Understanding the Impact of Personal Feedback on Face-to-Face Interactions in the Workplace

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ABSTRACT

Face-to-face interactions have proven to accelerate team and larger organisation success. Many past research has explored the benefits of quantifying face-to-face interactions for informed workplace management, however to date, little attention has been paid to understand how the feedback on interaction behaviour is perceived at a personal scale. In this paper, we offer a reflection on the automated feedback of personal interactions in a workplace through a longitudinal study. We designed and developed a mobile system that captured, modelled, quantified and visualised face-to-face interactions of 47 employees for 4 months in an industrial research lab in Europe. Then we conducted semi-structured interviews with 20 employees to understand their perception and experience with the system. Our findings suggest that the short-term feedback on personal face-to-face interactions was not perceived as an effective external cue to promote self-reflection and that employees desire *long-term* feedback annotated with *actionable attributes*. Our findings provide a set of implications for the designers of future workplace technology and also opens up avenues for future HCI research on promoting self-reflection among employees.

CCS Concepts

•**Human-centered computing** → **Ubiquitous and mobile computing systems and tools;** *Empirical studies in collaborative and social computing; Information visualization;*

Keywords

Face-to-Face Interaction, Personal Feedback, Social Sensing, Workplace Behaviour

1. INTRODUCTION

The collective behaviour of employees shapes the organisation culture and has proven to play a critical role in an organisation's success [22]. Significant efforts have been put into understanding how the collective behaviour patterns – energy levels, face-to-face interactions, unspoken and implicit signals across employees – can directly affect employees' collaboration and productivity.

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Indeed, spontaneous face-to-face interactions between employees (e.g., during coffee breaks) have been shown to improve task completions [38], to foster innovation and creativity by enabling the flow of ideas and inspiring fresh thinking [19, 25, 27, 34, 39].

To this end, a number of recent research studies leveraged pervasive sensing technology to automatically capture face-to-face interactions to further augment our understanding of workplace behaviour. Olguin et al. used wearable badges for measuring face-to-face interactions to understand employees' job satisfaction [33]. Mark et al. investigated social network usage and face-to-face interactions captured through wearable cameras to understand workplace happiness [29]. Brown et al. reported the interaction diversity present in modern multi-cultural organisations by gathering face-to-face contact information [4]. This body of research has primarily aimed at offering *collective* feedback on workplace behaviour. These aggregated feedback have been shown to be useful to the *management* for informed decision making with respect to different organisation dynamics, e.g., high performing team formation, rearrangement of workplace, etc. However to date, little is known as to how this information is perceived by employees themselves at a personal level.

In the field of psychology, literature has long studied the impact of *cues* as a way to help people develop self-knowledge which could help them to adapt their behaviour and attitude in life [2, 13]. Cues are *internal* or *external* events which have a signalling significance to an individual, subsequently affecting their learning and behaviour. For example, a blood pressure monitoring device could act as an *external cue* signalling an individual about their stress-level. Social psychologists have also argued that behavioural feedback cues could affect how we experience ourselves as we sometimes make inference about our own attitude based on observation of external cues derived from our interpersonal behaviour [2]. Furthermore, short-term feedbacks to individuals have been shown to play a critical role in creation of long term habits [10]. In this vein, several works in Computational Social Science have explored the impact of external cues as *immediate* personal feedback on workplace behaviour. Systems such as Chat Circles [37], Second Messenger [9] and Meeting Mediator [26] have recurrently shown that these external cues were successful in influencing engagement and collaboration practices. While these works have investigated the impact of external cues on instant behavioural change (e.g., people's attitude in vocal participation), their impact on non-immediate i.e., *long term* voluntary self-reflection is yet to be studied.

In this paper, we borrow tenets form the social psychology and evaluate an external cue which visualises employees' face-to-face interaction patterns of recent past (*short-term*) in the workplace at a personal scale. We aim to understand how individuals perceive this external cue and whether this could augment their self-knowledge and aid in long term voluntary self-reflection. We thus posit the following research question: *is the short-term feedback on face-to-face interaction pattern at workplace an effective external cue to raise employees self-knowledge about their workplace behaviour?*

To answer this research question, we designed and developed a novel mobile system that captures, models, quantifies and visualises face-to-face interactions. Our system is composed of a mobile application (Android and iOS), a location infrastructure based on Wi-Fi and Bluetooth, and a data processing infrastructure. Collectively, this system first captures location traces left behind by users to detect co-located groups, then applies a classification technique to detect face-to-face interactions and finally visualises these interaction patterns in two distinct feedback that are designed with principles grounded on established literature [34]. We had a unique opportunity to deploy this system in an industrial research lab with 47 employees for a period of 4 months. We gathered application usage data including the volume of interactions and impressions (i.e., the number of views of the visualisation feedback) across all the users. We then interviewed 20 employees to understand their subjective perception and experience with the feedback application. We studied the effectiveness of the face-to-face interaction feedback as an external cue by quantitatively analysing interactions, impressions and the relation between the two and qualitatively assessing the underlying reasoning.

Our results suggest that the majority of the employees did not perceive the short term feedback on face-to-face interaction pattern as an effective external cue, and the feedback did not lead to any subliminal changes in interaction patterns. However, all the employees desired long-term feedback capturing personal interaction patterns in the workplace together with actionable attributes. Taken together these and the rest of our findings uncover factors that most influence perceptions of personal behaviour feedback in the workplace. We thus make the following contributions:

- Design, development and deployment of a cross-platform mobile system that captures, models, quantifies and visualises face-to-face interactions at workplace;
- First of its kind longitudinal study of assessing the effect of quantifying and visualising face-to-face interactions with 47 employees over 4 months period in an industrial research lab, which is further qualified though in-depth semi structured interviews with 20 employees;
- A set of design implications for future workplace technology designers to develop applications and tools that could offer effective external cues to help employees improve their self-knowledge about their behaviour.

2. RELATED WORK

Face-to-face interaction is one of the implicit signals that has been identified as a key contributor in instigating collaborations and creating emotional bonds in modern organisations [19,27]. Our work is aimed at automatic capturing and visualisation of face-to-face interactions, with a belief that this feedback will assist individuals in voluntary reflection of their workplace behaviour and attitude.

2.1 Face-to-Face Interaction

A large body of literature in Computer-Supported Cooperative Work (CSCW) and organisation science has studied multiple aspects of collaboration to uncover what contributes to a successful workplace [6, 15, 21]. Fussell et al. [15] studied the coordination techniques and communication tactics that would help improve team performance. Kraut et al. [28] showed that most successful collaborations happened when people were in the same team. Cummings et al. [6] studied impact of existing relations between dyadic collaborators and showed that prior experiences could help reduce the barriers such as distance and interdisciplinary gap, thus facilitating a successful collaboration. Alternatively, a separate body of works has examined how collaborations are made and the factors that contribute to the formation of face-to-face collaborations. In this vein, Zipf [39] demonstrated that human physical proximity is a key that leads to communication. Other works have also resonated similar findings. For instance, works by Hagstrom and Kraut indicated that informal contact that results from frequent opportunities for communication often leads to collaboration [19,27]. Hua et al. [23] have examined the effect of the workplace layout and topology on collaboration, and presented that the value of shared areas in workplace collaboration lies largely in their ability to accommodate impromptu encounters which can initiate interactions that lead to creative development.

Recently, due to the proliferation of pervasive devices such as smart-phones and wireless badges, a more *quantitative side* of social science has been explored to help understand individuals' behaviour in the workplace. These studies, ranging from uncovering sources of disruption [30,31] to capturing and visualising the mood of the organisation [14,16,29], have taken an important first step in helping management to understand the health of their organisation. Various technology probes have been used in the past to explore face-to-face interactions through active sensing [4,5,11,33]. Olguin et al. [33] have looked at using wearable electronic badges for measuring face-to-face interaction, conversations and physical proximity. Brown et al. took a similar approach by using wearable badges to track serendipitous interactions in a workplace and evaluated the effect of workers' cultural backgrounds on their interaction diversity [4]. Kelley's Bell Stars study in a research organisation showed that the star performers had a diverse network of colleagues that they interacted with [25]. In the same vein of understanding how ideas flow, Pentland [34] showed that patterns of communications are important predictors of a team's success, and that these patterns carry vital information for better people management.

2.2 Social Visualisation

Providing social feedback during face-to-face interactions for the purpose of improving group communication is an active area of research. A number of systems, such as Chat Circles [37], visualisations of turn taking based on audio input [24] have shown that social proxies influence collaboration behaviour. Research has also shown that the visual feedback on communication patterns during group meetings can lead to an *immediate* behavioural change amongst employees [9, 26]. More precisely after a week long usage of the proposed visualisation tool (i.e., the MeetingMediator) the results showed that the participants took action regarding their (lack of) engagement in collaborations. Therefore the overall pattern of interactions amongst individuals had improved dramatically.

These past studies either have been conducted to assess the impact of collective feedback on collaboration at an organisation scale, or they assessed the immediate impact of the visualisations on short term behavioural change. In contrast, in this paper we are interested in taking an individual lens to understand how individuals perceive the visualisation of face-to-face interactions within the workplace as an external cue that could impact *long term* voluntary self-reflection. That is if this cue is effective we expect users to report a raise in their self-knowledge of workplace behaviour, as well as a subliminal change in interaction pattern triggered by the changes in self-knowledge level.

3. SYSTEM DESCRIPTION

Our study is part of a larger multifaceted initiative that aims to uncover the hidden dynamics of modern enterprises grounded upon the past work in the published literature [32, 36]. In this initiative, we gather various space metrics (e.g., spatio-temporal usage, noise, air quality) and people metrics (e.g., location, dwell time, face-to-face interactions) to offer actionable insights on various aspects of an organisation for better space and people management. The system reported here essentially aims at facilitating *personal growth* through expansion on one's self-knowledge of interpersonal behaviour at workplace. Our objective is to assess whether users found the visualisation of their face-to-face interaction as an effective external cue, and whether the feedback helped them to make inferences about their own workplace behaviour. To this end, we capture face-to-face interactions from location traces left behind by users' smartphones and then present them in a mobile application through carefully designed feedback. In the following, we describe the co-location detection engine, underlying interaction detection model, visualisation feedback design and implementation of the system that are used to facilitate this study.

3.1 (Co-)Location Detection Engine

To detect face-to-face interaction, we first need to identify when people are co-located in the workplace. To do so we first need to track an individual's location, and then derive co-location from location traces across individuals. Previous work has shown that people carry their mobile phone at the workplace, 48% of the time within arm-reach and 82% of time within 5 meters [8], making the phone's location a good approximation for users' location in the offices. Grounded upon this rationale, tracking an individual's location essentially means tracking the location of the individual's phone. We build upon this heuristic and track mobile devices using a state-of-the-art localisation technique based on RSS (Received Signal Strength) fingerprinting. Our localisation infrastructure relies on Wi-Fi and Bluetooth (iBeacon)[1] for supporting both Android and iOS devices. Following the standard RSS based localisation methods, the entire workplace was fingerprinted at a 1m x 1m granularity with available Wi-Fi access points and iBeacons, and the fingerprint database was uploaded on the server backend. We leveraged 30+ existing Wi-Fi access points available in our workplace, and 45 iBeacons[2] which we placed at different locations within our office.

On the user end, we developed a smart-phone application both for Android 4+ and iOS 8+ platform that scans for the visible WiFi access points or iBeacons in a background process, and records their names and RSS every 15 seconds. This data is then sent to a backend where a localisation algorithm based on k-Nearest Neighbours matches it against the pre-populated fingerprint database, and outputs a (x,y) coordinate for the location of the mobile device running the application. The locations of multiple mobile devices are then passed through a grouping algorithm that determines co-located devices by modelling temporal variations observed in the locations across a set of devices [36]. This in turn is used to determine co-located individuals.

An important aspect of our system is that it relies on ordinary smartphones and network infrastructure to detect interactions. This means that the participants did not require to wear or carry additional hardware with them. This ensured that the burden on study participants was minimal and less privacy invasive as we did not use any audio or vision sensing. However, our system requires employees to possess a smartphone (running either Android or iOS) equipped with the application that captures location traces in a background process. This means to capture a face-to-face interaction, all the employees engaged in the interaction need to carry smartphones with our application running either in the foreground or in the background.

3.2 Interaction Detection Model

Once we have detected co-location, we need to distinguish face-to-face interaction from simple co-presence. In order to do so, we build a model based on sociology theories [18,35] that reason upon the spatio-temporal properties of face-to-face interactions. More specifically, we leverage two variables that are exhibited in every co-located group engaged in a face-to-face interaction: *duration* and *size*.

The duration (d) represents the amount of time that an interaction lasted, from the time of formation to its decomposition. Duration is a simple metric but a good indicator for differentiating various types of interactions. For example, a co-location with short duration (e.g., less than 10 minutes) could be more representative of spontaneous interactions (i.e., coffee breaks at the workplace and casual chats) than a planned meeting.

The size (N) represents the number of distinct individuals in the interaction. In the domain of social psychology [35], size has been shown to play an important role in determining the nature of groups. That is as the size of the human group grows, the group becomes more depersonalised. Furthermore, as the number of persons in the interaction N increases, the duration of the interaction also increases so to allow the individuals to mutually involve in the communication and cognitive/visual attention [18]. For example, while a two minute interaction for 2 persons could be long enough for a social chat, a 5 person interaction might require more than 5 minutes. This is because as the number of persons increases, the longer it takes for the ceremonial rituals[3] of interactions formation and decomposition [17]. Moreover, it is more likely for the focus of attention (e.g., topic of the conversation) to be shifted when more individuals are part of a verbal interaction, leading to a longer duration. In addition, as the interaction duration(d) increases, the likelihood of an interaction between a large number of individuals decreases. This is because it is less conventional for a large number of people to actively and mutually interact with each other for a long period of time (e.g., 10 people actively interacting for over 2 hours). We can model this property as a sub-linear growth.

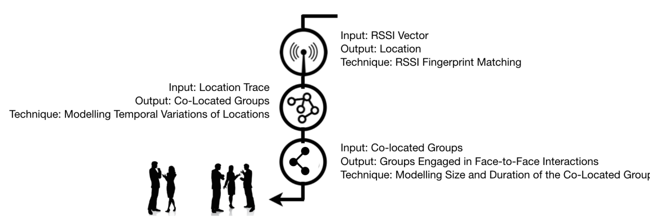


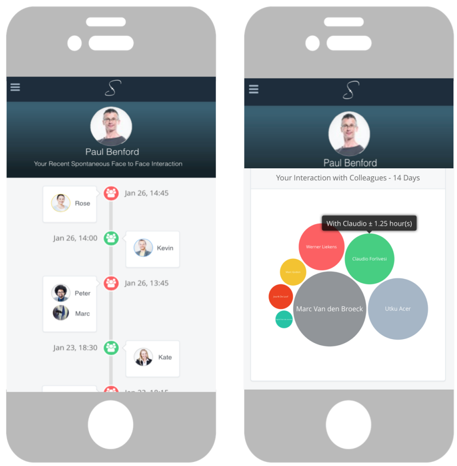
Figure 1: The pipeline of the face-to-face interaction detection

Accordingly when a co-located group is detected by co-location detection engine, we model the duration and size of the group against a log normal distribution with $\mu = 3.5$ and $\sigma = 0.9$ to infer the composition (and decomposition) of a group engaged in face-to-

[1]We selected both technologies as Wi-Fi scanning at the device end is not allowed on the iOS platform.

[2]http://estimote.com

[3]The ceremonial ritual refers to the conversations or actions that are necessary to keep participants in line and give a closure to the mutual activity sustained in the interaction.



(a) (b)

Figure 2: (a) Interaction history and (b) intensity feedback

face interactions. The entire processing pipeline is depicted in Figure . Two distinct advantages of our parametric classification model is that it does not require any learning period and it can operate efficiently at realtime.

It should be noted here that this model for inferring face-to-face interactions is not absolute, i.e., it cannot guarantee that all face-to-face interactions are captured, nor that all captured gatherings are face-to-face interactions. With systematic evaluation using self-reported ground truth (which is out of scope of this paper), we found that our system can capture approximately 80% of the face-to-face interactions when all participants run our application in their smartphones [36].

3.3 Mobile Application Experience

Quantification of face-to-face interactions can be visualised in many different ways. In "The New Science of Building Great Teams", Pentland argued that the two important metrics for quantifying the patterns of informal communications in a workplace are *energy* and *engagement* [34]. Here, *energy* captures the number of exchanges between an individual and her team members whereas *engagement* corresponds to the distribution of these exchanges amongst the team members. Borrowing these metrics, we designed two distinct visualisations and presented them in the aforementioned mobile application: *interaction history* corresponding to *energy* and *interaction intensity* corresponding to *engagement*. These visualisations offered feedback on personal face-to-face interactions accumulated over the most recent 14 days (i.e., the near past as opposed to distant) grounded upon the psychology principles that suggest that the critical role of short-term feedback in enhancing one's self-knowledge about her own behaviour [10]. These two visualisations are described below.

Interaction History: This visualisation as illustrated in Figure 2(a) provides a timeline of user's face-to-face interactions with other colleagues in the recent past (i.e., 14 days). The visualisation is independent of the nature of the interaction (e.g., duration of the interaction, topic), and purely focuses on the number of these exchanges (i.e., energy). The rationale behind this presentation is to provide a short-term feedback on spontaneous interactions, especially to offer opportunities for follow-up connections with new contacts.

Interaction Intensity: This visualisation as illustrated in Figure 2(b) presents the intensity and distribution of a user's face-to-face interaction with different individuals. Essentially, each bubble represents an individual, and the size of the bubble represents the intensity of the user's collaboration with that individual. The intensity represents the relative exchange between different individuals and captures two aspects: i) interaction frequency - the number of times of the face-to-face interaction, and ii) interaction duration - the total durations of the face-to-face interaction. Accordingly, we define an intensity metric which is computed as follows:

$$P_i = wa_d^i + (1-w)a_f^i \tag{1}$$

$$a_d^i = \frac{d(a^i)}{d_{max}(a)} \tag{2}$$

$$a_f^i = (1 + log\frac{|S|}{|a_s^i \in S|})^{-1} \tag{3}$$

Here P_i is the interaction intensity with person i, $|S|$ is the total number of face-to-face interactions with all the persons, and a_s^i is the number of face-to-face interactions with person i. $d(a^i)$ is the total interaction duration with person i and $d_{max}(a)$ is the maximum interaction duration across all persons. w is a weight parameter, and we set it to 0.6 to give higher weight to the face-to-face interaction duration. A higher P value indicates a stronger interaction intensity, and a lower value indicates the reverse.

Finally, the application offers a number of location-based services, such as locating a colleague or an empty meeting room, and recommending the most popular area in the workplace based on the density of people's locations. These services act as incentives for sharing their location.

4. RESEARCH STUDY

To understand the impact of personal feedback on face-to-face interactions in the workplace, we conducted an *in situ* study. The research was conducted between January 2015 to April 2015 in an industrial research labs in Western Europe.

4.1 Methodology

Following the precision tracking methodology [29], our goal was to capture as complete picture as possible about face-to-face interactions in the workplace. To this end, we conducted a *mixed method* study, in which we first collected and analysed usage logs from the aforementioned mobile application to understand efficacy of the interaction visualisation. We analysed two metrics: *impression* and *interaction*. The *impression* data allows us to get a sense as to the number of times each user viewed the visualisation feedback and serves as a proxy for understanding the effectiveness of this information as an external cue to promote self-reflection. Furthermore by analysing the relation between *interaction* and *impressions* we can get a sense as to whether the impressions caused any subliminal changes in interaction patterns, that could have been triggered by improvement in self-knowledge.

It is important to recognise that the quantitative analysis from the application data alone can only provide an approximation and cannot be used as evidence to fully to answer our research question. This is because user experience with the application might have been influenced by multiple factors, including internal factors such as the design of the application, as well as the external factors such as varying schedules in the workplace, job responsibilities, etc. Furthermore, as we have explained earlier that our system cannot guarantee that it captured every single face-to-face interactions across all our participants during the study period. Therefore, we complement our quantitative analysis with qualitative interviews to gather insights regarding the effectiveness of the visualisation feedback. We describe each component of our study methods next.

4.2 Application Usage Log

The application was used by 47 employees (6 were female[4]) for 87 working days (excluding weekends and holidays). The application logged two metrics: *interactions* and *impressions*. *Interactions* refer to the face-to-face interactions among individuals as described earlier, whereas *impressions* refer to the events when a user viewed the application page that visualised interaction intensity and history (Figure 2).

Two of the participants faced issues with running the app on their phones during the study, and thus we excluded their data from the subsequent quantitive analysis. Table 1 reports some statistics regarding the usage of the application by the participants. Accumulatively 657.59 hours ($\mu = 13.99$, $\sigma = 19.85$) of application usage were recorded; 7059 interactions and 5210 impressions were captured. Table 1 also reports the percentage of the participation days by the users, as well as the number of active days in the system - wherein the former corresponds to the full duration a user was observed in the system even if not active throughout, while the latter corresponds to the total number of days that the system detected user activity (including impressions, interactions or any other communication with the server).

On an average, every user was engaged in 150.19 interactions ($\sigma = 204.98$) throughout the study period. These interactions happened amongst a limited set of contacts - on average each user met with 9 distinct others ($\sigma = 5.84$). Finally, we observed a skewed distribution in regards to the number of impressions per user (μ=110.85, σ=138.68), with most of users with small number of impressions and only a few with very high impression. We provide more details on these observations along with a thorough quantitative analysis in the Results section.

Looking to these data through a gendered lens, we run Mann-Whitney's U tests to evaluate whether the impression and interaction counts were differed by gender. For impression, we did not find any effect of the gender group ($U = 89.5$, $Z = -1.36$, $p > 0.05$). For interactions, however, we found a significant effect of gender group ($U = 63$, $Z = -2.19$, $p < 0.05$), which indicated that females had more interactions than males.

Parameter	μ	Distribution	σ
Total Usage Hours	13.99		19.85
% of Participation in Days	48%		38%
Number of Active Days	13.23		12.58
Total Interactions	150.19		204.98
Unique Contact Size	9.00		5.84
Total Impressions	110.85		138.68

Table 1: The extracted logs and their properties per user basis

4.3 Semi-Structured Interviews

Following our quantitive study and four months into the deployment, we sent an email to the participants inviting them for semi-structured interviews. Out of the 47 users, 20 agreed to participate in the semi-structured interviews. They were aged between 28 and 61 years, and 4 were female. The interviews were semi-structured, involved one interviewer and one note taker, and lasted for an hour. The entire session was audio recored and later partially transcribed to complete the observer's notes.

In the interviews, we asked the participants about their perception of the interaction visualisations and whether they altered their interaction behaviour due to the visualisations. We engaged in open ended discussions to gain a better understanding of the design space of feedback visualisation. To this end, we followed an interview technique called *laddering*[5] to uncover the core values behind users' reactions. We analysed the interview data by counting users' answer to the effectiveness of the external cue and coding the subjective responses. Observations against these codes were then analysed using affinity diagramming [3] to derive themes. Finally, we also asked the participants about whether they considered themselves as introvert or extrovert.

5. STUDY RESULTS

In this section, we report the insights from our study by analysing the application usage logs and interview responses. In order to assess the efficacy of the visualisation as an external cue to promote self-reflection, we first study the impression volume and subjective perception of the employees. We argue that the volume and temporal pattern of the impressions are good indicators of whether employees were interested in this feedback, and found them as a source to help expand their self-knowledge of their workplace behaviour. That is, if the visualisation was effective as an external cue, from the quantitive analysis we except the users to have high volume of impression distributed across time.

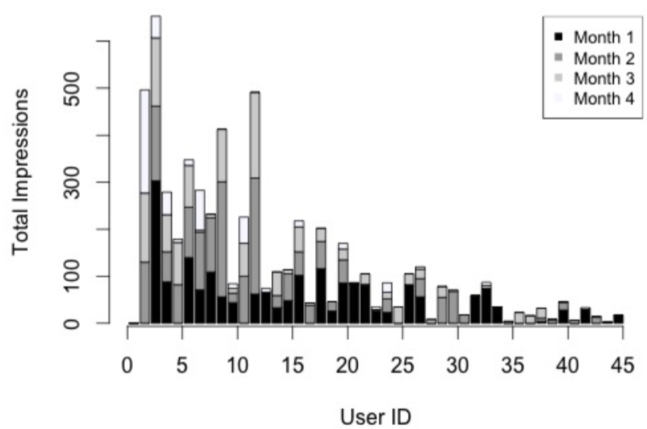


Figure 3: Total number of impressions per user for each deployment month.

Figure 3 illustrates the total number of impressions for each user at the given month of deployment. Based on this illustration we make two observations. Firstly, we notice that majority (70%) of the users had less than 200 impressions overall (μ=110.85, σ=134.68), and that some of these users viewed the feedback only a handful number of times in the first two months of the deployment. Secondly, we observe that a subset of the users had high volume of impressions, that were distributed across four months of the study.

These findings from our quantitative analysis were supported by the user interviews. Only 5 participants (out of 20) found the presentation of the interaction history (Figure 2(a)) useful. The major-

[4]This gender ratio corresponds to the actual ratio of the female employees in our organisation.

[5]http://www.uxmatters.com/mt/archives/2009/07/laddering-a-research-interview-technique-for-uncovering-core-values.php

ity of the participants mentioned that they are already aware of their recent interactions with colleagues, and can easily recall them without the need of a supporting visualisation. The subjective feedback on the visualisation showing interaction intensity (Figure 2(b)) was also similar as the majority ($n = 13$) of the interviewees found the presented information intuitive and unsurprising. A particular remark was:

> *"If you could add how productive were my collaborations with a teammate, it would be useful. Just knowing the amount of interactions is not enough.."*

Similar comments were received from other participants where they desired actionable attributes qualifying their face-to-face interaction patterns.

The minority with high impression volume and rate, suggested different reasons for their interest in the feedback. One participant stated:

> *"I find the interaction history extremely useful as I am new in the company and the app helps me to make new connections."*

Others stated that their job responsibilities (e.g., communication, sales, etc.) require them to interact with others in the company frequently so they found the visualisation feedback useful. They mentioned that the feedback helped them to understand how many interactions they had and how these interactions were distributed amongst their contacts.

Examining this minority group based on their self reported personality traits (introvert vs extrovert), we noticed that they corresponded to the self-reported extroverts. Indeed, when examining the volume of interactions and impressions under this lens for all the users, we observed significant differences between the two groups ($p - value < 0.0001$) revealed through the Fisher's Exact test. The mean impression counts for introverts and extroverts were 159 and 315 respectively, while the mean interaction counts were 96 and 141 respectively. This demonstrates that the self-reported extroverts had more interactions and impressions per user as compared to self-reported introverts.

These observations highlight that for many the visualisation feedback did not offer information beyond the internal cues that the employees already held regarding their workplace behaviour. Indeed a pattern that emerged out of our interviews was regarding the temporal granularity of the visualised information. Participants ($n = 17$) suggested that if this information was presented at a longer resolution, corresponding to a monthly or yearly summary of their interactions at the workplace, they *might* find it useful. It was highlighted that the visualisation of data accumulated over a longer period could help, not only with memory augmentation but also to enable individuals to make a mental mapping of their productivity and their past behaviour. This finding is in contrast to the visualisation techniques used in Quantified Self literature, wherein the focus is on providing short-term, in-the-moment feedback to the users and long term visualisation are typically provided as optional features in the system.

Our interview results also suggest that the majority of the users ($n = 17$) would not reflect on the visualised feedback in their current form to modify their workplace behaviour. One participant stated:

> *"For me these charts wouldn't be a reason to go and grab the person for coffee or talk to him.."*

To support this observation with a bigger sample set, we delved into the interaction data from the application usage log. As it was reported in the Table 1, users had varying degree of interactions with some users encountering more people than the others. We analyse the number of interactions of the application users over time to get a sense as to whether impressions were followed by any subliminal change in interaction patterns. More specifically, if the impressions had a positive impact on the user to seek an alternative behaviour at workplace, we would expect to see a positive (or negative) trend of interactions over time. Figure 4 presents the number of interactions per active day per user and suggests that the rate of interaction do not show any upward or downward trend. Furthermore, we did not observe any differences in the interaction behaviour between the subset of users with high *impressions* (i.e.top 30%) versus the rest.

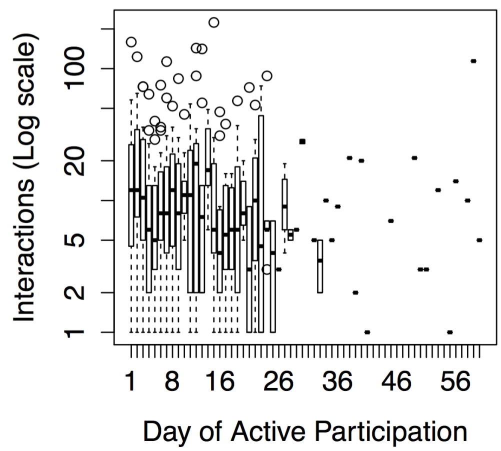


Figure 4: Number of interactions per participation day.

To summarise, we observed that not all the participants perceive the feedback on face-to-face interaction pattern as an effective external cue. Indeed majority claimed that the information that was provided corresponded to their internal cue and did not add any value. Another observation that stood out was the need for a rather longer-term feedback that could help employees to make a mental mapping between their interaction patterns and their longer goals. Furthermore, for the the visualisation feedback to be more effective external cue, the participants wanted concrete actionable attributes (notions such as productivity) that along with the interaction information could lead them towards their goal.

6. DISCUSSION

In the earlier section, we presented the results emerged from the study that suggest that *short-term* feedback on face-to-face interaction pattern in the workplace was not found to be an effective external cue that promotes self-reflection. During the interviews, we engaged in open-ended discussions with the participants to explore alternative feedback modalities and different other factors that may or may not influence the design of future workplace technologies, especially intended to offer personalised feedback on workplace behaviour. In this section, we discuss two such factors that we found most compelling. We also present three suggestions for future workplace technology design based on the insights we gained in the study.

Research on gamification [7] has shown that the use of game design elements such as leadership boards, badges and points could act as participation incentives in non-game contexts [1, 20] including in the enterprise environment [12]. Grounded upon these works, we wanted to understand whether this consensus regarding the effect of gamification holds for face-to-face interactions in the workplace. During the interview, we probed users on whether visualising their standings in the organisation in terms of personal interactions might cause them to self-reflect. We discussed concepts like leaderboard, or ranking that can reflect the extent to which an individual interacts with everybody else within the enterprise.

We found that 16 out of 20 participants strongly opposed the quantification and visualisation of their interaction ranking - particularly in a shared setting, e.g. a leaderboard. Participants mentioned that employees should not be judged based on their interactions in the workplace, and also raised concerns that a competition-based system may cause people to develop artificial behaviour in the workplace so to improve their ranking. One remark was:

> *"Oh, I think this can easily be cheated. People will try to increase their ranking to appear on top. This is not good."*

An interesting finding, albeit contrary to above, was that while most participants showed resistance against public rankings, many (n=10) expressed a desire to privately compare their own interactions against other employees in a subtle way. These suggests that competition is an interesting feedback dimension in the workplace that needs to be further explored, in particular to understand the fine balance between public exposure and personal awareness.

Previous works on social physics have shown that individuals benefit from a diverse network of connections outside their immediate team [25]. Our discussions revealed that participants would prefer to see a relationship structure of employees in their workplace and suggestions on increasing their own interaction network, e.g. how one can connect to someone specific, and who is the best intermediary in one's network to facilitate this new connection. A common feedback from the participants was regarding the possible annotation of the relationships, either qualifying past interactions results or expertise of the unknown contacts. This desire for network diversification is not surprising as established literature on online social network analysis have shown this is as a natural human characteristics. However, embedding this into personal feedback on physical workplace behaviour is an interesting topic for future exploration.

Before concluding this section, we present three design suggestions based on the insights uncovered in this work. We expect that these suggestions will guide future designers to assess carefully the functional space of workplace applications aimed at personal gratification. Furthermore, we hope that these suggestions will open up and shape interesting directions for future research in the workplace technology area.

1. **Design for Long-Term Feedback:** We observed that all of our participants desired feedback on their workplace behaviour accumulated over a longer period of months or years. It was evident that the short-term feedback did not offer any additional value than the internal cue. Delving into this during the interviews, we understood that long-term feedback is appealing because not only it enables employees to recall their distant past interactions but also serves as an external cue that could help them to adapt their behaviour and attitude in the workplace, e.g., managing and extending personal network, better management of time spent at workplace, etc. While we do not advocate completely ignoring the short-term feedback, designers of future workplace technology intended to be used as behavioural feedback tool should pay particular attention to long-term feedback.

2. **Design with Actionable Attributes:** One key insight emerged from this study is that it is absolutely critical to incorporate actionable attributes in the feedback design. It was evident from our analysis that majority of the employees did not find the feedback informative as it lacked qualification for actionable reflection. During the interviews we were constantly reminded that if those interaction moments could be qualified with some subjective (e.g., a very *productive* chat, an *exciting* discussion etc.) employees would have more benefits. They mentioned that these would have allowed them to improve their self-knowledge and act as necessary, e.g., to reconnect with specific individuals or to reassess the productivity of informal interactions. We thus call attention to workplace technology designers to accommodate actionable attributes in the feedback design.

3. **Design with Community Awareness:** We observed differential pattern by different user communities. For example, female employees had more interactions than their male counterparts, self-reported extroverts had higher engagement than their introvert colleagues. Also, we noticed that individuals with different job responsibilities had striking differences in their impressions about the feedback application. We see interesting dynamics emerging here, different communities have different drives towards behavioural feedback, and it is important to recognise the personality, gender, and occupation differences while designing feedback to meet the demands of respective communities.

7. CONCLUSIONS

In this paper we explored the impact of offering personal feedback on face-to-face interactions in an industrial workplace. Although previous literature has examined the impact of quantifying interactions in the workplace through collective feedback, to the best of our knowledge there are no previous works that address the impact of visualising this information at a personal scale. To accommodate this research we have designed and developed a mobile system consisting of a cross-platform mobile application, a location infrastructure and a data processing infrastructure. The system hosts a novel data processing pipeline to detect face-to-face interaction from location traces at real time without requiring any additional contact-sensing (e.g., microphone, infra-red badge, etc.) or infra-structured sensing (e.g., camera, etc.). We had a unique opportunity to deploy this system to study the impact of feedback on personal interactions in an industrial workplace with 47 employees over 4 months, accompanied by in-depth interviews of 20 employees. Our results suggest that the majority of the employees did not perceive this feedback as an useful external cue to promote self-reflection. However, all the employees desired *long-term* feedback capturing personal behaviour in the workplace qualified with *actionable attributes*.

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