AGILE: GIScience Series, 7, 19, 2026. https://doi.org/10.5194/agile-giss-7-19-2026
Proceedings of the 29th AGILE Conference on Geographic Information Science, 16–19 June 2026.
Eds.: Evelyn Uuemaa, Alexander Kmoch, Holger Virro, and Simon Scheider
This contribution underwent peer review based on a full paper submission.

From Missingness to Motivation: A "Living Dataset" Perspective on Volunteering Geographic Information

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Abstract. OpenStreetMap (OSM) is the most popular, and arguably most successful, volunteered geographic information (VGI) project. The scale of OSM's goal of mapping the world through individual contributions necessitates a long development time, while the ever-changing nature of the real landscape precludes the possibility of ever "completing" the map. Thus, OSM is a living dataset. With this perspective in mind, we reexamine the motivations for contributing to OSM and the outputs of those motivations. Whereas a pathway from motivation to mapping may explain any individual contributor's experience, we argue the whole OSM project represents a more complex system in which biased and missing data can be both a driver and a consequence of the VGI model of collaboration. We also reflect on the ways in which the exogenous shock of the proliferation of generative and geoAI may disrupt this system.

Submission Type Short Paper

Contribution Type Theory

BoK Concepts [GS] GI and Society, [OI] Organizational and Institutional Aspects, [WB] Web-based GI,

Keywords Volunteered Geographic Information (VGI), OpenStreetMap (OSM), Motivations, Missing Data

1 Introduction

Volunteered Geographic Information (VGI; Goodchild, 2007) is a widely-recognised example of technology's capacity to democratise knowledge. Through open access to large geospatial datasets and the tools required to construct them, VGI enables numerous downstream applications of spatial data. Since its inception in the early 2000s, OpenStreetMap has emerged as the largest-scale dataset of intentional VGI, engaging over ten million volunteer contributors (OpenStreetMap, 2026).

Yet the principle of democratisation is implicitly limited by technical and motivational barriers to participation. Uneven composition of "the crowd" has important implications for the spatial balance and representativeness of the resulting data (Shin et al., 2025; Sutton et al., 2023). Understanding the causes and consequences of the OSM model of collaboration is important to contextualise the dataset and its properties for its downstream applications which range widely from humanitarian aid (Herfort et al., 2021) to the development of specialist orienteering maps. It also provides insights for organisations seeking to replicate the VGI model in other collaborative settings.

Prior work has focused on the motivations of OSM contributors and issues of data quality as independent issues. Yet OSM is a live and complex system of collaboration, with contributors joining the project at different stages in the development of the social internet, the OSM project, and indeed the real world that it is trying to map. As such, a singular causal pathway from motivated contributors to a volunteered geographic dataset may overlook important differences in context, as well as possible systems of feedback. In this paper, we consider the interaction between motivations and data quality, and the effects of that interaction on a critical property of VGI, namely that which is *not* mapped.

Box 1. The Core Values of OSMF (OpenStreetMap Foundation, 2023).

The Best Map: We want to make the best map data set of the world

Free and Open: Our data is available under a Free and Open licence to everyone

Community: OSM is powered by its community. Engage positively, be a good and respectful neighbour and assume good intent.

Useful: We want OSM data to be used as widely as possible.

Ground Truth: OSM favours objective personal knowledge and "Ground Truth" over all other sources

Self motivated: OSM wants you to map the things you care about and will ensure that you have the freedom to do so.

2 Motivations for Volunteering Geographic Information

Motivation to volunteer is a complex phenomenon, and the subject of a literature broader than VGI. Strict rational actor models of behaviour, struggle to explain volunteering behaviour except through the narrow possibility that volunteering advances one's career prospects. Accordingly, explanations of volunteering behaviour tend to emphasise altruism (e.g. Bussell & Forbes, 2002) or forms of non-economic self-interest (e.g. Hackl et al., 2007). Stukas et al. (2016) combine the two, arguing some volunteers are altruistic "other-oriented" while others take their motivation from self-interest or extrinsic sources (such as community service programmes).

Drawing on this literature, Budhathoki and Haythornthwaite (2013) contribute the foremost investigation of the motivations behind volunteering VGI. In a survey of over 400 OSM contributors, they identify six categories of motivation by factor analysis. Belief in project goals ranks highest, while personal promotion and monetary reward rank lowest. Generally, these results (see Table 1) support a view of OSM contribution as an altruistic volunteer activity.

Table 2. Factors motivating OSM volunteers. Data from Budhathoki & Haythornthwaite (2013)

Motivation	Importance to OSM Contributors (Mean response on 1-7 Likert Scale)
Belief in project goals	6.14
Altruism	5.73
Self-efficacy regarding local knowledge	5.58
Learning	5.29
Personal Need	5.2
Personal Promotion	4.04
Monetary Reward	2.14

The salience of "self-efficacy" is also noteworthy: contributors may be particularly motivated to volunteer geographic information that they feel uniquely qualified to provide, either through local knowledge or cartographic skill. This aligns with evidence that donating labour generates greater satisfaction than equivalent financial contributions (Brown et al., 2019). Thus, part of OSM's appeal may be enjoyment of the work itself (Budhathoki et al., 2010), indeed Budhathoki & Haythornthwaite (2013) consider that OSM contribution might be well-modelled as a leisure activity as well as a voluntary one. This contrasts with more recent work on corporate contributors, who tend to contribute either to improve the parts of the map they use or to align the map with their needs (Ochoa-Ortiz & Re, 2025).

It is important to note that there may be an element of social desirability bias in the self-reported motivations of both individual and corporate contributors. Clary & Snyder (1999) also note that volunteering can have a protective function, in which volunteering behaviour is used as an offset against other "negative" activities, including those which are driven by self-interest. Thus, for some, admitting in a survey to a self-promotion or financial motivation is itself in tension with the protective motivation for volunteering. Nonetheless, the ordering of factors motivating OSM contributors is generally similar to volunteering behaviour in general (Clary et al., 1996), with altruistic factors outweighing social and personal considerations.

OSM contribution should also be considered as a process (Fritz et al., 2017), from deciding to volunteer and discovering OSM, to registering for an account, learning to make edits, and sustaining participation. The motivations, and indeed demotivations, of contributors may vary throughout this process. For instance, self-efficacy triggered by noticing an error may prompt a first edit, whereas sustained contribution may depend on a sense of community membership and commitment to broader OSM ideals. Some factors may motivate or demotivate depending on stage; for example, community norms and language (or "folksonomy"; Mocnik et al., 2017) may deter newcomers but motivate established contributors. Indeed, a central contribution of Budhathoki & Haythornthwaite's survey (2013) is to consider differences in motivation between "serious" and "casual" mappers. Thus, the system is too complex to be represented by a singular relationship between some set of commonly-held motivations and a series of types of contribution.

3. Quality and Missingness in VGI

The VGI model of mapmaking offers significant benefits over corporate, academic, or public-sector alternatives in terms of cost, scalability, and community-building. However, critics have pointed to data quality as a concern, with the open-source editing model permitting equal editing rights to contributors who are (or are perceived to be) anonymous or inexpert (Flanagin & Metzger, 2008).

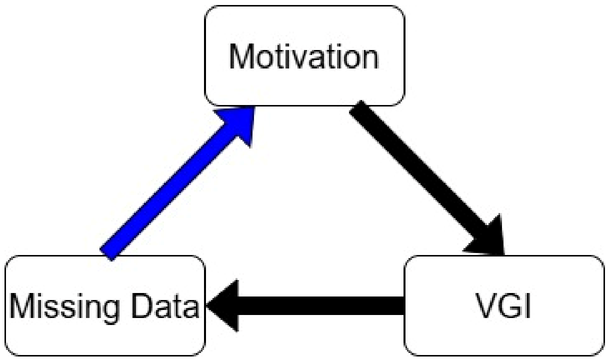
Early empirical analysis of OSM demonstrated mixed levels of agreement between its features and those depicted on authoritative datasets (Girres & Touya, 2010; Haklay, 2010). However, fifteen years on, there has been plentiful opportunity for early errors to be corrected and the map to converge towards ground truth. Indeed, more recent assessments do suggest increasing levels of accuracy, but also highlight significant regional heterogeneity (Barrington-Leigh & Millard-Ball, 2017; Biljecki et al., 2023; Borkowska & Pokonieczny, 2022). Where such heterogeneity is correlated with levels of economic deprivation, OSM contributes to harmful inequalities in the availability of data (Atkinson & Brandolini, 2001; Galimberti et al., 2023; Scott & Rajabifard, 2017). Evidence suggests this correlation exists within (Borkowska & Pokonieczny, 2022; Mullen et al., 2015) and across (Graham & Zook, 2011; Huck et al., 2021; Sutton et al., 2023) countries: mapping is most available in Europe and North America and lower in the Global South.

Concern around quality has therefore turned particularly towards the question of *completeness* (Basiri et al., 2019). Although features can be mapped incorrectly, critics of OSM's quality have tended instead to focus on where they are not mapped at all. Indeed, one consequence of the VGI model is that we cannot be sure that any given feature will ever be mapped (Hagenauer & Helbich, 2012). These unmapped features can be conceptualised as missing data. Features that are systematically not mapped (missing not at random, MNAR) can represent a more severe threat to downstream analytical and inferential tasks than features that are missing completely at random (MCAR) (Little & Rubin, 2002). In authoritative mapping organisations, human or sensor error might lead to completely random missingness, but procedures to ensure standardisation and coverage across the map extent should mitigate systematic omissions. In the VGI context, however, omissions depend on what volunteers choose to add (and thus what not to add) in each of their changesets.

4. The Interaction Between Motivations and Missingness

Critically, VGI typically allows volunteers to choose which information they contribute. For this reason, a volunteer's contribution style can be driven by their particular motivations. The most basic example is contribution volume. A motivated and capable volunteer will be more likely to contribute (or contribute more) data than one who is unmotivated or lacks capacity (due to e.g. technical skills, internet access etc.; Michie et al., 2011). Because use of one's local knowledge is a common motivation (Budhathoki & Haythornthwaite, 2013), and the majority of motivated and capable volunteers live in Europe or North America, an intrinsic property of any given feature – its location – is correlated with the probability that it will be missing from the map. Thus, the data is MNAR. Beyond locality, the demographics of OSM contributors are also highly nonrepresentative of the general population (Sutton et al., 2023), and thus biases in what is not mapped may originate from the preferences and knowledge of a disproportionately male, highly educated contributor base.

Figure 1: We argue Missing Data is not only consequence of VGI motivations (black arrows, existing literature), but also a cause (blue arrow).



Prior work on the motivations and biases of OSM contributors has tended to identify this causal pathway from motivations to the output of the map (moderated by contribution style) (e.g. Budhathoki & Haythornthwaite, 2013; Coleman et al., 2009; Sutton et al., 2023). However, owing to its scale, OSM is necessarily a live collaboration and thus most volunteers discover the project middevelopment, encountering a partial map. Thus, the outputs of earlier VGI can be a motivational trigger for new contributors.

An obvious example is the case of user noticing an error on the map near their home and registering an account to correct it. Instrumentality of local knowledge is a known common motivator (Budhathoki & Haythornthwaite, 2013). In this case, even though the decision of what to map was not-at-random, the effect at the system-level is one of self-correction to the spatial distribution of both map missingness and the contributor base. However, this mechanism exists in parallel with other motivating and enabling factors, such as access to the technology required to map, expertise in GIS, and sufficient free time to contribute. Each of these may bias recruitment towards users concentrated in similar areas, such that local knowledge is only corrective of MNAR biases at the local scale and reinforces them over larger spatial intervals. Demonstrating a similar dynamic under a very different motivational trigger, Kamptner & Kessler (2019) find that building fires increase edit counts rapidly. Locally, this represents useful correction, but at scale, crisis-driven correction exacerbates spatial biases because events in urbanised and Western areas are more likely to be reported to existing contributors. More structured efforts to leverage missingness as a motivation exist in the form of “mapping parties” (Fritz et al., 2017) and the Humanitarian OSM initiative (Herfort et al., 2021), both of which incentivise edits in areas far from contributors’ home regions, helping to redress biases without substantially changing contributor geography.

In this context, it is worth revisiting the most motivational factors items from Budhathoki & Haythornthwaite's (2013) survey. Of the six highest-rated items, only two hint at an understanding of the importance of redressing heterogeneity in missingness on the map. Three point to factors that are independent of coverage. The remaining motivator, on local knowledge, is likely to exacerbate existing MNAR biases in missingness insofar as most existing contributors already live in well-mapped areas. However, this also represents an opportunity: concerted efforts to recruit new contributors with local knowledge of undermapped areas could leverage this powerful motivator to instead reduce the bias of the map.

The age of Budhathoki & Haythornthwaite's (2013) survey also merits consideration. At the time of the survey, OSM was a little under ten years old, with important elements of its community, like the “state of the map” conference, dating from the late 2000s. Now into its third decade, the map itself is significantly more developed, and thus motivations for contributing may differ. In particular, instrumentality of local knowledge is a less powerful motivator if one’s local area is already very well-mapped, so new contributors in well-mapped developed nations may be joining with intentions to map more globally.

Table 2: The association between motivations and existing biases in OSM coverage. Items in italics are the highest-rated motivations, others are selected motivations with particular influences on missingness.

Motivations tending to mitigate MNAR biases	Motivations stemming from existing MNAR biases	Motivations unrelated to map completeness
OSM will not succeed in developing a world map without the community. (6.16)	I contribute to OSM because I can provide accurate information from my local knowledge. (6.01)	Digital map data should be available for free. (6.45)
It is important to help others by providing digital maps that are available for free. (6.13)	When I see errors on the map for the area in which I live, I correct them. (5.94)	I find maps fascinating (6.05)
I contribute to OSM because the map data I am looking for does not exist elsewhere. (4.88)	I contribute to OSM because I have the freedom to select the areas to map. (5.50)	I enjoy contributing to OSM (6.0)
Contributing to OSM helps to develop a new perspective about the geography of the world. (4.80)		
Contributing to OSM allows me to highlight social issues (these can be environmental, political or other social issues) that are important to me. (4.18)		

Indeed, completeness – while itself a goal of OSM – can also act as a demotivator. The 2008 mass-import of US roads from the “TIGER/Line” dataset illustrates this. The import was criticised on grounds of quality and also concern that removing the “low-hanging fruit” might deprive first-time contributors of a gateway to future editing (Zielstra et al., 2013).

5. VGI and AI

As a “living dataset”, OSM is sensitive to the ever-changing environment of the social internet. The tools and context for contributing VGI change in parallel with the contributing careers of individuals, such that the motivators for new contributors in 2026 may be rather different to those that for those who joined in 2004.

The proliferation of generative AI, and perhaps just as importantly the narratives relating to generative AI in the public consciousness (Gilardi et al., 2024), are creating a novel social information environment (Zhou et al., 2023). See et al. (2025) note that this innovation will surely change the dynamics of VGI. Generative AI has the potential to influence both the motivation and missingness aspects described above.

Narratives around AI may produce new motivations for VGI. Narratives connecting AI to misinformation may produce a demand for more human-verified information, which may drive contributing behaviour by individuals whose output is perceived to be more accurate or authentic by users. Similarly, if other parts of the social internet, such as message boards, become (or are perceived to have become) overrun with "AI slop", then there may be a desire to return to collaborative web 2.0 spaces, particularly those in which content production is non-textual like OSM where such content is harder to conceptualise. Geodata has a particular allure as something "grounded" which could, in principle, be verified first-hand by visiting the location to which it is attributed. On the other hand, the power of geoAI models to readily produce spatial insights might render some of OSM's functionality obsolete, reducing the motivation for volunteers to contribute. Further, to the extent that there are ways in which AI-generated content can be submitted to OSM, the scalability of the technology threatens that such avenues will be pursued to exhaustion. Where the quality of generated data is high, this represents a similar threat to motivation as is created by the import of authoritative datasets. Where it is low, a large volume of corrective editing work is created which may be demoralising.

The outlook for AI tools themselves is mixed. On one hand, AI tools can be used to facilitate better mapping. Centaur VGI (Huck et al., 2021) is an AI system that generates proposed geometries and classifications from satellite imagery over previously unmapped areas, which human contributors can then edit or veto before adding to OSM. Such a system can easily be targeted at particularly underrepresented areas of the map in order to redress missingness biases. Similarly, inferential (rather than generative) AI models might themselves be an appropriate tool for understanding the complex patterns of missingness that exist in VGI datasets (Herfort et al., 2023), and highlighting not only those areas that are most missing, but those which might best redress existing biases if mapped. In this sense, AI tools can contribute to both the targeting and mapping of underrepresented regions.

Conversely, AI trained on the OSM dataset will lead to worse applied GIScience outcomes. Bias-unaware AI models will learn at even rates from information regardless of its spatial sparsity, and so areas of training data that are high in missingness due to historic contributor motivations will be simply overlooked in downstream inference tasks. Whereas heterogenous motivations have created the relatively visible and tractable problem of missingness on the map in the past, the use of OSM data as training data threatens to propagate that known bias into an array of unexpected and unseen biases in geoAI outputs. Detecting and correcting these biases is a significantly harder problem once input data are passed through "black box" models. Where data is present, but quality is low, models will learn correct relationships less readily and may even learn incorrect ones. In principle, GIScience has an opportunity to provide training datasets with global (thus "unselected") coverage. This lies in contrast to the unavoidable selection biases in data introduced by large corpora of natural language data. Yet in practice, VGI data may in fact inadvertently entrench biases of technological availability, with the effectiveness of AI covarying with the same "*digital divide*" (Ragnedda & Muschert, 2013) that drives inequalities in OSM (Sui et al., 2013).

The counterweight to this outcome is to understand the shortcomings of VGI as training data so that models can be explicitly bias-aware when learning from these datasets. A comprehensive understanding of the interaction between motivations and missingness in VGI is a critical part of the context that a geoAI model and those responsible for its training must understand alongside the raw data of, for example, the OSM dataset.

6. Discussion

We have argued that the "living" nature of the OSM dataset complicates its data generating process. Contributions to the map are an outcome of contributor motivations, but these motivations may vary systematically over time in response to myriad contextual factors, including the extent and distribution of missingness on the map. Exogenous shocks, such as the proliferation of generative and geoAI can rapidly change the context of the social internet against which motivations for contribution are developed.

Understanding VGI in the OSM context as a complex system reframes potential interventions to motivate contributors. What motivates longstanding users may enhance existing biases or put off first-time contributors. Effortful attempts to redress regional incompleteness such as mapping parties may work in the short term but are not scalable and do not redress the more fundamental bias in the spatial distribution of contributors themselves. The arrival of generative and geoAI must be understood in this context – the opportunities and threats that it seems to represent will likely have unexpected consequences within the complex ecosystem of OSM contribution.

Future work is planned to provide a more robust empirical test for our argument than can be gleaned from the earlier work of Budhathoki & Haythornthwaite (2013). A study of first-time users of OSM will allow us to establish both their initial motivations and indicators of missingness as a motivation, such as edit density relative to baseline completeness, and temporal clustering of edits following local events.

Data and Software Availability Statement

This paper does not contain directly associated data or software.

Declaration of Generative AI in writing

The authors declare that they have used Generative AI tools in the preparation of this manuscript. Specifically, the AI tools were utilized for a first round of review to identify errors and omissions in the language of the manuscript. This was conducted prior to multiple rounds of human review. Generative AI was not used for generating scientific content, research data, or substantive conclusions. All intellectual and creative work, including the analysis and interpretation of data, is original and has been conducted by the authors without AI assistance.

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