p.m.), off-peak (5:00 p.m. to 12:00 a.m.), and night (1:00 a.m. to 8:00 a.m.), to examine periods of the day in which users contribute the most. As the hourly data were given in Coordinated Universal Time (UTC), we converted these times based on the global time zone corresponding to users' country of residence as declared in the survey. Where multiple time zones exist across particular countries, due to the lack of specific user location, we assigned one universal time zone to users who live in such countries (e.g., United States, Canada, and Australia). This might have affected users' time data by up to four hours. For the spatial analysis, the number of national data sets to which users have made edits were used (as collated on the HDYCOSM Web site at https://hdyc.neis-one.org/).

Kruskal–Wallis Test

To evaluate the effect of gender and age groups on OSM contributions, a Kruskal–Wallis test was designed. Kruskal–Wallis is a nonparametric one-way analysis of variance, which measures the median ranks to test whether the sample originates from the same distribution (Vargha and Delaney 1998). It would normally have a numeric dependent variable

Table 1. Descriptive statistics of OpenStreetMap participants by gender and aggregated

Gender	Age	n	Subtotal (%)
Female	Economically active	26	35 (13%)
	Others	9	
Male	Economically active	177	227 (86%)
	Others	50	
Prefer not to say	Economically active	3	3 (1%)
Total		265	265 (100%)

Table 2. Variables from the survey and the OpenStreetMap (OSM) Web page

Type	Variable	Description
Survey	userID	ID used in OpenStreetMap
	Gender	Men/Women/Prefer not to say
	Age	Economically active (25–54), Others (< 25, ≥ 55)
OSM Web page	userID	ID used in OpenStreetMap
	Changesets per day	Weekdays, weekends
	Changesets per hour	Core (9:00 a.m.–4:00 p.m.), off-peak (5:00 p.m.–12:00 a.m.), night (1:00 a.m.–8:00 a.m.)
	No. of contributed countries	Number of countries the users contributed

(Y) and categorical variables ($X1$, $X2$) for independent groups that do not fulfill the assumptions for a parametric test (Xia 2020). It also allows samples of distribution of unequal size, which is appropriate for such crowdsourcing projects that happened to have a skewed number of participants (Xia 2020; Brunner et al. 2021).

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{g} \frac{r_i^2}{n_i^2} - 3(N+1), \tag{1}$$

where N is the total number of observations, n_i is the number in the ith group, and r_i^2 is the total sum of ranks in the ith group. The H statistic is tested against the χ^2 distribution appropriate to the degree of freedom $k-1$, where k is the number of groups. If H is smaller than χ^2, then the null hypothesis is rejected and vice versa. For the analysis, each variable was ranked in ascending order. We apply this order to all variables. As an example, the ranks to compare the weekdays and weekends are indicated in Table 3.

The study set the following null hypothesis (H_0):

- There is no difference between gendered and age groups over time (weekdays/weekends and between core, off-peak, and night)

Table 3. Example of how average rank is assigned for each group variable

Group	Variable	Average rank
Gender	Men	188.5
	Women	406.5
Age	25–44	131.5
	< 25, ≥ 45	349.5
Week	Weekdays	109.5
	Weekends	327.5

Measuring Spatial Diversity of OSM Contributors

This study uses the SID or Gini–Simpson index, to quantify the level of spatial diversity of each participant. The idea of SID is that if we randomly select two changesets in OSM, when replaced, they will represent a different type (different country in our context; Tramer 1969). The equation is described as follows:

$$D' = 1 - \frac{\sum n(n-1)}{N(N-1)}, \tag{2}$$

where n denotes the number of contributions from a particular country, and N represents the total number of contributions by the user. The index ranges between 0 and 1, where the lower D value indicates less chance of diversity (i.e., the person or the group tends to contribute domestically), whereas the higher value indicates the opposite (i.e., the person or the group tends to contribute globally; Daly, Baetens, and De Baets 2018).

The widely used Shannon's diversity index takes into account the "richness" (total number of contributions in the ecosystem) and "evenness" (how evenly are distributed across countries) to the output (Gauvin et al. 2020). In contrast, SID places more emphasis on richness, meaning that the data set with high unique contributions will suggest a higher level of diversity, even though it is unevenly distributed (Thukral et al. 2019). This method was chosen because most of the OSM users tended to contribute to a few countries and a small proportion of edits in other countries are hardly noticeable. Another reason is due to the convenience of interpretation; that is, if two people had a D' index of 0.70 and 0.24, respectively, the former with a 70 percent chance of choosing different countries out of two chances can be seen to have more diversity than the person with 24 percent. Shannon's interpretation of 5 and 1 as the most and least diverse scores, respectively, are relevant numbers but require context.

Because the study focuses on how demographic characteristics have affected spatial biases, we computed every individual D' score and aggregated by gender and age groups with statistical measures.

Exploring the OSM Contributions by Demographic Characteristics

Days of the Week

The average volume of OSM contributions between genders for each day of the week is presented in Figure 2. A consistent level of contributions is observed for male participants on weekdays just around 1,000. By contrast, the average number of changesets made by female participants was approximately 543, almost half the number of men's contributions. The prefer not to say group contributed consistently around 250 changesets every day with slightly more on Saturdays. The difference of changesets became greater on weekends for men, increasing to around 1,200, whereas female participants' contributions decreased by 130 changes. Thus, during weekends, the difference in changesets between men and women increased significantly, with men contributing three times more than women.

Figure 3 shows the number of weekly contributions by gender and age groups. For male participants, both the economically active and the others groups exhibit a similar trend across the week, where an average increase by 50 to 100 in OSM contributions is shown on weekends compared to weekdays. By contrast, women in both age groups showed a similar level of contribution during weekdays at around 500 to 600, but the contributions of others were halved on weekends. We also discovered that economically active women have higher variability of contribution throughout the week. This was because although women have contributed less on average, the changesets of one particular age group (ages twenty-five to twenty-nine) outweighed that of men in this group. The prefer not to say group presented the same results from the aggregated results, as the users were all economically active.

Hours of the Day

The assessment of contributions by hour reveals the average pattern of OSM contributions over a twenty-four-hour period. The temporal patterns of contributions from men and women were largely similar, where men show a gradual rise in activity between 5:00 a.m. and 6:00 p.m., followed by a decline from 7:00 p.m. to

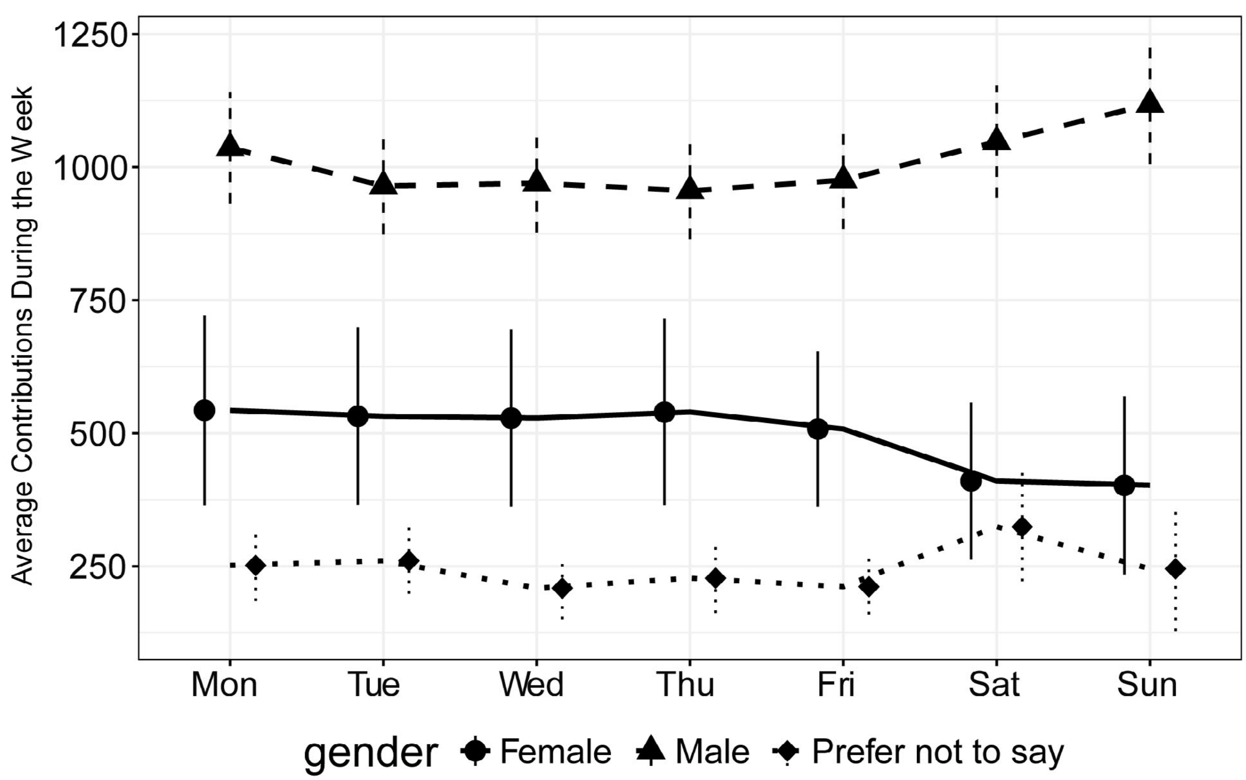

Figure 2. Average observations of weekly contributions by gender groups.

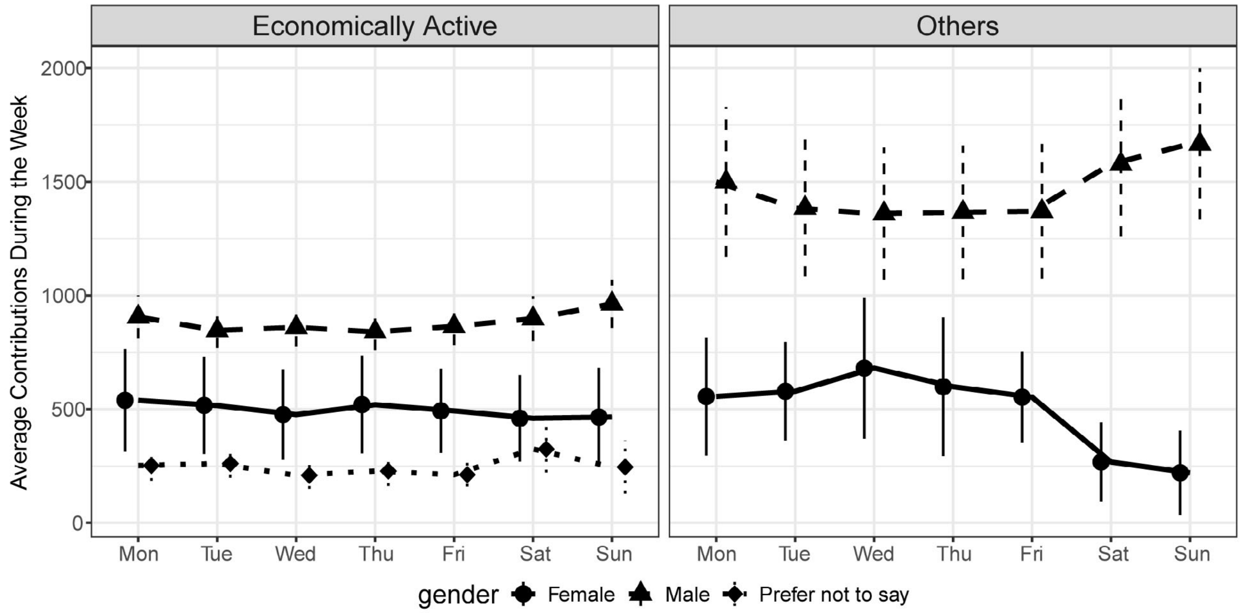

Figure 3. Averaged OpenStreetMap (OSM) contributions on the days of the week by gender and age groups.

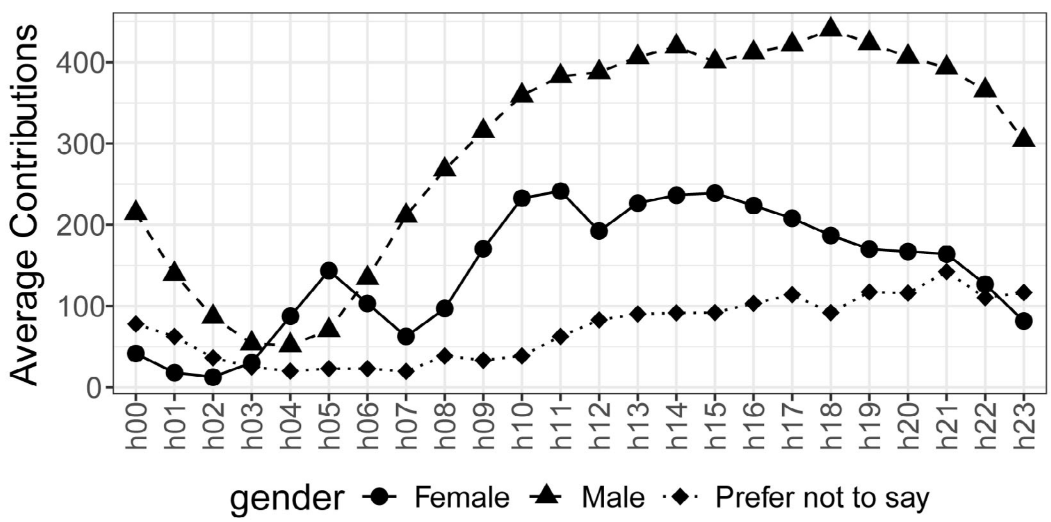

Figure 4. Hourly averaged observations of OpenStreetMap (OSM) contributions by gender groups.

4:00 a.m. Women, on the other hand, show an earlier rise in activity in the early morning hours, with a notable decrease at 3:00 p.m. This decrease arguably corresponds to women's lifestyles such as child-care responsibilitieslike school pickup times generally occurring between 3:00 p.m. and 4:00 p.m. globally.

Throughout the twenty-four-hour period, men contributed an average of 80 to 400 edits per hour, whereas women contributed a lower range of 20 to 270 edits per hour (see Figure 4). An unusual peak in female contributions was observed at 5:00 a.m., with a few dips at 7:00 a.m. and 12:00 a.m.

Examining gendered contributions by age (see Figure 5), men's contribution in the economically active age group showed a low of thirty contributions at 5:00 a.m., gradually rising to a peak of 460 at 6:00 p.m., and then declining in the later hours. On the other hand, women in the economically

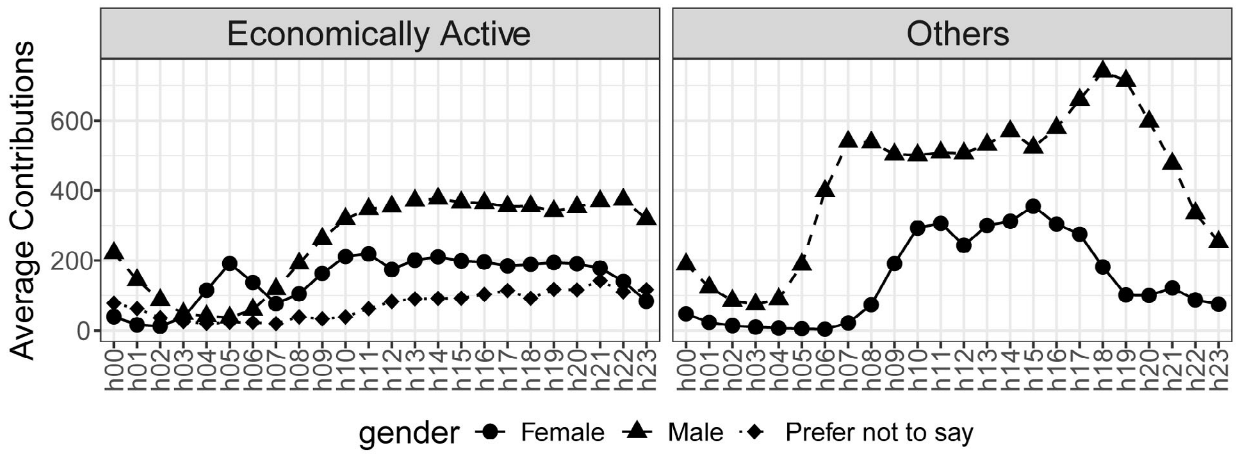

Figure 5. Hourly averaged OpenStreetMap (OSM) contributions by gender and age groups.

active age group peaked at 5:00 a.m., reaching slightly over 200 contributions, fluctuated in the morning hours, and then hit the second peak at 11:00 a.m. with 230 contributions. Their contribution declined from the early evening. The prefer not to say users contributed far fewer edits than the other groups, with a low of 19 at 7:00 a.m. and a high of 142 at 9:00 p.m.

The others group consistently had higher average contributions than the economically active group. Women in the others group had contributed more between 9:00 a.m. and 5:00 p.m. than those in the economically active group, reaching nearly 400 contributions. Men in the others group hit a low of around 100 changes at 3:00 a.m. but showed a remarkable increase to 400 changes by 7:00 a.m., which further increased to around 700 changes at 6:00 p.m. Women in the others group also showed greater variability in their contributions between 09:00 a.m. and 9:00 p.m., remaining more active than their economically active counterparts.

The hourly contributions were aggregated as core, off-peak, and night (see Figure 6). We arbitrarily categorized the core hours between 9:00 a.m. and 4:00 p.m., off-peak hours between 5:00 p.m. and 12:00 a.m., and night hours between 1:00 a.m. and 8:00 a.m. The data showed that the overall mean was highest during the core hours at 378 changes (median = 153), followed by off-peak hours at 360 changes (median = 116), and night hours at 131 changes (median = 8). Although the averaged changesets ranked in order of highest activity as core, off-peak, and night, the outliers showed the opposite order, peaking at 6,130, 7,594, and 12,154 changes, respectively. This indicates that superusers or individuals who tend to volunteer outside working hours contributed more during off-peak and night hours.

Countries Contributed by OSM Users

Two hundred sixty countries were contributed by 265 OSM users (see Figure 7). Among these countries, the United Kingdom, the United States, and Germany accounted for 60 percent of the total contributions.

Breaking down these contributions by the users' demographic groups, men in the economically active group contributed to an average of forty countries. This was marginally higher than the thirty-one countries contributed to by women. In the others group, men's contributions increased by four countries, whereas women's contributions decreased by five countries. Users of the prefer not to say group contributed to eighteen countries on average (Table 4).

Kruskal–Wallis Test

Checking Assumptions

A nonparametric test was used because the distribution of the data in each demographic group did not fulfill the assumptions of normality; that is, the sample size of $n \geq 30$, homoscedasticity (homogeneity of variance), and the independence between variables. Figure 8 illustrates that the total contributions

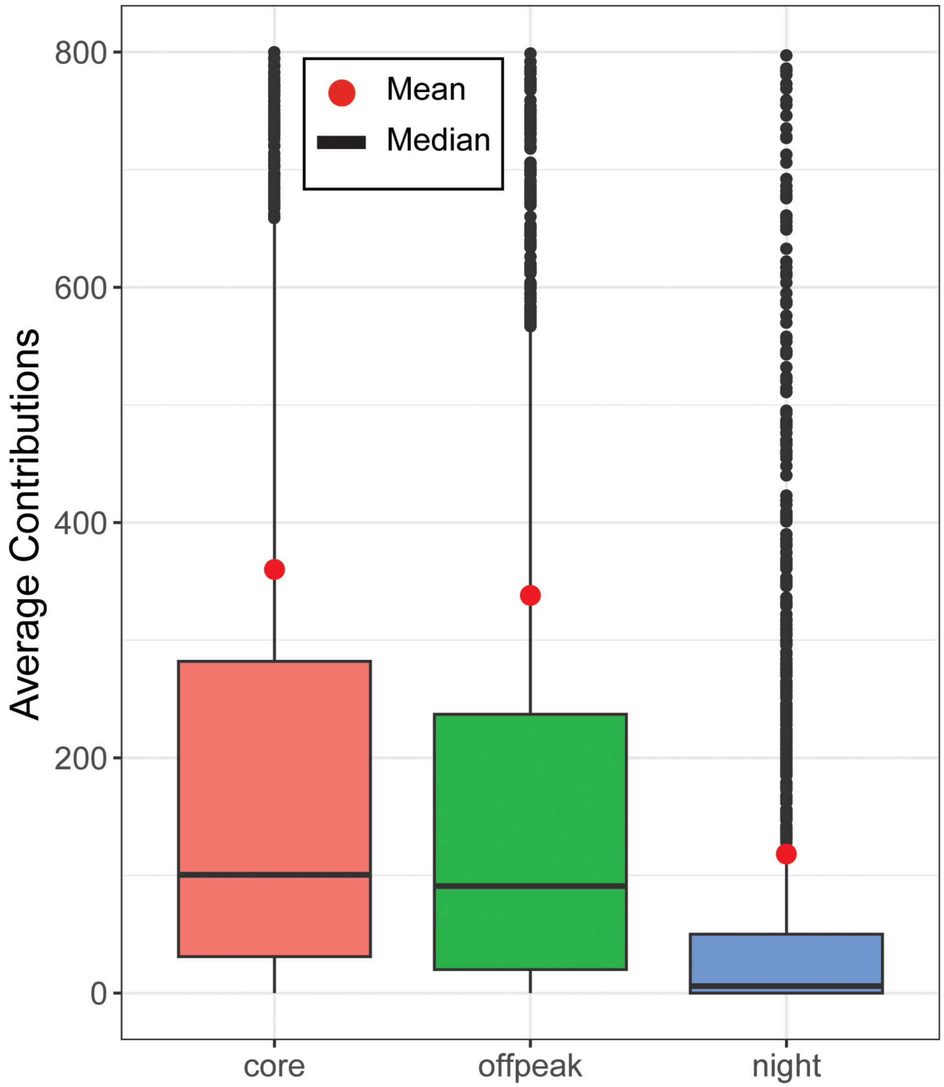

Figure 6. Boxplots illustrating OpenStreetMap (OSM) contributions by core, off-peak, and night hours.

between gender and age groups were concentrated below 2,500. For each component, the female contribution is more than the prefer not to say group, but significantly less than those of their male counterparts, particularly on weekends (Figure 8A) and across age groups (Figure 8B). Figure 8C shows that the contribution, in general, is greater for the economically active group both during weekdays and weekends compared to the other aged group. The distribution of the hourly contributions neither followed the normality nor the homogeneity of variance (see Figure 8D and 8F). We transformed the data using logarithm and box-cox transformation methods, however, due to the long-tailed distribution, the methods did not qualify for Shapiro's normality test and Levene's test for equality of variances. Therefore, a Kruskal–Wallis test was applied.

Results

Days of the Week. To conduct a nonparametric Kruskal–Wallis test, all variables of gender (three groups), age (two groups), and days of the week (two groups) that contained categorical or continuous observations were transformed to ranks (see Table 5). The combination of three gender and two age subgroups with the two temporal variables resulted in ten groups. The differences in ranks

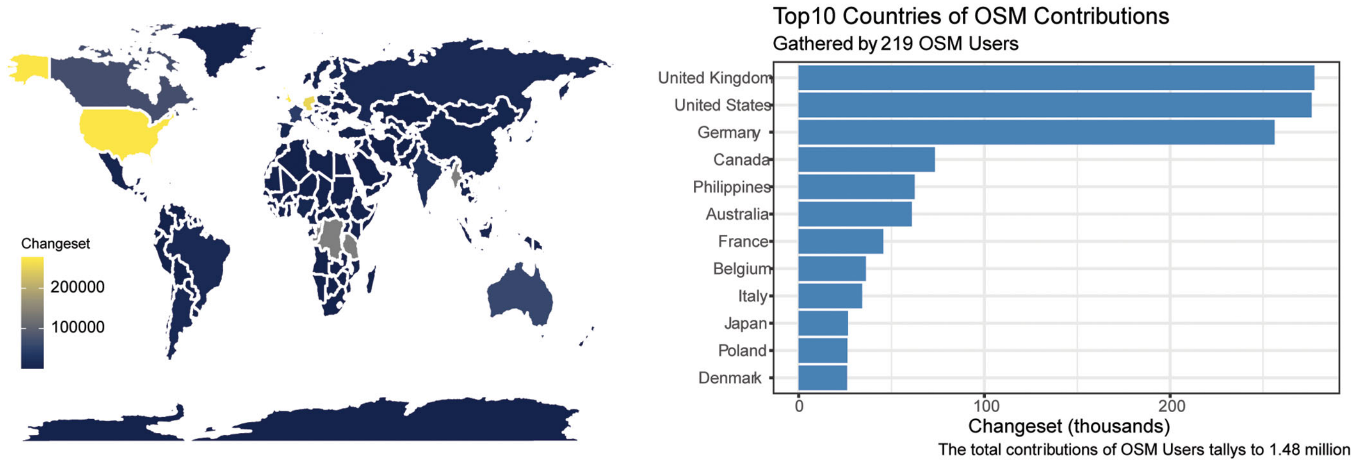

Figure 7. Top ten countries contributed by the OpenStreetMap (OSM) users illustrated with a map and chart.

Table 4. Descriptive statistics of the contributed countries by demographic groups

Gender	Age	*n*	Minimum	M	*SD*	Maximum
Female	Economically active	26	1	31	52	260
	Others	9	5	26	32	103
Male	Economically active	177	1	40	47	235
	Others	50	1	44	54	260
Prefer not to say	Economically active	3	4	18	20	42

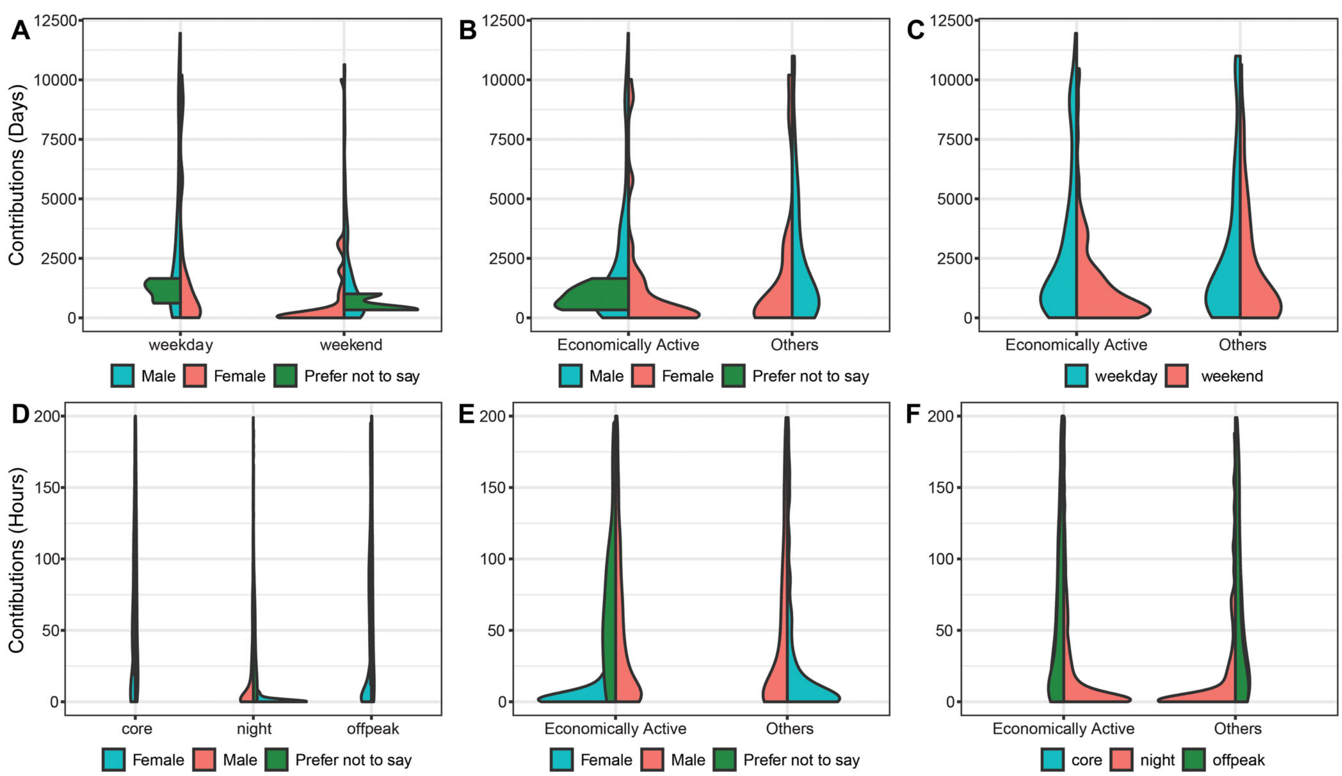

Figure 8. Checking the homogeneity of the data between gender and days of the week, gender and age groups, and days of the week and age group.

Table 5. Descriptive summary of weekday–weekend ranks

Gender	Age	Week	*n*	Minimum	Maximum	Median	M	*SD*
Male	Economically active	Weekday	177	24.0	529.0	345.0	319.8	138.6
		Weekend		5.0	518.0	224.0	232.4	134.9
	Others	Weekday	50	17.5	530.0	345.0	328.8	156.9
		Weekend		2.5	520.0	266.25	271.1	157.5
Female	Economically Active	Weekday	26	13.0	525.0	164.5	202.3	164.1
		Weekend		2.5	489.0	55.0	125.9	144.5
	Others	Weekday	9	17.5	490.0	268.0	261.8	174.4
		Weekend		13.0	377.0	37.0	93.6	122.6
Prefer not to say	Economically Active	Weekday	3	187.0	301.0	264.0	250.7	58.2
		Weekend		119.0	235.0	128.0	160.7	64.5

among these groups are shown due to the varying number of participants in each group. For example, economically active men had 177 participants during the weekdays and showed a median of 224, whereas women in the same group had 26 participants with a median of 164.5.

The Kruskal–Wallis test comparing the weekday to weekend ranks of OSM contribution by gender and age group is categorized in Table 6. In the economically active group, the test revealed significant weekday–weekend differences in both female users ($H = 32.81$, $p \leq 0.01$) and male users ($H = 4.35$, $p \leq 0.05$). Males in the others group showed similar results to the economically active group ($H = 4.31$, $p \leq 0.05$), whereas females in the others group showed a marginally significant outcome ($H = 3.57$, $p = 0.058$). Users in the prefer not to say group did not show a statistical difference between weekdays and weekends. Figure 9 is a visual representation of the statistical results.

Hours of the Day. In line with the days of the week, the variables for implementing the Kruskal–Wallis test for the hours of the day were transformed into ranks (see Table 7). The combination of three hourly variables with three gender and age subgroups resulted in twelve groups. It is important to note that the rank values vary based on the number of observations, and the absolute values do not represent a greater contribution.

The hourly Kruskal–Wallis test results indicated a statistical difference between gender and age groups for three time periods across all age groups (see Table 8). These results are also visualized in Figure 10. As a result, all three gender groups within each age group had statistically different outcomes across the three categorical hours of the day.

Table 6. Kruskal–Wallis output on OpenStreetMap contribution between gender groups: Weekdays vs. Weekends

Gender	Age	*H* (or χ^2)	*p* value
Female	Economically active	32.81	<0.010
	Others	3.57	0.058
Male	Economically active	4.35	<0.050
	Others	4.31	<0.050
Prefer not to say	Economically active	2.30	0.100

Note: *H* (or χ^2) and the *p* values show whether there was a gender difference.

Spatial Bias of OSM Contributors

The SID outcomes for each gender group are summarized in Table 9. Male participants showed more variation than female participants, with mean scores of 0.707 and 0.551, respectively. This means that if we ask the male participants to pick two random random changesets they have made, there is, on average, a 71 percent probability that the two changesets come from different countries. Women scored 56 percent on average. Those who chose prefer not to say had an average SID of 0.77, but careful interpretation is needed as the high score is a result of the small sample size. Examining the distribution of SID (see Figure 11), men's distribution is skewed toward 1, indicating that many had more statistical opportunity to pick different changesets from different countries. By contrast, two peaks of diversity patterns of the female users mean that the spatial preference within the group contrasts significantly.

Decomposing the gender groups by age (see Figure 12), male participants have systematically scored higher in diversity measures across both age groups. Those SID scores of men were 0.71 in both age

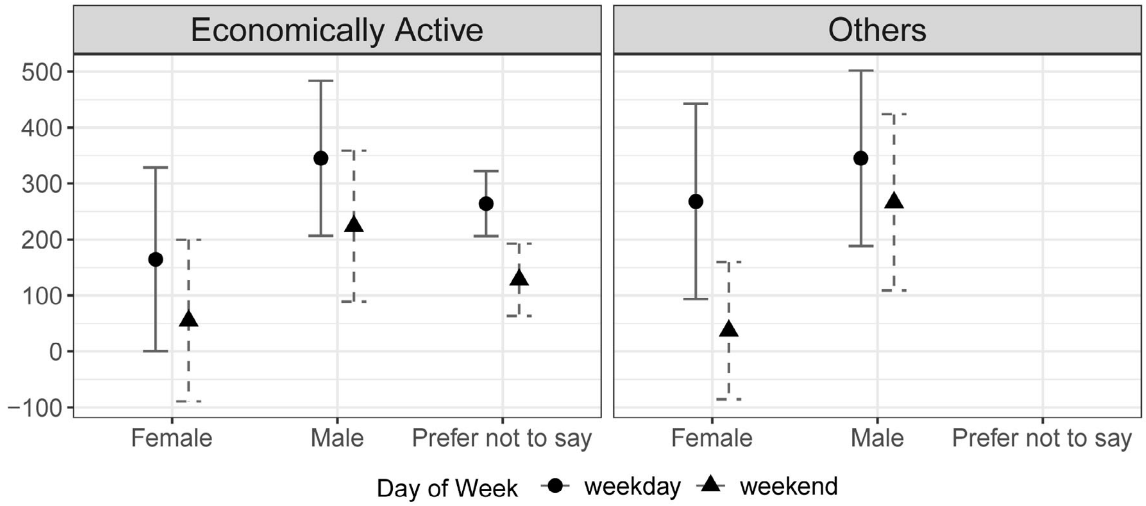

Figure 9. A graphical output of the weekly Kruskal–Wallis test from Table 6.

Table 7. Descriptive summary of core, off-peak, and night hours in ranks

Gender	Age	Hour	*n*	Minimum	Maximum	Median	*M*	*SD*
Female	Economically active	Core	208	393.0	6,225.0	2,444	2,781.6	1,809.3
		Off-peak		393.0	6,351.0	879	1,285.4	1,318.8
		Night		393.0	6,192.0	1,864	2,450.3	1,829.0
	Others	Core	72	393.0	6,137.5	3,470	3,411.8	1,863.1
		Off-peak		393.0	4,911.5	393	1,111.0	1,163.1
		Night		393.0	5,844.0	1,991	2,611.5	1,678.2
Male	Economically active	Core	1416	393.0	6,350.0	4,083	4,013.3	1,435.3
		Off-peak		393.0	6,317.0	1,695	2,104.6	1,586.7
		Night		393.0	6,354.0	3,956	3,805.7	1,562.1
	Others	Core	400	393.0	6,355.0	4,381	4,032.4	1,684.8
		Off-peak		393.0	6,360.0	1,578	2,252.3	1,928.5
		Night		393.0	6,358.0	4,175	3,960.2	1,747.3
Prefer not to say	Economically active	Core	24	2085.5	4,167.5	3,096	3,161.6	584.9
		Off-peak		393.0	4,184.0	1,791	2,010.6	1,014.4
		Night		1799.5	4,609.0	3,507	3,533.9	730.8

Table 8. Kruskal–Wallis output on OpenStreetMap contribution between gender groups at core, off-peak, and night hours

Gender	Age	H (or χ^2)	p value
Female	Economically active	96	<0.01
	Others	65	<0.01
Male	Economically active	983	<0.01
	Others	199	<0.01
Prefer not to say	Economically active	72	<0.01

Note: H (or χ^2) and the p values show whether there was a gender difference across demographic subgroups.

categories, whereas women in the economically active group had 0.56 and the others group had 0.52 on average. This implies that the spatial diversity among male participants is higher on average and less variable between age groups. By contrast, female participants showed a greater standard deviation in their scores, ranging from 0.24 to 0.80. This indicates that the area of contribution significantly varies among female participants, possibly because there were only thirty-five female users, of which six were superusers.

Discussion and Conclusion

Main Findings

Using an online survey of OSM users, this study has examined the temporal and spatial biases in the contributions of OSM users by their demographic

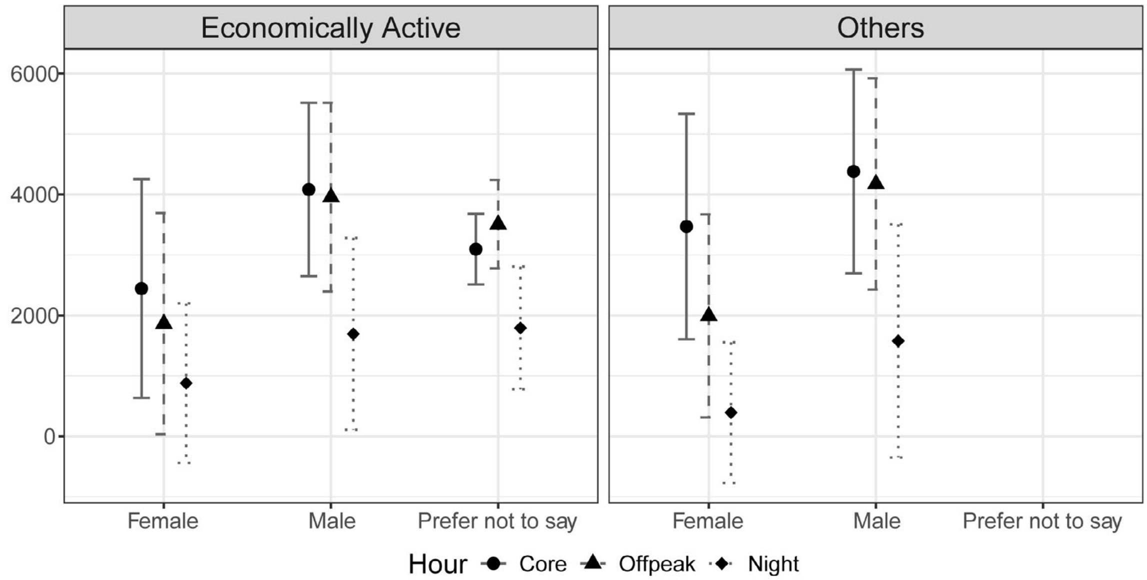

Figure 10. A graphical output of the weekly Kruskal–Wallis test.

Table 9. Summary statistics of Simpson Index of Diversity by gender groups

Gender	*n*	Minimum	Maximum	Median	M
Female	34	0.059	0.997	0.648	0.551
Male	216	0.067	0.999	0.801	0.707
Prefer not to say	3	0.579	0.984	0.746	0.770

backgrounds. When comparing the activity of gender groups across the week, we observed that women, on average contributed less during weekends than on weekdays. In contrast, men in most age groups exhibited more consistent temporal contribution patterns, with less difference between weekdays and weekends (i.e., their temporal contribution patterns were more consistent). These patterns were statistically supported by the nonparametric Kruskal–Wallis test. The weekly results revealed a statistically significant difference between gender groups ($p < 0.01$). We recognized, however, that, although the men's OSM contributions were higher than women during the week (see Figure 2), the gender differences in the others group were statistically less noticeable ($p = 0.16$). Over the course of the day, women showed fluctuations in their activity, whereas men's activity is much more consistent. Using the Kruskal–Wallis test, we ascertained a statistically significant difference between genders across the core, off-peak, and night hours. This result reveals that male participants were likely to contribute a greater number of contributions at any time of the day.

Comparing both gender and age groups, we found that the average changesets in the others age group were distinguishably high. Contributions by male participants in the others group ranged from 1,200 to 1,700 throughout the week, whereas those in the economically active group were less than 800. Women in the others group showed marginally higher contributions across weekdays than those in the economically active group, but contributed less during weekends. Considering that there were only a few participants below the age of twenty-four in the others group, these results contradicted our assumption that younger participants tend to contribute more due to their familiarity with technology and Web communications (Bright, De Sabbata, and Lee 2018; Meppelink et al. 2020). We speculate these unexpected results are due to an inclination toward volunteering among individuals over fifty, some of whom might be retired and have more spare time, as well as a greater willingness to commit more time to extracurricular activities. Additionally, males in the economically active (twenty-five- to forty-four-year-old) age group are likely committing more time in front of computers and showing greater interest in visiting new locations (Gauvin et al. 2020).

In terms of identifying contribution differences in spatial patterns, SID was used to evaluate differences in the number of countries to which demographic groups contribute. Overall, our findings showed that men scored higher than women, with SID values of 0.71 to 0.52, respectively. This means that 71

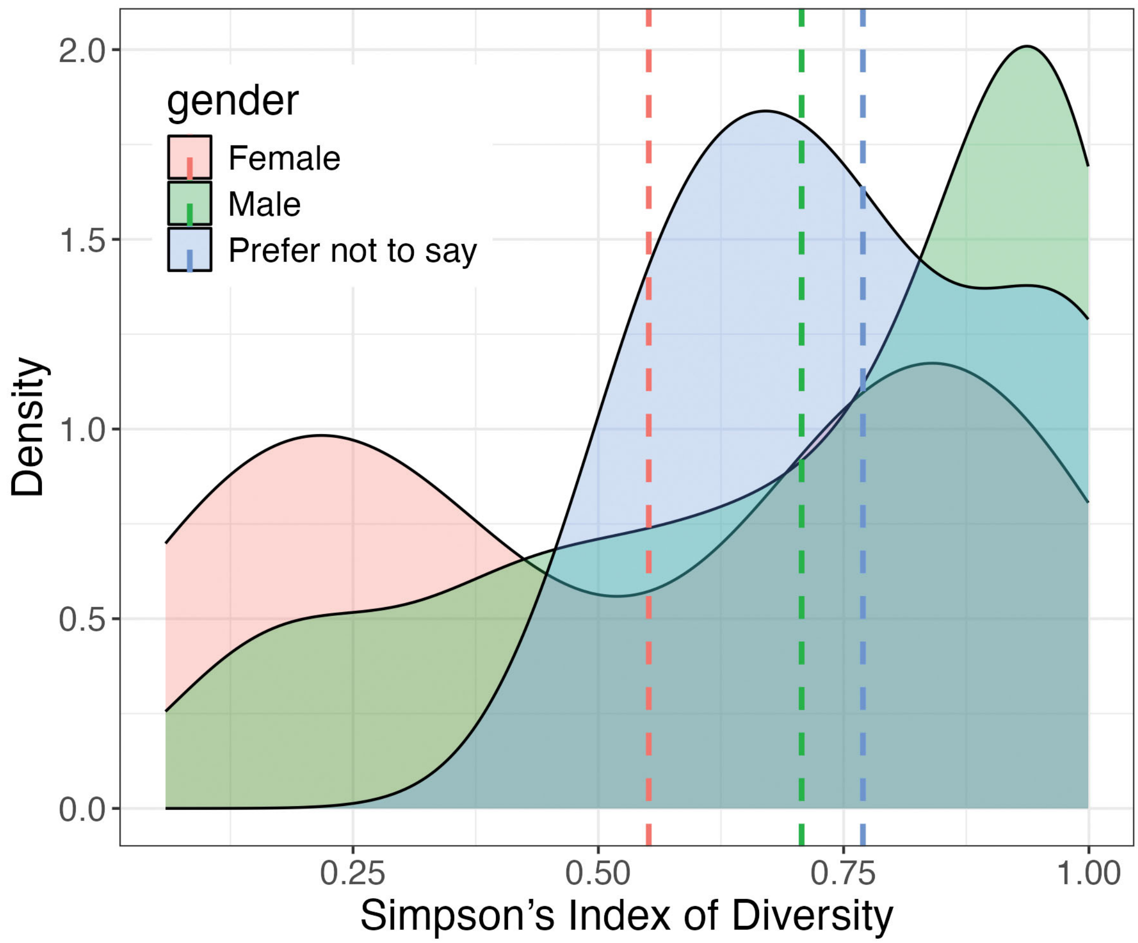

Figure 11. Density distribution of the Simpson Index of Diversity by gender groups. The dotted lines are the mean of each group.

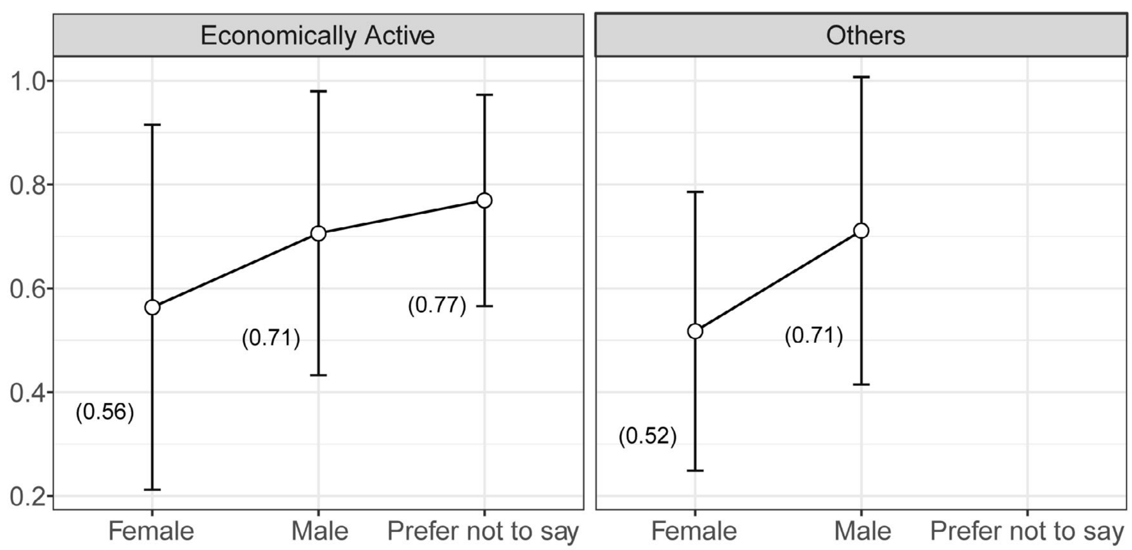

Figure 12. Simpson Diversity Index mean scores by age and gender groups.

percent of men had a chance to contribute to more diverse areas, compared to 52 percent of women. The SID scores were consistent for men in both age categories, whereas women's scores varied between 0.24 and 0.80 when comparing individual scores. This indicates significant variation in the areas of contribution among female participants, possibly due to the small number of female users (thirty-five individuals), of whom six were superusers. Further investigation might consider the particular countries to which women contribute. Evidence has shown, for example, a greater inclination in women than men toward humanitarian mapping, which tends to be focused on developing countries where targeted mapping activities are tasked, suggesting gendered motivational differences (Gardner and Mooney 2018).

Theoretical Contribution

Our findings contribute to the broader theoretical discussions on gender and space, and nonbinary identities, particularly through the lens of geographic information systems (GIS) and volunteered geographic information (VGI).

Gendered Spaces in Digital Mapping. Geographic scholarship has long examined the intersection of gender and space, exploring how gendered power dynamics influence the use and perception of spaces (Rose 1993; Massey 1994). Our study extends the body of literature by highlighting how these dynamics extend into digital spaces such as OSM. From our research, we found some big differences in how men and women contribute to the map, which tells us that even when we are making digital maps, gender still plays a role. Women with lower SID scores indicate a more localized and potentially restricted range of contributions, which could be linked to the specific areas of personal knowledge and interest they choose to contribute to compared to men (Stephens 2013; Gardner et al. 2020; Korpilo et al. 2022). This shows that gender is likely to have an impact on geospatial practices, and although the gaps are believed to be narrowing, these biases still exist in digital mapping activities.

Gendered Time Use. Existing scholarship has highlighted the gendered nature of leisure time (Craig and Mullan 2013) and quality (Yerkes, Roeters, and Baxter 2020). Our findings in relation to the timing and quantity of contributions—over both the hour of the day, and day of the week—support the idea that there are gendered differences in patterns of engagement with volunteer mapping as a leisure activity. Men (and to some extent, contributors in the prefer not to say category) saw increased contribution levels at weekends, whereas women saw decreased levels of contribution. Similarly, although each gender category shared a similar pattern in contributions over the day—particularly once economic activity is accounted for—peaks and troughs seemingly indicate different structures to leisure time. The nature of these patterns indicates that they might be linked to responsibilities often disproportionately associated with particular gender categories (e.g., caring), although further data collection is required to fully establish the extent to which this can be considered a causal link.

Nonbinary Identities. Our study also recognizes the limitations of not fully accounting for a full range of gender identities. Although the original survey conducted in 2018 included options for respondents to identify themselves as male, female, others, or prefer not to say, the majority of valid respondents were either male or female, with fewer than five respondents replying prefer not to say. We acknowledge, though, that the inclusion of prefer not to say implicitly hints at the complexity of gender identity beyond the binary. The market research firm Ipsos has highlighted increased public interest in gender identity, and estimated that around 2 percent of adults in Great Britain identify as transgender (including nonbinary), but that this is around 4 percent in younger adults. They proposed a five-category framework of man, woman, nonbinary, my gender is not listed, and prefer not to say (Wing 2023). Although increasing the heterogeneity of gender identity subgroups can weaken estimations of mapping activities associated with these identities, it is crucial for future research to incorporate more diverse gender categories to better capture the diverse experiences and contributions of all users (Richards et al. 2016; Yeadon-Lee 2016).

Methodological Contribution

This article contributes to the literature on participation biases in VGI or geographic crowdsourcing in three ways. First, we used a survey of OSM user demographics and matched them with their spatial and temporal changesets, enabling the decomposition of the study by gender and age. Because OSM does not openly provide personal or demographic data, this joint analysis of survey and OSM resources has opened up the possibility of linking observed volunteering routines by demographic groups, first uniquely interrogated by Gardner et al. (2020).

Second, we applied a nonparametric statistical method to measure the relationship between demographic profiles and two types of OSM edits. This approach allowed us to understand the weekly and hourly contribution patterns by gender groups as well as that of superusers, without normalizing the data into a statistically ready status. Until now, temporal contribution patterns in OSM have been largely absent from analyses of OSM user preferences and behaviors.

Third, by applying the SID index, we extended the boundary of the current literature, suggesting a more or less limited geospatial interest. This knowledge can be used to improve the current way of reporting national geospatial interests, instead of showing heat maps or point-based maps. Although SID does not provide any specific location data or consider richness (evenness), it corresponds well with the idea of the overall dominance of contributions being concentrated in a few countries; that is, that certain demographic groups demonstrate a spatially specific bias.

Implications for Practice

The findings from our study have important implications for the design and implication of crowdsourcing platforms, particularly those such as OSM that rely on volunteers. Understanding the demographic biases regarding their contribution time and quantity can possibly help developers create a more inclusive and equitable ecosystem.

Initially, the significant variability in spatial contributions, as indicated by the SID scores, shows that men contribute to a statistically broader range of areas compared to their female counterparts. This highlights the need for targeted outreach to support underrepresented groups in community participatory efforts. Local events such as Missing Maps, a humanitarian mapping initiative, can encourage contributions from these groups by providing incentives and fostering a more inclusive platform (Bailur and Sharif 2020). Additionally, creating community support groups and forums, similar to R-Ladies, which empowers women in the R programming community, can provide necessary support and encouragement to women and other underrepresented groups in the mapping community. Additionally, partnerships with educational institutions and community organizations can help reach potential contributors who might not otherwise participate (Aroyo et al. 2019; Temiz 2021). These initiatives can help build a more diverse and equitable contribution base for platforms like OSM (Mulder et al. 2016).

In addition, the biased contribution patterns by gender and age suggest that platform designers, including those at OSM, should consider a wider spectrum of contribution modes. For example, the lower contributions from women, particularly during weekends, might reflect their increased caregiving responsibilities and reduced leisure time compared to their male counterparts (Craig and Mullan 2013; Ferrant, Pesando, and Nowacka 2014). Even though some women might not have nurturing responsibilities or prefer not to engage in full mapping activities during weekends, platforms could offer more flexible participation options to accommodate different schedules and time constraints. Simplifying the current process, which involves multiple pages and clicks to reach the editing stage, could be a significant improvement. User experience researchers could help streamline this process and enable micro-contributions, allowing users to make smaller, quicker contributions. Additionally, sending push notifications and reminders could help increase participation among women. These measures can make it easier for users to contribute at their convenience, ultimately fostering a more inclusive and diverse community.

Limitations and Future Research

Despite the findings, our study has some limitations. First, the raw data of hourly OSM contribution was all based on UTC, which needed standardizing. Because the survey participants did not provide information about the city (only the country) in which they were dwelling, we assumed a single time zone for each country, which was not necessarily accurate for users in countries with multiple time zones. One way to deal with this is to give a rough assumption that one's lowest activity hour can, for example, be 3:00 a.m. (or 4:00 a.m.), and allocate the lowest observation to 3:00 a.m. More accurate time zone information provided by the user would overcome this issue.

Second, there was an unequal number of participants between gendered groups. The study sample contained 30 female and 188 male participants, or six times more male than female participants. The gender imbalance was amplified, however, when the individuals were grouped in age cohorts. As a result, we were not able to disentangle the spatial nor temporal behaviors of the female participants over age fifty. Future studies might examine more representative gender and age sampling to identify biases given the disparity in respondent numbers across genders.

Third, the nonparametric Kruskal–Wallis test has weaker assumptions compared to the parametric tests. Our results, however, can corroborate the gendered bias on OSM participation argued by previous studies, with a temporal perspective (Schmidt and Klettner 2013; Stephens 2013; Gardner et al. 2020).

Fourth, although SID has given a general idea of the participants' mapping patterns, the index is only used as a comparative measure rather than the score itself. From previous studies, Shannon's index ranges between 1.5 and 3.5 are considered "diverse" irrespective of the results compared by different groups (Gaines, Harrod, and Lehmkuhl 1999). Women's diversity at 0.56 and 0.52, however, themselves provide a less clear representation of whether the groups have globally contributed. This can be improved by collecting more data from active OSM users, which can increase the index value.

Future Research

Future research should explore contributions by demographic factors such as educational background and conduct in-depth interviews to verify findings of OSM contributions across demographic groups. Such efforts will provide further insights into specific preferences and behaviors of contributors, especially those who contribute to the greatest quantities.

Disclosure Statement

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Data Availability Statement

Zoe Gardner conducted the survey questionnaire in 2017 that captured respondents' OSM username and demographic indicators. The data used in this study were confidential and could not be made publicly available.

Notes

1. The rationale of the original survey (published on OSM forums to advertise the survey) stated its interest in gender dimensions in OSM, which might have skewed the sampling progress toward women.
2. The analysis was also conducted with regrouped age data according to the UK standard (Economically active: 18–64; https://www.ethnicity-facts-figures.service.gov.uk/work-pay-and-benefits/unemployment-and-economic-inactivity/economic-inactivity/latest), but the number of others were not enough to be able to conduct a robust statistical analysis.

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