A Case Study on Capturing and Visualising 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, with little attention being paid to how this information is perceived by the employees. In this paper, we offer a reflection on the automated feedback of personal interactions in a workplace through a longitudinal study of capturing, modelling and visualisation of face-to-face interactions of 47 employees for 4 months in an industrial research lab in Europe. 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 by most, and that employees desire *long-term* feedback annotated with *actionable attributes*.

ACM Classification Keywords
H.5.m. [Information Interfaces and Presentation (e.g. HCI)]: Miscellaneous

Introduction
The collective behaviour of employees shapes the company culture and has proven to play a critical role in an organisation's success. 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. Indeed, the serendipitous interactions between employees (e.g., during coffee breaks) have been shown to improve task completions [23], to foster innovation and creativity by enabling the flow of ideas and inspiring fresh thinking [12, 14, 20].

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 [2,15,19]. 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 such as high performing team formation, rearrangement of workplace, etc. However to date, little is known as to how this information is perceived in *practice* by employees themselves at personal level. From theoretical perspective social psychologists have long 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 [1].

In this paper, we borrow tenants 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 personal scale. We aim to understand how individuals perceive this external cue and whether this cue 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 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 and a location infrastructure based on WiFi and Bluetooth. The 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 [20]. We deployed our system in a Nokia research lab and trialled with 47 employees for a period of 4 months, gathering application usage data including the volume of interactions and application views (i.e., impressions). 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 provide insight into the factors that most influence perceptions of personal behaviour feedback in the workplace.

Background and 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 bounds in modern organisations [14]. 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 [16,17] to capturing and visualising the mood of the organisation [15, 18], 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 [2, 3, 7, 19]. Olguin et al. [19] have looked at using wearable electronic badges for measuring face-to-face interaction, conversations and physical proximity. Brown et al. took a similar approach and used wearable badges to evaluate the effect of workers' cultural backgrounds on their interaction diversity [2]. Kelley's Bell Stars study in a research organisation showed that the star performers had a diverse network of colleagues that they interacted with [12]. In the same vein of understanding how ideas flow, Pentland [20] showed that patterns of communications are important predictors of a team's success, and that these patterns carry vital information for better people management.

From visualisation perspective, a number of systems, such as Chat Circles [22], visualisations of turn taking based on audio input [11] 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 [6,13]. 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. In contrast to our work, the 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 behavioural change.

System for Face-to-Face Interaction Feedback

Our study is part of a larger multifaceted initiative that aims to uncover the hidden dynamics of modern enterprises [18, 21]. 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 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. Figure 1 illustrates the system architecture that captures location traces from mobile devices and model face-to-face interactions. The back-end server is implemented in Node.js with MongoDB storage and hosts the localisation and co-location engine and runs the interaction classification processes. The front-end generates and delivers the visualisations through HTML 5.

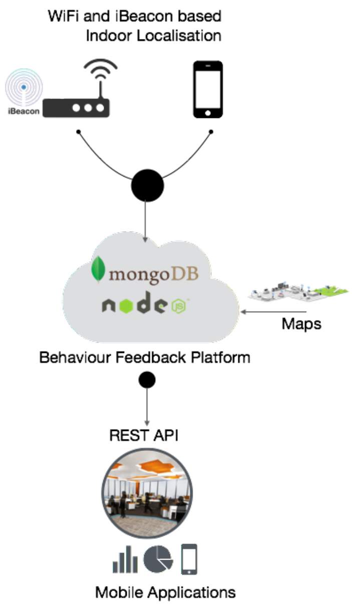


Figure 1: System architecture of the prototype system

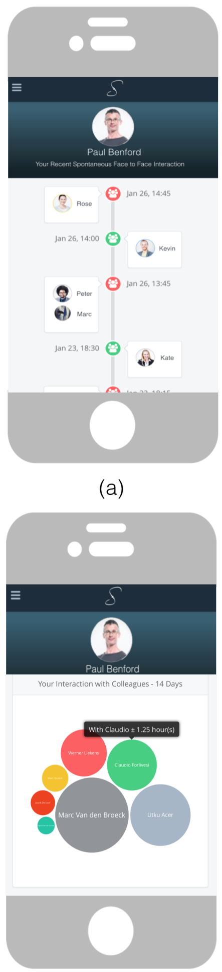
Location and Co-Location Detection Engine
To detect face-to-face interaction, we first need to identify when people are co-located in the workplace. To do so we first need to track an individual's location, and then derive co-location from location traces across individuals. Previous work has shown that people carry their mobile phone at the workplace, 48% of the time within arm-reach and 82% of time within 5 meters [5], 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 WiFi 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 WiFi access points and iBeacons, and the fingerprint database was uploaded on the server backend. We leveraged 30+ existing WiFi 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 (individual) by modelling temporal variations observed in the locations across a set of devices.

[1]We selected both technologies as WiFi scanning at the device end is not allowed on the iOS platform.
[2]http://estimote.com

Face-to-Face Interaction Classification Model
Once we have detected co-location, we distinguish between simple co-presence and face-to-face interaction by building a classier model based on sociology theories [9] 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 and casual chats) than a planned meeting. The size (N) on the other hand represents the number of distinct individuals in the interaction. As the size of the human group grows, the group becomes more depersonalised. Similarly, 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 [9]. This is because as the number of persons increases, the longer it takes for the ceremonial rituals of interactions formation and decomposition [8]. Moreover, it is more likely for the focus of attention (e.g., topic of the conversation) to be shifted when more individuals are involved in a verbal interaction, thus leading to a longer duration.



(a)

(b)

Figure 2: Visualisation of (a) interaction history and (b) intensity

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 likely 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. Based on these two variables and their interplay we empirically defined a model that can detect composition and decomposition of an interaction group. This model corresponds to a log normal distribution.

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 [21]. Two distinct advantages of our classification model is that it does not require any learning period and it can operate efficiently at realtime.

Mobile Application for Feedback Visualisation
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* [20]. 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. 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 follow-up opportunities 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. This intensity is modelled as:

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

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

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

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 (as an incentive for location sharing), 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.

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 a Nokia research lab.

In order to capture as complete picture as possible about face-to-face interactions in the workplace, we conducted a *mixed method* study, in which we first collected and analysed usage logs from the mobile application to understand efficacy of the interaction visualisation. We analysed two metrics: *impression* and *interaction*. The *impression* corresponds to the number of times each user viewed the visualisation feedback thus 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.

However, 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, as 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. Therefore, we complement our quantitative analysis with interviews to gather insights regarding the effectiveness of the feedback.

Application Usage Log

The application was used by 47 employees (6 were female[3]) for 87 working days (excluding weekends and holidays). The participants were selected by snowball sampling, and no compensation was paid to them. 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. Accumulatively 657.59 hours ($\mu = 13.99$, $\sigma = 19.85$) of application usage were recorded; 7059 interactions and 5210 impressions were captured. 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.

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

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

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.

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 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.

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 also asked the participants about whether they considered themselves as introvert or extrovert. 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* to uncover the core values behind users' reactions. We analysed the interview data by counting responses to the effectiveness of the external cue and coding the subjective responses. Observations against these codes were analysed using affinity diagrams to derive themes.

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 quantitative analysis we expect the users to have high volume of impressions distributed across time.

Figure 3 illustrates the total number of impressions for each user at the given month of deployment. Based on this illustration we make the following observations: 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. We also observe that a subset of the users had high volume of impressions, that were distributed across four months.

Figure 4 captures the temporal decay by illustrating the total number of impressions per day for the duration of the deployment. We observe a high number of impressions due to the novelty effect during the first three weeks of the deployment. However this behaviour does not sustain and the number of impressions clearly decreases over time. However we found that the average number of impressions for the top 30% users, plotted as inset of Figure 4 remained stable overtime.

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

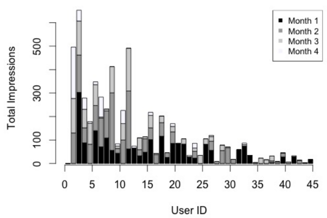


Figure 3: Total number of impressions per user for the given deployment month.

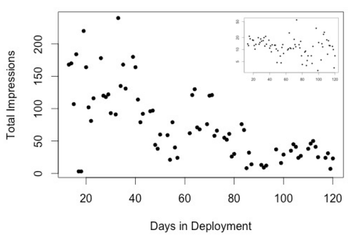


Figure 4: Total number of impressions over the deployment time by all users. The inset depicts the *Average* number of impressions per day for the top 30% users.

the interviewees found the presented information intuitive and unsurprising. A particular remark was:

> *"I don't think I look at it much...I can recall this, and I know it already..No surprise."*

Another participant suggested:

> *"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. However, 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., 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.

Our in-depth user interviews of both groups also indicated that the participants responses was less influenced by the visualisation itself but rather by the information that was presented. That is 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 [4].

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 grab the person for coffee or talk to him.."*

To support this observation with a bigger sample set,

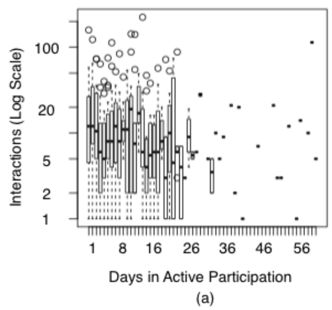


Figure 5: Number of interactions per participation day.

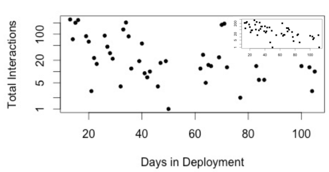


Figure 6: Total number of interactions (log scale) over the deployment time by all users. The inset depicts the same information for the top 30% users with the highest impression.

we delved into the interaction data from the application usage log. Our logs indicate that 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 5 presents the number of interactions per active day per user, and Figure 6 illustrates the number of interactions from all users during the four months of deployment. Both these figures suggest 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% users) versus the rest.

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-term 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.

Discussion

We offer following guidelines to future workplace technology designers based on the insights we gained in this study.

Design for Long-Term Feedback: We observed that all of our participants desired feedback to be accumulated over a longer period, at a time granularity of months or years. It was evident that the short-term feedback did not offer any additional value than the internal cue and subconsciously possessed knowledge. 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., better time management 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.

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 the interactions could be qualified with subjective (e.g., a very *productive* chat, an *exciting* discussion etc.) or objective attributes (e.g., tips on *Node.js*) 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.

Concluding Remarks

We presented the design and deployment of a system to explore the impact of offering personal feedback on face-to-face interactions to employees of an industrial lab. This work was an initial exploration into understanding the impact of personal interaction feedback. As such, we only evaluated a limited techniques for visualising the interaction metrics. Future research could design and evaluate other feedback visualisation schemes for personal interactions. Certainly, the results presented here must be interpreted in the context of the culture in which they were collected. We expect our results to be most appropriate for designers of future workplace technology in Western Europe or countries with similar cultures and work practices [10]. Furthermore, the type of work and workplace culture could also influence how interactions are perceived in the workplace. For example, the need and importance of face-to-face interactions are likely to be very different in a scientific research organisation as opposed to a sales organisation or a call centre. These differences must be taken into account when interpreting the results reported in this study.

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