GI_Forum 2018, Issue 2
Page: 275 - 293
Full Paper
Corresponding Author:
shivam.gupta@uni-muenster.de
DOI: 10.1553/giscience2018_02_s275

Connecting Citizens and Housing Companies for Fine-grained Air-Quality Sensing

Shivam Gupta, Auriol Degbelo and Edzer Pebesma
University of Münster, Germany

Abstract

The complex nature of air quality suggests the need for fine-scale air-quality monitoring in cities. With 1 in 8 deaths worldwide being associated with air pollution in 2012, communities have started partnering with academic institutions and with state and federal agencies to assess local air quality and address these concerns. Participatory sensing has recently become one popular method for collecting air-quality information. It offers the prospect of collecting data at finer levels of granularity, but is subject to at least two significant challenges: data gaps (due, e.g., to the lack of calibration, maintenance and replacement of sensors), and citizens' concerns regarding privacy). We argue that including housing companies as stakeholders in participatory sensing frameworks may be beneficial in overcoming these challenges. A survey of housing companies suggests that they are willing to participate in air-quality monitoring for cities. The ideas presented here are pertinent to the design of more robust and privacy-aware participatory sensing frameworks.

Keywords:

air pollution, participatory sensing, privacy, volunteered geographic information, housing companies

1 Introduction

Air pollution has a huge impact on human health. Research has shown associations with a broad range of health issues, including mortality, asthma and low birth weight (Kelly & Fussell, 2015). In 2015, long-term exposure to ambient, fine particulate-matter air pollution (PM2.5) was associated with 4.2 million deaths worldwide, representing 7.6% of total global deaths (Cohen et al., 2017). Rapid urbanisation accompanied by surging air pollution have led to increasing regulatory measures for air pollution monitoring. Nevertheless, such measures have done little to reduce exposure, since the vast majority of the world's population continues to reside in areas with air quality concerns (Brauer et al., 2015).

Air pollution concentration monitoring is usually undertaken by environmental or government authorities using networks of fixed monitoring stations, equipped with sophisticated, specialized, instruments for measuring various kinds of pollutants such as carbon monoxide (CO), nitrogen oxides (NOx), sulphur dioxide (SO2), ozone (O3) and particulate matter (PM). The measurements from these instruments are generally considered reliable because the governing authorities ensure the standard procedures for instrument calibration, data collection and analysis. Usually, regulatory control measures are taken after the analysis of a long time-series of data. However, regulatory air-monitoring systems do not assess variability in air quality at a sufficiently detailed spatial scale (Jerrett et al., 2005), because of the cost and expertise required by expensive air quality monitoring stations.

Geographic information systems (GIS), deterministic models (e.g., AIRMOD, RLINE, SHEDS), and remotely-sensed data have been the bases for most of the air pollution modelling efforts (Özkaynak, Baxter, Dionisio & Burke, 2013). Now, with recent progress in GPS/GIS-enabled devices like mobile phones, low-cost navigation devices and measurement sensors, individual citizens can also contribute to the flow of geospatial data about health-related environmental factors (Fang & Lu, 2012; Lunar, Lizards, Gabrielli & Buses, 2012) by taking part in activities that are broadly referred to as participatory GIS, crowdsourcing or volunteered geographic information (Mooney, Corcoran & Ciepluch, 2013). Various environmental monitoring technologies and communications systems have led to the increased availability of air pollution sensing devices (Jiao et al., 2016). These affordable and easy-to-use technologies can result in the rapid evolution of air pollution monitoring approaches (Fang & Lu, 2012; Jiao et al., 2016). With the help of these technologies for collecting large environmental datasets, participatory sensing has recently become popular because of people's concerns about the negative impacts of environmental factors (Commodore, Wilson, Muhammad, Svendsen & Pearce, 2017).

There is a strong conceptual overlap between the terms 'participatory sensing' and 'volunteered geographic information' (Haklay, Mazumdar & Wardlaw, 2018; Mulalu, 2018). We define participatory sensing (PS) here, after Christin, Reinhardt, Kanhere & Hollick (2011), as people's voluntary use of devices to contribute data for their own benefit and/or that of the community. For environmental monitoring, the data aspect is of particular importance. Our understanding of the complex relationship between air pollution and human health has improved substantially over time, but data gaps and the resultant uncertainties still limit our ability to fully assess the adverse impacts of air pollution. In order to fill this gap, non-professionals and citizen communities have emerged recently to help in the data collection process (Clements et al., 2017). The core of any successful PS approach entails three essential ingredients: technology, data and people. By making use of increasingly high computing powers, high-performance networks, storage and ever-more-sophisticated sensors, PS can help in collecting and analysing environmental data. A typical PS application involves data being collected by volunteers' own devices (mobile phone-enabled / independent sensor), and then forwarded to a central server for processing. The captured data is augmented with metadata such as location, time, identification and context information, for further processing. The data is made available to individuals or communities, depending on their needs.

Scientific research can also benefit from well-prepared crowd-sourced observation campaigns. A high-density sensor network of PS has significant potential for improving the spatial monitoring of environmental variables (Schneider et al., 2017). Thus, with the help of PS, it is now possible to provide a picture of various environmental variables at a fine spatial scale and high resolution (Fang & Lu, 2012). Community participation may also help to build trust and to empower participants and communities, especially when the data is community-managed and owned, giving the community an opportunity to be weighted equally with industry and regulatory bodies (Clements et al., 2017). In the recent past, PS has been effectively used to monitor various environmental phenomena such as noise, air, radiation and water pollution (D'Hondt, Stevens & Jacobs, 2013; Hemmi & Graham, 2014; Little, Hayashi & Liang, 2016; Weissert et al., 2017). However, despite their advantages, PS approaches raise their own issues, for example human error, varying data types (e.g., quantitative and qualitative), reliability of low-cost sensor measurements, data quality, the stability of data sources, malicious use of devices, maintenance and calibration issues, and the privacy of participants (Lunar et al., 2012).

The aim of this article is to discuss the prospect of involving housing companies as stakeholders in air quality sensing initiatives. Including them as a player could be helpful to address two issues of current PS frameworks, namely data completeness challenges and privacy protection concerns. Section 2 presents PS frameworks and elaborates on some of the current issues in PS. Section 3 suggests involving housing companies as a third player in PS frameworks to address issues related to the sparsity of PS nodes, maintenance of sensors, and location privacy threats for participants. Section 4 presents the results of a survey we conducted to assess housing companies' willingness to join PS initiatives for monitoring air quality. Finally, Sections 5 and 6 present the discussion and the conclusion, respectively.

2 Background

Environmental research for cities requires fine-grained data for an accurate assessment of city phenomena. GIScience can be helpful in addressing various environmental challenges of cities by using a wide range of key concepts that contribute to urban intelligence – representation, connection, coordination, measure, networks, movements, participation or even sensors, to list but a few of them (Batty et al., 2012). These urban sensing approaches have the potential to generate a 'data commons' – that is, a data repository generated through decentralized collection, shared freely, and amenable to distributed sense-making for the pursuit of science, but also for use in advocacy, art, leisure and politics (Cuff, Hansen & Kang, 2008). GIScience's approach of connecting urban citizens as active sensors for data collection has the capacity to contribute effectively to the spatial intelligence of cities (Roche, 2014). The major advantage of using PS frameworks for environmental monitoring is their potential to increase the spatial resolution of atmospheric measurements, to identify variations below the city or regional levels, down to street-level or even smaller units (Apte et al., 2017; Gabrys & Pritchard, 2015). As Goodchild (2007) pointed out, the most important value of such information may be in what it tells us about local activities, in various geographic locations, that generally go unnoticed. There are numerous citizen science programmes that actively collect data from members of the public for environmental monitoring, including air pollution data (Boulos & Resch, 2011; da Costa, 1999; Elen et al., 2012; Honicky, Brewer, Paulos & White, 2008). Nonetheless, there are still some important open issues concerning PS frameworks. These are discussed briefly below.

Data Completeness Challenges

Traditional data collection methods for air pollution levels, using sophisticated monitoring stations, are often sparse at intra-city level (Schneider et al., 2018). Compared to conventional procedures for collecting air pollution data using sophisticated monitoring stations, PS can be very different (Elwood, Goodchild & Sui, 2012). For instance (and unlike PS), there may be no fallacious values due to malicious data contribution in official monitoring sources. Balanced spatial spreads for data sources are expected in official monitoring sources, yet this may not be the case in PS. Data quality in PS also needs considerable attention. Furthermore, the list of components of spatial data quality varies from author to author (see Degbelo, 2012; Devillers et al., 2010). The focus of this section, however, is on accuracy and completeness. Both are critical, since inaccurate or incomplete environmental data impact not only the action taken by policy makers, but also the general public's perception of the environment.

When monitoring air pollution or other environmental disturbances with low-cost technology, citizen-led initiatives are typically challenged about the validity or accuracy of their data (Gabrys & Pritchard, 2015). In the case of air quality monitoring specifically, evaluations of low-cost sensors for PM show that they perform reasonably well (AQ-SPEC, 2017). Often, these data sources can be useful for providing ongoing indications of changes in air quality, rather than absolute measurements (Gabrys & Pritchard, 2015). Since PS is open to the contributions of volunteers, it is possible that corrupted data might be included. Indeed, people sometimes act selfishly, exploiting the resources for their own benefit, and PS frameworks are prone to such user behaviours (Mousa et al., 2015). Users, for instance, may start using sensors intended for outdoor air quality measurements for measuring the air quality inside their houses, thus skewing the results.

With respect to completeness, the spatial density of the overall PS network is key to the inferences which can be made from the PS data. It has been discussed in the literature (Gibson, Ostrom & Ahn, 2000) how the amount of spatial detail in a dataset influences the types of patterns which can be detected during the analysis process. In the context of PS, the number of participants actively contributing data does not necessarily correlate with the amount of spatial detail in the PS dataset. For example, many people collecting data at one location (immediate surroundings) may be contributing redundant data, a fact which is relevant when assessing data quality (Budde et al., 2017) because it places limits on the spatial coverage of the data (Jaimes, Vergara-Laurens & Labrador, 2012; Thepvilojanapong et al., 2010). Furthermore, PS approaches sometimes suffer from issues of representativeness (also called 'lurkers phenomena' (Lombi, 2018)), when a large number of participants do not actively contribute to the campaign. Other factors which may contribute to incomplete data collection in the PS framework include inadequate maintenance of the sensors and their calibration. For example, temperature and humidity have a significant effect on gas-phase air quality sensors, leading to their decreased sensitivity, which requires re-calibration and cleaning over time (Lewis et al., 2016). Citizens may be interested in participation but be unwilling to handle repeated replacement, calibration and maintenance of the sensors for accurate measurements. If not well maintained, these sensors can produce corrupt data, and bring about false results in the overall data analysis.

Privacy Concerns

PS involves people, who may have ethical concerns about their privacy. If participants use their personal devices to collect data (e.g., Fang & Lu, 2012), as discussed in the literature (Kotovirta, Toivanen, Tergujeff & Huttunen, 2012; Liu, Liang, Gao & Yu, 2018) one of the key challenges in integrating them into a PS approach is the issue of 'privacy'. As PS involves the creation of data including time and the participant's location (see Christin et al., 2011), the disclosure of such data comes with location confidentiality threats for participants, which should be mitigated. These threats deserve attention because '[o]ur precise location uniquely identifies us, more so than our names or even our genetic profile' (Duckham & Kulik, 2006). Participants' ambivalence due to privacy concerns may reduce their interest in participating and contributing in the data collection process.

The problem of privacy is not new, and several works have pointed out the need to address it (Bowser & Wiggins, 2015; Cuff et al., 2008; Keßler & McKenzie, 2018; Kotovirta et al., 2012; Liu et al., 2018; Richardson et al., 2013). The technical challenges in providing privacy in PS originate from the simultaneous presence of several mutually untrusted (and/or potentially unknown) entities, including participants, data consumers and service providers (Eugster, Felber, Guerraoui & Kermarrec, 2003). Methods have been proposed to preserve and increase awareness about citizens' privacy (Agrawal & Srikant, 2000). Offering participants and data collectors cryptographic tools has been proposed (De Cristofaro & Soriente, 2013), as have various other tools, such as k-anonymity and l-diversity, which mask sensitive information, in order to protect participants' information in the PS system (Huang, Kanhere & Hu, 2010). However, it is still a challenge to prove that participants' privacy is truly protected when PS systems are deployed in real-world scenarios (Christin et al., 2011). Methods using anonymous reputation architectures (Androulaki, Choi, Bellovin & Malkin, 2008) or pseudonyms (Li & Cao, 2013) have also been proposed to solve privacy and incentive-related conflicts in PS. However, they are vulnerable to identity-based attacks (Niu, Wang, Ye & Zhang, 2018). In addition, the privacy-enhancing peer-to-peer reputation system proposed by Kinateder & Pearson (2003) was not well utilized because of a lack of trust between PS participants and data collectors. Personal data may in principle be gathered, analysed and used with participants' consent (Taylor, Floridi & van der Sloot, 2016), but the discussion about threats to privacy is ongoing in PS (Jiang, Bregt & Kooistra, 2018).

3 Method

The remainder of this article discusses the prospect of involving housing companies as stakeholders in air quality sensing initiatives to address the issues of privacy and data completeness. In Section 'Involving housing companies' we argue for involving housing companies; in Section 'Would housing companies want to join participatory sensing?' we present a survey used to assess the actual interest of housing companies in being involved.

Involving housing companies

Decent housing is essential for both individual and economic growth. Housing quality impacts individuals' wellbeing, health and inclusion in society (Hulchanski, 2002). Housing companies in general are partners in urbanization, owning residential properties and offering maintenance (and further services) to their tenants. These residential spaces usually have conditions, such as single-family home ownership or function as cooperatives that are rented on tenure. Some housing companies have established partnerships with various organizations, education institutions and government to develop new services (e.g., services related to mobility) for residents (Bäumer, 2004). Product-oriented services, such as mobile applications to communicate about the residential space facilities and social services, are new marketing strategies.

Location is one of the main selling points for housing companies because view, safety and local facilities in a home's vicinity are criteria which may influence a buyer's decision. Air pollution is one of the hidden elements attached to a location and can impact the buyer's behaviour. In recent years, the sale prices of traditional housing in certain parts of various cities have fallen because of environmental factors associated with the locations (Chen & Chen, 2017; Le Boennec & Salladarré, 2017). According to Eurostat's recent statistics on the quality of life (QoL) indicator 'natural and living environment', 77% of EU citizens believe that the environment has an impact on their quality of life, and 87% believe that protection of the environment is least in part the responsibility of citizens. 95% of EU citizens believe that protecting the environment is important to them personally (Eurobarometer, 2011). These statistics suggest that involving housing companies in PS initiatives can lead to a win-win situation. On the one hand, housing companies can tackle the issue of the fall in property values, and develop environment-related services by getting involved in the PS process. In particular, offering services that address the health impact of environmental factors can influence buyers' overall choice of housing location. PS can also help to address some of the issues mentioned in Section 2. The proposed approach both draws upon existing low-cost tools for air quality monitoring (see Clements et al., 2017 for a recent review) and can support the vision of future smart cities (Batty et al., 2012; Degbelo et al., 2016).

Would housing companies want to join participatory sensing?

There have been very few studies in PS research, if any, looking into whether housing companies would want to be involved as stakeholders in PS. Understanding their perception regarding participation in PS frameworks is important if they are to be involved in improving air quality monitoring close to the citizens' living spaces. Additionally, their involvement could help fill the gaps of PS. The current research investigated housing companies' perceptions of two main QoL indicators, namely 'health' and 'natural and living environment'.

The target population for the survey consisted of executive and planning officials of various housing companies in Germany. The companies are from a network of businesses which utilize various GIS applications and services for their work. The survey was administered online and on paper to 179 individuals from 71 housing companies established in 42 major cities of Germany. It ran from June 2017 to January 2018. Participation in the survey was voluntary, and participants did not receive compensation for their participation. The questionnaire consisted of 16 questions (in German), which were a combination of multiple-choice, dichotomous and Likert-scale questions, designed to collect the perceptions of housing companies regarding: (1) QoL indicators in general, (2) 'health' and 'natural and living environment' QoL Indicators, (3) using low-cost air quality sensors to collect air quality data, and (4) sharing data with public and related institutions. Other important aspects could have been covered, especially in relation to specific interests and public requirements, but we wanted to avoid the survey becoming complex and time-consuming, as it was aimed at higher officials of housing companies.

In total, we received 18 responses (1 response online, 17 on paper). Of these, one was incomplete and was discarded from the analysis. It is not, at this point, possible to draw any conclusions about non-response bias (i.e., the degree to which the respondents sampled differ from the survey population as a whole; see Johnson & Wislar, 2012), because recent statistics about the number of housing companies in Germany are scarce. To give the reader an impression of orders of magnitude: a report by Consilia Capital (Moss, 2011) in 2011 listed about 84 housing companies in Germany. Given that we sampled 71 companies randomly, it is likely that any non-response bias has been minimal for the current dataset.

4 Results

The main results of the questionnaires concern the four topics listed above.

QoL indicators in general:
83% of the participants indicated that they have considered the QoL indicators suggested by Eurostat for development and planning purposes (Figure 1). But when asked about the information they have about their residents' QoL, only 11% were very well informed, 61% of them were well informed, and 28% of them were not informed (Figure 2). The fact that the majority of participants were well informed about their residents' QoL suggests that housing companies may indeed be in a good position to contribute to further improvements of their QoL.

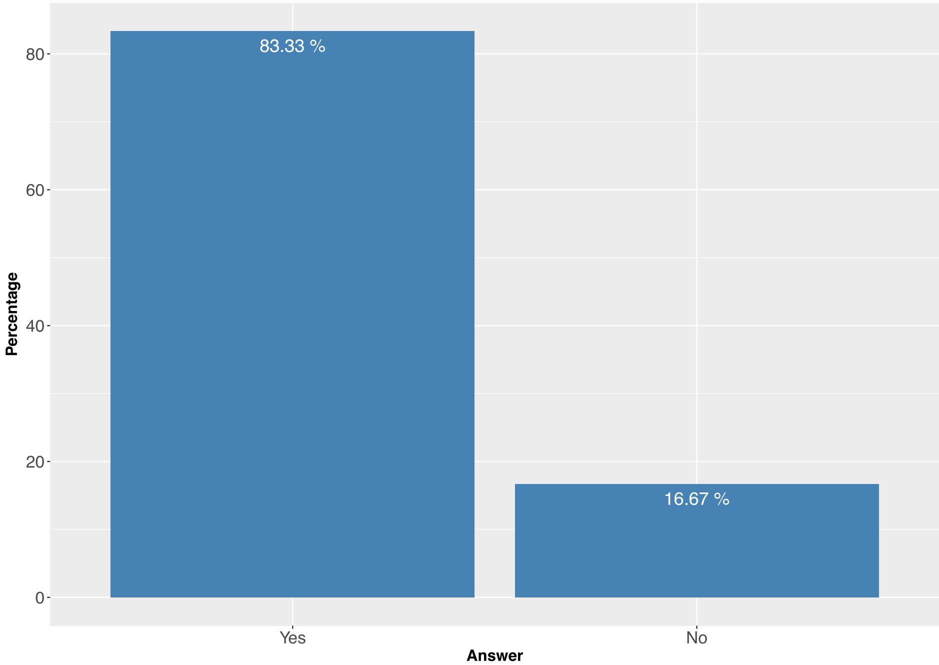

Figure 1: Have you ever considered quality of life indicators for the development and planning of housing spaces?

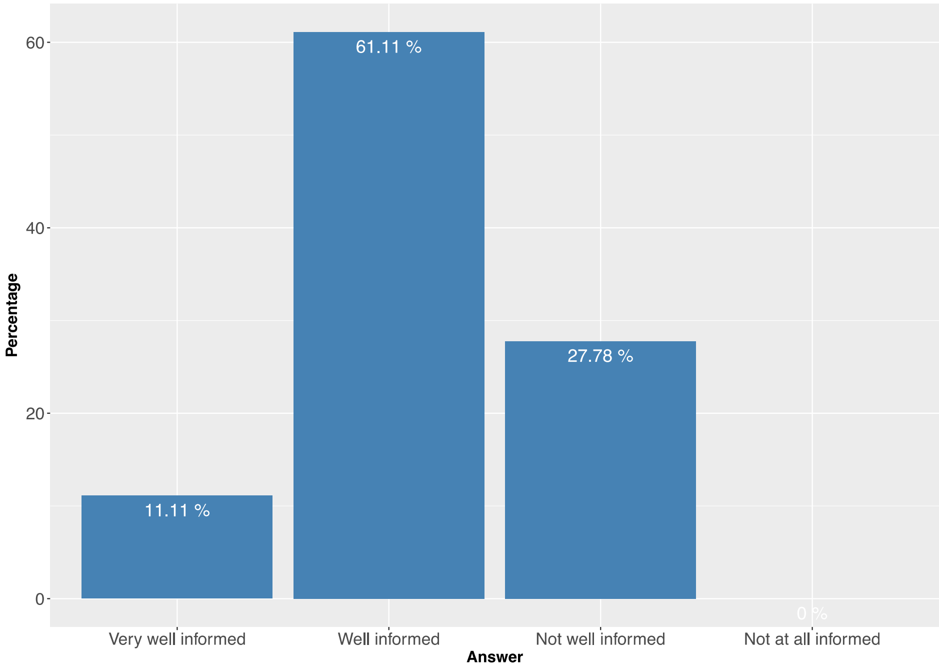

Figure 2: How informed do you feel about the quality of life of residents in your housing spaces?

QoL indicators for 'health' and 'natural and living environment':
As shown in Figure 3, a high percentage of participants (41%) saw health as a very important indicator of QoL, and about 71% believed it to be an important indicator. Regarding the indicator 'natural and living environment', the participants surveyed did not see it as being as important as health but still viewed it as important (41%). The rest (59%) ranked it as not so important (Figure 4). When asked about both indicators taken together (i.e., 'health + natural and living environment'), 17% believed them to be 'very important' and 78% 'important', while only 6% saw them as not being important (see Figure 5).

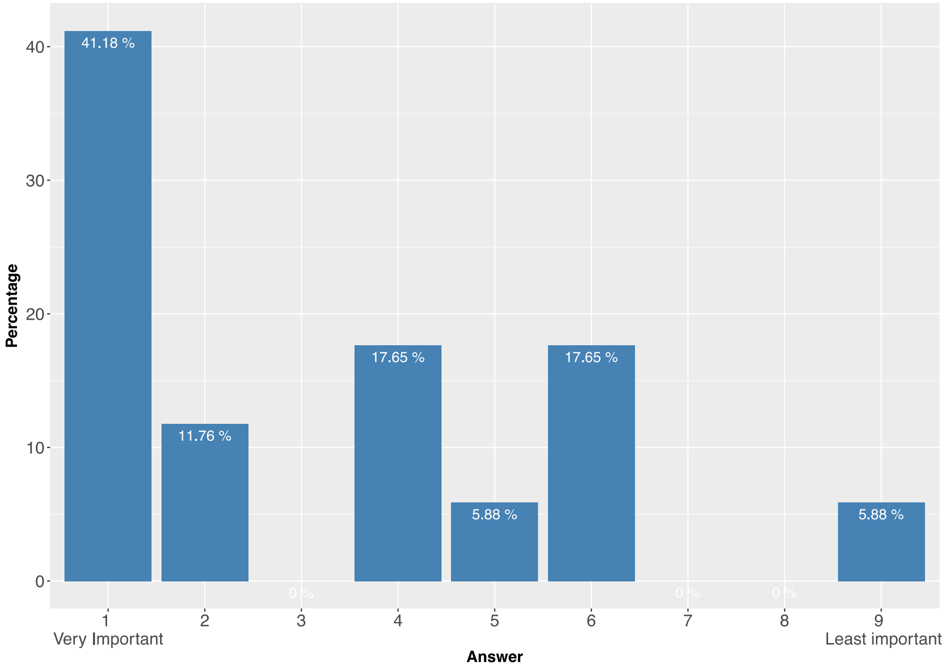

Figure 3: How important is 'Health' as QoL indicator for what your company plans and develops?

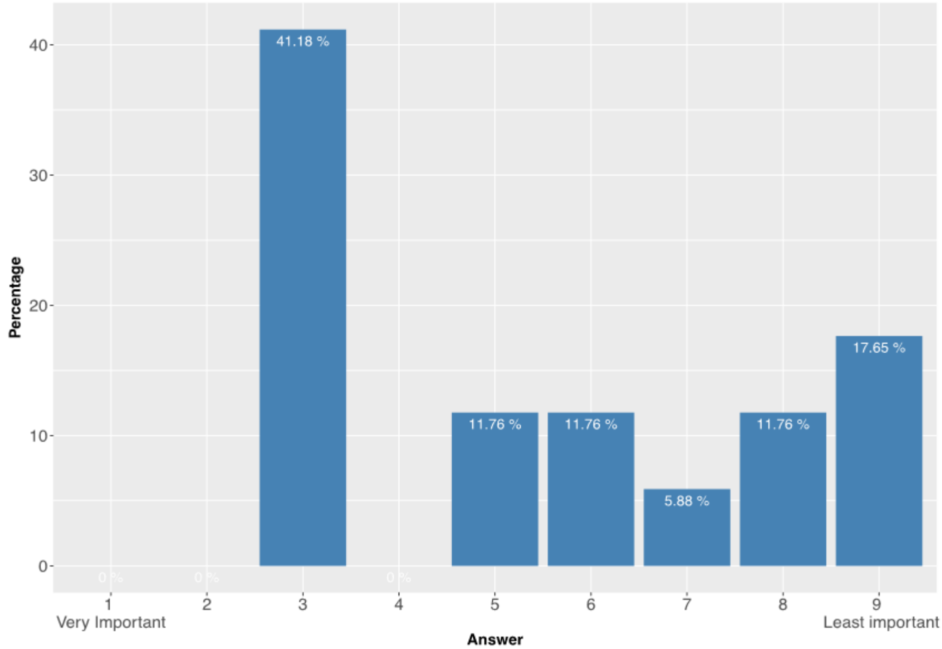

Figure 4: How important is ‘natural and living environment’ as a QoL indicator for what your company plans and develops?

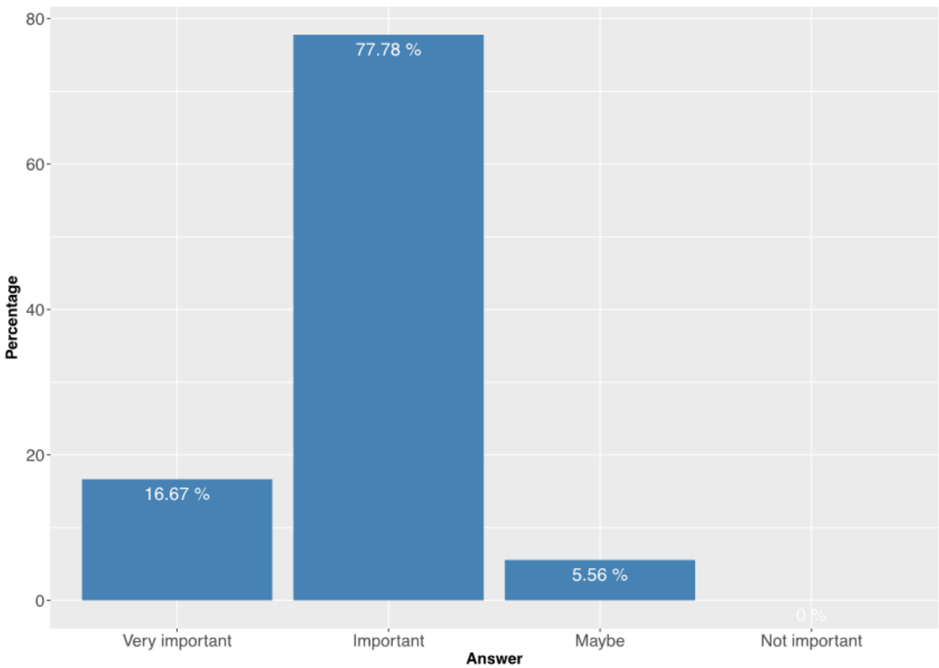

Figure 5: How crucial are ‘health’ and ‘natural and living environment’ combined for housing space development plans?

Low-cost air quality sensors for data:

Interestingly, as indicated in Figure 6, a large proportion (78%) of participants expressed interest in using low-cost sensors to measure air quality around the housing space so that they could control it, and so that residents could be advised to take measures if necessary.

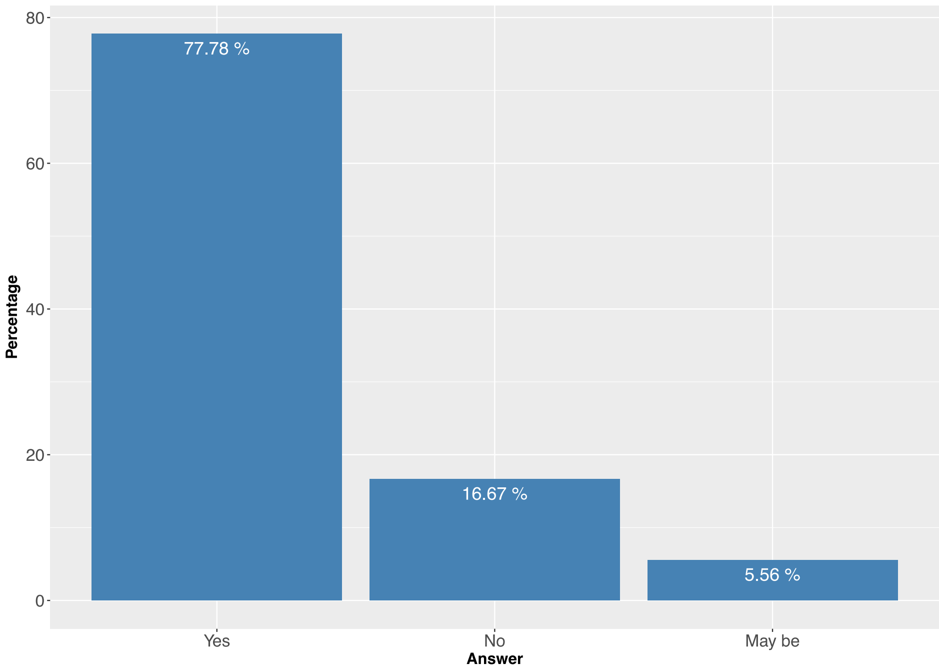

Figure 6: Would you like to use low-cost sensors to measure air quality around the housing space, so that you can control it and so that residents can take appropriate measures when necessary to breathe safely?

Sharing data with the public and related institutions:

Only a small proportion (17%) of the participants said they were very interested in sharing air quality monitoring data with institutions which could help in analysing the data or prediction; a large proportion (50%) expressed moderate interest; 22% of them indicated little interest. A small proportion (11%) of participants were not interested in sharing the data (Figure 7). Moreover, when asked about sharing data with the residents, the majority of companies were reluctant (44% said 'No', and 22% selected 'others', meaning they answered neither 'Yes' nor 'No'). As shown in Figure 8, only 33% of the companies were interested in sharing the data with residents. This negative response may be attributed to the lack of trust due to data quality and privacy concerns existing at this point in time (Gabrys & Pritchard, 2015). Overall, the results suggest a difference, from the point of view of housing companies, between data-sharing with institutions and data-sharing with residents. The exact nature of this difference and the reasons for it need further investigation (e.g., through follow-up interviews).

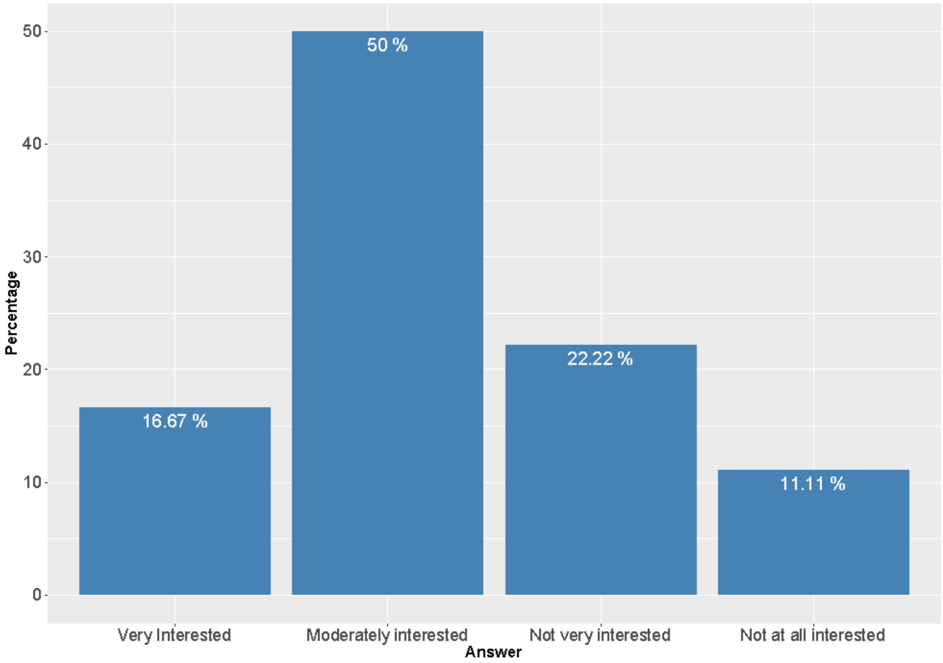

Figure 7: What would be your take on sharing air quality monitoring data with institutions which can help in data analysis and air quality monitoring and prediction, so that residents could also get forecasts of poor air quality?

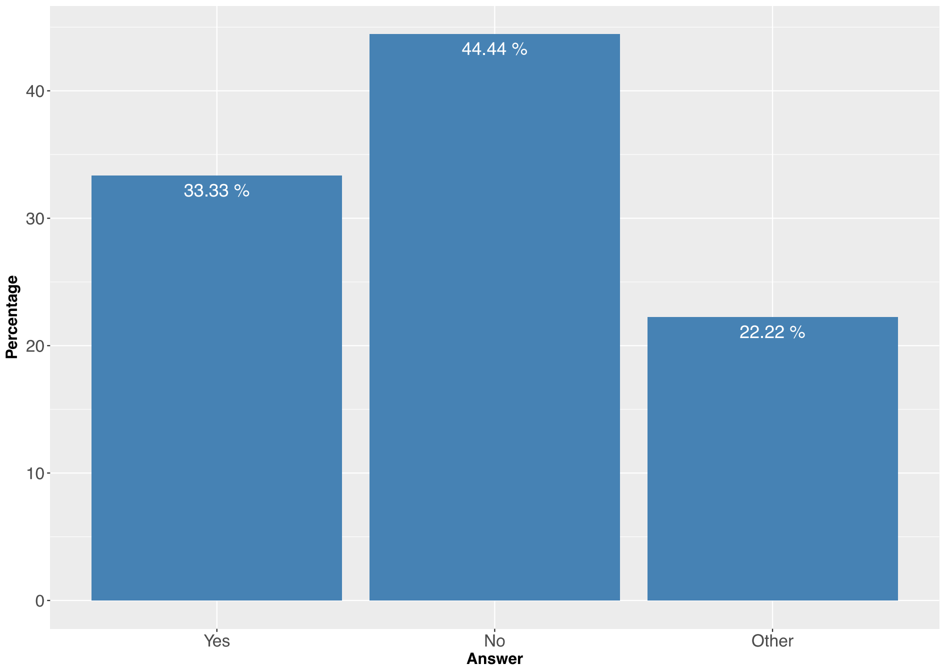

Figure 8: Would you like to provide air quality information to residents like other housing-related services, so that residents can protect themselves from the impacts of harmful pollutants?

Limitations:

The results give some insight into housing companies' standpoints as regards QoL indicators, as well as data collection and sharing. There are, however, a few limitations to mention with respect to the data itself. First, there is the non-response bias from which all surveys suffer (although, as discussed above, this bias might be small). Second, the survey used paper and an online survey to examine 71 housing companies' perceptions. However, to maintain the anonymity of the participants we did not request the housing company's identity. This means that the exact number of *distinct* companies which took part in the survey is unknown to us. Most responses (14 out of 17) came from different cities and therefore indicate different housing companies. The remaining three came from one city in Germany (Hamburg) and may have been from the same housing company. Whether the responses come from 15 different housing companies or 17, they reflect the view of 17 planning/executive members currently active in the housing business in Germany. It would be interesting to see whether these views are shared by other planning/executive members in other countries.

5 Discussion

The previous section has illustrated that the housing companies surveyed not only find QoL indicators to be important, but also that they would be willing to use low-cost sensors to measure air quality around the housing space. This indicates that involving them as stakeholders in participatory sensing initiatives for air quality monitoring holds promise. They could play the three roles of PS applications listed in Christin et al. (2011). They may act as *campaign administrators*, i.e., initiate PS campaigns by inviting their tenants (from time to time) to collect data in order to raise awareness about air quality. They may also design, implement, manage and maintain PS infrastructures for specific residential areas (which is a typical role of campaign administrators). They may act as *participants* when they instal low-cost sensors to collect air-quality data continuously. Finally, they can also act as *end-users* when they visualize the data collected, reflect on it, and take evidence-based measures to improve residents' QoL.

The next two subsections reflect on advantages and drawbacks of including housing companies as stakeholders in PS systems.

Addressing data completeness challenges

As discussed in Section 2, PS data suffer from issues of accuracy and completeness. Housing companies as *participants* could (in agreement with the residents) instal low-cost sensors on the roofs of buildings to collect air quality data. Involving a large number of housing companies in cities would help monitor air quality at a finer spatial granularity, thereby helping to address the completeness issue. By identifying optimal locations, the structure and extent of the air quality monitoring network could be defined (see Gupta, Pebesma, Mateu & Degbelo, 2018), and PS data handling and completeness could be managed more efficiently. Housing companies as *campaign administrators* could maintain PS infrastructures (one of the key issues at the moment), leading to more reliable nodes in the PS network and reduced chances of erroneous contributions from the PS nodes. This approach would also overcome the problem of malicious data caused by the exploitation of PS devices by some individuals for their personal purposes (Budde et al., 2017). The lurker phenomenon is also partly addressed here, because the amount of data generated for air quality would no longer depend on a few individuals. Finally, housing companies as *end-users* could provide broadcasting services related to the surrounding environment, keeping citizens updated about air quality (without being responsible for device management).

The participation of housing companies in PS frameworks could, furthermore, (a) help them make services for their residents more attractive and up-to-date; (b) create an image of themselves as being ecological and innovative; (c) show potential customers the importance of very localized air quality monitoring around their property; (d) maintain customer loyalty by being resident-friendly; and (e) provide data not only to their residents, but to the city at large.

There are, however, also a few drawbacks to the approach. The survey has shown, for example, that some housing companies may not be willing to share their data. This poses the question of the ownership of the jointly-collected air quality datasets, and it is unclear how the mediation between the different stakeholders (city council, citizens, researchers, housing companies) could be best orchestrated. In addition, successfully addressing data calibration and maintenance issues relies on the commitment of housing companies which, though likely, may not be guaranteed. Finally, it is also possible that housing companies might act as *lurkers* in the proposed framework (but this is less likely compared to individual-level data-gathering because of the spur that a competitive market puts on housing companies' business).

Addressing privacy concerns

Privacy is another constraint which impacts on participation in the PS approaches, as discussed in Section 2. Getting participants to contribute without identifying them has attracted a lot of attention in previous work. By involving housing companies as one of the contributors in PS, we can facilitate shifting sensitive individual-level information to group-level, identifying people only as belonging to a large and otherwise undefined group living at a certain location, ensuring what has been termed 'group privacy' (Taylor et al., 2016). By doing this, we would no longer need central data analyses and collection at the individual level; housing companies could be involved in collecting information at this group level. Furthermore, the data collected would be inherently dis-aggregated and therefore anonymous from inception. This, in turn, could be helpful in making data easily accessible and open for sharing.

There are, however, a few drawbacks to group privacy, and it is worth mentioning that there is always a trade-off between information-sharing and services. There is thus the possibility of individuals missing some interesting personalized service due to the lack of more fine-grained location data. In addition, the scientific community has yet to provide effective techniques to fully prevent the identification of participants when their data is integrated with other data sources. It may therefore not be possible to guarantee the full anonymity of residents.

Further opportunities for GIScience

Beyond addressing issues of data completeness and mitigating the threat to location privacy, involving housing companies in PS networks presents additional opportunities for GIScience. For instance, as pointed out in Richardson et al. (2013), spatial data holds an enormous potential for health research. Distributed spatial infrastructures are key to tap into this potential. A PS initiative with residents and housing companies as participants could provide valuable input for such an infrastructure. Another area where such an initiative would be beneficial is in open smart cities. Roche (2014) presented four dimensions of a smart city: the intelligent city (i.e., social infrastructure and civic spatial engagement practices), the digital city (i.e., urban informational infrastructure), the open city (i.e., governance based on the concept of open democracy), and the live city (i.e., continuous adaptability to change). The approach proposed here is arguably relevant to the dimensions of the 'digital city' (feed the urban informational infrastructure), 'open city' (enable the democratization of environmental data collection), and 'live city' (provide material for fine-grained assessment and decision-making regarding environmental change).

6 Conclusion

Participatory sensing (PS) has a great potential for monitoring air quality in cities, but its success depends on the number of participants, and the spread and quality of data collected. In this paper, we discussed two open issues of PS frameworks for air quality monitoring: data completeness and privacy. We proposed the inclusion of housing companies as a further stakeholder in PS frameworks for data collection in order to mitigate current data gaps and privacy issues. To understand how housing companies perceive their inclusion, we conducted a questionnaire (N=18) administered to executive and planning staff of housing companies in Germany. The companies surveyed showed interest in using low-cost sensors for air quality monitoring and in sharing data with institutions which can analyse and process data for proper understanding; they showed less inclination to share the data with the public. Further work is needed to establish whether people who live in the housing companies' properties would be willing to use such services at all. The view of the residents would be critical for the ultimate adoption in the real world of the approach proposed.

Acknowledgements

The authors gratefully acknowledge funding from the European Commission through the GEO-C project (H2020-MSCA-ITN-2014, Grant Agreement Number 642332, http://www.geo-c.eu/). We thank Mr. Hans-Christoph Tielbaar and his team from Hansa Luftbild AG for valuable support for the survey. We also thank the anonymous reviewers and the English-language editor for their constructive feedback.

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