

# Quantified Workplace: Opportunities and Challenges

Akhil Mathur, Marc Van den Broeck, Geert Vanderhulst, Afra Mashhadi, Fahim Kawsar  
Bell Laboratories, Alcatel-Lucent  
firstname.lastname@alcatel-lucent.com

## ABSTRACT

We present the design of a Quantified Workplace system which has been deployed in two European offices of a research organization since October 2014. So far, the system has collected more than 680,000 samples of various environment metrics in the workplace (e.g., noise, air quality, ...) and 57,340 data points on the indoor location of employees. In addition, the system has received 7504 participatory inputs from the users about their moods and physical activities in the workplace. We present the system and its different services, discuss our initial findings on the user engagement, and highlight the challenges of device heterogeneity, privacy and trust. We conclude by discussing potential applications of workplace quantification that can be developed using the data we are collecting.

## Categories and Subject Descriptors

H.4.m [Information Systems Applications]: Miscellaneous

## Keywords

Quantified Workplace, Physical Analytics, Participatory Sensing

## 1. INTRODUCTION

The collective behavior of employees within an organization shapes the organization culture and has proven to play a critical role in an organization's success [4, 5]. Significant effort has been put into understanding how the collective behavior patterns – energy levels, unspoken and implicit signaling and activity dynamics across employees – can directly affect employees' productivity [2, 9, 10]. Besides, past research has found that environmental factors such as noise, temperature, color also influence the productivity of the teams in an organization [6–8]. These past studies clearly demonstrate that by quantifying collective behavior using various metrics, a reliable and illuminating picture of the hidden workplace dynamics can be uncovered, which in turn can be converted into actionable insights.

However, in a real-world setting, the aforementioned vision runs into several practical challenges. As found by [1, 12], data collec-

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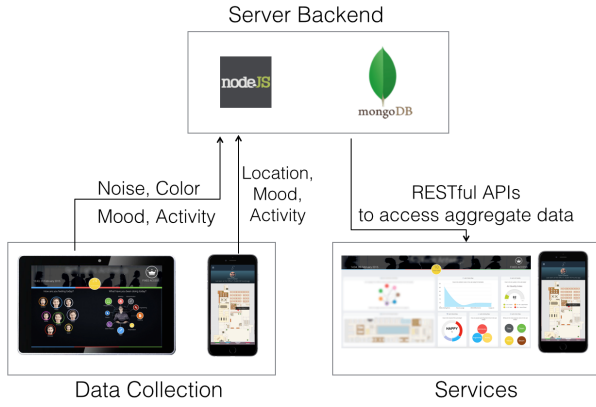
tion in the workplace raises *privacy concerns* among employees. Further, these privacy concerns could adversely affect the adoption of any sensing technology by the employees, eventually resulting in the generation of lesser data to produce actionable insights. Another potential obstacle in deploying a real-world Quantified Workplace system is the *mobile device heterogeneity* among employees. Apart from negatively affecting the data collection, it can also cause disillusionment with the system among those employees who do not have compatible software on their phone to run the Quantified Workplace application.

In this paper, we present a Quantified Workplace system and report about our initial experience with deploying the system in two European offices of a research organization. We provide a description of the different workplace metrics that we captured through public terminals as well as personal devices, and the associated data services provided to the users. We discuss approaches for addressing privacy concerns of employees with physical quantification in the workplace, and also highlight challenges in implementing location-based services in the workplace owing to the device heterogeneity. The paper concludes by suggesting potential application areas for workplace quantification such as *People analytics* and *Environment Management*. Overall, this paper raises several questions on designing real-world workplace quantification systems, which we believe will result in interesting discussions during the workshop.

## 2. RELATED WORK

In the past, researchers have explored different ways of quantifying physical activities in the workplace. Olguin et al. [9] looked at using wearable electronic badges for measuring face-to-face interaction, conversations and physical proximity among employees. Brown et al. took a similar approach of using wearable badges to track serendipitous interactions in a workplace and evaluate the effect of worker's cultural backgrounds on interaction diversity [2], and to study how the physical design of workplaces combines with organizational structure to shape contact patterns [3]. These works, however, were primarily short research studies focusing on measuring the impact of a particular metric in the workplace – there was little discussion on how these technologies will be adopted in a real workplace. Our work is focused on exploring how to design holistic Quantified Workplace systems that would be acceptable to different stakeholders (e.g., employees, management) in the workplace, and also result in sustained usage beyond a research study. Further, we also focus on using commodity hardware (e.g., tablets and phones) to collect physical metrics instead of relying on specialised sensing infrastructure.

In the privacy literature, workplace privacy has mainly been examined from an information privacy perspective. In [12], Stone



**Figure 1: System Architecture.**

et. al found that information collected during recruitment such as education, family background and medical history could compromise user privacy. Other works have studied privacy concerns with respect to online activities of employees (e.g. email, OSN) [13, 14]. Recently, motivated by the advancements in ubicomp research, privacy literature has begun examining workplace privacy from the perspective of the physical work environment. In their work aimed at expanded the notion of privacy at workplace, Ball et al. [1] found three major types of privacy concerns among employees: personal information privacy, working environment privacy, and solitude privacy. We aim to add to this knowledge of privacy in physical spaces through the real-world deployment of a Quantified Workplace system and evaluating user responses to it.

### 3. SYSTEM

The physical quantification of a workplace includes quantifying physical metrics of both the work environment and the people in the workplace. As we will describe later, our prototype system collects people metrics such as indoor location, moods, physical activities and environment metrics such as noise, color of clothes and air quality ( $CO_2$  levels).

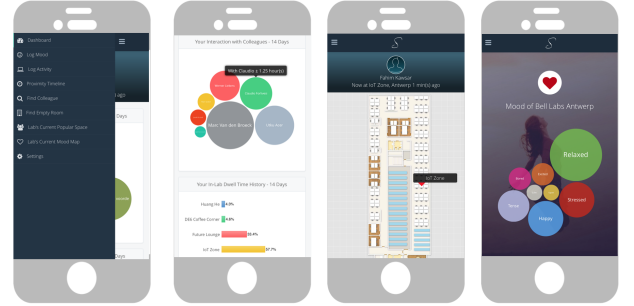
Further, the collection of people-related metrics could be done either passively or in a participatory self-reporting manner. Our goal is to collect data in a manner which is realistic in today's workplaces, does not overburden the user by requiring them to provide too many participatory inputs, and is also acceptable from a privacy perspective. As such, we collect the emotional data (namely, mood) from employees in a participatory manner, whereas location data is collected passively with strict privacy safeguards as we will describe in the coming sections.

Finally, we decided to collect participatory inputs in two different ways: i) a personalized approach where users could provide inputs through a mobile application installed on their phones, and ii) in an anonymous manner through publicly placed input terminals (tablets) in the workplace. By adopting these different approaches of participatory sensing, we want to understand if users have any preference towards a certain way of sensing in the workplace and as to why.

In this section, we describe the design and implementation of our Quantified Workplace system consisting of a mobile application for personalized sensing, a tablet application for anonymous data collection and a dashboard application for visualizing the collected data. Figure 1 shows the high-level architecture of the system.

### 3.1 Data Collection

Our system collects different workplace metrics in two different ways either through personal mobile applications or through public tablet applications. We describe both in the following.



**Figure 2: Mobile application – list of data services, dashboard showing physical interaction history with colleagues and dwell time in different locations, search result of colleague finder, and personal view of mood maps of the office.**

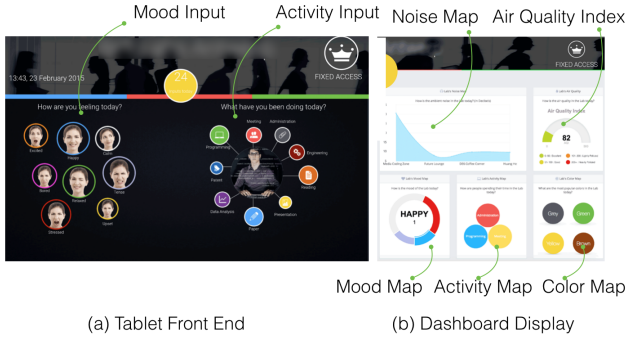
#### 3.1.1 Mobile Application

Our prototype mobile application (Figure 2) is developed both for Android 4+ and iOS 8+ platforms and features a HTML5 front-end. We used the application to collect three metrics:

1. **User Location:** For indoor localisation of employees in the workplace, we employed a WiFi RSSI fingerprinting technique for Android, and an iBeacon-based technique (built on Bluetooth Low Energy) for iOS.<sup>1</sup> The entire workplace was fingerprinted at a 1m x 1m granularity and the fingerprint database was uploaded on the server backend. Every 15 seconds, the application passively scanned for the visible WiFi access points or iBeacons, and recorded their names and RSSI. This data was encoded in a JSON array and sent to the back-end where a localization algorithm based on k-Nearest Neighbors matched it against the pre-populated fingerprint database, and outputted a (x,y) coordinate value with a semantic label for the location.
2. **Self-Reported Mood:** The application collected mood inputs from the users through a self reporting mechanism. Users are presented a set of 8 pre-defined moods to select the one that reflects best their current mood. We sampled the moods based on Russell's Circumplex model of affect [11] from the behavior psychology literature.
3. **Self-Reported Activity:** Activity inputs are also collected through a self reporting approach, and employees can select their primary work-related activity in the day from a pre-populated set of 8 activities<sup>2</sup>, e.g., meetings, writing, programming, administration, etc.

<sup>1</sup>In the Discussion section, we explain the need of two different indoor localisation techniques.

<sup>2</sup>The set of activities selected are handcrafted based on the nature of the workplace, a research organization, in which this study was conducted. As such, they should not be considered either complete or generic.



**Figure 3: Tablet application and dashboard**

### 3.1.2 Tablet Application

Similar to the mobile application, users could input their moods and work activities on the tablets (as illustrated in Figure 3(a)), however, the data was collected in a semi-anonymous manner, i.e., users did not have to identify themselves, but they were asked to input their department name along with each participatory input. In addition, the tablet also passively sensed two ambient metrics:

1. **Noise:** We collected the ambient noise levels around the tablet. We took an audio sample every 15 seconds, which contained the maximum observed audio amplitude near the tablet in a period of 15 seconds.
2. **Color of Clothes:** We collected the color of clothes worn by the employees, and aggregated them to determine a set of dominant colors in the workplace at any instance of time. For capturing color we used the front-facing camera on the tablet. When we detect a significant change in the reading of ambient light sensor of the tablet, it was assumed that a person is walking by the tablet. At that instant, the front camera (passively) took an image of the scene, which was analyzed to find the dominant color in the image while filtering out the background.

Finally, we used one Netatmo weather station<sup>3</sup> to measure the air quality in the office.

## 3.2 Back-end Server

All the collected data (environment metrics and participatory inputs) were sent to a Node.js back-end server. The server stored the data in a MongoDB database and provided RESTful APIs for accessing the aggregated data.

## 3.3 Data Services

Based on the collected data, our system provided both personalized and group-level services to the users. The personalized services were provided through the mobile application, and for collective group-level services, we deployed a large screen dashboard in the workplace which showed visualizations of various workplace metrics as we shall discuss in the coming sections.

### 3.3.1 Personalized Services

These services are primarily designed to offer users personal insights regarding their everyday work behavior, and include the following primary features:

1. **Personal Dashboard:** Users can see a visualization of their co-location history with other colleagues, their dwell time in different locations across the workplace, as well as the history of their self-reported moods and activities over a period of time.
2. **Search a Colleague:** Users can search the physical location of any employee on the mobile application. On receiving a search query for a certain employee, the system looks for the latest (x,y) coordinate for that user in the database. The (x,y) coordinate is then converted into a semantic location inside the office and visualized on the floor plan of the office as shown in Figure 2 along with the associated timestamp.
3. **Find an Empty Meeting Room:** On their mobile application, users could query for the nearest empty meeting room in the building. To implement it, we first manually defined (x,y) bounds for each meeting room in the database. Our room-finding algorithm scans through the list of all meeting rooms, and if any user's (x,y) coordinate falls within the bounding box associated with the room, it is marked as 'Occupied', else it is marked as 'Empty'. The algorithm outputs the meeting room which has the least Euclidean distance with the user's location<sup>4</sup>.

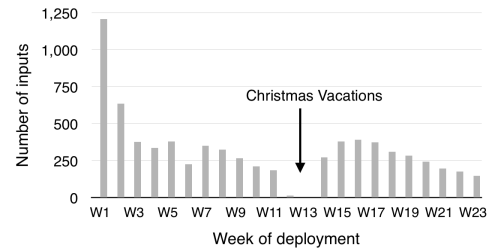
### 3.3.2 Collective Services

The dashboard optimized for large screens (as illustrated in Figure 3(b)) was implemented as a dynamic HTML5 web application and shows various charts representing different workplace metrics in real-time – including a noise map of the office, a mood map showing the aggregate mood of the office, an activity map highlighting different activities of the office, an air quality index, and a color map showing the most popular colors in the office.

## 4. DISCUSSION

In this section, we present our initial observations on the user engagement with the system, and discuss the challenges and future research opportunities in the area of physical quantification in a workplace.

The system is in active deployment at two European offices of a research organization since October 2014, and so far (till March 13, 2015) 46 users have installed the mobile application. To date, the system has collected 535,186 noise, 89,143 color and 57,340 user location values. In addition, it has received 7504 participatory inputs from the users in 104 business days (excluding weekends and vacations).

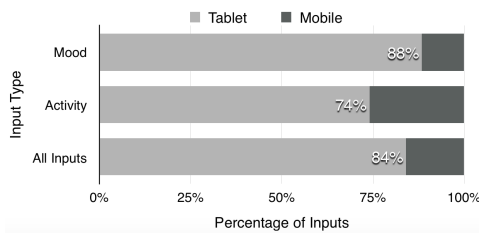


**Figure 4: Distribution of participatory inputs over time.**

<sup>4</sup>This approach has its limitations, in that it does not capture the scenario where a meeting room is occupied by people who do not have our application installed or running.

<sup>3</sup><http://www.netatmo.com/>

Figure 4 shows the distribution of participatory inputs over the course of deployment. In the first week, the system received a total of 1208 inputs – this high number could be attributed to the novelty effect. However, in the subsequent weeks, the usage became more stable (weekly  $\mu = 303, \sigma = 110$ ). Mood inputs comprised 69.5% of all participatory inputs, while the remaining 30.5% were activity inputs. Interestingly, 84% of all participatory inputs were provided on the tablets. Figure 5 shows the distribution of participatory inputs (i.e., mood, activity, all inputs) on tablets and mobile phones. Our data collection exercise is still ongoing and while we analyse the dataset for potential insights about workplace dynamics, we would like to discuss two explicit challenges that we have faced during this data collection process - and we hope they would instigate interesting discussions during the workshop. Both of these challenges are concerned with *Engagement Dynamics* with the Quantified Workplace system.



**Figure 5: Percentage of participatory inputs on tablets and phones.**

## 4.1 Challenge of Device Heterogeneity

In a workplace, different employees may use different mobile phone platforms (e.g., Android, iOS). In a survey with 80 users inside a technology research organization, we found that Android (49%) and iOS (35%) were the most popular mobile platforms, but there were many users (17%) who were using other platforms. Moreover, nearly 31% of the users had an OS version launched before 2012. We believe that the usage of feature phones and older operating systems may be higher in organizations (e.g., retail stores) where technology usage is not the primary focus. This device heterogeneity raises several challenges for a mobile-based Quantified Workplace system. From the initial feedback from our users, we found that they perceive the outputs of the Quantified Workplace system as a reflection on their workplace. As such, if due to platform limitations, some users are unable to install the Quantified Workplace application on their phones and contribute to the quantification process, it will likely reduce the overall trust in the system outputs. In our prototype system, the users could participate in the quantification process even if they do not have a supported phone, i.e., through the public tablets. This design decision ensured that no employee felt excluded from the system and everyone had the opportunity to let their opinion count in the system outputs. In the workshop, we would like to further this discussion about bringing the feeling of inclusion for all stakeholders in collective quantification systems.

Device heterogeneity could also affect the indoor localization services in a workplace. For example, with the iOS, application developers can no longer access the list of WiFi access points in the environment through Apple APIs<sup>5</sup>. As a result, WiFi-based indoor localization has become infeasible on iOS devices, and we

<sup>5</sup><http://stackoverflow.com/questions/9684341/iphone-get-a-list-of-all-ssids-without-private-library>

had to rely on alternate technologies like iBeacons<sup>6</sup>, which requires a very dense deployment to achieve the same level of accuracy as the WiFi localization approaches. As a part of the workshop, we would like to discuss network-centric indoor localization techniques which minimize the reliance on specific mobile platforms.

## 4.2 Challenges of Privacy and Trust

Past research [1] has shown that employees' privacy concerns in a workplace extend into the physical space as well. Revealing one's location to a Quantified Workplace system may be considered a breach of both *work-environment privacy* and *solitude privacy* as defined by Ball et al. [1]. To address the privacy concerns, we have incorporated two privacy-by-design features in the system. Firstly, we only collect user's locations when they are inside the workplace – as soon as a user leaves the workplace, we stop the location tracking and the mobile application displays a confirmation message to the user – “You are out of office now”. This feature is currently implemented by scanning for workplace-specific WiFi access points and iBeacons from the mobile application. That is, if the specific APs or iBeacons are visible, we assume that the user is inside the workplace. Secondly, the application lets users decide how they want to share their location data. They can choose to keep their location private, share it with their team, or share it with the entire workplace, e.g., if they share it only with their team, nobody outside their team can search for the user's location through the application.

Moreover, our results show that 84% of the participatory inputs were provided anonymously through the tablets. Through initial user feedback, we learned that users had concerns inputting moods or activities on a personalized application, as they felt the data could be accessed by the management. This suggests that there is a need to explore anonymous methods of collecting participatory inputs from the users.

In the workshop, we would like to further this discussion on incorporating privacy and anonymity in the design of Quantified Workplace systems.

## 4.3 Applications of Workplace Quantification

The Quantified Workplace system presented in this work opens up a number of different application use case for the future enterprises, where combination of user location and mood, and environment metrics could be used to quantify subtle enterprise dynamics and to yield a reliable and illuminating picture of the enterprise, which in turn can be transformed into objective and actionable insights. Basically, we foresee two broad areas of applications with our Quantified Workplace system.

The first is concerned with *Environment Management* - by looking at people's movement trajectory, dwell time, and proximity with other users we can uncover a detailed view on how enterprise spaces are used by individuals and groups, and where most interaction happens through real-time visualization of the space utilization and interaction heat maps across an organization. On the one hand, these would allow enterprise management to reflect on space management. On the other hand, individuals and teams would be better informed about their environment such that they can increase their task and communication efficiency. For example, one application that could leverage this space intelligence might provide real-time space occupancy information, to enable employees to identify nearest meeting rooms available for impromptu meetings as we have shown in our prototype application. Another application could combine this occupancy information with energy data to of-

<sup>6</sup><https://developer.apple.com/ibeacon/>

fer real estate planners to do better resource management, optimum deployment and predictive maintenance planning.

The second application area is *People Analytics* – by looking at people movement trajectories, dwell time and mood, we can understand the hidden behavioral and communication patterns that exist within an organization. Based on location data, diversity measures for individuals and teams such as how frequently and how much time individuals spend in informal short-lived communication within and across teams can be developed. In addition to characterizing individuals, we can also detect informal communities, group of people who interact closely, and will enable individuals to discover their peers with similar behavioral profiles. For the enterprise management, this would enable them to know their employees better, whereas for individuals this would allow them to discover unknown peers, and help them join groups who share identical behavioral traits to have better homophily, e.g., people who have same extra-curricular interests, or who share identical time or activity routines. People analytics could also provide insights and predictions on how mood varies based on location, co-location, activity, and community membership. The model can be enriched by external data such as weather and inferred data such as traffic conditions while coming to work, etc.

## 5. CONCLUSION

This paper described the design and initial findings from the deployment of a Quantified Workplace system in two European offices of a research organization. Over a period of 24 weeks, we have collected an extensive amount of data on environment and people-related physical metrics in the workplace, which, as a next step, we will analyze to uncover dynamics of interpersonal interactions within the workplace. We have also outlined potential applications related to people and space analytics that could be developed over this dataset. In the workshop, we hope to receive some early feedback on our system, as well as to discuss the potential of opening up our collected dataset for future research in this community.

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