Roam-IO: Engaging with People Tracking Data through an Interactive Physical Data Installation

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ABSTRACT

Newly emerging urban IoT infrastructures are enabling novel ways of sensing how urban spaces are being used. However, the data produced by these systems are largely context-agnostic, making it difficult to discern what patterns and anomalies in the data mean. We propose a hybrid data approach that combines the quantitative data collected from an urban IoT sensing infrastructure with qualitative data contributed by people answering specific kinds of questions in situ. We developed a public installation, Roam-io, to entice and encourage the public to walk-up and answer questions to suggest what the data might represent and enrich it with subjective observations. The findings from an in the wild study on the island of Madeira showed that many passers-by stopped and interacted with Roam-io and attempted to make sense of the data and contribute in situ observations.

Author Keywords

Physical Data Installation; Urban Spaces/IoT; Data

CSS Concepts

• Human-centered computing~Interaction Design

INTRODUCTION

Sensor technologies are used for tracking people and animals in urban and rural spaces [48, 53]. The data collected are used to analyse movement patterns, people counts, etc., to better understand population and conservation concerns [48, 50, 53]. The presence and movement of humans in a given place and time is typically detected by recording sounds, movements or radio/WiFi signals emitted from a device they are carrying. While the streamed data, when aggregated temporally and spatially, provides new insights that are helpful for the purposes intended, they usually only offer a partial account of what is happening in the places where the monitoring is taking place. Moreover, there can be anomalies, absences, noise and other deviations in the data that make it difficult for algorithms to determine what is really happening. While machine learning algorithms can identify such events, it is more difficult to generate possible reasons or explanations about what is behind changes in the data. Moreover, these algorithms do not have the capability to capture opinions, perspectives and other contextual semantics.

DIS '19, June 23–28, 2019, San Diego, CA, USA

ACM 978-1-4503-5850-7/19/06…$15.00
https://doi.org/10.1145/3322276.3322303

Figure 1. Roam-io: a physical installation that asks passers-by to answer a range of data questions.

Following methods from citizen science, crowd-sourcing and a recent growing interest in general human-data interaction, our research is concerned with how the general public can help with exploring and interpreting such data. We suggest that they can provide information about the surroundings in which data is collected and, in doing so, offer explanations about the data in context. In the same way as the general public are called upon to help in forensic science, we propose they can play a role in *forensic data science* [13]. To examine what this role could be, we developed a **public installation with the aim of engaging the public in interpreting collected data about 'people counts'**, data about where people go around a popular tourist island (Madeira).

Currently, Madeira, with only a population of 270,000 people, has about 1.2 million tourists visiting it per annum (many arriving each day on large cruise ships). The motivation for choosing this domain is that the local authorities have become increasingly concerned about the economic, ecological and social impact of tourism on the island. To track where tourists visit, an infrastructure has been set up throughout the island that measure people counts, using passive Wi-Fi hotspot analysis. The hotspots, dotted around the island, count the number of Wi-Fi-enabled devices within an area to estimate the number of people in that region. While this can help assess the impact of visitors on areas on the island, it has so far only been able to provide a sketchy picture of activity on the island. The tourist board and local authorities are interested in discovering more about what lies behind the data being collected and use it as a planning resource.

In this paper, we explore how a new physical interface can help by enticing passers-by (tourists and locals) to provide additional data and their understanding of what the people data means. Our approach was to see if passers-by would leverage their in-situ capability and knowledge to enrich the data with interpretations and their own observations. The physical installation, called Roam-io (see Fig. 1), was designed to: (i) entice passers-by to walk up and interact with it, (ii) engage them in exploring data through visualizations and interactive questions, (iii) see whether they would help explain anomalies and changes in the data, and (iv) assess whether they were willing to complement the Wi-Fi data logs with their own interpretations and opinions.

BACKGROUND AND RELATED WORK

While online crowdsourcing platforms provide opportunities for the public to contribute their data, automated tracking technology has so far provided fewer opportunities for human intervention. The idea of forensic social science [13] has been promoted as a new approach to data analysis: the compilation and interpretation from unstructured data arising from digital traces that allows new theories to be generated. Within HCI, it is increasingly argued that we should be pushing more to bring humans into the data loop. For example, there have been calls for a human-data interaction (HDI) approach, that emphasizes placing "*the human at the centre of the flows of data, and providing mechanisms for citizens to interact with these systems and data explicitly*" [40]. Outside academia, similar calls for change are being put forward, such as the data humanism approach proposed by Lupi [33]. The question this raises is how best to engage the general public so they can (i) explore and engage with data, and (ii) help provide new understandings and possibly generate insights about this data. One promising approach has been to provide visualisations on public displays. In particular, asking questions has been found to be a motivating factor for public engagement when exploring data sources, as questions can entice people's curiosity [8, 32].

Public Data Visualizations

Scientific and information visualizations have been developed to facilitate the analysis and communication of data [3, 19]. Most visualizations are designed primarily for experts who have specific domain knowledge [1, 43]. However, now that large amounts of data have become accessible for the general public, it raises the question of how and whether the established information visualizations developed for expert use are legible and meaningful for non-experts. Pousman et al. [43] suggest four types of information visualization that might be suitably employed for a wider audience: (i) ambient, (ii) social, (iii) artistic and (iv) personal/persuasive. Ambient information visualizations [42] are interfaces that "*reside in the environment*" and require "*attractive addition*" to be noticed and usable in public spaces. Early examples include InfoCanvas [36] that allows people to explore data through a painting interface, the Information Percolator [21] that visualizes data through bubbles, and the Ambient Rabbit [37] that encodes data in an anthropomorphic shape, mimicking a rabbit. Other kinds of ambient visualisations are designed to represent power consumption and energy usage. For example, PowerSockets [22] and What-I-See [44] visualize the power consumption on power sockets using in situ visualizations. Other approaches have also explored how ambient displays can provide various forms of eco-feedback that is easy to understand and act upon [9, 10, 45].

In recent years, a number of physical visualizations have been developed, in the form of data sculptures [38], physicalizations [26] and physical ambient visualizations [24]. Likewise, the goal is to make data more accessible for non-expert users through designing tangible interfaces. For example, Vande Moere et al. [39] studied how to visualize energy consumption on house facades. Similarly, Koeman et al. [30, 31] visualized data about a busy high street in Cambridge, UK, using a temporary chalk visualization. Loop [46] is an example of a physical data representation of personal activity. An innovative design was the Bicycle Barometer [5] that visualized opinions collected by passers-by. Mikusz et al. have also explored public awareness displays on IoT data [34]. These visualizations demonstrate that data can be successfully conveyed in public/urban environments. However, the focus has been largely limited to presenting data to passers-by and homeowners in the form of non-interactive visualisations. While opinions have been represented as aggregate visualisations [12, 30], there has been little research investigating how the general public can be encouraged to interact and interpret urban data through visualisations.

Public Installations for Opinion Gathering

A number of novel interfaces have been developed for supporting public interaction with information [2, 25, 28, 41]. Early prototypes, like Opinionizer [2], demonstrated how technologies can be designed to allow people to express opinions, perspectives or share personal data. This led to a range of interactive technologies, focused on human-centred data collection. Schroeter et al. [47] visualized public opinions that were collected through tweets or text messages. Similarly, VoiceYourView [52] used speech recognition and natural language processing to gather real-time feedback in public spaces, while MyPosition [51] visualized live polls on large projection screens. Others have explored the efficacy of using physical tangible input mechanisms for public opinion gathering. Koeman et al. [30] successfully deployed a three-button physical voting system to collect information about community issues. Taking a similar approach, Mood Squeezer [12] allowed users to express their mood by squeezing coloured balls placed in public spaces. PosterVote [49] allowed community members to vote on traffic calming measures. VoxBox [15] replaced the paper questionnaire with a large interactive installation using familiar physical knobs, dials and sliders to ask people questions. Similarly, Smalltalk [11] explored how physical questionnaires could help children articulate opinions. Sens-us [14] transformed the UK census into physical questionnaire kiosks. These studies reported that the public were drawn to them and willing to share information and explore aggregated data.

Another approach to data analysis is crowdsourcing [29], where work is done by a group of volunteers. Examples focus on mobile and situated crowdsourcing [16]. For example, CommunitySourcing [20] has been proposed to crowdsource tasks in a physical space using an information kiosk, applying design principles from physical computing to facilitate crowd work. Goncalves et al. [17] explored how in situ crowdsourcing can be leveraged to estimate queue times. Similarly, Hosio et al. [23] studied situated crowdsourcing markets. Both demonstrated how in situ installations are an effective way of collecting feedback from the public.

Human Data

It is increasingly accepted that the role and practices around personal and corporate data systems can be better understood from the perspective of end users [4, 40]. However, the rise of public city-wide sensing infrastructures and data sensors are currently not in an accessible form to enable this to happen [35]. Previous studies have shown how tensions can arise between citizens and city-wide data infrastructures managed by central authorities [18, 35]. Few attempts, like Smart Citizen [6], moved the data collection process into the public arena, creating a participatory data collection process. Despite making the data public in a crowdsourced way, it was not able to produce public insights or lead to public action [1]. Other attempts like the Urban Observatory [54] and DataBox [4] have since begun to democratize personal and city-wide data. However, we need to understand much more about what mechanisms and methods can be used to engage the public in meaningful human-data interaction.

ROAM-IO

Roam-io (Figure 1) is a public installation that provides passers-by in a public space, like a street or building, with the opportunity to explore and add their interpretations to data being collected via an urban IoT platform. It was designed as a voluntary walk-up and use interface, making it attractive and intuitive to use. It employs a question and answer interface with the aim of encouraging passers-by to make suggestions about urban data patterns presented to them in visualisations and to describe what is happening around them.

Beanstalk Sensing Infrastructure

Although Roam-io was designed to work with any IoT sensing network, for this particular deployment, the Beanstalk [55] urban sensing infrastructure was used. Located on Madeira, Beanstalk was designed in collaboration with the local authorities and tourist board in an effort to better understand the impact of tourism on the island. Prior to our intervention, Beanstalk had been operational for one year. During this time, it has collected masses of raw data on tourist counts and people flows, using passive Wi-Fi hotspot analysis. However, the Beanstalk data has only been able to provide a rough approximate picture of where tourists go on the island and when. It was not clear, for example, why there were sudden peaks or troughs in the number of people at various locations at unexpected times, and how that impacts the different regions. Although the system detects similar counts of people in a certain area on two different days, the perceived busyness and impact on the people present in that space might be different. The lack of qualitative insights when analysing quantitative data sets poses challenges for reasoning and building an understanding of what is happening.

The aim of our study was to see whether a public physical data installation like Roam-io could help obtain a more extensive understanding of these patterns and anomalies by asking people to add their knowledge, observations and interpretation of the data. In particular, we were interested in determining whether the public would **engage** and **interact** with Roam-io by adding related information that could help us understand the sensed activity patterns, such as demographics or people's perception of a place (e.g., perceived noise, busyness, and safety).

Hybrid Data Collection through Questions

Our hybrid data approach combines quantitative data collected from a distributed urban sensor system with qualitative data, contributed by passers-by. The motivation for the approach is to create a voluntary-based system that encourages people to participate and learn more about the data. Hence, considerable thought went into what we should and could ask passers-by in terms of themselves, the environment, and the collected data sets. We decided upon 4 main types of questions:

Type 1: Factual questions

Factual questions help users reflect on their knowledge about the environment they are visiting and provide an insight into how much people know about the place they are visiting.

Type 2: Contextual questions – demographic

Demographic questions provide anonymized information about who is using the system, e.g., nationality, age, or visitor history. This helps understand who is visiting the installation and how other answers can be interpreted.

Type 3: Contextual questions – environment

Asking people questions about their surroundings allows for collecting contextual information about what is happening in the vicinity of the deployed system. Examples such as the level of noise, busyness, or mood can help build a broader picture of the vibe at a particular point in time.

Type 4: Data and visualization questions

By showing people visualisations of the data collected in the area, they can become aware of what data is collected, and can comment, suggest or disagree with the interpretation of that data. This question type was made available in the form of visualizations for the public to inspect, comment, dismiss, or annotate with interpretations and opinions that the council or data scientists might not have anticipated. The visualizations were simplified visual representations of the real-time "raw" data used, showing trends, and changes.

Design Principles Used for Roam-io

Public physical interfaces can lead to much engagement and diverse participation from the public [11, 15, 25, 30]. Empirical studies [28] and data design workshops [27] show how animate friendly-looking objects with anthropomorphised characteristics are more inviting, engaging and approachable compared to standard kiosks. Inspired by these findings, we designed Roam-io to have *subtle* anthropomorphised properties to create a friendly and open interface for people to approach in a public setting. To entice participation, Roam-io was based on 5 core design principles (derived from prior work) intended to facilitate public voluntary interactions:

D1. *Public*: to enable the public to use the system, it should be designed for, positioned and used in public spaces. The system should be straightforward to use, yet provide options to express opinions, comments and perspectives. By placing the installation in a public space, it can support a broader community and social activities and interactions around the display [2].

D2. *Voluntary opt-in*: participation should be on a voluntary basis without any predefined incentive or forcing function. To avoid forcing people to 'complete' a set of questions, the system is stateless and does not track the answer- or completion state of individual users. The system should allow users to easily walk up or walk away from the interface at any point in time.

D3. *Approachable*: to ensure broad participation, the system should provide a noticeable curiosity invoking, and approachable interface that enables input from passers-by [26]. The system should be usable by individuals and groups to enable different type of answering patterns and interactions related to the data and questions.

D4. *Physical*: rather than relying on touch interfaces or other gesture-based methods, the design should employ a constrained and unambiguous set of physical buttons that clearly communicate their purpose and provide a path of least resistance and low learnability [11, 15].

D5. *Anthropomorphism*: to entice public participation and overcome display and interaction blindness [25], the design should incorporate subtle anthropomorphised elements to make the installation more approachable, friendly-looking and recognizable to passers-by.

Roam-io Interface

Figure 2 shows the design of the physical interface components of Roam-io. The inputs and outputs are designed to be distinct and 'obvious' as to where to read the questions and how to answer them. Two main panels are used: a visualization panel at the top of the installation (Fig. 2A), and an interaction panel at the bottom (Fig. 2B). The top visualization panel (Fig. 2A) comprises two displays: (i) an upper display that shows information sources, such as the visualisations related to the question asked of the user; and (ii) a central display that shows the questions or feedback text.

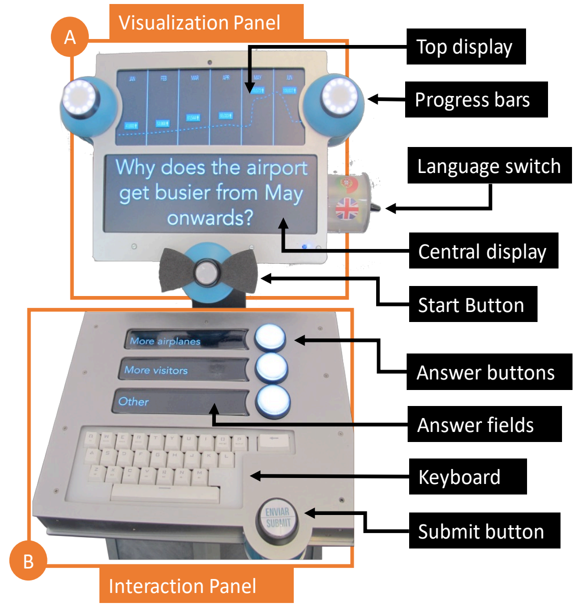

Figure 2. The interface components of Roam-io.

Interface and Design Features

Roam-io's central display presents the user with the information related to the island, while the top display is used to show auxiliary data, such as visualisations. The two-display approach enables each output space to be associated with a particular function (the prompting question and the auxiliary information needed to answer the question). At the top of Roam-io's central display are two protruding spheres designed to look like a big pair of eyes, each with a white centre and surrounding blue iris. These were designed to appear as if Roam-io is attending to the user as they interact with it. They also act as progress bars, providing a visual indication for how long an answer will be displayed. A button mounted underneath the central display is used to start the interaction. This button is dressed up as a bow-tie to provide a further form of subtle anthropomorphism, suggestive of an agent, who serves up questions in a playful way. These two features provided a level of anthropomorphism that suggest, draw and sustain a user's attention. A language switch attached to the right side of the top display allows users to toggle between English and Portuguese – to accommodate for both locals and tourists. To answer questions, the bottom interaction panel (Fig. 2B) provides three answer fields. The adjacent buttons act as the input selectors for answering the questions. The user can select one of the two predefined answers or select a third 'other' option. Pre-defined options allow for quick responses; while the other option enables users to enter information themselves. Selecting the third 'open' option, illuminates the keyboard to allow the user to write a response. The choice for 3 answers was governed by our design goal (and prior work [11, 15, 25, 30]) to make the system easy to use. Furthermore, the questions were tailored for 3 answers.

Modes and Interaction

Roam-io has four modes. When not in use, the central display shows a message inviting people to press the blinking start

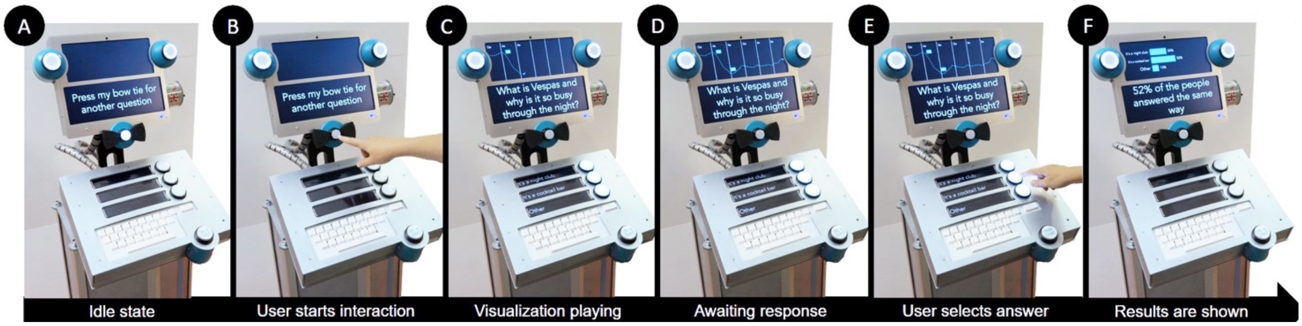

Figure 3. Overview of the different interaction steps when using *Roam-io*. To start the users press the button in the center of the installation (A-B); the system will then present users with a data visualization, picture, video and question (C-D); after the user selects an answer from the panel (E), Roam-io will give feedback to the user and show the overall results (F).

button located on Roam-io's bow-tie (Fig. 3A). This button is intended to entice people to approach Roam-io. When pressing the start button (Fig. 3B), Roam-io goes into question mode and a question appears on the centre display (Fig. 3C). If the question relates to data, the auxiliary visualization appears in the top display (Fig. 3C). For example, when questions are asked about data, an animated visualization (Fig. 6) is shown. The top display supplements the data with photos, videos or animations relevant to the question. During the question mode, the bottom display shows three potential answers and activates the adjacent buttons to indicate to the user that the answers are selectable. After showing the question, Roam-io goes into input mode where it awaits input from the user (Fig. 3D). After the user answers the question, the device goes into response mode (Fig. 3E) and presents the user with the percentage of other people who have answered the same option (Fig. 3F – centre display). Roam-io visualizes the results in the top display in the form of bar charts to show users the percentage of answers for each option (Fig. 3F – top display). The result is displayed in textual form in the bottom display; e.g., "27% of the people answered the same". This feedback gives users a sense of participation, scale of answers from other people, shared opinions and invokes further curiosity to learn more.

Pilot Study

To explore whether Roam-io was effective in attracting people and collecting answers, we deployed an early prototype with similar types of questions but relevant to the local context at a one-day event in London. During the one-day deployment a continuous stream of people walked up and used it, (465 in total during 265 interactions). 1741 answers were collected and observed interactions ranged from a few seconds to 10 minutes. The results indicated that (a) people were enticed by the installation and understood the questions, (b) people were willing to spend time answering questions about data and the environment, and (c) that a number of social interactions occurred around the installation that enabled prolonged engagement. Overall, the study helped build an initial understanding on how the "novelty effect" can be leveraged to attract people for public interaction with data.

USER STUDY

To study how passers-by interacted with Roam-io we conducted an in the wild study in Madeira. Since there are known problems (e.g., [25]) with public installations, **the primary goal of this study was to verify if and how people use Roam-io to interact with, and contribute data**. In line with our research questions on how to engage the public with urban data in situ, our study focused specifically on:

- **G1. User Participation:** was Roam-io successful in attracting passers-by to engage them in answering questions?
- **G2. Answering Questions:** did people answer many questions? How long did they spent answering questions?
- **G3. Data Results:** what interpretations do people make about the data collected from Wi-Fi hotspots? Can they really provide additional insights into the collected data?
- **G4. Contextual Data:** are users willing to contribute observations and subjective information? What kind of observations do they make? Does it fit the ground truth?

Deployment Area and Data Collection

Roam-io was deployed for 6 full days (between approx. 10am and 5pm) during off-peak season in an *indoor public space* next to one of the tourist offices (Avenida Arriaga) in Funchal, the capital of Madeira. An information poster and disclaimer were placed next to Roam-io to inform passers-by about the project. All the interactions with Roam-io and answers given were all logged. We also filmed some of the interactions with Roam-io (with permission). The videos were analysed and coded by three researchers to find patterns. We counted all passers-by (both those who ignored and those interacted with Roam-io). Ground truth in this study was derived from the sensor data of Beanstalk and a manual check of the video logs and coding to verify if people's contextual contributions were accurate with what was filmed.

Participants

As the location was publicly accessible, Roam-io was available to anyone passing by. The study did not require any specific demographic, knowledge, expertise, or age to participate. No participants were actively recruited. Passers-by, thus, participated on a voluntary basis with no compensation. They could simply walk up to the device to start using it and could leave at any time.

Question types and visualisations

Roam-io was set up with 34 questions to enable a broad set of data input as well as allowing for long interactions without repetitions. These included 5 demographics questions about nationality and language, 8 contextual questions asking the user to describe the environment, 10 data questions in which users were asked to comment on an infographic, and 11 factual questions about Madeira (examples in Table 1).

Type	Question
Contextual *Environment*	Describe the people around you? Are they... What is the current mood here? What is the average age around here? Does this place feel busy to you?
Contextual *Demographics*	Why are you here? What nationality are you? How often have you been in Madeira?
Data	Why is it busiest around lunchtime? Why are there more people at the port in the morning? Why is it quieter in Funchal on a Sunday?
Factual	How many people use the airport on an average day? From what country do most tourists come from? How many tourists come to Madeira each year? What is the wettest month of the year?

Table 1. A selection of the questions asked by *Roam-io*.

Each question had two prescribed answers or could be answered free-form via the keyboard. The keyboard was not available for factual questions. The order of questions was pseudo-randomized to ensure each category of questions received an equal amount of answers. Each of the 10 data questions were assigned to a specific data visualization (as seen for example in Fig. 2) representing actual data extracted from the Beanstalk sensing infrastructure. The visualization depicted historical tracking data (across days, weeks and even months). Each question asked users to 'vote' for the best interpretation or contribute a new interpretation of that data set. The visualisations were designed as simplified graphs that could be easily read, showing peaks and troughs in people flows at different locations and times on the island. We were interested in finding out what people made of these kinds of visualizations. For example, did a peak on a Saturday afternoon indicate an influx of people visiting a tourist site in the city centre or was it representing locals attending a festival? This hybrid data was then to be shared with the local tourist board, and other communities to help them develop a better understanding of the impact of the people flows on specific areas and public spaces.

RESULTS

Overall, during our deployment in Madeira, we observed that 15% of passers-by, who were near the tourist information centre, approached and interacted with Roam-io. This rate might appear low (about 1 in 5 passers-by) but is comparable and even outperforms the rates found in other studies of public kiosk usage [11, 15]. The majority of interactions lasted between 1 and 5 minutes, with outliers of consecutive use up to 20 minutes. 50% of all interactions were individuals, while the other 50% consisted of group interactions. The questions triggered interesting behaviours, such as group discussions, cheering or frustrations, and reading questions out loud. The type of question triggered different reflections, as there was a difference between the time people spent responding to data questions as compared to the conceptual and factual questions. Finally, the resulting hybrid data set contained insightful data, with contextual answers, factual answers, and consistent consensuses for the data interpretations.

User Participation from Video Logs

The video analysis showed that during the deployment, 1569 people walked past Roam-io and of those, 231 people (14.72%) stopped to interact with the installation. These included a diversity of people, from young children to elderly, tourists and locals, and various nationalities. Just over half of the interactions recorded (55.6%) were group-based, with two or more people using Roam-io at the same time (the other 44% being individuals). During the group interactions, it was typical to observe each member having a go at answering the questions rather than just one person. One person would read the question out aloud to the group, and together they would then discuss potential answers for that question. This type of social interaction is illustrated by the group of passers-by in Figure 4 who approached Roam-io (A), read the question out loud (B), discussed possible answers (C) and finally committed an agreed answer (D).

Figure 4. A group of passers-by approach Roam-io (A) to read the question and answers (B-C) before submitting (D).

Observed body language of the people who interacted with Roam-io indicated they often spent time thinking about the questions before answering them. Some passers-by raised their hands in the air when they didn't know the answer; others made cheering gestures when they discovered the majority of other answers that had been input before them were the same. In some cases, passers-by were observed appropriating Roam-io, using it for other purposes than what it was designed for. For example, some people used it to translate words or phrases from one language to the other (English and Portuguese) by switching between the two languages and looking at the translations on the screen. A number of people (13%) returned to interact with Roam-io again for a second and even third time. Some of them brought other people along (e.g., family members or friends) and showed them what to do, acting as 'champions' explaining how to interact with Roam-io and answer questions.

Duration and Engagement of Interactions

On average, interactions lasted between 1 and 5 minutes, with some people staying for up to 20 minutes. We categorize these intervals heuristically based on the user's intent ranging from answering one question to long engagement:

***Interaction attempts (IA)*:** attempts lasting less than 30s and consisting of people being enticed to approach and try out Roam-io before losing interest and leaving the interaction. Mostly, these users answered 1 or 2 questions.

***Short interactions (SI)*:** short interactions typically lasting between 30s and 1 minute. For these interactions, we observed users that approached and used Roam-io for a smaller number of questions, but lost interest and left. Note that answering a question only lasts 10 second, meaning that people could still answer up to 6 questions in SI.

***Long interactions (LI)*:** long interactions lasting between 1 and 5 minutes and constituting individuals or groups of people who were committed to answering a substantial number of questions. In these cases, we observed groups talking together to work out answers, as well as individuals who spent considerable time answering questions.

***Sustained interactions (SUS)*:** sustained interactions lasting more than 5 minutes. Although these were less frequent, they demonstrated people's long-term commitment, answering most if not all the questions presented by Roam-io. Often, several keyboard answers were given during these sustained interactions by either one or multiple users.

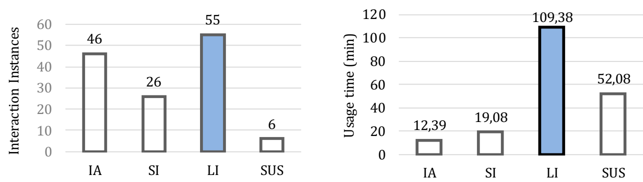

Figure 5. Instances and usage time for the 5 interaction duration categories (IA: <30s, SI: <1m, LI: <5m and SUS: >5m).

Answering Questions

Figure 5 shows the four interaction types and time spent. The data shows that most questions were answered by people who spent more than 1 minute interacting with Roam-io, indicating that these answers were provided by people who committed themselves to answering the questions.

Response Times per Question Category

The logs revealed that there were significant differences in the time taken to respond to factual, contextual and data questions. Factual questions were answered the quickest, with an average time of 5.5s ($\sigma = 2.7$s). Contextual questions took a bit longer to answer with an average of 8.9s ($\sigma = 5.8$s). When answering these questions, people were observed looking around, e.g., to assess how busy or noisy the location was. The data visualisation questions took the longest to answer, with an average of 11.8s ($\sigma = 6.7$s). Further analysis (using a Kruskal-Wallis test, with Dunn's Multiple Comparison post-hoc test) showed that the difference in response times between the three types of questions was statistically significant ($p < 0.0001$), confirming that the difference in time needed to answer items of the three question categories generalises across the whole data set.

Types of Answers and Interpretation of Data Visualisations

A total of 1035 answers were provided by the passers-by. Of these, 66% were answered in English while 34% answered in Portuguese. The three types of questions received roughly the same number of answers: 346 contextual answers, 345 data answers, and 344 factual answers. The number of answers submitted for the data questions was 345, of which about 10% were new interpretations of the data entered by keyboard. Overall, all questions received a consensus across the three options (2 predefined answers and the free-form 'other' option), with an average consensus rate of 53.8% ($\sigma = 11.7\%$) indicating that people clearly selected one option over the other two. The keyboard input was also used in several instances to add new interpretations, or to explicitly state that the user did not know what the answer was.

106 free-form answers were submitted using the keyboard. Of these, 73 were in response to a contextual question and 33 were responses to data questions. Passers-by used the free-form input to provide more in-depth contextual information (their own observations) but also interpretations of the data visualisations, that the researchers and tourist board had not considered. For example, when asked why a central area of Funchal was so busy early on a Saturday morning, one passer-by typed in that it was the time of the arrival of the "*bolo do caco*" - a traditional Portuguese bread that is sold then at many stalls. It was also found that the contextual answer provided through Roam-io revealed an error in the raw tracking data, as many people indicated that data was wrong. E.g., for the airport measurements, passers-by indicated a different amount from what was measured, and we found that the sensor was incorrectly calibrated, thus, highlighting an error in the raw data collected by Beanstalk.

Data Results from User Interpretation

345 data answers were provided, of which 33 were new insights entered through the keyboard. Figure 6 (top) shows the answers given to the data question that asked, *"Why are there so many people in this area around 4AM in the morning?"* alongside the visualization for one day. The majority or responses selected that people were returning from a nearby nightclub. Other answers given through the free-form input included "*people live there"* or "*people are looking for free 'play'*". Figure 6 (middle) shows the percentage of answers given to the question "*why are there more people at the airport on Mondays?".* People answered that there are more tourists that fly to the island on Mondays, while one third suggested that there are more business flights on that day. Figure 6 (bottom) shows the passers-by's responses to the question, "*why does it get busier in the area from May onwards?"* There was a clear consensus among the answers given that there were more events happening in May, while a small number suggested a change of weather. In some instances, people did not directly answer the posed question but instead provided related information from which an answer could be inferred, e.g., when asked *"do you come here often?",* one person typed, "*I do not live in Madeira*", from which the answer could be inferred as a *no* and in addition deduce they were not local. Some answers were quite humorous, e.g., when asked *"why is the airport so quiet after lunch?",* one person typed "*pilots on toilets*", while another suggested "*planes need to recharge*". We observed how many people were prepared to attempt to interpret the data visualisations of which some were quite revealing – including suggestions not considered by the tourist board. These

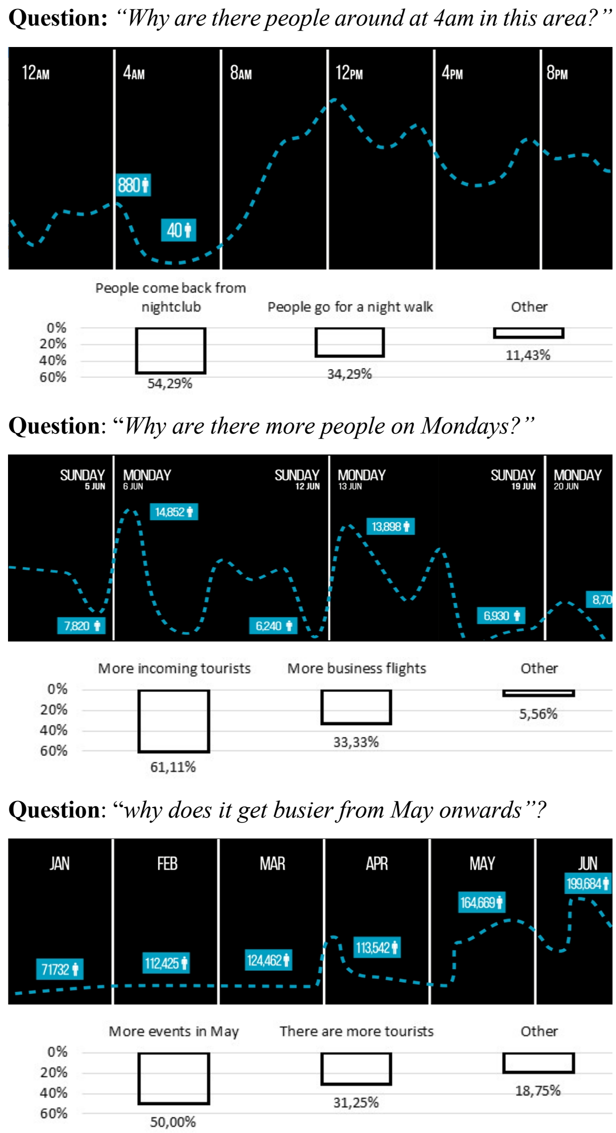

Figure 6. A summary of the answers to three questions alongside the visualization presented via Roam-io.

had to do with people attending certain bars, nightclubs, youngster hanging out on the beach, local boat companies with long waiting lines, or delayed arrival times of the cruise ships. Although the above examples (see Fig. 6) were fairly obvious, they demonstrated that it was an effective way of getting passers-by to think about what was happening in different places on the island. Furthermore, the results were informative to the tourist board. For example, it helped them develop more insightful and better-designed questions about the impact of tourism on the island.

Contextual Data Results

We were also interested in the extent to which the contextual data (observations by passers-by) were useful for understanding more about the people count data collected from the Beanstalk infrastructure. By matching the user-generated data with the count estimation from the Wi-Fi data, we were able to analyse the relations between the estimations and perceptions of people. Figure 7 shows, for one day, the answers provided by passers-by for the contextual questions, including how they described where they were in terms of the mood, noisiness, busyness, and who they were with, against the people counts provided by the Beanstalk infrastructure. On this day, the perceived mood and busyness changed greatly depending on the time of day. Busy and noisy periods were described by the users at the same time the system detected more people. Passers-by also described the mood being largely happy when the people count from Beanstalk was lowest. When the people count from Beanstalk was lowest, passers-by described the mood as being largely happy, but quiet and boring. In the morning, passers-by described the space as 'very busy' but 'quiet', while after lunch (2pm), people felt 'bored' and things were 'quiet' and 'not so busy'.

Mood	Happy	Happy	Angy	Happy	Happy		Bored			Happy
Noise	Quiet	Quiet	Quiet	Quiet	Very Noisy	Quiet	Quiet	First class	Not bad	Quiet
Busyness	Very busy	Very busy	Very busy		Very busy	Not so busy		Not so busy		
People	Alone	Family	Family	Family	Family		Family	Family		

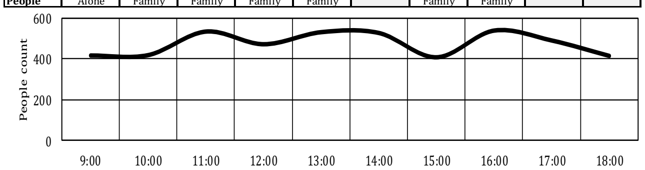

Figure 7. Comparing a day of people counts collected from the WiFi hotspots estimating number of people present with the perceptions provided by passers-by interacting with Roam-io.

Figure 8 shows explicitly the relation between the people count and the number of contextual answers given by the passers-by. Figure 8A shows the quantitative data: the red line shows the daily people count numbers from the Wi-Fi hotspots, the yellow and green lines show the number of answers for each day (yellow is the raw number, green is the scaled number to show the relation to Wi-Fi counts). The blocks in Figure 8B show instances of qualitative data collected through Roam-io. These include whether the user was a frequent visitor, what kind of people the user observed around them, the perceived busyness, how noisy they felt it was in the environment, the estimated age of the people around them, or the mood of the public at that time. These exemplified how Roam-io can construct a qualitative overview of what is happening in a space at a certain time.

Summary of Results

User Participation – Roam-io was able to attract >200 participants who spent between 1 and 20 minutes interacting with the system individually or in a group.

Answering Questions – More than 1000 answers were provided on facts, demographics, data, and contextual information. 106 free-form answers were entered via keyboard.

Data Results – Passers-by confirmed existing data interpretations and, in some case, suggested new ones.

Contextual Data – More than 300 observations on perceived busyness, type of people, noise, age and mood were collected through the Roam-io interface.

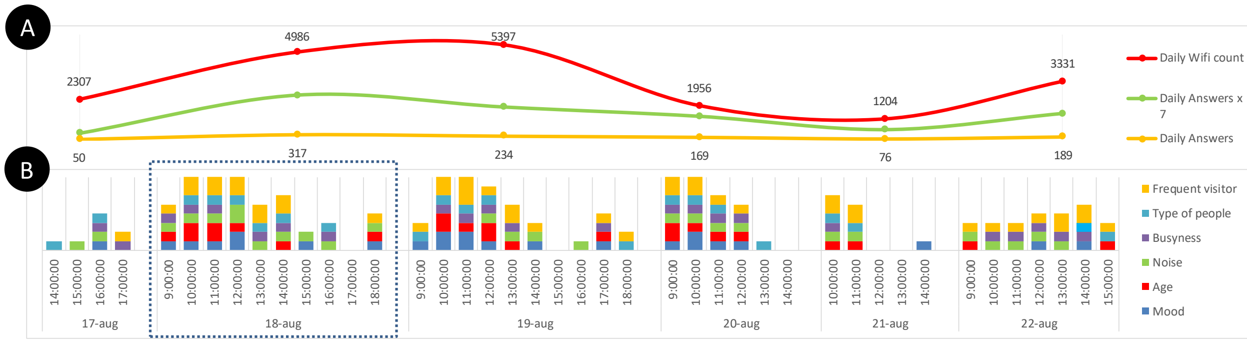

Figure 8. Overview of the hybrid data set. A shows the numbers of WIFI count and answers (real values and scaled). B summarizes the qualitative data (such as noise, age, or busyness) collected with Roam-io. Each block is one data point.

DISCUSSION

In this paper, we explored the design of a novel physical data installation aimed at eliciting public interaction with data. We demonstrated the potential of combining quantitative sensor data with qualitative user input. By including people in the data collection and interpretation loop, our study showed how a participatory process, that invites the public to not only have access to sensed data collected about themselves but also contribute to, enriched their interpretation of the data. Overall, our study demonstrates that the public is *willing* and *able* to spend a significant amount of time interacting with a public data installation to contribute new contextual data, by answering questions about data presented to them in the form of simple visualisations.

The Role of a Physical Data Installation

From our study, we conclude that Roam-io exhibited a strong level of 'playful' anthropomorphism and interactivity. Its design (i) overcame interaction blindness [25] to attract a wide range of different user (ages, backgrounds), and (ii) afforded a 'walk-up' and use experience where people could answer questions without the need for any learning. Many of the observed participants, such as elderly people, families or younger children, are unlikely to be the ones who would download a specialist tourism app or go to a website to answer questions. Through an easy to use installation, people can decide in situ if they want to explore the system and use it, or simply walk away. Furthermore, in contrast to apps or websites, such public interfaces elicit group dynamics and reflections [25]. In line with previous work [11, 15], we argue that a physical installation can attract a more diverse user group. During our study, we observed that most answers were contributed by people who spent at least a few minutes using the system (when answering one question takes about 10 secs), indicating a strong level of engagement. These long interactions suggest a willingness by a diversity of the public to interact with questions about data and their surroundings.

Challenges of Hybrid Data Collection through Questions

Two main challenges when designing a hybrid data collection approach are (i) how to ask the right questions about a given topic or data set, and (ii) asking the right amount of questions so that users do not disengage. The questions and answers used in Roam-io were constructed around three data collection goals: demographic data, contextual data and interpretations of spatiotemporal data about people flows. Specifically, for the contextual goals, we focused on interpretations like mood, busyness, noise and type of people in the space. These questions have a temporal character and can be connected to other data sources that vary over time. But other categories of questions could also be chosen to explore other elements (e.g., safety or gender) depending on the location and purpose. Because of the high number of questions, we received about ±30 answers per question. This was sufficient for most of the factual, demographic and data questions as the numbers provided a convincing consensus or result. However, the temporal property of some of the contextual questions, where people describe perceptions about the environment at a certain point in time, lead to fewer responses within certain time windows. Although for many qualitative descriptions of the environment (such as busyness or perceived noise) a low number of answers is sufficient to build an accurate picture, there are cases where a larger number of answers for each question might be needed to understand the dynamics in the space. There is, thus, a trade-off between the type of question, and the number of answers needed to validate the quality of the resulting data and interpretations. This can lead to either a focused dense data set with many qualitative answers for few questions, versus a broader data set with a wide range of data points and observations.

Accuracy of Human-Contributed Data

A question our study raises is how accurate are the answers that people provide about what they see, or think is happening? In our study, the contextual answers provided by passers-by correlated with the levels of people counted using Beanstalk. Most observations and reflections by people, thus, matched our ground truth. The findings from our study even showed how sometimes the general public was able to provide new insights that could lead to questioning the validity and accuracy of sensed data. e.g., passers-by made better guesses about the number of people arriving at the airport, than the raw data itself. However, as with any user-generated content platform, there are challenges related to how to verify quality and correctness [7]. For the data presented in this study, we manually verified the contextual environmental data against the video material. This allowed us to assess the contextual answers against ground truth. We further used the degree of correctness of the factual questions as an indicator for the overall quality of the data set. This suggests that there is an opportunity to build validation or verification mechanisms and tools, similar to those from the Crowdsourcing [29] or user-generated content [18] communities, into the data collection installation to explore ways to automate this process. Roam-io could, for example, include validation questions where answers from the public are presented back to other passers-by for verification. For free-form answers, techniques such as NLP could be used to analyse user input.

Understanding and Contributing Data

Although many of the responses provided for the data questions suggested most people understood the question, it is less clear to what degree they understood or were intrigued about the data represented in the visualisations. The relatively low number of open-ended answers provided to explain the data visualizations could suggest that in many cases people agreed with the pre-defined answers. However, for some data questions that require a deeper understanding it might be the case that what a passer-by can interpret and suggest about a set of data visualisations which they see for the first time, is limited. Our findings showed how many of the passers-by did not explicitly elaborate or explain their interpretations of the data. Although they answered the data questions, it is likely that many did not necessarily perceive the questions to be "about data". However, it should also be noted that it may only require a few new insights that can prove to be very useful for the local community/authority. Hence, it is not necessary that a large number of data interpretations are elicited; maybe a few tourists, locals or others can provide inside information for a particular event, playing a valuable role, as proposed in forensic data science [13].

Usefulness of Hybrid Data Set

Besides being of interest to the general public in terms of learning more about who visits where on the island, this data set can also help local authorities and tourist boards in their monitoring of people visiting places and policy-making strategies. Hence, we argue that combining the two forms of data provides an alternative and arguably enriched account for local authorities and other communities involved in the planning and management of urban spaces. Furthermore, by sharing data openly and publicly in the form of a 'commons', it could increase transparency, ensuring that everyone who contributed could also access, use and share the data. Although in this particular study Roam-io was integrated with the Beanstalk infrastructure and deployed to collect data about the spaces around the tourist office, the findings suggest that this kind of hybrid sensing approach could be used with other datasets, locations and spaces, using other categories of questions, answers and visualizations.

LIMITATIONS AND FUTURE WORK

Our study demonstrates the strong potential for hybrid data sets collected through physical data installation, but also points to a range of questions for future work:

Designing for Participatory Data Collection

Although, as mentioned, there are ways to verify the accurateness and appropriateness of human-contributed data, there are more fundamental research questions that need to be addressed concerning how to design for participatory data collection mechanisms. Specifically issues around human error, shared redaction of new data, or an advanced contribution-based Q&A system could help construct dynamic participatory data collections.

Structured vs Unstructured Interaction

While our 3-button physical interface approach was simple, it constrained the complexity of the user interaction leading to new insights. More semi-structured approaches with, e.g., voice-based interaction could make the free-form answers richer and easier to enter. Future research could compare voice and touch interfaces to determine which are most used and natural when used in a public setting.

Connecting Nodes

Our study focused on one particular domain – tourism – which directly influenced the interactions, group dynamics, and resulting data sets. However, we argue that the approach could be scaled up with a 'connected' deployment where data is directly compared and shared across sites about the entire island (in contrast to one area).

Public interaction with Data

Our study demonstrated that people are willing to contribute their insights about data, but more work is needed to examine to what degree people understand data, and how this understanding affects the quality of the hybrid data set.

CONCLUSION

Automated data collected from urban IoT sensing infrastructures can be enriched by collecting qualitative data contributed by people answering specific kinds of questions in situ. We have shown how designing and deploying a new type of voluntary public data installation provides a richer picture of public spaces that can help explain and account for behaviour – in this case the flow of tourists on an island. Our 'in the wild' study demonstrated how Roam-io engaged the public at large in answering a range of questions while also trying to interpret data visualisations. The resulting hybrid data set was able to provide new information and insights for the stakeholders. Enabling the public to answer contextually relevant answers in combination with suggesting interpretations of data visualisations for a given phenomenon, has potential for enabling the public to perceive and understand data about themselves and the environment while also providing new insights that can inform the management of public services.

ACKNOWLEDGEMENTS

This work was funded by the ICRI Sustainable Connected Cities Institute. We wish to acknowledge our fellow researchers Dina and Mara Dionísio and the support of LARSyS (Projeto Estratégico LA 9 - UID/EEA/50009/2013) and MITIExcell (M1420-01-0145-FEDER-000002). Thanks to our anonymous reviewers for their feedback and helpful suggestions for the improvement of the manuscript.

REFERENCES

1. Mara Balestrini, Tomas Diez, Paul Marshall, Alex Gluhak, and Yvonne Rogers. 2015. IoT Community Technologies: Leaving Users to Their Own Devices or Orchestration of Engagement? Endorsed Transactions on Internet of Things 15, 1.
2. Harry Brignull and Yvonne Rogers. 2003. Enticing people to interact with large public displays in public spaces. In Proceedings of INTERACT, 17–24.
3. Stuart K. Card, Jock D. Mackinlay, and Ben Shneiderman (eds.). 1999. Readings in Information Visualization: Using Vision to Think. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA.
4. Amir Chaudhry, Jon Crowcroft, Heidi Howard, Amir Chaudhry, Jon Crowcroft, Anil Madhavapeddy, and Richard Mortier. 2015. Personal Data: Thinking Inside the Box.
5. Sandy Claes, Karin Slegers, and Andrew Vande Moere. 2016. The Bicycle Barometer: Design and Evaluation of Cyclist-Specific Interaction for a Public Display. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI ’16), 5824–5835.
6. Tomas Diez and Alex Posada. 2013. The Fab and the Smart City: The Use of Machines and Technology for the City Production by Its Citizens. In Proceedings of the 7th International Conference on Tangible, Embedded and Embodied Interaction (TEI ’13), 447–454.
7. José van Dijck. 2009. Users like you? Theorizing agency in user-generated content. Media, Culture & Society 31, 1: 41–58.
8. Daniel C. Edelson, Douglas N. Gordin, and Roy D. Pea. 1999. Addressing the Challenges of Inquiry-Based Learning Through Technology and Curriculum Design. Journal of the Learning Sciences 8, 3–4: 391–450. 5
9. Jon Froehlich, Tawanna Dillahunt, Predrag Klasnja, Jennifer Mankoff, Sunny Consolvo, Beverly Harrison, and James A. Landay. "UbiGreen: investigating a mobile tool for tracking and supporting green transportation habits." In Proceedings of the sigchi conference on human factors in computing systems, pp. 1043-1052. ACM, 2009.
10. Jon Froehlich, Leah Findlater, and James Landay. 2010. The Design of Eco-feedback Technology. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI ’10), 1999–2008.
11. Sarah Gallacher, Connie Golsteijn, Yvonne Rogers, Licia Capra, and Sophie Eustace. 2016. SmallTalk: Using Tangible Interactions to Gather Feedback from Children. In Proceedings of the TEI ’16: Tenth International Conference on Tangible, Embedded, and Embodied Interaction (TEI ’16), 253–261.
12. Sarah Gallacher, Jenny O'Connor, Jon Bird, Yvonne Rogers, Licia Capra, Daniel Harrison, and Paul Marshall. "Mood squeezer: lightening up the workplace through playful and lightweight interactions." In Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, pp. 891-902. ACM, 201
13. Amir Goldberg. "In defense of forensic social science." Big Data & Society 2, no. 2 (2015): 2053951715601145.
14. Connie Golsteijn, Sarah Gallacher, Licia Capra, and Yvonne Rogers. 2015. Sens-Us: Imagining a Citizen-led, Dynamic, and Localized Census. In Proceedings of the 2015 British HCI Conference (British HCI ’15), 319–320.
15. Connie Golsteijn, Sarah Gallacher, Lisa Koeman, Lorna Wall, Sami Andberg, Yvonne Rogers, and Licia Capra. 2015. VoxBox: a Tangible Machine that Gathers Opinions from the Public at Events. In To appear in the Proceedings of the 9th International Conference on Tangible and Embedded Interaction 2015.
16. Jorge Goncalves, Simo Hosio, Vassilis Kostakos, Maja Vukovic, and Shin ’ichi Konomi. 2015. Workshop on Mobile and Situated Crowdsourcing. In Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers (UbiComp/ISWC’15 Adjunct), 1339–1342.
17. Jorge Goncalves, Hannu Kukka, Iván Sánchez, and Vassilis Kostakos. 2016. Crowdsourcing Queue Estimations in Situ. In Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing (CSCW ’16), 1040–1051.
18. Mordechai (Muki) Haklay and Patrick Weber. 2008. OpenStreetMap: User-Generated Street Maps. IEEE Pervasive Computing 7, 12–18.
19. Jeffrey Heer, Stuart K. Card, and James A. Landay. 2005. Prefuse: A Toolkit for Interactive Information Visualization. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI ’05), 421–430.
20. Kurtis Heimerl, Brian Gawalt, Kuang Chen, Tapan Parikh, and Björn Hartmann. 2012. CommunitySourcing: Engaging Local Crowds to Perform Expert Work via Physical Kiosks. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI ’12), 1539–1548.
21. Jeremy M. Heiner, Scott E. Hudson, and Kenichiro Tanaka. 1999. The Information Percolator: Ambient Information Display in a Decorative Object. In Proceedings of the 12th Annual ACM Symposium on User Interface Software and Technology (UIST ’99), 141–148.

22. Florian Heller and Jan Borchers. 2011. PowerSocket: Towards On-outlet Power Consumption Visualization. In CHI '11 Extended Abstracts on Human Factors in Computing Systems (CHI EA '11), 1981–1986.
23. Simo Hosio, Jorge Goncalves, Vili Lehdonvirta, Denzil Ferreira, and Vassilis Kostakos. 2014. Situated Crowdsourcing Using a Market Model. In Proceedings of the 27th Annual ACM Symposium on User Interface Software and Technology (UIST '14), 55–64.
24. Steven Houben, Connie Golsteijn, Sarah Gallacher, Rose Johnson, Saskia Bakker, Nicolai Marquardt, Licia Capra, and Yvonne Rogers. "Physikit: Data engagement through physical ambient visualizations in the home." In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems, pp. 1608-1619. ACM, 2016.
25. Steven Houben and Christian Weichel. 2013. Overcoming Interaction Blindness through Curiosity Objects. In CHI Extended Abstracts, 1539–1544.
26. Yvonne Jansen, Pierre Dragicevic, Petra Isenberg, Jason Alexander, Abhijit Karnik, Johan Kildal, Sriram Subramanian, and Kasper Hornbæk. "Opportunities and challenges for data physicalization." In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, pp. 3227-3236. ACM, 2015.
27. Hans-Christian Jetter, Sarah Gallacher, Vaiva Kalnikaite, and Yvonne Rogers. "Suspicious boxes and friendly aliens: exploring the physical design of urban sensing technology." In Proceedings of the First International Conference on IoT in Urban Space, pp. 68-73. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), 2014.
28. Wendy Ju and David Sirkin. 2010. Animate Objects: How Physical Motion Encourages Public Interaction. In Persuasive Technology, Thomas Ploug, Per Hasle and Harri Oinas-Kukkonen (eds.). Springer Berlin Heidelberg, 40–51.
29. Aniket Kittur, Ed H. Chi, and Bongwon Suh. 2008. Crowdsourcing User Studies with Mechanical Turk. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '08), 453–456.
30. Lisa Koeman, Vaiva Kalnikaité, and Yvonne Rogers. 2015. "Everyone Is Talking About It!": A Distributed Approach to Urban Voting Technology and Visualisations. In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems (CHI '15), 3127–3136.
31. Lisa Koeman, Vaiva Kalnikait\.e, Yvonne Rogers, and Jon Bird. 2014. What Chalk and Tape Can Tell Us: Lessons Learnt for Next Generation Urban Displays. In Proceedings of The International Symposium on Pervasive Displays (PerDis '14), 130:130–130:135.
32. George Loewenstein. 1994. The psychology of curiosity: a review and reinterp. Psychological Bulletin 116, 1: 75–98.
33. Giorgia Lupi, 2017, Data Humanism, the Revolution will be Visualized. Published online at https://medium.com/@giorgialupi/data-humanism-the-revolution-will-be-visualized-31486a30dbfb#.bh07dh315. Retrieved Feb. 2017.
34. Mateusz Mikusz, Steven Houben, Nigel Davies, Klaus Moessner, and Marc Langheinrich. "Raising awareness of IoT sensor deployments." (2018): 9-8.
35. Donald McMillan, Arvid Engström, Airi Lampinen, and Barry Brown. 2016. Data and the City. In Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems (CHI '16), 2933–2944.
36. Todd Miller and John Stasko. 2001. The InfoCanvas: Information Conveyance Through Personalized, Expressive Art. In CHI '01 Extended Abstracts on Human Factors in Computing Systems (CHI EA '01), 305–306.
37. Thomas Mirlacher, Roland Buchner, Florian Förster, Astrid Weiss, and Manfred Tscheligi. 2009. Ambient Rabbits Likeability of Embodied Ambient Displays. In Ambient Intelligence, Manfred Tscheligi, Boris de Ruyter, Panos Markopoulus, et al. (eds.). Springer Berlin Heidelberg, 164–173.
38. A. V. Moere. 2008. Beyond the Tyranny of the Pixel: Exploring the Physicality of Information Visualization. In 2008 12th International Conference Information Visualisation, 469–474.
39. Andrew Vande Moere, Martin Tomitsch, Monika Hoinkis, Elmar Trefz, Silje Johansen, and Allison Jones. 2011. Comparative Feedback in the Street: Exposing Residential Energy Consumption on House Facades. In Human-Computer Interaction – INTERACT 2011, Pedro Campos, Nicholas Graham, Joaquim Jorge, Nuno Nunes, Philippe Palanque and Marco Winckler (eds.). Springer Berlin Heidelberg, 470–488.
40. Richard Mortier, Hamed Haddadi, Tristan Henderson, Derek McAuley, and Jon Crowcroft. 2014. Human-Data Interaction: The Human Face of the Data-Driven Society. Social Science Research Network, Rochester, NY. Retrieved August 5, 2016 from
41. Jörg Müller, Florian Alt, Daniel Michelis, and Albrecht Schmidt. 2010. Requirements and Design Space for Interactive Public Displays. In Proceedings of the 18th ACM International Conference on Multimedia (MM '10), 1285–1294.
42. Zachary Pousman and John Stasko. 2006. A Taxonomy of Ambient Information Systems: Four Patterns of Design. In Proceedings of the Working Conference on Advanced Visual Interfaces (AVI '06), 67–74.

43. Z. Pousman, J. Stasko, and M. Mateas. 2007. Casual Information Visualization: Depictions of Data in Everyday Life. IEEE Transactions on Visualization and Computer Graphics 13, 6: 1145–1152.

44. Filipe Quintal, Clinton Jorge, Valentina Nisi, and Nuno Nunes. 2016. What-I-See: A Tangible Visualization of Energy. In Proceedings of the International Working Conference on Advanced Visual Interfaces, 120–127. Retrieved August 4, 2016 from

45. J. Rodgers and L. Bartram. 2011. Exploring Ambient and Artistic Visualization for Residential Energy Use Feedback. IEEE Transactions on Visualization and Computer Graphics 17, 12: 2489–2497.

46. Kim Sauvé, Steven Houben, Nicolai Marquardt, Saskia Bakker, Bart Hengeveld, Sarah Gallacher, and Yvonne Rogers. "LOOP: A physical artifact to facilitate seamless interaction with personal data in everyday life." In Proceedings of the 2017 ACM Conference Companion Publication on Designing Interactive Systems, pp. 285-288. ACM, 2017.

47. Ronald Schroeter, Marcus Foth, and Christine Satchell. 2012. People, Content, Location: Sweet Spotting Urban Screens for Situated Engagement. In Proceedings of the Designing Interactive Systems Conference (DIS '12), 146–155.

48. Vassilios Stathopoulos, Veronica Zamora-Gutierrez, Kate E. Jones, and Mark Girolami. "Bat echolocation call identification for biodiversity monitoring: a probabilistic approach." Journal of the Royal Statistical Society: Series C (Applied Statistics) (2017).

49. Alex S. Taylor, Siân Lindley, Tim Regan, David Sweeney, Vasillis Vlachokyriakos, Lillie Grainger, and Jessica Lingel. "Data-in-place: Thinking through the relations between data and community." In Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems, pp. 2863-2872. ACM, 2015.

50. Woody Turner, Sacha Spector, Ned Gardiner, Matthew Fladeland, Eleanor Sterling, and Marc Steininger. "Remote sensing for biodiversity science and conservation." Trends in ecology & evolution 18, no. 6 (2003): 306-314.

51. Nina Valkanova, Robert Walter, Andrew Vande Moere, and Jörg Müller. 2014. MyPosition: Sparking Civic Discourse by a Public Interactive Poll Visualization. In Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work & Social Computing (CSCW '14), 1323–1332.

52. Jon Whittle, William Simm, Maria-Angela Ferrario, Katerina Frankova, Laurence Garton, Andrée Woodcock, Jane Binner, and Aom Ariyatum. "VoiceYourView: collecting real-time feedback on the design of public spaces." In Proceedings of the 12th ACM international conference on Ubiquitous computing, pp. 41-50. ACM, 2010.

53. A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi. 2014. Internet of Things for Smart Cities. IEEE Internet of Things Journal 1, 1: 22–32.

54. Urban Observatory. Retrieved August 4, 2016 from http://www.urbanobservatory.org/

55. Tracking platform – Beanstalk. Retrieved August 8, 2016 from http://beanstalk.m-iti.org/category/tracking-platform/