Beyond "Geo" HCI: Exploring Cultural Dimensions of Disparity in OpenStreetMap Road Safety Metadata

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Peer production systems like OpenStreetMap exhibit well-known information gaps along socioeconomic and population density lines, causing issues for end users when AI tools, such as autonomous vehicles, rely on this incomplete data. Prior work has shown these trends, but how they influence important semantic metadata remains unclear. In this study, we focus on three OpenStreetMap metadata tags that are essential for road safety. Contrary to the expected socioeconomic and population density trends, our findings reveal that cultural factors play a significant role in influencing tag production. Moreover, we find that automated contributions can negatively impact human tag production in OpenStreetMap, despite the potential of these automated imports to address data gaps. Our results add nuance to the trade-offs of automated imports and shed light on how the public and practitioners can more effectively improve metadata coverage.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

OpenStreetMap (OSM), known as the "Wikipedia of maps", is one of the most prominent Volunteered Geographic Information (VGI) projects. Like other peer production systems, such as Wikipedia [29, 68], it exhibits information gaps, or systemic disparities in content coverage [4, 23, 36, 95]. In Wikipedia, for instance, these information gaps manifest as limitations in topic coverage within language editions [45]. Similarly, in OpenStreetMap, the uneven distribution of content means that downstream applications that rely on OpenStreetMap data may encounter less comprehensive and lower-quality content in rural or socioeconomically disadvantaged areas [37, 96]. These kinds of disparities can hamper effective disaster relief efforts by hindering precise location addressing in urgent situations [4], and can pose physical safety risks for users of navigational and other spatial tools [21, 55, 60, 87]. While the full extent of these information gaps and their consequences is not yet fully understood, prior work does suggest that systemic disparities in coverage does impact downstream tools relying on this data, creating risks to physical safety.

In most cases, research studies on information gaps in OpenStreetMap have tended to focus their analyses on volunteer contribution rates [37, 49] or compare the quality and completeness of the map to external sources [16, 65, 116]. While contributor behavior and geometric quality are important dimensions for understanding how effective OpenStreetMap

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is, research in this space has focused less on the *semantic information* that is present in OpenStreetMap as well. In OpenStreetMap, semantic metadata is represented through tags applied to *nodes*, *ways*, and *relations* — the geometric representations of points of interest (POIs), such as buildings, roads, or other entities on the map. These tags represent semantic metadata as *key-value* pairs, and serve both as the mechanism for differentiating types of geometries — for instance, the difference between ways that represent roads versus rivers — as well as providing additional detailed metadata like street names. In other words, in order for OpenStreetMap data to be useful for end-user applications, this semantic information becomes critical. For instance, metadata associated with street networks, like street names, speed limits, and other properties of roads, are necessary pieces of information for a variety of applications, including navigation, street network analysis, transportation planning, and map generalization, among others [79, 80].

One way of helping create data in OpenStreetMap is the direct import of authoritative spatial data from institutional and governmental agencies using automated tools [49]. These automated imports vary in scale — from city-specific datasets like tree locations [106] to national-level road networks [105] — and in type, importing both geographic entities themselves as well as annotations and tags (referred to as "semantic metadata"). However, over time, this use of bots has sparked debates within the OpenStreetMap community regarding their impact and benefits. For example, automated imports have been associated with quality problems [32, 110, 113], potentially hindering continued participation by volunteers [74], which may in turn limit the maintenance work necessary to ensure high-quality metadata in OpenStreetMap [32, 113]. While automated imports may be a useful technique for quickly adding new information to OpenStreetMap, how these automated imports affect metadata coverage (or lack thereof), remains unclear.

Taken holistically, potential issues with coverage in OpenStreetMap — both in terms of overall contributions as well as the production and geographic distribution of metadata, created by human contributors or by automated imports — cascade through the systems that rely on this data, potentially creating real physical safety risks for users. However, the extent of this problem, particularly concerning metadata tag production, is not well understood. Thus, our work here starts to address this issue by focusing on an initial set of tags in OpenStreetMap that pertain to safe driving conditions: speed limits, the number of lanes, and road surface types. We conduct a large-scale quantitative investigation to understand the mechanisms of various human geographic, cultural, and socioeconomic predictors on road safety tag production, as well as the potential value or cost of automated imports in OpenStreetMap. Specifically, we pose two primary research questions to understand the spatial dependence and spatial heterogeneity between various local characteristics and road safety metadata coverage.

RQ1 To what extent do automated imports aid or hinder road safety metadata production in OpenStreetMap?
RQ2 How do various geographic attributes influence the coverage of road safety metadata in OpenStreetMap?

To address these questions, we employ a spatial regression technique — the Spatial Durbin Model — following best practices [21, 97]. This approach allows us to explore *how* various dimensions predict road safety tag coverage. Our work here makes three primary contributions to CSCW and the "geoHCI" field [42]:

- We find concerning evidence that automated imports may impede tag production in OpenStreetMap. While our results indicate that automated imports do increase the overall completeness of the map, they may hinder human metadata production, which is particularly concerning in our focus setting — road safety.
- We extend prior "GeoHCI" information gaps research, showing that cultural factors such as demographic diversity and political climate are significant predictors of road safety metadata production.While prior work finds similar trends along socioeconomic status and population density dimensions, our work here complicates these trends and contributes new, important analytical dimensions.

- Our findings add depth to our understanding of metadata production in OpenStreetMap, and suggest important implications for how we understand peer production processes. Consequently, we provide recommendations for peer production communities and platforms, as well as researchers in this field.

2 RELATED WORK

Prior work has extensively focused on addressing disparities in peer production settings. In our study, we extend this line of research by investigating the effects of various predictors on tag coverage within OpenStreetMap, building upon and drawing inspiration from three primary bodies of prior research: geographic gaps in peer production systems, the effectiveness of automated imports, and tagging metadata in OpenStreetMap.

2.1 Geographic Disparities in Peer Production

In recent years, researchers have shown considerable interest in examining geographic coverage biases in peer-produced datasets. This work can be broadly categorized into two camps: (1) comparing OpenStreetMap with ground truth data obtained from official reference datasets as a metric of "quality" (e.g. [14, 25, 69]), and (2) evaluating OpenStreetMap against human geographic and socioeconomic dimensions to assess how successfully OpenStreetMap coverage serves people (e.g. [38, 49, 62, 66, 96, 115]). Both bodies of work reach similar conclusions: there are clear disparities in OpenStreetMap coverage. Even though the global completeness of the OpenStreetMap road network stands at approximately 80% [11], OpenStreetMap data exhibits significant biases due to the concentration of the OpenStreetMap community in the global North [76, 93]. Moreover, these disparities in OpenStreetMap coverage and quality suggest that data completeness and quality tend to be lower in less densely populated and economically disadvantaged regions [38, 49, 62, 66, 96, 115].

In addition to examining general OpenStreetMap data, some research has explored variations in specific types of content. For instance, Herfort et al. [44] showed that mapping efforts on roads and buildings in OpenStreetMap are heavily biased towards regions with higher Human Development Indexes (HDIs), neglecting areas with lower and medium levels of human development where the majority of the population resides. Neis et al. [76] found that densely populated regions of Germany and the US even have OpenStreetMap road networks that expand beyond the scope of reference data, due to the inclusion of more detailed features, such as pedestrian and cycle paths. Gröchenig et al. [34] demonstrated that while the OpenStreetMap data in certain regions were nearly complete, completeness for specific types of content relied on a well-defined sequence of how the community activity plays out. Moreover, Thebault-Spieker et al. [94] showed that some types of content are produced in a very local manner, whereas others are substantially less local, suggesting that "self-focus bias" may be one underlying mechanism behind these disparities.

2.2 The Effectiveness of Automated Imports

OpenStreetMap is broadly designed to build an important spatial database resource through "collective intelligence" — voluntary, independent contributions. However, one approach to addressing structural information gaps, as discussed in 2.1, is the involvement of institutional and governmental agencies in data production within OpenStreetMap. This involvement can vary in spatial scale, from city-specific datasets [106] to national-level data [105], and differs from mapping activities and organized projects undertaken by individuals and communities. Data imported by these institutional and governmental agencies, referred to as *automated imports*, supplement the data collected by individual contributors [17, 30, 31, 40, 114]. For example, significant portions of OpenStreetMap were imported from the U.S. government's TIGER/Line street dataset [102]. Similarly, in many geographic peer production settings, reliance on automated editing is common. For instance, Wikipedia articles often contain bot-generated text using census statistics [103]. Automated imports help establish a "baseline of production", particularly in less active communities or regions. Johnson et al. [49] showed that in Wikipedia articles about urban places, approximately 4.5% of the content is generated by bots or batch editors. However, this proportion exceeds 23% for articles about rural places. These interventions complicate the notion of "peer production", since these efforts now consist of both human editors and automated or semi-automated software agents [17, 30, 31, 40, 114].

Given these more complicated information production dynamics, understanding how these automated activities affect human contribution activities in OpenStreetMap becomes an important topic. Previous research demonstrates that while automated imports contribute to increased completeness and enhanced consistency, particularly in sparsely populated regions [92, 113], automated contributions are often viewed as inferior in quality compared to content generated by human contributors. For example, Zielstra et al. [113] noted issues like disconnected and mismatched roads between previously contributed data and the imported TIGER/Line data in the United States, necessitating post-import corrections. Grinberger [32] concluded that imports could introduce biased data from specific institutions into OpenStreetMap, raising concerns about the usability of the imported data. Moreover, Witt et al. [110] investigated the impact of large data imports on contributor activity, finding that a majority of users who participated in an import were influenced by the automated imports, as evidenced by their initial contributions coinciding with the import period. However, other studies suggest that imports may have a chilling effect on additional contributions, potentially due to the mapping appearing "complete" [74].

2.3 Tagging Metadata in OpenStreetMap

OpenStreetMap specifies different types of content through the application of metadata to the spatial entities on the map, although less attention has been given to the interpretation and annotation of the data [10]. Tagging the spatial map data itself is a more flexible and user-driven approach, with an unbounded and uncontrolled vocabulary, similar to social media tags [91]. This process is further complicated by the fact that tagging is open-ended and relies more on norms than rules to ensure the usefulness of tags, if applied at all [41]. However, OpenStreetMap does have a taxonomy of recommended tags, and prior work has shown that, generally, the tags applied align with this taxonomy [41].

OpenStreetMap's editing interface provides tools designed to aid in adding relevant tags [8], but despite this, Atwal et al. [9] found that a significant majority of mapped features have limited or no descriptive tags, even in regions with high OpenStreetMap network coverage. Mooney and Corcoran [71] showed that the average number of tags per object in OpenStreetMap tends to be relatively low, typically around 2-3 tags per object. Furthermore, prior work in OpenStreetMap demonstrates that the generalized power-law distribution patterns around content production in peer production persist in the tag production process as well, wherein a small percentage of contributors are responsible for performing the majority of tagging [33, 71, 75].

3 METHODOLOGY

To address our research questions, which sit at the intersection of these three bodies of prior work, we first needed to construct a spatial dataset for our analysis. Moreover, because our research questions involve using spatial data, we also needed to account for the spatial nature of our data with specialized spatial statistical approaches. In this section, we define the details of this dataset and provide important context about our spatial analysis approach.

3.1 The Selection of Road Safety Tags

Transportation research and official reporting identify three key features of road safety: speed limits, road widths, and road surface conditions [1, 27, 82]. The World Health Organization (WHO) has documented that a 1% increase in mean speed is associated with a 4% increase in the likelihood of a fatal crash [1, 82]. Road width is also a crucial safety factor, especially on high-speed roads, where narrower lanes are linked to an increased risk of lane departure-related crashes [1]. Further, road surface conditions, including hazards like potholes and ice, result in over 42,000 annual fatalities in the United States alone [27].

Beyond the safety of road engineering itself, and more relevant to CSCW and the HCI community, these road properties are also important for personal navigation technologies. Lin et al. [60] highlighted the crucial role of these three road properties in consumer navigation technologies and road accidents associated with them. Their analysis of 158 detailed news reports found that missing or inaccurate information about these three road properties in in-car navigation systems were contributing factors in 25% of the reported "Death by GPS" cases. Lin et al. [60]'s work also points to a broader conclusion: missing or incomplete road safety data propagates through downstream technologies that rely on these datasets. This is particularly relevant to companies like Tesla, which may be building algorithms with this data, but also impacts Apple Maps and other user-facing applications that rely on OpenStreetMap.

Our study here focuses on the potential risks to users stemming from incomplete road safety data in OpenStreetMap. We center our analysis on three popular [77], specific tags in OpenStreetMap that reflect important aspects of road safety: `maxspeed=*`, `lanes=*`, and `surface=*`.

3.2 Spatial Unit of Analysis

Our study is geographically focused on the United States. This decision was influenced in part by the comprehensive nature of the OpenStreetMap network within the U.S., characterized by a significant number of active contributors [81], communities [78], and substantial institutional automated imports [74]. Additionally, the availability of detailed and regularly updated census data from the U.S. Census Bureau [19] provides a rich resource that facilitates a thorough exploration of our research questions.

Following common practice in geographic human-computer interaction research [42, 43, 48, 49, 59, 97], our analysis is focused at the county level. There are 3,143 counties in the U.S., which are both administrative divisions below the state governments and standard units of analysis for demographic studies due to available summary data from the U.S. Census [53]. Counties present a varied range of characteristics, irrespective of their population size [3].

3.3 Construction of Dependent Variables

As mentioned earlier, our investigation in OpenStreetMap centers on three specific road properties that pose a significant risk to physical safety when absent, especially for technologies powered by OpenStreetMap data. In OpenStreetMap, these road properties are represented as tags associated with "ways" (the geometry elements that include roads in OpenStreetMap). The tag for speed limits is `maxspeed=*` [108], and the tag for road surface is `surface=*` [109]. OpenStreetMap does not have a tag that directly reflects the width of the road, but road lane widths in the U.S. are typically standardized [2]. Therefore, we rely on the OpenStreetMap tag `lanes=*` [107], which describes the number of lanes on a given road, to characterize road width.

To begin, we extracted the full history of OpenStreetMap data, from the "history planet" dump as of June 2023 [104]. To ensure that our analysis focuses only on accessible roads for cars, we excluded ways with tag values that indicated the roads were inaccessible to cars, as defined by the OpenStreetMap documentation on how to apply these tags [101]. Examples of excluded tags include: `highway=footway` and `highway=steps`, etc. Ultimately, this resulted in an overall dataset of 166 million unique road segments, and the full edit history associated with each road segment. Because coverage is a metric of "completeness", we rely on the current state of the road segments as of July 2023, rather than interrogating the contribution history that got the map to its current state.

However, because tag application on a given road segment may result either from human edits or automated processes (e.g., bots or imports), we do differentiate between these two sources of metadata. Automated edits often involve bulk updates or imports from external datasets, which are distinct from manual, human-produced contributions. In constructing our dependent variables, we focus on "human-produced" tag coverage, in order to correctly isolate automated imports, and focus our analysis on how our human-focused variables correlate with peer production coverage output. We describe our process for identifying automated tag applications in Section 3.4.1.

We computed our dependent variables — coverage for three specific tags — for each of the 3,143 counties in the United States, as shown in Figure 1. Specifically, we computed coverage as the percentage of car-accessible "ways" within each county that had been tagged with each specific road property (`maxspeed=*`, `lanes=*`, and `surface=*`):

$$\text{Human Coverage Rate} = \frac{\text{Number of car-accessible ``ways'' with human-created specific tags}}{\text{Total number of car-accessible ``ways'' in the county}} \times 100\% \tag{1}$$

This coverage rate provides a standardized measure of the extent to which these specific safety-related tags are represented in OpenStreetMap within each county's accessible road network. We show descriptive statistics for all of our variables in Table 1.

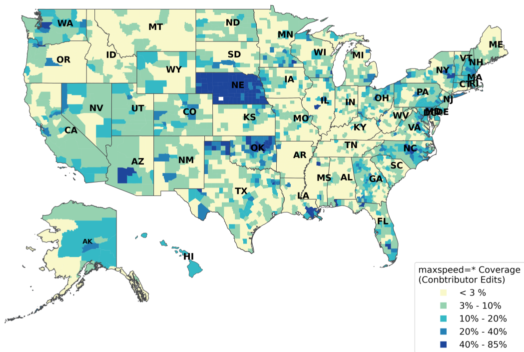
Importantly, each of these types of metadata *could* reach 100% coverage in the United States. After all, all car-accessible roads have speed limits, have a surface treatment, and the width can be measured. Therefore, the denominator for our coverage analysis is the full set of roads in OpenStreetMap. Moreover, road property coverage in OpenStreetMap tags is distinct from the overall geometric completeness of OpenStreetMap [14, 25, 69]. Thus, our coverage metric does not reflect how complete OpenStreetMap is overall by comparison to some ground truth definition, but instead represents how well the currently mapped roads in OpenStreetMap are covered by each tag.

3.4 Explanatory Variables

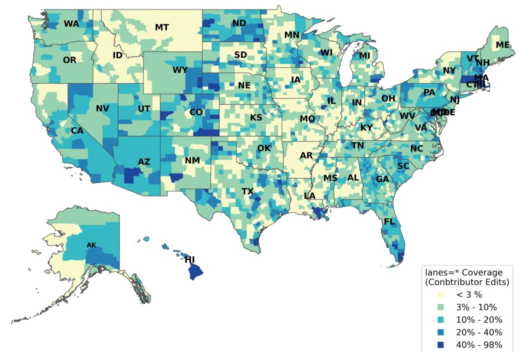
In order to develop a holistic understanding of the dimensions that influence tag coverage, we developed eight metrics in total, covering human geographic, cultural, and socioeconomic factors, as well as automated imports. These eight metrics span four distinct categories, each representing known important factors in peer production settings [38, 49, 62, 66, 96, 115]. Socioeconomic status, human geography dimensions, and automated content production have been shown to influence content production in OpenStreetMap [96] and other peer production communities [38, 49, 62, 66, 96, 115], and thus likely have some influence on tag production as well. Moreover, because our focus is road safety tag production, we also included new cultural factors — vote margin and ethnic diversity in the county — as possible predictors of metadata annotation behavior, which is a different type of content production work than the creation of new entities on the map. Descriptive statistics are shown in Table 1, and we have mapped these variables in Figures 2 and 3. We computed each of these variables at the county level, for every county in the United States.

3.4.1 Automated Imports.

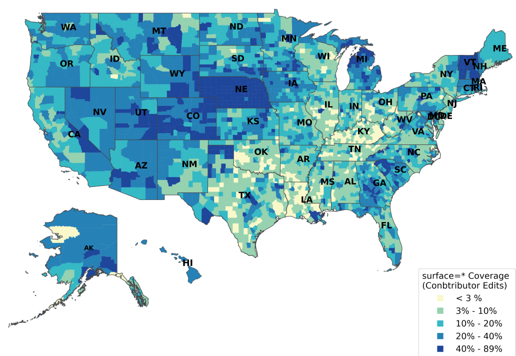
Our first category aims to explore the correlations between safety tag coverage and automated imports in OpenStreetMap. This investigation is motivated by prior work demonstrating the significance of automated approaches in



(a) `maxspeed=*` Coverage



(b) `lanes=*` Coverage



(c) `surface=*` Coverage

Fig. 1. Distribution of Road Safety Tags Coverage Edited by Contributors at the County Level (n=3143).

content production within systems like OpenStreetMap and their potential influence on the quality and dynamics of contribution in peer production settings [49, 113, 114]. We operationalize this category as two metrics — a *% Safety Metadata Automation* variable and a *% Other Metadata Automation* variable, to capture the extent to which tag-specific edits and general edits (excluding the safety tags) are made through automated imports in each county. These two variables are disjoint from our independent variables, which focus exclusively on human-created coverage, as shown in Figure 1.

Unlike other peer production systems where automated tools are explicitly identified, OpenStreetMap lacks such labeling, making it challenging to directly categorize contributions. To address this, we adopt established methodologies [49, 113, 114] to define automated imports as edits within a changeset that occur at a rate faster than once per second and include at least 1,000 changes. We compute each of these variables as:

- **%Safety Metadata Automation**: This metric quantifies the proportion of vehicle-accessible ways in a county that have received at least one automated edit applying safety-related tags. For example, to compute % Safety Metadata Automation for the `maxspeed=*` tag, it is calculated as: The number of car-accessible ways with automated edits applying the maxspeed=* tag, divided by the total number of car-accessible ways in the county, multiplied by 100%.

Table 1. Descriptive statistics of the Major Variables (n=3143)

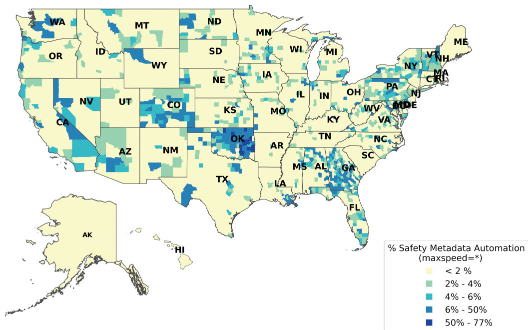
Category	Variable	Minimum	Maximum	Mean	Std.deviation
Dependent Variables	`maxspeed=*` Coverage	0.0%	89.3%	7.7%	12.8%
	`lanes=*` Coverage	0.0%	85.4%	8.6%	9.9%
	`surface=*` Coverage	0.0%	98.6%	18.7%	17.3%
Automated Imports	% Safety Metadata Automation (`maxspeed=*`)	0.0%	77.6%	2.1%	5.9%
	% Safety Metadata Automation (`lanes=*`)	0.0%	92.3%	3.4%	9.9%
	% Safety Metadata Automation (`surface=*`)	0.0%	93.7%	3.9%	10.8%
	% Other Metadata Automation	0.0%	93.7%	28.6%	17.6%
Human Geography	Population Density	0.01	27819.8	104.7	696.4
	Rural-Urban Classification	1	9	5	2.7
Cultural Factors	Margin of Votes	-81.7%	93.1%	31.4%	32.3%
	Ethnic Diversity Index	0.0%	80.5%	31.3%	16.8%
Socioeconomic Factors	Educational Attainment Index	0.0%	78.8%	23%	9.9%
	Unemployment Rate	0.6%	14.7%	3.6%	1.2%

- **% Other Metadata Automation**: This metric reflects the broader proportion of tag production in a county, that is unrelated to road safety tagging. In % Other Metadata Automation, automated edits applying any safety-related tags (`maxspeed=*`, `lanes=*`, `surface=*`) are excluded to ensure that this is an independent variable from our % Safety Metadata Automation metric, above. Moreover, this variable is identical in all three of our models. Thus, in Figure 2, we plot this variable once. Taking the `maxspeed=*` tag as an example, % Other Metadata Automation is computed by dividing the number of car-accessible ways in the county that have received automated edits on other tags excluding the `maxspeed=*` tag by the total number of vehicle-accessible ways in the county, then multiplying the result by 100%.

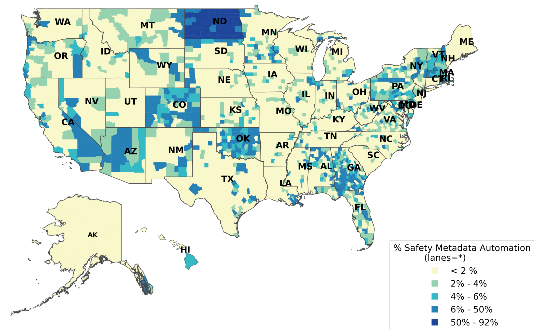
3.4.2 *Human Geography.*

Our next category focuses on two key variables within the realm of human geography — population density and the rural-urban classification of a county, which represent how people distribute themselves spatially. Prior studies have shown that these variables help predict coverage variations in OpenStreetMap and other peer production systems [38, 49, 62, 66, 96, 115].

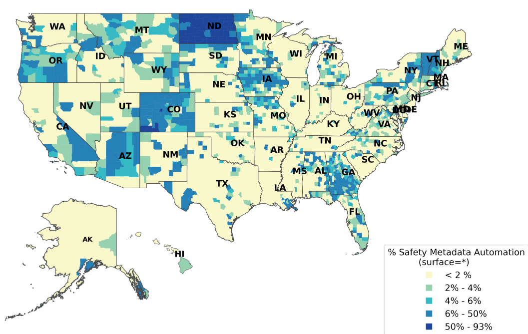
- **Population Density**: Population density is a metric obtained from the U.S. Census Bureau, measured as the number of inhabitants per square kilometer [38, 49, 66]. We transformed this variable with a log_2 transformation to ensure that this variable followed necessary modeling assumptions.
- **Rural-Urban Classification**: Whereas population density summarizes how many people live in an area, there are other aspects of urbanization that population density does not capture [3]. Therefore, we also labeled each county according to the Rural-Urban Continuum scheme defined by the United States Department of Agriculture's Economic Research Service (USDA-ERS) [3], which characterizes the level of urban development within a specific county. This official scheme ranges from 1 to 9, categorizing counties using a number of different factors and reflecting the degree of urbanization in every county. A higher number in the Rural-Urban



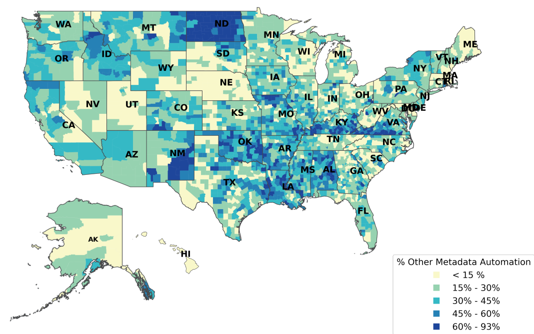
(a) Distribution of % Safety Metadata Automation on `maxspeed=*`



(b) Distribution of % Safety Metadata Automation on `lanes=*`



(c) Distribution of % Safety Metadata Automation on `surface=*`



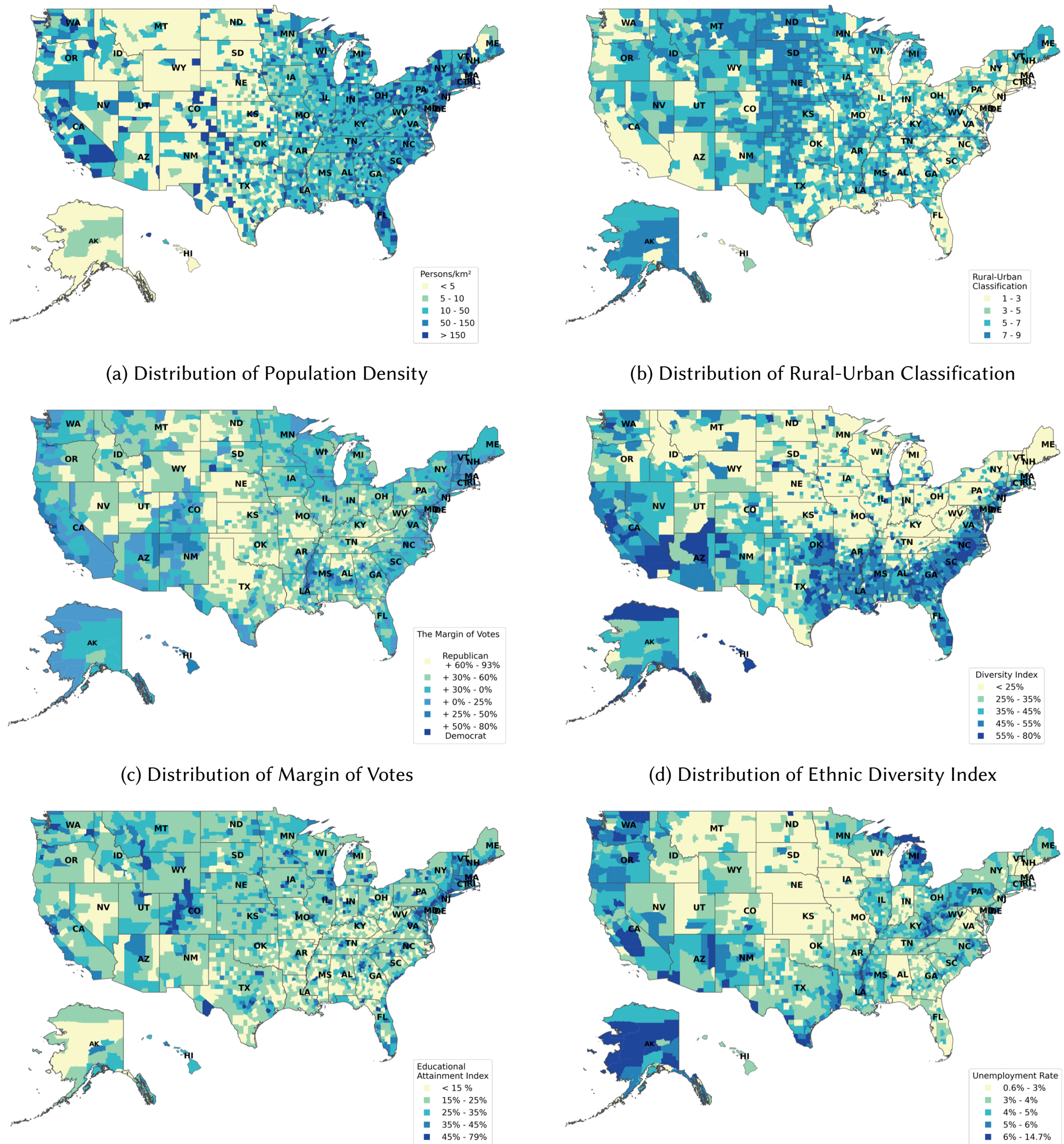
(d) Distribution of % Other Metadata Automation

Fig. 2. Distribution of %Automated Imports Variables at the County Level (n=3143). (a) % Safety Metadata Automation on `maxspeed=*`; (b) % Safety Metadata Automation on `lanes=*`; (c) % Safety Metadata Automation on `surface=*`; (d) % Other Metadata Automation;

Classification denotes a more rural county, while a lower number signifies greater urbanization within that county — 1 is “most urban” and 9 is “most rural”.

3.4.3 Cultural Factors.

Previous research has established that various cultural phenomena can significantly shape the contributions of peer production contributors in platforms like OpenStreetMap. Studies such as those on the influence of sports team losses, protest movements, and breaking news events highlight the impact of cultural elements on contributor behavior [51, 58, 98]. Complementing this, Lin [61]’s research on global collaboration and contributor identities in OpenStreetMap, Budhathoki and Haythornthwaite [18]’s survey of mappers’ motivations, and Bittner [13]’s analysis of diversity in volunteered geographic information systems collectively underline the critical role of cultural factors, including political leanings and demographic diversity, in shaping mapping practices. Given these insights, our study incorporates two cultural dimensions — the margin of votes and the ethnic diversity index — in order to explore how cultural dimensions influence tag content production in OpenStreetMap.



(a) Distribution of Population Density

(b) Distribution of Rural-Urban Classification

(c) Distribution of Margin of Votes

(d) Distribution of Ethnic Diversity Index

(e) Distribution of Educational Attainment Index

(f) Distribution of Unemployment Rate

Fig. 3. Distribution of Other Variables at the County Level (n=3143). (a) Distribution of Population Density; (b) Distribution of Rural-Urban Classification; (c) Margin of Votes; (d) Ethnic Diversity Index; (e)Educational Attainment Index; (f)Unemployment Rate;

- **The Margin of Votes**: We computed the "margin of votes" for each county based on the voting data from the US Presidential Election in 2020, provided by the Associated Press [1]. This variable captures the political climate

[1]https://apnews.com/hub/elections

of a county, measured as the difference between the percentage of votes for Democratic candidates and the percentage of votes for Republican candidates in a given county. Positive margins indicate a higher percentage of Democratic voters, negative values indicate a higher percentage of Republican voters, and margins near zero indicate a roughly equal balance of voters across the political spectrum.

- **Ethnic Diversity Index**: We also incorporated a demographic diversity metric based on U.S. Census data. Following best practices, we computed the "ethnic diversity index", which describes the degree of racial diversity within a specific geographic region, with values between 0 and 1 [50, 67]. Values near 1 indicate that the county's population encompasses individuals from all U.S. Census racial categories: White, Black or African American, Hispanic or Latino, American Indian or Alaska Native, Asian, Native Hawaiian, or Pacific Islander.

3.4.4 *Socioeconomic Factors.*

The last category of variables we included in our analysis focuses on the socioeconomic conditions for each county in our dataset. Prior work has shown disparities along socioeconomic lines in OpenStreetMap [38, 49, 66, 96], so we include these variables to assess whether this previously observed trend holds in the context of tag production specifically. Previous studies use metrics such as "median household income" [96, 97] to represent socioeconomic status. However, due to the number of variables in our model, we were concerned about collinearity between "median household income" and our human geography variables when studied across the United States. Therefore, we instead selected metrics of educational attainment and employment as reflections of socioeconomic status, and ensured that all variables were sufficiently independent (described below in Section 3.6.1).

- **Educational Attainment Index**: We computed an educational attainment index for each county based on data from the U.S. Census Bureau, which reflects the proportion of individuals holding a bachelor's degree or higher [26], normalized per thousand people. In other words, this variable serves as an indicator of the educational achievement and knowledge base of the population.
- **Unemployment Rate**: The unemployment rate, calculated using data from the U.S. Census Bureau, represents the average annual ratio of unemployed individuals to the total population in a specific area. This economic indicator measures joblessness within each county, offering insights into the area's overall economic health.

3.5 Analytical Approach: Spatial Durbin Model

The core approach of our analysis is an investigation into how various attributes of counties, and of their neighboring regions, influence the coverage of road safety metadata. However, the relationship between our variables of interest and our outcome variables can be influenced by spatial autocorrelation existing in our data — neighboring regions may exhibit similarities in data because they are neighbors, violating traditional statistical assumptions. To address this issue, we adopt the Spatial Durbin Model [73], following recommendations from prior geoHCI research [21, 97]. Due to the complexities of spatial data and the mathematical construction of the Spatial Durbin model, we adhere to common practice and do not report model coefficients (e.g., [21, 97]). Instead, we report "direct" and "indirect" effects of these models. "Direct" effects describe the statistical relationship between the independent variables and the dependent variable *within the same county*. On the other hand, "indirect" effects describe the statistical relationship between the independent variables *in neighboring counties* and the dependent variable *of the county in question*.

In our study here, we constructed three Spatial Durbin models, one for each of our tag coverage dependent variables: speed limit coverage (`maxspeed=*`), number of lanes coverage (`lanes=*`), and road surface coverage (`surface=*`). Each of our models included the eight independent variables described above, along with the necessary terms that encode the spatial structure of our data, using a "Queen's" weights matrix in which all adjacent neighboring counties are considered part of the neighboring area.

3.6 Robustness Checks

3.6.1 Multicollinearity and Spatial Outliers. When including numerous human geographic, cultural, and socioeconomic variables in our analysis, there can be a risk of these variables being correlated, which would violate statistical assumptions. Recent literature has indicated the robustness of spatial regression models to multicollinearity, especially in large sample sizes, where multicollinearity should be treated similarly to standard regression models [15, 28]. Additionally, spatial regression analyses are susceptible to spatial outliers — observations that significantly deviate from local patterns due to anomalies in geographic, economic, or social contexts [6, 89].

To address this, we employed both traditional Variance Inflation Factors (VIF) and Pairwise Correlation Matrices to systematically identify potential linear relationships among explanatory variables, as shown in Table 6 and Figure 4 in the appendix. VIF quantifies how much the variance of a given predictor is inflated due to collinearity, with high values indicating a strong linear association with other variables that could affect model reliability. In our study, all variables exhibit VIF scores below 2.2, with most values close to 1, well under the commonly used threshold of 5 [52, 56, 63, 70], indicating minimal collinearity. Furthermore, Pairwise Correlation Matrices (see Figures 4 in the appendix) revealed that most pairwise correlations are around 0.2 to 0.5, with none exceeding the commonly accepted threshold of 0.7 [24, 57]. These findings confirm the absence of strong linear dependencies among variables and provide confidence in the robustness and interpretability of our spatial regression models.

In addition to addressing multicollinearity, we examined spatial outliers, which can distort regression results. We used Local Moran's I to detect spatial anomalies in the dependent variable, ensuring that extreme localized deviations did not bias the spatial autocorrelation patterns explicitly modeled by the Spatial Durbin Model (SDM). Since SDM accounts for spillover effects in both the dependent variable and predictors, controlling for such deviations helps maintain model stability. For independent variables, we used Z-scores instead of Moran's I, as SDM already incorporates spatial dependencies in predictors. Here, extreme values — rather than spatial clustering — pose a greater risk of distorting both direct effects (on local observations) and indirect effects (on neighboring areas). Z-score-based detection effectively identifies these outliers, preventing undue influence on model estimates. To assess the robustness of our results, we conducted regressions with and without the flagged outliers. The coefficients and significance levels remained stable, indicating that these outliers did not substantially influence our findings (see Table 7 in the appendix). Furthermore, these outliers represent meaningful variations in local tag production rather than data anomalies. Removing them could obscure important spatial patterns, potentially limiting the model's ability to capture localized effects. Therefore, we retained them in the final models to ensure a comprehensive representation of spatial dynamics.

3.6.2 Alternative Independent Variables: Weighting of Ways. To ensure that our findings are not sensitive to specific methodological choices, we conducted additional robustness checks using alternative metrics. Specifically, we examined: (1) re-weighting ways by length rather than treating all ways in OpenStreetMap equally, and (2) comparing descriptive statistics before and after applying this alternative weighting scheme. These checks help confirm that our conclusions remain stable under reasonable modifications in data processing.

In our primary analysis, ways were weighted equally when computing the coverage of key OpenStreetMap tags (e.g., `maxspeed=*`, `lanes=*`, `surface=*`), meaning that each road segment contributed equally to the overall coverage calculation regardless of its physical length. This approach provides a straightforward way to assess metadata completeness and capture the mapping behavior in OSM, as it reflects the extent to which contributors add metadata across different road segments without prioritizing any specific type of road. However, an alternative approach is to weight ways by their physical length, which better accounts for their relative importance in the transportation network. Since longer roads may contribute more substantially to mobility and infrastructure, length-weighting prevents shorter segments from disproportionately influencing coverage estimates.

Figure 5 presents the distribution of tag coverage under both the original and alternative reweighting metrics, along with a correlation analysis indicating a strong alignment between the two approaches (correlation: `maxspeed` = 0.92, `lanes` = 0.88, `surface` = 0.91). These high correlations suggest that the weighting method has minimal impact on the overall coverage patterns. To further assess the robustness of our findings, we re-estimated the spatial regression models using the length-weighted coverage metrics and variables, as shown in Table 8 in the appendix. The results indicate that coefficients, significance levels, and effect sizes remain consistent with the primary analysis, confirming that the observed relationships are not sensitive to the choice of weighting scheme.

3.7 Methodological Limitations

Our work, based on the methodological decisions we made, has some limitations regarding the generalizability of our findings. First, we confined our analysis to the United States, limiting the applicability of our results to other countries. Second, our focus here was primarily on spatial variations, whereas prior work [96] has demonstrated temporal variations as well. Exploring spatiotemporal trends related to the ones we describe here could be an interesting direction for future research. Third, as is common in many geographic studies, we selected counties as our geographic unit of analysis. However, it is important to acknowledge the Modifiable Areal Unit Problem (MAUP) in geography, which means that the spatial unit we selected may have an impact on the trends we show here. Expanding studies like this to investigate state-level trends or even smaller scales, such as census tracts, represents an important direction for future research.

4 FINDINGS

As noted above, we ask two primary research questions in this study and explore these questions through our eight variables of interest across 4 categories, using Spatial Durbin Modeling (SDM). In each subsection below, we highlight the relevant categories of variables in our SDM model to help clarify and triangulate the trends in our results for each research question, in turn.

4.1 RQ1: To what extent do automated imports aid or hinder road safety metadata production in OpenStreetMap?

4.1.1 Automated Imports: Trade-off Between Efficiency of Automated Imports and Localized Knowledge Contribution.

Turning to our first category of variables, which represent the use of automated public data imports in OpenStreetMap, we observe substantial direct and indirect effects of both `% Safety Metadata Automation` and `% Other Metadata Automation` on tags coverage, as shown in Table 2.

First, our models demonstrate that `% Safety Metadata Automation` — the proportion of automated edits for each road safety tag — shows generally intuitive and positive correlations with the coverage of the three tags of interest. Specifically, when comparing two otherwise identical counties, a county with 10% more automated edits for the `maxspeed=*` tag is predicted to have 4.98% higher coverage of `maxspeed=*` compared to the other. We find similar trends trend for the `lanes=*` tag and `surface=*`, where for two counties that are otherwise equivalent, but one has

Table 2. The Direct and Indirect Effects of Automated Imports Factors on Road Safety Tags Coverage across US counties. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Automated Imports	% Safety Metadata Automation	`maxspeed=*`	0.498***	0.573***
		`lanes=*`	0.414***	-0.057
		`surface=*`	0.480***	-0.033
	% Other Metadata Automation	`maxspeed=*`	-0.161***	-0.187***
		`lanes=*`	-0.165***	-0.042
		`surface=*`	-0.412***	-0.247***

a 10% higher rate of automated imports, our model predicts a 4.14% and a 4.8% increase in `lanes=*` coverage and `surface=*`, respectively.

Our Spatial Durbin Model (SDM) captures the indirect effects of metadata automation on neighboring counties. For example, our results for the `maxspeed=*` tag suggest that if a county's neighbors increased their percentage of automated imports of this tag by 10% on average, the model predicts a 5.73% higher coverage of `maxspeed=*` tags within the county itself.

Our second metric, `% Other Metadata Automation`, captures the proportion of ways that had other automated metadata creation, excluding the road safety tags we study here (i.e., `maxspeed=*`, `lanes=*`, and `surface=*`). Analyzing this variable in more detail shows negative trends for both the direct and indirect effects in our models. When comparing two otherwise identical counties, our model predicts a county with 10% `% Other Metadata Automation` would show 1.61% less coverage for `maxspeed=*` tags, 1.65% less coverage for `lanes=*` tags, and 4.12% less coverage for `surface=*` tags. Moreover, the indirect effects results suggest that these negative trends extend beyond the county itself. For instance, if neighboring counties increase their percentage of automated contributions by 10%, the model predicts 1.87% lower `maxspeed=*` tag coverage and 2.47% lower `surface=*` tag coverage within the county in question.

Holistically, while automated imports *in general* seem to negatively influence coverage for our three road safety tags, we see an intuitive reversal of this trend when focusing on tag-specific automated imports. In other words, targeted automated imports can support improved tag coverage, whereas general automated imports may hinder the production of road safety tags, even when this automated production happens in neighboring areas. While our results cannot speak to causal mechanisms, this may be an indication that automated production of metadata disincentivizes human effort around metadata production, and may suggest important trade-offs between the efficiency of automated processes and the nuanced, localized knowledge provided by human mappers. We discuss this in more detail in Section 5.1, below.

4.2 RQ2: How do various geographic attributes influence the coverage of road safety metadata in OpenStreetMap?

4.2.1 *Human Geography: The Marginalized Influence on Tag Production.*

Turning to our two human geographic variables — population density and rural-urban classification — we were surprised to find that these factors have only a marginal influence on road safety tag coverage, in contrast with prior literature that emphasizes their importance in peer production systems [38, 49, 62, 66, 96, 115].

For the first variable, population density, we find a counterintuitive but minimal and negative effect on `maxspeed=*` coverage. As shown in Table 3, the SDM results suggest that for two counties that are otherwise identical, one with

Table 3. The Direct and Indirect Effects of Human Geographical Factors on Road Safety Tags Coverage across US counties. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Human Geography	Population Density	maxspeed=*	-0.001*	-0.003
		lanes=*	0.000	0.000
		surface=*	-0.001	-0.003
	Rural-Urban Classification	maxspeed=*	0.000	0.001
		lanes=*	-0.000	-0.006**
		surface=*	0.009***	0.017***

twice the population density of the other, our model predicts a marginal but statistically significant decrease of 0.1% in `maxspeed=*` coverage. This small negative effect is unexpected, particularly given the established role of population density in shaping outcomes in peer production systems. Furthermore, we see no statistically significant effects for `lanes=*` and `surface=*` coverage, as well as no significant indirect effects for any of our three coverage variables.

Similarly, our rural-urban classification metric also largely shows small or not statistically significant effects on tag coverage. More specifically, we finds no statistically significant direct effects between ruralness and coverage of `maxspeed=*` or `lane=*` metadata. For `surface=*` coverage, we find a statsitically significant, but small, direct effect: for two otherwise identical counties, where one county is one class more rural (e.g., moving from 8 to 9), the more rural county is predicted to have a 0.9% increase in `surface=*` coverage. Turning to our indirect effects results, our model predicts that a county, where all neighboring counties shift one class toward greater ruralness, would see 1.7% increase in `surface=*` tag coverage and approximately 0.6% decrease in `lanes=*` tag coverage. We find no significant indirect effects between the urban-rural variable and `maxspeed=*` tag coverage.

Overall, our findings suggest that human geographic variables like population density and rural-urban classification [38, 49, 62, 66, 96, 115], which prior work has shown to be robustly predictive in general peer production settings, are either not significant predictors of road safety tag coverage or exhibit negligible effect sizes. For instance, while population density shows a statistically significant relationship with `maxspeed=*` coverage, the effect is both minimal and negative, suggesting that higher population density may not enhance contributions to specific road safety tags. Similarly, rural-urban classification demonstrates no significant effects for most tags, with the exception of the `surface=*` model, where rural counties exhibit a slight increase in tag coverage. This result may be due to unique characteristics of rural road networks — these areas often have fewer roads overall, and the roads that do exist are frequently major highways that may lack regular updates or maintenance both physically and in OpenStreetMap metadata.

4.2.2 *Cultural Factors: A New Dimension of Influence on Tag Production.*

Turning to our two variables that reflect cultural factors — the margin of votes and the ethnic diversity index — we find statistically significant and positive effects across most models. Specifically, as shown in Table 4, the direct effects in our SDM analysis reveal a positive relationship between the margin of votes and tag production for all three types of tags. More concretely, consider two hypothetical counties that are identical in all other characteristics but differ in their political alignment. If one county exhibited a tied vote in the 2020 election and the other showed a 10% higher Democratic preference (margin of votes increasing from 0 to 0.1), our analysis indicates that the latter county would tend to have a 0.17% higher `maxspeed=*` tag coverage, 0.31% higher `lanes=*` tag coverage, and 0.12% higher `surface=*` tag coverage. Turning to the indirect effects, we see no significant results for `surface*` coverage, but our

Table 4. The Direct and Indirect Effects of Cultural Factors on Road Safety Tags Coverage across US counties. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Cultural Factors	Margin of Votes	`maxspeed=*`	0.017***	-0.096**
		`lanes=*`	0.031***	-0.042*
		`surface=*`	0.012*	-0.024
	Ethnic Diversity Index	`maxspeed=*`	0.060***	-0.024
		`lanes=*`	0.118***	-0.017
		`surface=*`	0.033	0.057

results show statistically significant negative indirect effects for `maxspeed=*` and `lanes=*` coverage. For instance, if a county's neighbors exhibited a 10% higher Democratic preference, our model predicts a 0.96% decrease in `maxspeed=*` coverage and a 0.42% decrease in `lanes=*` coverage within the county itself. Although these effect sizes may appear modest, the margin of votes can shift significantly across election cycles, amplifying the practical implications of our findings. For example, in the 2024 U.S. Presidential Election, many counties experienced substantial changes in vote margins compared to 2020 [22]. For instance, during the 2024 U.S. presidential election, Starr County, Texas — a historically Democratic stronghold — flipped Republican for the first time since 1892 [20], with a swing in vote margin of approximately 8%. In Wisconsin, Michigan, and Pennsylvania, shifts exceeding 10% were not uncommon, driven by changes in voter turnout, demographic shifts, and political mobilization efforts. The standard deviation of vote margines, according to Table 4, is 32%, indicating that a 10% difference between counties is very normal in our data. These substantial differences in vote margins suggest that even seemingly small direct effects could translate into meaningful differences in tag coverage when scaled across regions or aggregated over time.

For our ethnic diversity index, our Spatial Durbin Model (SDM) results suggest a positive and significant relationship between the ethnic diversity index and the coverage of `maxspeed=*` and `lanes=*` tags. Specifically, in a comparison of two otherwise identical counties, our model predicts that a county with a 10% higher demographic diversity score will have approximately a 0.6% increase in `maxspeed=*` tag coverage and a 1.18% increase in `lanes=*` tag coverage.

Overall, while our findings reveal important nuances in the influence of cultural factors, one major takeaway stands out: a localized understanding of cultural dynamics and their impact on tag production is likely critical for systems like OpenStreetMap. Further investigation into how local conditions, community engagement, and other contextual factors shape road safety metadata contributions represents a valuable direction for future research. We explore these implications further in Section 5.3.

4.2.3 *Socioeconomic Influences: Divergent Effects on OpenStreetMap Tag Coverage.*

Finally, turning to our socioeconomic variables, we find results that are somewhat surprising and partially diverge from prior work. For the unemployment rate, the results indicate a statistically significant but modest effect on `maxspeed=*` tag coverage, with no significant relationship for `lanes=*` and `surface=*` tags. Specifically, our SDM model predicts that for two otherwise identical counties, where one has a 1% higher unemployment rate, the `maxspeed=*` tag coverage would decrease by 0.442%. At the time of writing this report (2023), the average U.S. unemployment rate was 4%, with state-level rates ranging from 2.0% to 5.2%. A 1% increase in unemployment represents a significant economic shift, often associated with substantial disruptions such as recessions or large-scale crises like the COVID-19 pandemic. Changes in unemployment are generally much smaller, as illustrated by the 0.2% average monthly change

Table 5. The Direct and Indirect Effects of Socioeconomic Factors on Road Safety Tags Coverage across US counties. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Socioeconomic Factors	Unemployment Rate	`maxspeed=*`	-0.442*	-1.101
		`lanes=*`	-0.168	0.584
		`surface=*`	-0.344	-1.737
	Educational Attainment Index	`maxspeed=*`	0.144***	0.120
		`lanes=*`	0.109***	0.155**
		`surface=*`	0.140***	0.330**

recorded between January and February 2024 [99]. Despite the substantial socioeconomic implications of such changes, their predicted impact on road safety tag production remains modest as shown in our models.

Shifting our focus to the educational attainment index, the results of the SDM show a consistently positive, albeit negligible relationship between the educational attainment of a county and the coverage of all three tags (`maxspeed=*`, `lanes=*`, and `surface=*`). Specifically, our model predicts that for two otherwise identical counties, a county with a 1% higher rate of educational attainment would see a 0.144% percentage point increase in `maxspeed=*` tag coverage, a 0.109% increase in `lanes=*` coverage, and a 0.140% increase in `surface=*` coverage. While these effects are statistically significant, the effect size is small, highlighting the marginal practical impact of educational attainment on OpenStreetMap contributions.

In addition to local effects, the educational attainment of neighboring counties also has a statistically significant impact on tag coverage, particularly for `lanes=*` and `surface=*` tags. For instance, A 1% increase in educational attainment in neighboring counties is associated with a 0.155% increase in `lanes=*` tag coverage and a 0.33% increase in `surface=*` tag coverage within the county itself. This suggests that both local and neighboring educational levels have some predictive weight, though with marginal impact on the richness of OpenStreetMap tagging. Notably, in the United States, national educational attainment over the past ten years (2011-2021) has seen a 7.5% increase, from 30.4% to 37.9%. A 1% shift in educational attainment is credible, but as noted, the influence of such a shift on road safety tag production in OpenStreetMap would be small.

Overall, our SDM model results broadly show either no significant effects, in the case of unemployment, or the effect sizes are nearly zero in the case of educational attainment. These results complicate and contrast with prior work [14, 25, 69], which tends to show that economically advantaged regions have more, and higher quality, content in peer production settings.

5 DISCUSSION

Taken holistically, our results present an important set of findings for geographic HCI and studies of peer production more broadly. Some results are highly intuitive: `% Safety Metadata Automation` increases coverage for those specific tags. However, other findings may be cause for concern: generalized automated imports (referring to `% Other Metadata Automation`) may contribute to undercutting human effort in the production of tag metadata, which could be detrimental in domains such as road safety. Additionally, some of our results challenge or complicate previously established biases in peer-produced data. In our analysis of the three road safety tags, we do not observe the pro-urban or pro-wealthy patterns of content production that might have been anticipated based on prior work. Instead, we find few significant patterns specifically for these variables, and when trends do appear, the effect sizes tend to be negligible, except in a few cases. Finally, our results do find significant and sizeable relationships between road safety tag coverage and indicators of regional culture, such as the political climate or the degree of ethnic diversity in the county. We discuss these findings in more detail now and develop two implications for what these results mean for OpenStreetMap and the CSCW research community.

5.1 Reflection on the Values of Automated Imports

Automated imports are an important dimension of data production in OpenStreetMap, which is often done by bots or other software agents. These imports are intended to allow governments and other organizations with large spatial datasets to quickly share this data with OpenStreetMap under the relevant licenses [17, 30, 31, 40, 114]. However, these imports have been somewhat controversial due to their deviation from the nature of 'collective intelligence' inherent in voluntary contributions, as well as issues with problematic imports [32, 113], though they may provide some benefits [72].

Our work here adds nuance to and extends prior work on the impact of data imports [32, 74, 92, 110, 113]. Specifically, our results rely on two metrics: `% Safety Metadata Automation` and `% Other Metadata Automation`. First, we found that, broadly, counties with a larger `% Other Metadata Automation` value — indicating higher proportions of automated imports overall — tend to have lower coverage of `maxspeed=*`, `lanes=*`, and `surface=*` tags edited by humans. This effect can even negatively impact neighboring counties in some cases. This result suggests that while using automated imports may be a useful tool to enhance overall metadata coverage in OpenStreetMap, it may undermine the human production of important safety metadata. However, surprisingly, when we focus on our road safety specific tags with our `% Safety Metadata Automation` variable, we find that counties with higher proportions of roads featuring safety tag automation tend to exhibit greater coverage of safety metadata edited by humans overall, and in some cases, this influences coverage in neighboring counties as well.

Taken holistically, understanding the benefits and consequences of these kinds of imports may benefit from analyses like those we present here. Knowing the consequences to OpenStreetMap's contributor community when imported data occurs can help governments and the editor community of OpenStreetMap make more targeted and contextualized decisions about which data to import, how, and what value or cost that might bring to OpenStreetMap. In particular, we see three key takeaways from our work here.

5.1.1 *Semantic Meaning Ought Not To Take a Back Seat to Geometric Completeness.*

While automated data imports can provide valuable baseline information, they also present significant challenges, particularly in terms of data quality and community development [32, 74, 110]. Our study builds on this discussion by focusing on metadata production, specifically safety-related tags in OpenStreetMap. We found that open-ended automated metadata production is negatively correlated with the human contribution to safety-specific metadata, potentially overshadowing or creating barriers for local contributors who might otherwise verify, update, and enhance the foundational infrastructure with nuanced information.

Similar negative effects of automation have been observed in other collaborative communities, such as Wikipedia [47] and GitHub [100]. For example, Lsjbot — one of the most productive bots on Wikipedia –generated a vast number of articles, enabling the relatively small Swedish Wikipedia community to become one of the largest language editions [35]. However, these articles were often only initial stubs, requiring substantial expansion by human editors [47].

Likewise, prior studies have suggested that it may be easier to attract new contributors to areas with no existing data, as opposed to regions where high-level infrastructure has been established through automation [12].

Overall, while data imports can provide valuable baseline information, we pose they should not overshadow or create barriers for contributors who verify, update, and add new information. Additionally, automated imports present challenges in filling gaps in specific tag coverage. We find that generalized automated metadata production seems to be at odds with specific road safety metadata production. This may be because government data sources lack the relevant metadata needed for OpenStreetMap, and the goals of governmental organizations may diverge from those of the OpenStreetMap community or local communities. Therefore, it is crucial to implement targeted interventions to fill gaps in specific tag coverage — such as speed limits, lanes, or surface — when this metadata is affected by automated imports. Moreover, recent research has focused on the role of corporate contributors [5, 88], who may behave similarly to automated imports and cause similar consequences. Exploring this further is an important direction for future work.

5.1.2 Assessing the Accuracy and Quality of Tagging in Specific Regions.

Our results indicate that the import of safety tags is positively correlated with human edits on these tags, suggesting that more targeted automated tag production may promote human follow-up effort and intertwining with human edits. While such automated imports can serve as an effective intervention for establishing a baseline in mapping, they also carry risks associated with low-quality and inaccurate tagging [32, 113]. For instance, Berkel and Pohl [12] found regional differences in metadata production practices among OpenStreetMap contributors. Moreover, automated edits can exacerbate these challenges by often failing to account for the nuances of local tagging practices and community norms. Unlike human contributors, who can draw on contextual knowledge and adapt to regional standards [64, 94], automated imports apply uniform rules that may not align with localized tagging conventions. This issue is further amplified by the ability of automated edits to extend seamlessly across geographical borders, leading to inconsistencies and potentially overriding established community standards.

Such conflicts can undermine trust in the data and create significant challenges for collaborative mapping efforts, particularly in regions with highly specific or diverging tagging practices. The consequences of these inaccuracies can be especially harmful if such erroneous tags are incorporated into downstream algorithms and tools. For example, inaccuracies in safety-related tags such as speed limits, lanes, and road surface information could directly impact navigation systems or infrastructure planning.

Therefore, our findings highlight the need for regular verification of the accuracy of automated imported tags, particularly in high-stakes safety contexts. Unlike Wikipedia, where bot edits can be relatively easily reverted or controlled, OpenStreetMap’s highly interconnected data structure makes quality assurance more complex. Errors in one element can cascade and affect other interconnected map features, amplifying their impact. Developing tools to facilitate and support maintenance efforts within OpenStreetMap represents a promising direction. Systems like OpenStreetMap could benefit from just-in-time confirmation mechanisms for critical metadata. For instance, existing functionalities in platforms like Apple Maps and Google Maps allow users to quickly verify whether an accident is still blocking traffic. Similarly, OpenStreetMap could explore mechanisms to prompt drivers or users to confirm whether speed limit data has changed or if construction is occurring. Ensuring the accuracy and reliability of this metadata is a crucial step in maintaining the integrity of mapping data and safeguarding the users who rely on it. Inspiration can also be drawn from Halfaker and Geiger [39]’s work on ‘ORES’, an algorithmic scoring service designed to incorporate input and facilitate discussion among a broad set of community members. Such systems could empower OpenStreetMap contributors to collaboratively assess and maintain the quality of automated edits, ensuring that automation enhances rather than undermines the mapping process.

5.2 Challenges and Opportunities for Equitable Mapping

Taken holistically, our results highlight the complex socio-political and demographic dynamics that shape tag production in OpenStreetMap. Rather than being primarily driven by economic conditions or population density, tag production exhibits stronger associations with political orientation, ethnic diversity, and educational attainment. These findings reinforce the notion that peer production in OSM is not merely a reflection of geographic need or infrastructural development but the matatdata production also shaped by social, political, and cultural structures.

Specifically, our findings indicate that the political orientation of a county serves as a predictive factor for tag production, indicating that metadata mapping activity may be influenced by ideological or community-driven motivations. This pattern aligns with the broader notion that contributors to OpenStreetMap are more likely to come from certain political or demographic backgrounds, leading to self-focus bias in mapping efforts [94]. Moreover, this supports the idea that local mapping initiatives often function as forms of advocacy, with contributors prioritizing the mapping of features that reflect their interests, values, or concerns [46]. Consequently, certain regions may receive disproportionate metadata enrichment, not necessarily due to objective infrastructure gaps but rather as a result of who is contributing and what they choose to map.

Our results also indicate that counties with greater ethnic diversity tend to exhibit more extensive tag production. This pattern may be driven by higher levels of civic engagement in diverse communities, where residents actively participate in collective efforts to enhance public resources, including digital mapping platforms [84]. Moreover, rather than mapping being solely dictated by infrastructural needs, community-driven efforts may prioritize documenting culturally significant landmarks, shared spaces, and local infrastructure that reflect the lived experiences of diverse populations [83]. In this context, metadata production may extend beyond geographic documentation to become a mechanism for representing communities, asserting spatial presence, and fostering digital inclusion.

Furthermore, our results suggest that areas with higher educational attainment tend to have more complete safety tag coverage, reinforcing the idea that metadata enrichment requires a different skill set than geometric mapping. While mapping geometry focuses on capturing the physical world, metadata tagging involves interpretation, classification, and contextual understanding, making it a more cognitively demanding task. Unlike road tracing, which has clear visual references, tagging metadata often requires contributors to make subjective judgments, particularly in the absence of strict validation mechanisms. This aligns with observations that expert mappers and professional cartographers tend to engage more deeply in semantic enrichment, while less experienced contributors focus on more straightforward mapping tasks [7]. The cognitive complexity of metadata annotation may explain why regions with higher educational levels exhibit more complete metadata coverage, as contributors in these areas may be better equipped or more motivated to engage in these higher-order tasks.

Given the complexity of metadata annotation, our findings suggest that targeted interventions are necessary to improve metadata completeness, particularly in regions with lower levels of education and lower engagement in peer production efforts. While platforms like OpenStreetMap have successfully enabled large-scale mapping efforts, metadata tagging remains a specialized task that requires contextual knowledge and classification skills, creating barriers for new or less-experienced contributors. One possible intervention is the adaptation of microtasking platforms to facilitate metadata annotation. Tools like microtasking platforms, such as the Tasking Manager used in OpenStreetMap's humanitarian mapping activities, could play a pivotal role in addressing this challenge [111]. By breaking down mapping tasks into smaller, region-specific components, these tools have been shown to effectively distribute mapping expertise, strengthen contributions, and ensure a more equitable mapping process across diverse regions. Another approach involves leveraging localized and thematic mapping campaigns to engage contributors based on their interests and lived experiences. Prior research has shown that participatory mapping is often shaped by civic engagement and advocacy goals [85, 90], which suggests that initiatives focusing on issues such as safety, accessibility, or environmental sustainability could encourage more inclusive metadata contributions. Thematic mapping campaigns designed in collaboration with local communities could foster participation from groups that might otherwise be underrepresented in OSM metadata production, ensuring that metadata reflects a broader range of perspectives rather than being shaped by a limited subset of contributors.

5.3 Beyond "Geo" HCI: Advancing Towards a Cultural Understanding of Spatial Trends

The GeoHCI literature [38, 49, 62, 66, 96, 112, 115] has generally shown that OpenStreetMap, along with other peer production systems, tends to be more accurate and complete in regions that are densely populated and socioeconomically advantaged. Our research both (a) broadly does not show these same patterns, and (b) points to additional patterns of disparity in the production of metadata tags in OpenStreetMap, particularly along cultural dimensions such as demographic diversity, and regional political orientation. Our Spatial Durbin Model (SDM) results do not identify statistically significant trends or benefits in tag production along these dimensions, a finding that diverges from more common themes in the geoHCI literature [38, 49, 62, 66, 96, 115]. Moreover, and importantly, because of how our statistical models are constructed, the trends we show here are *independent of* factors such as population density, local economic status, or the extent of urbanization in a county.

Our work complicates prior findings in CSCW and GeoHCI by revealing disparities in OpenStreetMap (OSM) contributions that align with the geographies of cultural dimensions, rather than more commonly studied factors such as population density or the urban-rural divide. Put simply, our findings suggest that cultural dynamics likely play a significant role in shaping the types of tags contributed to OpenStreetMap. Most importantly, these trends persist despite traditional dimensions like population density, not because of them. In other words, cultural dimensions independently predict variations in tag coverage, underscoring their critical influence on safety tag production.

Fully disentangling factors such as educational attainment, political orientation, and demographic diversity can be challenging, but represents a promising avenue for future research. Often, the underlying causal dynamics of these trends are deeply rooted in specific historical contexts and power structures [51, 58, 98]. For instance, Gröchenig et al. [33] found that tagging heavily depends on various influences, including geographical or legal borders, automated imports, unexpected events, and diverse community developments. Quattrone et al. [86] found strong correlations between users' participation characteristics and national cultural factors, such as power distance, individualism, pace of life, and self-expression, as well as Gross Domestic Product (GDP) per capita. We see this trend as warranting substantially more research to fully characterize this phenomenon. What cultural dynamics are at play in OpenStreetMap contributions? Whose culture and knowledge are valued? Some organizations in the peer production space are considering these ideas [54], but we suggest that the geoHCI research community might move beyond focusing on demographic trends, and might look to unpack terms like "localness"[94] and "more rich content"[49]. It may be fruitful to interrogate the underlying community and cultural dimensions that underpin volunteered geographic information more broadly. In our case, our results suggest that places with a higher margin of Democratic voters are more likely to have better coverage of important road safety metadata. Fully understanding the dimensions of these trends, and how they affect which types of content, is likely a critical direction for future work.

6 CONCLUSION

Through advanced spatial regression techniques, this paper addresses the need for a deeper understanding of tag production within OpenStreetMap using advanced mapping techniques. We found that the coverage of road-safety tags depends on localized cultural, demographic, and socioeconomic patterns, but does not exhibit common disparities along population density or urban-rural lines. Moreover, we found evidence that data imports can cause negative consequences for tag production in OpenStreetMap. Based on these findings, we develop recommendations for both practitioners and researchers, with an eye towards better supporting rich metadata production in OpenStreetMap. Our work highlights the importance of considering cultural and socioeconomic factors, and recognizing the influence of data imports in enhancing the coverage and depth of tags within OpenStreetMap.

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Table 6. Variance Inflation Factor (VIF) Scores Across Three Models. This table presents the VIF scores for the variables used in three models: `maxspeed=*`, `lanes=*`, and `surface=*`. Scores below 2 indicate low multicollinearity, supporting the validity of the regression analyses.

Variable	**maxspeed=***	**lanes=***	**surface=***
% Safety Metadata Automation	1.09	1.23	1.30
% Other Metadata Automation	1.11	1.27	1.30
Population Density ($\log_2$)	1.10	1.13	1.12
Rural-Urban Classification	1.43	1.43	1.44
Margin of Votes	2.17	2.17	2.20
Ethnic Diversity Index	1.45	1.39	1.41
Educational Attainment Index	1.94	1.94	1.95
Unemployment Rate	1.34	1.36	1.38

Table 7. The Direct and Indirect Effects on Road Safety Tags Coverage across US counties after removing outliers. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Automated Imports	% Safety Metadata Automation	`maxspeed=*`	0.523***	0.462*
		`lanes=*`	0.429***	-0.058
		`surface=*`	0.477***	-0.069*
	% Other Metadata Automation	`maxspeed=*`	-0.150***	-0.145**
		`lanes=*`	-0.161***	0.047
		`surface=*`	-0.404***	-0.284*
Human Geography	Population Density	`maxspeed=*`	-0.001*	-0.000
		`lanes=*`	-0.000	-0.000
		`surface=*`	-0.000*	-0.004
	Rural-Urban Classification	`maxspeed=*`	-0.002	-0.001
		`lanes=*`	-0.002	-0.002*
		`surface=*`	0.006*	-0.001
Cultural Factors	Margin of Votes	`maxspeed=*`	0.017**	-0.091*
		`lanes=*`	0.030**	-0.029*
		`surface=*`	0.010*	0.018
	Ethnic Diversity Index	`maxspeed=*`	0.064***	-0.026*
		`lanes=*`	0.113***	-0.033**
		`surface=*`	0.037	0.014
Socioeconomic Factors	Unemployment Rate	`maxspeed=*`	-0.409*	0.155
		`lanes=*`	-0.226	0.307
		`surface=*`	0.435	-1.408
	Educational Attainment Index	`maxspeed=*`	0.153***	-0.155
		`lanes=*`	0.115***	-0.143**
		`surface=*`	0.149***	-0.341**

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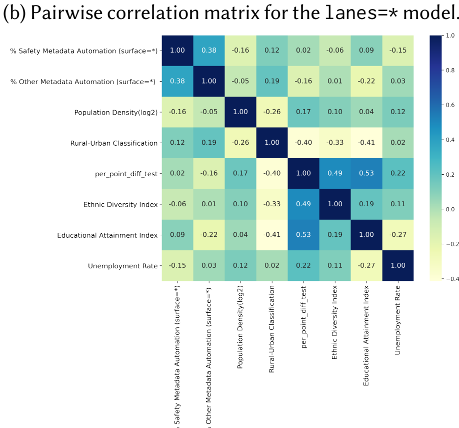
Table 8. Robustness Check: The Direct and Indirect Effects on Road Safety Tags Coverage (Length-Weighted) across US counties. Automated imports are also weighted by length accordingly. *p<0.05, **p<0.01, ***p<0.001

Category	Predictor	Tag	Direct Effect	Indirect Effect
Automated Imports	% Safety Metadata Automation	`maxspeed=*`	0.713***	0.069**
		`lanes=*`	0.525***	-0.071
		`surface=*`	0.640***	-0.030
	% Other Metadata Automation	`maxspeed=*`	-0.146***	-0.171*
		`lanes=*`	-0.125***	-0.036
		`surface=*`	-0.070***	-0.063*
Human Geography	Population Density	`maxspeed=*`	-0.000*	-0.002*
		`lanes=*`	0.000	-0.000*
		`surface=*`	-0.00	-0.003
	Rural-Urban Classification	`maxspeed=*`	0.000	-0.001
		`lanes=*`	0.000	-0.001*
		`surface=*`	0.001*	0.003
Cultural Factors	Margin of Votes	`maxspeed=*`	0.011**	0.002
		`lanes=*`	0.037**	0.020
		`surface=*`	0.020*	0.010
	Ethnic Diversity Index	`maxspeed=*`	0.058**	-0.018
		`lanes=*`	0.093*	-0.023
		`surface=*`	0.042*	0.010
Socioeconomic Factors	Unemployment Rate	`maxspeed=*`	-0.359*	-0.195
		`lanes=*`	0.232	0.236
		`surface=*`	0.235	0.266
	Educational Attainment Index	`maxspeed=*`	0.119***	-0.120
		`lanes=*`	0.012***	0.107
		`surface=*`	0.109***	0.105**

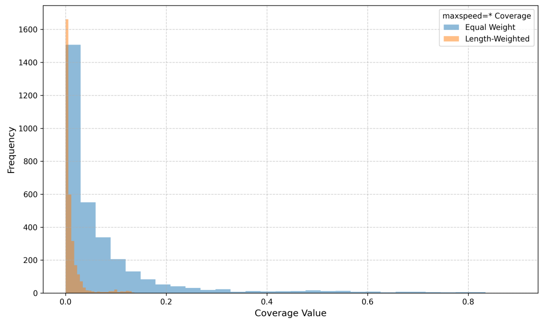
(a) Pairwise correlation matrix for the maxspeed=* model.

(b) Pairwise correlation matrix for the lanes=* model.

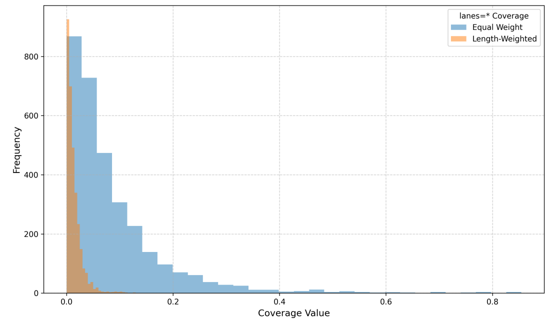


(c) Pairwise correlation matrix for the surface=* model.

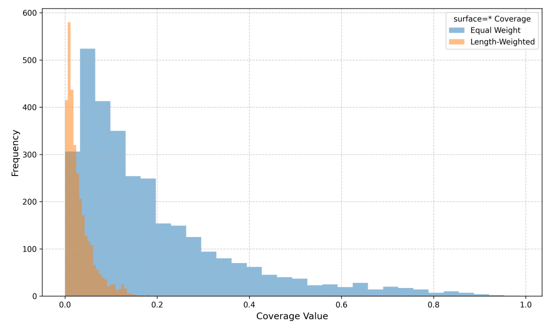
Fig. 4. Pairwise correlation matrices for maxspeed=*, lanes=*, and surface=* models. These matrices visualize the relationships between key variables, aiding in identifying patterns and potential multicollinearity.



(a) maxspeed=* Coverage



(b) lanes=* Coverage



(c) surface=* Coverage

Fig. 5. Robustness Check: Distribution of Road Attribute Coverage in OpenStreetMap Across U.S. Counties (n=3143). The figures compare the distributions of coverage for three key road attributes: speed limits (maxspeed=*), lane counts (lanes=*), and surface types (surface=*). Each distribution is presented under both the original and length-weighted metrics to assess the impact of weighting methods on tag coverage.