Remote Synchronous Crowd Support in Challenging Sports Events

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ABSTRACT

Social support is a most powerful expression of human beings. It can make humans overcome barriers that seem impossible. Research shows that athletes, who are supported through being cheered on during events, perform better. However, up until recently, little could be done to cheer athletes during races unless supporters were physically present at the event. We investigate ways in which remote online spectators can support athletes in real-time. Is the support from remote spectators effective? How can we design systems for real-time support and what factors influence their effectiveness?

To research this, we iteratively design online crowd interfaces, mobile applications, and devices that allow athletes to communicate with distributed spectators during sport activities. Athletes are able to broadcast their live performance to spectators through locative and biometric data sharing. Concurrently, remote spectators support the athletes by clicking a cheer button that instantly makes the athletes aware that a crowd is following their performance. We then conduct a series of investigations during multiple sport events, using different support modalities and diverse crowds. Results indicate that remote crowd support does motivate the athletes by making the athletes aware that they are being supported. More interestingly, if we categorise supporters into close relatives, acquaintances and unknown spectators, the most effective support seems to be that of acquaintances. This work also provides design guidelines for researchers and designers of remote crowd support systems.

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DECLARATION

This thesis is a presentation of the author's original research. No part of this work has been submitted for any other degree or qualification. All the work is the author's own unless otherwise stated.

The author of this thesis was the lead researcher on all the chapters.

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Chapter 1
INTRODUCTION

1.1 Motivation

Communication technology has changed profoundly in the last 50 years. Radically innovative infrastructures shaped the Internet by creating complex networks that allow many-to-many high-bandwidth communication to happen, in real-time across the globe. Today, processing power is ubiquitously embedded in what may have been unthinkable before, from cities to buildings to wearables, while devices got faster, cheaper and became mobile [30]. This resulted in a proliferation of social media applications, such as Skype, Facebook, LinkedIn, Twitter, and Weibo, which facilitate social interaction. These applications digitized many of the social communication processes within the real world.

This new form of communication attracted the attention of researchers who studied how social networks get distant persons closer [179], build communities [90] and facilitate social support [195]. However, communication applications still have substantial shortcomings. Current communication technologies necessitate considerable attention from the parties involved and many were not designed for users who need to give or receive support while they are conducting a challenging task [48]. In sports for example, it is difficult for an athlete to report on a physically and mentally challenging sport activity as the event unfolds and receive support from his or her social network in real-time. Research shows that athletes who receive support from spectators during sporting events, perform better [2,28,59]. However, up until recently, supporters had to be at the same location as the athletes to show their support. If effective, applications that provide instant remote support promise huge impact on communities. Shin et al. [173] p.6 identify three key components that characterise *real-time*. 1) Time: tasks must be completed "before their deadlines. For example, messages are required to be sent and received in a timely manner between interacting real-time tasks". 2) Reliability is fundamental, 3) "The environment under which a computer operates is an active component of any real-time system. For example, for a drive-by-wire system it is meaningless to consider on-board computers alone without the automobile itself". In this light, our view of real-time when applied to crowds supporting athletes, is that this support is sent to the athletes during and within the timeframe of the task, that is, before the task is completed. When applying this real-time approach to interaction, we use the term *synchronous interaction*. By this we refer to interaction in which the actions within the interaction can be reacted to (by a user or a system) instantaneously and this (may) trigger subsequent interaction.

Through a thesis by publication model, in this work we investigate whether it is possible to remotely crowd-support persons that are conducting a challenging task, in real-time. As for the challenging task itself, we specifically look at athletes participating in a sporting event as there is already evidence that the support of co-located spectators can have a positive effect on athletes [28,59].

Designing systems for real-time remote social support is not a trivial task. Much research exists on asynchronous social support. For example, we find many applications for supporting users trying to stop smoking or improving health habits over social networks through peer support [37,134,148]. This cannot be said for social support that needs to occur in sync with the task - synchronous support. Most of the above referenced studies were in fact designed for social support that is received over a long time period following the activity. In some cases this consists of days or even weeks. Nevertheless, research in social psychology has repeatedly shown that short timeframes between the action and the external support is likely to provide a more positive reinforcement than otherwise [92]. In this context, synchronous support promises greater value than asynchronous support.

In this work, we argue that systems that elicit real-time crowd support necessitate three main functions. 1) They have to make the supporter aware of what is happening during the activity with minimal distraction to the athlete. 2) They need to allow the supporter to freely express support while the event is taking place and 3) they need to aggregate and communicate this support back to the athlete in a most effective approach.

Currently, social network-based applications lack multitasking functionalities and make it particularly difficult for athletes who are engaged in highly challenging tasks, such as running a marathon, to interact with remote supporters. For example typing a Facebook text message while jogging is awkward at best. In hindsight, this seems to be a key reason why there are very limited applications that are designed to socially support users remotely as they are conducting challenging tasks. This contrasts with the real-world scenario where crowds on a racecourse cheer athletes as they enter line of sight. Nevertheless, **can athletes tell their story to remote spectators live, such that spectators can build an understanding of their performance?**

The spectators' understanding of the athlete's performance is fundamental to the relevance or otherwise of the support. This understanding, influences the spectators' engagement [153,154] and more importantly the athletes' belief that the support is based on their performance [44], that is, the support is not random.

If this were to be accomplished and remote spectators could indeed build an understanding of what is happening, **can the support of remote spectators be aggregated and communicated back effectively to the athlete as the event unfolds?**

We use the term "cheering" to refer to the social support that is show by spectators during sporting events. The Oxford English dictionary defines a cheer as "a shout for joy or in praise or encouragement". During sporting events, crowds often encourage the athletes to perform better by externalising their feelings as cheers [59]. Cheers may consist of sounds (e.g. shouting spectators), gestures (e.g. hand waving) and vibrations (e.g. the subtle vibrations that a very large cheering crowd creates. Research shows that this cheering can influence an athlete's performance during the game [59]. In this work, we convey remote support by communicating cheers in the form of sound and tactile feedback.

1.2 HeartLink

To investigate this, over a three-year period, we designed, prototyped and tested HeartLink, an online data sharing and feedback system (www.heartlink.co.uk). HeartLink lets remote spectators know how a sporting event is unfolding without distracting the athletes from their task. It broadcasts sensor-captured data from athletes, such as heart rate and geographic location, via mobile networks, to online spectators. Online spectators can in turn follow this data live on any Internet-connected browser. Spectators can also click the Cheer button on their interface. The Cheer button sends an instant alert to the athletes through audible and haptic feedback. In this way the athletes get the awareness that a crowd is remotely following their performance. This simple communication modality is adopted on the hypothesis that this is effective enough to make the athletes aware of the spectators, yet at the same time, it provides minimal distraction to the athletes. In each of the deployments, remote spectators can also share comments with each other through a public Facebook-like frame on the same interface. This collective commenting creates a community around the event. Additionally, the posted comments provide the researchers with valuable insights on the spectators' understanding of the data. We then iteratively deploy HeartLink with groups of athletes and online spectators during different sporting events. These will be discussed in detail throughout this thesis together with their respective findings.

1.3 State of the Art

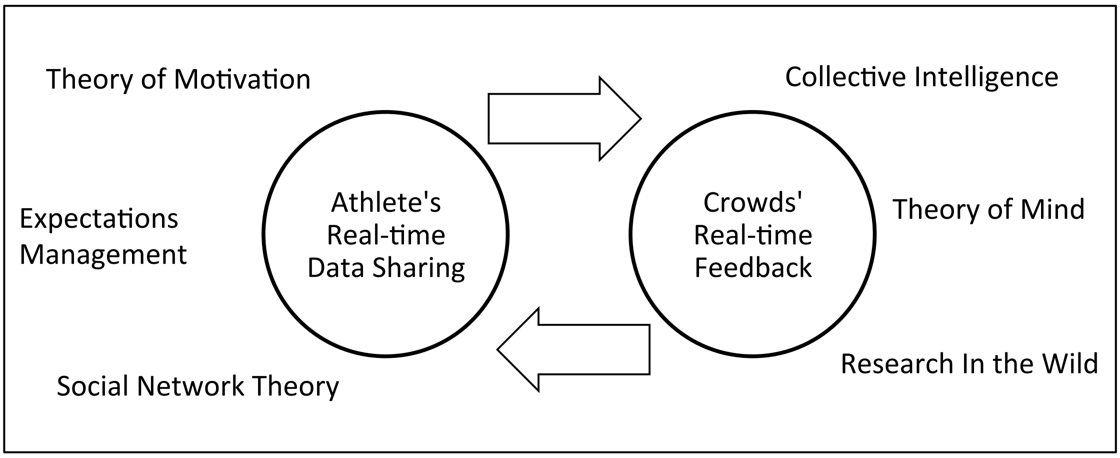

Figure 1: The process under observation

The relevant literature and methodology for each chapter is presented within each of the next chapters. Here we briefly summarise the state of the art in the field. Figure 1 shows the overall process under investigation that is composed of two components. A data sharing system communicates the athletes' performance and a feedback system allows spectators to communicate their support. This brings us to touch with literature from different fields including theories of motivation, expectations management and social network theory. Theories of motivation help us understand the effect that the external support may have on the athletes [49,51,160]. Expectations management shed light on how the impact of the support is dependent on the support that the athletes expect to receive [21]. Social network theory helps us understand how this impact may also be dependent on the relationship between the supporters and the supported [70].

On the other hand, our observed behaviour is guided by the Theory of Mind and Collective Intelligence. Theory of Mind describes the spectators' understanding of the effort that the athlete/s are enduring [10,80]. Collective Intelligence helps us understand how the support and actions of the individual supporters create the crowds' behaviour [108,162]. We explore this in a Research In–the-Wild (RIW) framework [15,157,158]. We will get back to this later on in this chapter.

To the best of our knowledge, no commercial application allowed remote spectators to support athletes in real-time at the start of this study. More recently, popular mobile applications for sports like Runkeeper, Runtastic and Endomondo implemented remote crowd support features with which social network friends can send cheers in the form of sound effects or tactile feedback to athletes. These systems however, offer little insight, that goes beyond the corporate branding, on the effectiveness of these features. Since studies that involve both real-time data sharing and feedback from remote crowds' are negligible in academia, we start by deriving insights from studies that looked into these approaches separately.

1.3.1 Sharing real-time data

In literature we find various studies that attempt to enhance the engagement of spectators by sharing live data [11,109,144,179,188]. Schnedelbach et al. [168] augment the experience of spectators by capturing and sharing telemetry data of participants at amusement rides. In their setup, telemetry data was projected to co-located spectators. This data included acceleration, heart rate, electrocardiogram, and live video that was captured form head mounted cameras. Similarly, Kurvinen et al. [103] conduct a field test of a prototype that captures and shares heart rate data of soccer players with parents and coaches that are located at the boarder of the pitch. Hallberg et al. [76] takes this approach further and broadcast athletes' telemetry data to online spectators. They use custom-build location and heart rate telemetry devices and deploy them in a 90-kilometer skiing event. The results from these studies suggest that automated sharing of sensors-captured data can build engagement between participants. This is primarily through the build-up of curiosity and the actors' urge to know more about what other social members are doing. These results are supported by other cases in literature that involve automated data sharing such as *Comob* [179] and *CenceMe* [126]. Unlike our objectives, providing two-way communication however was not within the scope of this work. In this regard, *Jogging over a distance* [131] is the closest representation to our work. Unlike earlier work, it is the first to provide a two-way communication system that connects two remote athletes during jogs. In this work, two joggers in different location hear each other and jog 'together'. Results indicate that the joggers were able to support each other as the event unfolded. In our work we take this further and seek to connect athletes with a remote crowd that can provide instant support. Through this, we then investigate whether the cited results are replicated in the novel context of crowd-athlete interaction.

1.3.2 Crowds' Feedback

For the support to be meaningful to the supported, the supporters must understand the context [189]. Research studies on social networking indicate that sharing personal data can be effective to facilitate social support [26]. However, the effects, if any, may be different in different contexts. For example, Beckmann et al. report that athletes' performance can suffer from the pressure posed by live television broadcasts and co-located spectators [13]. This motivates the need for a focused investigation to identify whether sharing data in real-time with a crowd that is supporting remotely, makes the athletes more or less involved in the activity being performed.

Many HCI researchers, particularly around long-term behaviour change, looked into supporting geographically distributed users who face challenging tasks by sharing one's activity with others. Challenges explored include maintaining physical activity exercises [4,111], stop smoking [196] and stop alcohol consumption [192]. For example Fish'N'Steps is one such system where daily steps are shared over a social network and uses peer pressure as encouragement to increase daily activity. Results repetitively indicate that the encouragement received by others can influence behaviour [111]. We are interested in investigating whether this influence occurs when the participants are made aware of remote support during and in sync with their activities.

Cheers are a very complex form of social interaction. Many academics investigated the dynamics and effects of this social behaviour both on the person who is cheering and on those who are cheered on [11,59,107]. The cheering behaviour is influenced by the reactions of the individual who is cheering. The behaviour of a group of cheering individuals creates the emergence of crowd behaviour [162]. This is expected to influence the performance of the athletes [59], who in turn, may influence the cheering crowd. While these phenomena have been explored within the co-located cheering context, we currently lack insight on how a remote cheering system could work. More importantly, we need to understand how the social network actors in such as system react. Additionally, we need to understand how the athletes experience being remotely cheered on and how a remotely located cheering crowd behaves.

1.4 Research Questions

We thus specifically investigate four research questions:

RQ 1. What is the athletes' experience when sharing data and receiving support from remote crowds during events?

Our position on 'experience' follows that proposed by Desmet et al. [52], namely, what is the perceived goodness or badness, pleasantness or unpleasantness when using the spectator support system in situ? Since the effect of the cheering on the athletes is dependent on the supporters' behaviour, we are also interested in studying:

> RQ 2. What influences the behaviour of the remote supporters during a live sporting event?

As regards 'spectators' behaviour', we investigate cheering patterns, cheer quantity, time that spectators spent on the site supporting the athletes and the nature of the messages that spectators post during the event.

> RQ 3. What are the key incentives for stakeholders to use systems that facilitate remote support in real-time, if any?

As stakeholders we consider 1) the athletes, 2) the spectators and 3) the event organisers. Finally, through the data collected, our observations and the experience gained while designing and deploying systems that facilitate real-time support from remote spectators, we contribute to the development of future systems by investigating:

> RQ 4. What are the key factors that need to be considered when engineering systems that facilitate support from remote spectators?

1.5 Relevant Fields

The complexity of this interdisciplinary exploration within Human-Computer Interaction brings us to touch with may research fields and theories. As early mentioned and depicted in Figure 1, in the course of this text we touch upon Theory of Motivation, Collective Intelligence, Theory of Mind, Social Network Theory and Expectations Management. The theories of motivation help us understand how receiving external encouragement makes athletes perform differently. Specifically, in

Chapter 6, we compare the observed athlete's experience of being cheered on, to Deci and Ryan's Self-Determination Theory (SDT) [50] and their more recent Organismic Integration Theory (OIT) [160]. OIT classifies extrinsic motivation, such as the motivation that may emerge from being cheered on, in four different categories ranging from least autonomous to most autonomous extrinsic motivation [160]. SDT identifies three ways in which extrinsic rewards can increase motivation: through increasing feeling of autonomy, competence or relatedness. Relatedness is the feeling of being part of a group or community and having a sense of belonging [75]. Cheering is expected to increase both the sense of competence and relatedness. The effect of the cheering on the athletes is expected to be influenced by the intensity of the cheering that the athletes expect to receive. Expectations management theory provides insight in this regard [21] (Chapter 6).

In hindsight, the bringing of these diverse perspectives into one study presents challenges. We could have opted towards breaking down the research problem into a number of smaller sections and look at the each section individually. For example, we could have conducted a study in which users in the role of spectators are presented with dummy data while the researchers observe their reaction. However, while this would have provided more control, it would have been very different than the real application where crowds support athletes live. We are interested in looking at the macro level, that is, observe and understand the dynamics of the ecosystem when it is in operation. Looking at the system under observation as an ecosystem, is fundamental for this study, as this determined the methodological approach adopted, the framing of the research questions, the measurement techniques that are used and the study limitations. The earlier presented Figure 1 shows the macro view of this ecosystem.

The work in this study primarily adopts a realism research paradigm with research problems being more descriptive than prescriptive. Realism is not constrained by the limitations of constructivism or critical theory and leaves from the researcher's objectivity [145]. Moreover, in this investigation, we were particularly interested in collecting non-technological motivations (for example experiences and social effects) on user influence and user motivation. These are external world phenomena that are often hard to quantify [81]. This approach is also adopted in existing research that involves spectator interaction or 'remote support' [76,103,168,183].

Up until now, the Human Computer Interaction field and related communities were at the forefront of the research area under investigation. The methodologies adopted varied widely however qualitative approaches are by far the most adopted due to their appropriateness to handle complexities when measuring individual or crowd behaviour and quantifying the effects on, say, motivation or excitement. In this regard, Table 1 (p.15) lists relevant studies that involve broadcasting participant's data to augment co-located or remote spectators' experience. These studies were collected from the ACM Human Computer Interaction publications and the references within. The last column in the table shows the methodology adopted for each account. This denotes a predominance of qualitative processes and descriptive methodologies.

Across the chapters, the literature review draws upon the online evolution of personal data sharing from areas of health [87,175], sport [76,131] and behaviour change [37,134]. We will review cases where personal data sharing is automated in ways that do not distract the data sharing user [166,183] and reference systems that allow real-time data sharing and crowd feedback [111,141,176]. Thus, this work combines three research areas: Data Sharing, Crowd Support and Synchronous Interaction as shown in Figure 2.

Synchronous interaction refers to interaction that happens in real-time. This has attracted the attention of many researchers in recent years particularly within the computer supported collaborative work (CSCW) area. Most studies indicated that synchronous interaction often provides the user with a more engaging experience than asynchronous interaction. For example, Cao et al. show that providing students of an online course with synchronous interactions raises the overall student satisfaction [27]. Similar outcomes are identified by Khot et al. [194].

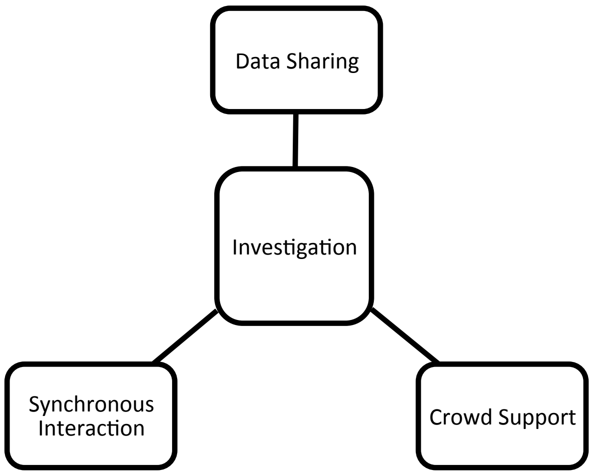

Figure 2: Interrelated areas

1.6 Methodological Considerations

We answer these questions through a research in-the-wild approach. Unlike traditional experimental methods that take place within the lab [88], research in-the-wild goes beyond observing existing practice and presents an opportunity to evaluate novel technology in the place where the technology is intended to be used [128,158]. Research in the wild is an old practice. Centuries-old inter-continent expeditions that inform ship design may classify within the definition. However, over the last decade, research in-the-wild became a common research practice in HCI. As in our study, HCI researchers often seek to explore new technology, test prototypes in the location in which they are intended for and understand how people interpret and appropriate the technology [36,38,134,155,174].

Kjeldskov et al. question the relevance of research outside the lab claiming that any in-the-wild research can be done in a lab setting [95,96]. We disagree - particularly when participants' behaviour may be influenced by complex real-life externalities. For example, Marshall et al. demonstrate that participants behave differently when using tabletop interfaces in public then in the lab [119]. Kieldskov's framing of research in-the-wild [95] seems to be limited to the evaluation of functionality of technological devices. In our case, we intend going beyond evaluating a specific system. We intend instantiating synchronous ecosystems where participants support other participants live during real sports activities in situ. An in 'the wild' setting is fundamental and part of the technology under observation itself.

Our 'in-the-wild' approach is truly in the wild. Prototypes are deployed with participants in different cities, countryside pathways, cycle lanes, nature parks and inside a lake. For example, the final prototype deployment connects athletes running a 170-mile race, from coast to coast, across the UK. In this setting, research in-the-wild allows us to compare and contrast the effect of mobile data connectivity on the proposed technology across different environments within the same deployment. This in-depth investigation would be hard to simulate in the lab.

Evaluating technology in-the-wild poses a number of added challenges. These challenges go beyond the lack of comfort that out of the studio participants are presented with [63]. An in-the-wild study may suffer from lack of control that a lab facilitates [96]. Consequently, extrapolating specific effects becomes difficult and researchers need to interpret data that is influenced by several externalities and

First Author	Year	Title	Motivation	Context	Main data collection
Florian 'Floyd' Mueller	2003	Exertion interfaces: Sports over a Distance for Social Bonding and Fun	Social Support	Jogging athletes)	Questionnaire, interviews
T Konberg	2003	Measuring Breathing and Heart Rate Data with Distribution over Wireless IP Networks	Sport/ Entertainment	Hockey players' data is shared with spectators in real-time	Research through design
Stuart Reeves	2005	Designing the Spectator Experience	Entertainment	Sport, art, performance and Exhibitions	Systems' review
Joseph Hallberg	2004	Enriched Media Experience of Sport Events	Entertainment	Skiing (athletes)	Research through design, questionnaire
Esko Kurvinen	2007	Are you alive? Sensor Data as a resource for social Interaction	Entertainment	Soccer match	Observations, interviews
Brandan Walker	2007	Augmenting Amusement Rides with Telemetry	Entertainment	Fairground rides	Review of existing systems
Holger Schnedelbach	2008	Performing Thrill: Designing Telemetry Systems and Spectator Interfaces for Amusement Rides	Entertainment	Roller coaster ride	Observations, interviews
Rodrigo de Oliveira	2008	TripleBeat: Enhancing Exercise Performance with Persuasion (Future work)	Sport	Behaviour change through smartphone application	Quantitative performance measure, questionnaire
Arttu Perttula	2010	Users as sensors: creating shared experience in co-creational spaces by collective heart rate	Entertainment	Hockey (spectators)	Observations, questionnaire, heart rate measures
Joe Marshall	2011	Breath Control of Amusement Rides	Entertainment	Ride control with biofeedback.	Observations, Interviews
Petr Slovak	2012	Understanding Heart Rate Sharing: Towards unpacking the physiosocial space	Research	Day-to day activities /Poker game	Field-trial with observations and interviews
Florian 'Floyd' Muller	2012	Balancing Exertion Experiences	Entertainment	Review	Observations, paired interviews
Paul Tennent	2012	The machine in the Ghost: Augmenting Broadcasting with Bio data	Entertainment	Haunted building Exploration	Observations

Table 1: Key related literature

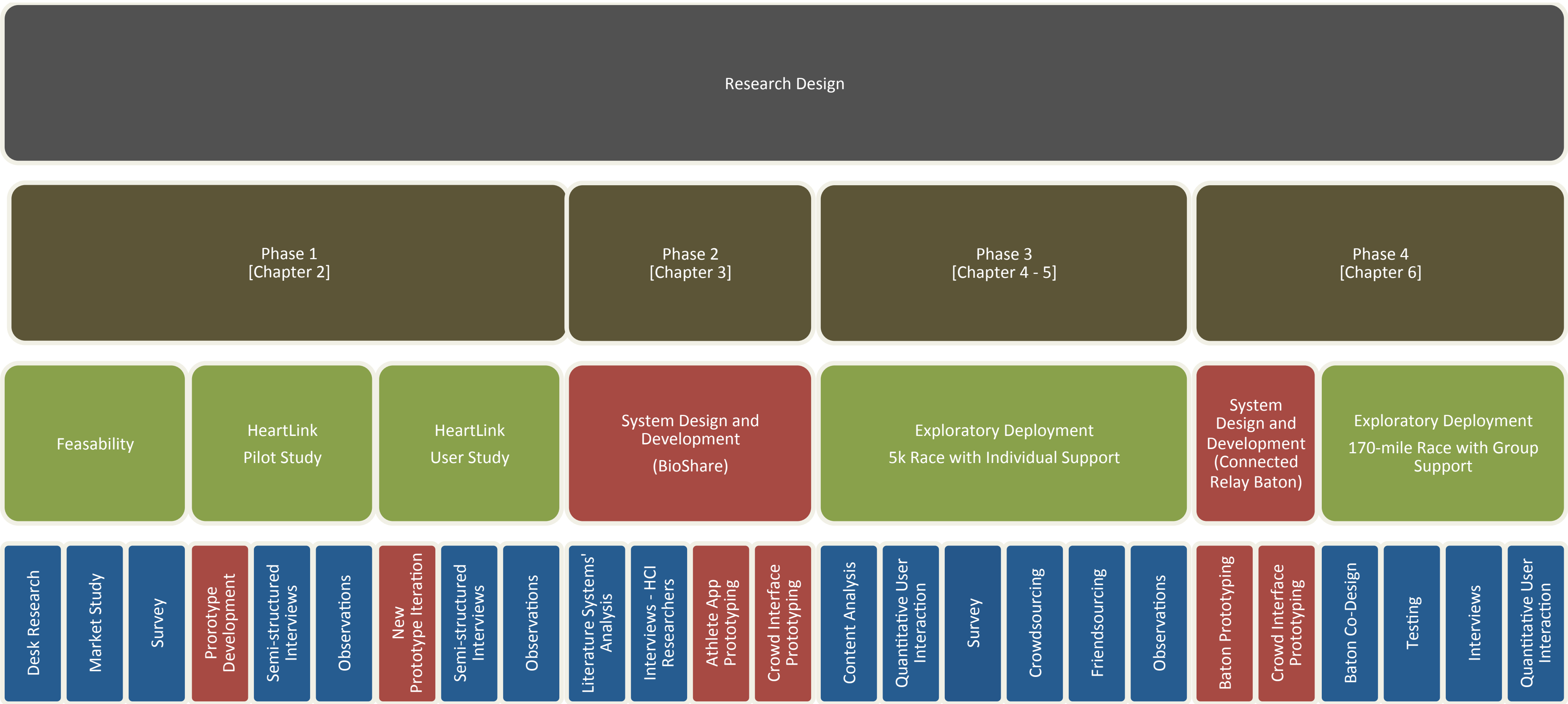

Figure 3: Research design phases: Chapters, Research Phases, Prototyping, / Methods

interdependencies [158]. To compensate for this, we use multiple methods of data collection. Where possible, we triangulate findings across different data sources. Eight data collection methods are used throughout the study, namely, online surveys, a literature review, a focus group, semi-structured interviews with athletes, spectators and HCI researchers, content analysis of social network comments posted during deployments, quantitative data of online users' interaction that is collected by the data server, observations, and research through designing four data telemetry prototypes and four online-crowd interfaces. Figure 3 shows the sequence of how these data collection methods were integrated.

The challenges that research in-the-wild presents are widely documented in literature [31,38,88,95,158]. However, over and above these challenges, our work faces additional unusual dynamics. Each of these augments the complexity of running the study. Namely, 1) the need for co-ordinating a group of co-located participants that are conducting a challenging task in-the-wild (athletes), 2) the need of co-ordinating a group of globally distributed participants (remote supporters) and 3) the need for all activities to operate in real-time with synchronous interaction at a global scale. The latter does not afford the traditional lab recruitment approach where the researcher schedules participants at a time when it is most convenient for each participant. In our case, all the participants have to synchronise with the live event.

In this context, recruiting participants, particularly online spectators, requires rigorous planning. Online spectators may be less difficult to recruit than co-located athletes since much less effort is needed when participating in an online task than when participating in a physically challenging task such as a long distance race. Additionally, there is typically no travelling involved. The participants do not feel they are being watched and they might do work in parallel to following or supporting the athletes. For example, Manson points out that they might have coffee while engaging in an online event [120]. Another important aspect highlighted by Mason is ‘Attrition’. In a lab experiment, it is very unlikely that a participant walks out of an experiment due to unstated pressure from being in a face-to-face situation. This does not apply to an online environment where participants may easily leave the experiment at the click of a button. The participants may also be distracted by various other factors such as surfing other websites, making errands or experience technical system failure, to mention a few. To monitor this, we follow recommendations by researchers [120] who suggest placing occasional prompts to monitor attention. The system then logs the time taken for each viewer to respond and this measure may then be compared to different participant groups and collected datasets.

Additionally, to mitigate complexity, we start with a small-scale deployment that has few participants, to then increment the scale of the deployment iteratively. This approach promises 1) incremental improvement, 2) contains any emergent ethical issues and 3) minimises risk of failure.

1.6.1 Innovation Management

Our assumption is that this form of support is in an early design stage of its life cycle. Each of the four deployments is independent from each other. Each deployment adopts a different approach and attempts to explore the field as broadly as possible within the scope of a PhD study. This approach is inspired by the concept fan techniques that is often used in new product development [110]. A different approach, that was initially considered, was an iterative design approach [83]. In this case, each design iteration incrementally improves the previous design towards a single solution. Such an approach could have involved conducting a detailed ethnographic study of existing co-located spectators in order to understand their cheering patterns and behaviours, and then, digitally replicate the identified user journey as close as possible to ‘real’ cheering. While this approach is valid, we felt that this approach risks limiting the innovation outcome to existing social dynamics in the analogue world. However, there could be new ways, both in process and modality of supporting an athlete remotely. These new processes and modalities might not exit because they are simply not possible in co-located cheering but might emerge in a remote-located cheering context. Secondly, a broad exploratory deployment (in contrast with an iterative design that is intended to refine a single approach) seems more appropriate for an exploration in an area that seems to be in the early life cycle of its innovation process. This approach promises a broader scanning of the horizon that would rapidly look at different design directions and concurrently highlight the directions that are most promising and merit further research.

1.6.2 Participants

All the deployments were conducted within a university context. Two different participant groups were recruited for each deployment; athletes and spectators. In all four studies, the athletes were regular long distance runners. In total 22 runners participated. 18 were university students and 4 were academics. On the other hand, spectators were recruited though word-of-mouth (Phase 1 and 2), advertisements within university social groups, for example, a university running club (Phase 3 and 4), and through crowdsourcing (Phase 3). In total 418 spectators interacted with the athletes across the four phases. A more detailed account of the participants of each study will be presented within the respective phases.

1.7 Key Themes

Figure 4: Word cloud for the text in Chapter 2 to 8

Figure 4 shows a word-cloud for the corpus within Chapter 2 to 8. We place this here to give the reader an overview of the themes that this multidisciplinary research touches upon. Themes in data, sports, biometric data, distributed crowds, real-time interaction, communities and support emerge within this work in HCI. This work is primarily informed by existing literature in wearables, health (from an HCI perspective), quantified-self, ubiquitous computing (particularly research in the Internet of Things), gamification and mobile interfaces. Figure 5 positions the key themes across which this investigation sites. In Figure 5, themes are classified in sets. We must note that the delineation of these sets is blurred and the elements within them are often interrelated.

Secondly, unlike co-located cheering, in the solutions that are deployed in this study, athletes and spectators are linked with technology. This is done through ubiquitous computing [8], mobile interfaces [79], synchronous interaction [135,164] and by designing and deploying a technology-enabled object as an Internet Of Things (IOT) device. In all the deployments, the spectators are distributed. Though distributed, the spectators form a crowd that is expected to demonstrate emergence of collective behaviour [117]. In other words, the actions of the individual spectators, collectively, create the crowd's behaviour that is not necessarily the sum of the individual actions [162]. Michael Bernstein uses the term Crowd-Powered Interfaces to refer to interfaces which are constructed by the actions of many. Through a number of cases studies, he highlights the technical and motivational challenges that lie within these interfaces [19]. In this work, Bernstein highlights the need of subdividing the crowds' tasks, in our case the cheering, into small tasks. Secondly is the need to filter or review the results. If the interface is a real-time crowd powered interface, the latter becomes more challenging. Literature in crowd-powered interfaces presented numerous cases were system designers compensate for these issues by, say, limiting the influence of the crowd on the interface or averaging the interaction across multiple individuals [2,28,59].

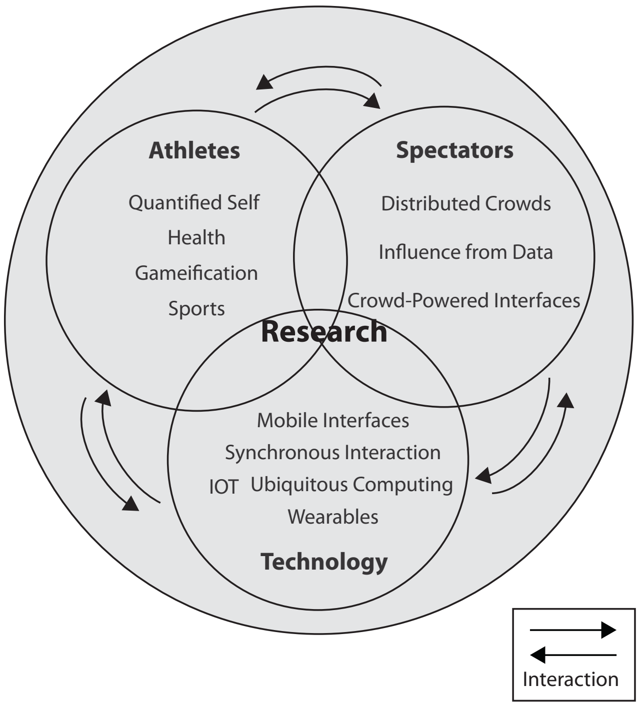

Figure 5: Related themes

Over the last two decades, communities with diverse interests have been increasingly collecting and logging personal information thus giving rise to the quantified-self movement [156]. Within sports, athletes logged data through different ad-hoc and generic devices such as smartphones, wearables and biometric sensors [114,181]. An increasing number of athletes not only logged this data for personal use but also started sharing this data with others [10]. The willingness of humans for self-disclosure dates back to before the Internet era. In 1969 Worthy et al. conducted a series of experiments that concluded that the more intimate self-disclosure was, the more others liked them as assessed in a post-experiment assessment. Moreover, this liking was not influenced by whether the situation permitted eye contact or not [199]. The latter is relevant in our research as we attempt to digitise a social communication setting that traditionally involves eye contact. Similar outcomes are found in more recent times were data sharing is used as a form of engagement over social networks and to encourage nudging in applications that seek behaviour change [37].

A common type of data that athletes collected and shared is data that is related to their performance and/or biometric data such as the athlete's heart-rate. Most popular mobile sport applications such as RunKeeper, Runtastic and Nike+, allow users to collect and share performance data that is based on geographical location sensing (e.g. speed, pace and geographical position) and biometric data (e.g. sensing heart rate or respiration rate) [66]. There have been numerous studies that looked into the effect that sharing location-related data has on both the person sharing the data and the person seeing the data [85,87,103]. However, as we shall further elaborate upon in the next chapter, there have been very few studies that looked into the effect of sharing biometric data, such as heart rate, outside the medical domain. Consequently, in our work we are interested in seeing how presenting such data might influence cheering.

1.8 Overview of Studies, Methods and Findings

This thesis is composed of four key standalone phases as follows.

1) We first conduct a feasibility study to assess the viability of investigating real-time support from remote crowds in a sporting context, identify any ethical issues that may arise from the study, and gather preliminary insights on how to design systems for remote spectator support. This feasibility study is composed of desktop research and two in-the-wild deployments during two sporting events (Chapter 2).
2) With the insights gained in Phase 1, we then design and build BioShare, a customisable research tool that facilitates sharing live data over social networks and allows remote spectators to send instant feedback (Chapter 3).
3) We deploy a customised version of BioShare called HeartLink, in an ad-hoc in-the-wild 5k event with 5 athletes and 140 remote spectators (Chapter 4, 5).
4) Finally we conduct a fourth in-the-wild deployment during a 24-hour 170-mile relay race with 13 athletes and 261 spectators. This study compares and contrasts the effect of increased challenge and loneliness over the previous deployment (Chapter 6).

The next sections briefly describe each of these phases and how each phase leads into the next. We present the methods used together with an overview of the learning outcomes from each of these phases.

1.8.1 Phase 1: Feasibility study - desktop research, a pilot study and a user study

Phase 1 assesses the viability of investigating remote crowd support. It also gathers insights on possible ethical issues that should be taken into consideration when deploying events in-the-wild within this context and captures requirements for system design.

Through desktop research we first review existing commercial mobile phone applications that are designed for sports activities. We find that applications at the time of conducting the study, do not allow spectators to communicate with athletes during events. We also identify that academic research on sports applications is very limited particularly when it comes to the sharing of live personal data. In this light, before conducting in-the-wild deployments, through an online survey we assess the readiness of participants from a university setting, to share personal data while conducting sports activities.

A pilot study and a user study are then conducted. These seek to understand the technical issues involved when athletes share data in the wild. These also gather primary data on the athletes' and the spectators' experience. The pilot study takes place during a triathlon in the Lake District and focuses primarily on validating the technology. The user study is conducted during a charity run in Lancaster, UK. This focuses primarily on capturing the participants' experience. Analysis of the data that was captured through observations, server-interaction logs, interviews and content analysis of online discussions during the events, indicated that research in remote-crowd support is worth pursuing. However, the use of third-party communication applications that were used to share athletes' data within an in-the-wild research context, presented a number of challenges that included a lack of control on data integrity and reliability. These also limited the ability to measure user experience and behaviour thus motivating the development of a bespoke data sharing system for researching remote spectator support: BioShare.

In summary, this phase contributes 1) a confirmation that further research in remote crowd support is worth pursuing, 2) provides preliminary insights on how to build crowd support systems around the athletes and the spectators, and 3) highlights the need to create a dedicated tool for researchers working in this area. Further details on Phase 1 are presented in Chapter 2 as published in ACM CHI'13 proceedings [42].

1.8.2 Phase 2: System Design and Development

In Phase 2 we design and develop BioShare. The requirements capturing for developing Bioshare involve three stages.

a. We first reanalyse the data collected in Phase 1 and identify key system requirements.
b. We are interested in making Bioshare relevant for other researchers working in this area. Consequently, to validate whether the insights gained from our experience in deploying two in-the-wild studies match the requirements of researchers who developed closely related systems, we then compare and contrast our insights with those of closely related systems that are referenced in literature.
c. We find that the systems that are referenced in literature lack details on how these systems were developed and details on issues that emerged during their development, if any. Thus, we further investigate past systems' development by interviewing HCI researchers who created closely related data sharing systems for research applications.

The developed system consists in a native Android mobile application that can broadcast locative and physiological data of users over mobile networks and receive feedback from online crowds. A web interface together with a dedicated backend allows distributed crowds to follow and communicate with the data-sharing users. BioShare is open-source and is designed such that it can be configured for different study requirements.

In addition to contributing BioShare as a tool for researchers, this phase contributes a set of requirements for spectator support systems in the presented context. These include ethical considerations, design for adaptability and the need to give the user entire control over the shared data. A detailed account of Phase 2 can be seen in Chapter 3 as published in ACM DIS'14 proceedings [41].

1.8.3 Phase 3: Deployment in an 5k-road race

A customised version of BioShare, HeartLink, is then deployed in a 5k-road race with 5 athletes and 140 remote spectators. In this deployment we seek to 1) capture the experience of athletes when sharing data and receiving remote support (RQ1) and 2) identify what influences supporters' behaviour during a live sport event (RQ2). Pilot studies suggested that spectator engagement is influenced by both the data that is presented (e.g. the effort that the athlete is exerting) as well as the social relation between the athlete and the supporter. To validate this, we recruit two spectator groups. One spectator group was recruited through the athletes' own social networks. Thus, the spectators in this group knew the athletes. A second spectator group was recruited from a crowdsourcing platform and thus these spectators had no social connection with the athletes. Additionally, to compare whether different data types, particularly heart rate data, influences the spectators' engagement, all the spectators were randomly assigned to one of two conditions. One group was presented with locative data while a second group was presented with both locative data and heart rate data of the athletes. The results indicate that having a social tie with the athletes increases engagement in supporting the athletes. These spectators cheer more and spend more time supporting. Spectators who were presented with the additional heart-rate data in their interface also cheer significantly more. Additionally, through a focus group, the athletes suggest that the motivation for athletes to use remote spectator-support systems is dependent on the effort that the task entails and the degree of loneliness that the event presents. Thus to further investigate this, we conduct a fourth in-the-wild deployment during a 24-hour 170-mile long relay race across the UK.

In summary, Phase 3 contributes the following:

1. Through quantitative data, it highlights differences in spectator behaviour across spectators who are presented with different visuals, and spectators who have different social relationships with the athletes. For example we find that spectators who are presented with additional information about the heart rate of the remote participants are likely to send more cheers.
2. Through qualitative data, it identifies key motivations for using live remote cheering systems. For example, we identify that spectators' behaviour depends on their understanding of why the athletes are conducting the task (e.g. egoistic vs. altruistic objectives in participating in an event). As regards the athletes' motivation, we identify that the impact that the cheering has on the athletes is relative to their expectations. This and similar outcomes, will be supported through theories of expectations management [1] and self-determination theory [42].
3. It identifies the effect on athletes from sharing live data and being cheered on remotely. Athletes indicate that real-time remote support is more effective in non-competitive events (for example a charity run) that competitive events.

A detailed account of Phase 3 is presented in Chapters 4 and 5. Chapter 4 is published in ACM CHI'15 proceedings [44] while Chapter 5 is currently under review.

1.8.4 Phase 4: Deployment in a 170-mile relay race

For this event, BioShare is customised and embedded in a running relay-baton form factor. This baton works as an interface between the remote crowd and the athletes. The baton's form-factor also provides enough space to store the needed energy for the 24-hour long event. Following a co-design process with the athletes, the prototyped baton collects and broadcast data in real-time and vibrates whenever a remote supporter clicks a cheer button on the web interface. Additionally the baton also calls out the name of the person who sent the cheer. In this way the athletes get an awareness of where the cheers come from.

This phase presents a number of contributions. Through these deployments, we further analyse and deduce user-motivations for using real-time crowd-support systems (RQ3). Athletes report motivation from: receiving remote support, building followship, having a proof of accomplishment, satisfying a social need to connect with others, democratising sport events and facilitating mindfulness about the event, among others.

Additionally, the data collected through these deployments provide insight on key factors that need to be taken into consideration when engineering real-time crowd support systems (RQ4). These are presented in three categories:

1) Spectators' expressiveness i.e. the design of how spectators can externalize their support. This can range from a highly controlled form (e.g. simple binary 'Likes') to a more open approach such as user-generated communication (e.g. live audio streaming of aggregate cheers from spectators' microphones).
2) Context applicability i.e. we identify contexts where remote spectator support seems most pertinent. Findings indicate that these systems seem to be most valuable in challenging events and where the athletes feel lonely (e.g. participating in an unaccompanied setting at nighttime). On the other hand remote support appears less useful in competitive events.
3) The design of the data flows within the social network. Here designers need to consider how system users (athletes, spectators or organisers) communicate and design communication flow.

Further details on Phase 4 are presented in Chapter 6. This is currently under review for publication in the ACM CHI'16 proceedings.

1.9 Revisiting the Research Questions with Findings

In this section, we present the main findings of the study in relation to the research questions.

RQ 1. What is the athletes' experience when sharing data and receiving support from remote crowds during sporting events?

In all the deployments, the athletes commented positively about having spectators follow their performance live and being cheered on (Chapter 2, 4, 6). Our findings indicated that spectator support systems are most effective in situations where the task is challenging and in contexts where the athletes might feel lonely due to the nature of the challenge itself (Chapter 6). The athletes also repetitively report that the system is more relevant in non-competitive events than competitive events as the cheering may distract the athletes from the needed mental concentration (Chapter 4). However, our finding also show that the users' experience when sharing data and receiving support is dependent on individual personalities and expectations (Chapter 4).

RQ 2. What influences the behaviour of the remote supporters during a live sporting event?

In Chapter 4 and 5, we identify 4 key factors that influence the behaviour of remote supporters: 1) the social tie strength between the spectators and the athletes, 2) the type of data that is presented to the spectators, 3) the spectators' belief of athletes' motivation to participate in the race, and 4) the spectators' incentive for recruitment.

RQ 3. What are the key incentives for stakeholders to use systems that facilitate remote support in real-time, if any?

We identify nine incentives. The presented systems can be use to 1) receive live support, 2) build a community of followers, 3) as a proof of accomplishment, 4) as a way to democratise support in sporting events, 5) to triggering support mindfulness, 6) to create new social connections, 7) to satisfy a social need to connect, 8) for reaching a new audience, and 9) for event control (See Chapter 6 for a detailed review of these findings).

RQ 4. What are the key factors that need to be considered when engineering systems that facilitate support from remote spectators?

While each of the four in-the-wild deployments in this study contribute to RQ4, Chapter 3 empirically identifies and presents system requirements for remote crowd support applications. Chapter 6 presents key design considerations that should be taken into account when engineering these systems. This work highlights the need to 1) design for 'Spectator Expressiveness (i.e. how spectators express and communicate their emotions, 2) identify key contextual factors that influence the impact of remote crowd support (e.g. the difficulty of the task at hand) and 3) the design of the network configuration in this social context.

1.10 Research Contribution

Identifying technology-mediated designs to support others who are undergoing a challenging task just when the support is needed could have huge positive impact in sports and beyond. To conduct this study, we developed and deployed HeartLink, a systems that enables two-way communication between athletes and remotely located spectators. This allows fans that, say, do not afford to be physically present at the event's location to support the athletes, or allows non-famous athletes to recruit support from their personal online social networks. In this work, we describe our experience of designing and deploying HeartLink in different contexts. The design process was driven by literature, insights collected through reflection, and interviews with HCI design experts, athletes and spectators. This experience could be relevant for future designers of these systems. Moreover, through evaluating the deployments in-the-wild during sporting events, we capture and present the athlete's experience of being remotely cheered and identify factors that influence spectators' behaviour.

We use running as a challenging task as this provides conditions for repeatability, research observation and existing studies that show that supporting crowds can have a positive effect on co-located runners [28,59,168]. In future work, the insights that are drawn from this work could be compared and contrasted with applications outside sports where real-time remote social support features are needed.

1.11 Related Work since Publications

Since the publication of the papers that are presented in this study, a number of other researchers contributed to related areas or referenced this work. Google scholar lists 42 peer-reviewed articles that cite these papers at the time of writing, indicating that our work has drawn attention from research in sports [99,129,142,185,191,200], social networks [91,123,143,175], personal informatics [56,57], activity sensing [101,102], engaging crowds [59,61], interaction design [74], crowdsourcing [76,103,115] and games [178].

Similar work recently explored ways of engaging spectators during sporting events in a co-located context [61]. Run Spot Run is a research application that lets spectators at a racecourse record and tag video footage of the event. Quite successfully, a small group of co-located spectators (n=17) tagged 412 clips during a city marathon. We believe that systems like Run Spot Run could enhance applications like HeartLink where co-located spectators video-document the event and potentially stream the content live to remote spectators.

Since our first deployment, the research community also presented new innovative materials that can now broaden the impact and effectiveness of systems like

HeartLink. Mauriello et al. study a set of innovative wearable textile displays that can give real-time feedback to athletes running together in groups [121]. They report that through real-time group feedback, 'Social Fabric' helps groups stay together and improves motivation in the activity. This and similar novel communication technology promises further novelty if combined with HeartLink. These wearable textile displays could mitigate some of the technical challenges that were captured during our deployments such as issues related to the weight of the devices used, form factor and ergonomics. Similar work was also done by Walmink et al. [191].

Finally, worth mentioning is the work of Woźniak et al. [200]. They explore remote cheering during amateur races through RUFUS. RUFUS is a prototype device that is carried by athletes together with smartphones, to alert them whenever remote spectators send cheers. Their results support our published findings (particularly Chapter 2 and 4). Following a deployment in a city marathon with live remote cheering, they report that athletes and spectators show 'increase in motivation and enhanced race experience through feeling connected'.

1.12 Thesis Structure

The chapters in this document respect the time sequence in which the work is conducted. In the next chapter, **Chapter 2**, we present the preliminary work that is conducted to verify whether the planned research in crowd support is worth pursuing. This consists of a pilot study and a small user study that are conducted during a Triathlon in the Lake District and a Charity Run in Lancaster, UK. The results from this work provide insights that feed into the requirements capturing, design and development of Bioshare. This is presented in **Chapter 3**: System Design.

The developed system is then deployed in a 5k-road race with 5 athletes and 140 online spectators. Here we analyse the effect that data sharing has on the crowd watching the live event and the effect of real-time feedback from the crowd on the athletes. These are presented in **Chapter 4** and **5** respectively. **Chapter 6** presents the fourth deployment that is conducted during a 170-mile relay race across the UK. Here we compare and contrast the effect of cheering during an event of a longer duration and increased loneliness. In this chapter, we also provide recommendations for designers of real-time crowd-support systems. The concluding chapter, **Chapter 7**, presents a summary of the findings, identifies research impact and gives direction for future work.

Chapter 2
PILOT STUDY

Published as:

Curmi, F., Ferrario, M.A., Southern. J. & Whittle, J. HeartLink: Open Broadcast of Live Biometric Data to Social Networks, in *CHI'13: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ACM Press (2013), pp. 1749-1758.

2.1 Abstract

A number of studies in the literature have looked into the use of real-time biometric data to improve one's own physiological performance and wellbeing. However, there is limited research that looks into the effects that sharing biometric data with others could have on one's social network. Following a period of research on existing mobile applications and prototype testing, we developed a system, HeartLink, which collects real-time personal biometric data such as heart rate and broadcasts this data online. Insights gained on designing systems to broadcast real-time biometric data are presented. In this paper we also report emerging results from testing HeartLink in a pilot study and a user study that were conducted during sport events. The results showed that sharing heart rate data does influence the relationship of the persons involved and that the degree of influence seems related to the tie strength prior to visualizing the data.

2.2 Introduction

In recent years accessing one's own biometric data has become relatively easy and unobtrusive yet there has been little use outside medical [98,113] and sports applications [147,198]. In addition, while various studies showed that sharing personal data over social networks could have positive effects on the user [134,175], there have been very few studies that went as far as sharing biometric data in real-time. Observing someone else's biometric data is only recently becoming common with data sharing networks like Runkeeper or Endomondo. But is visualizing others' biometric data in real-time engaging?

To start exploring this perspective we designed, implemented and tested a system named HeartLink. HeartLink collects heart rate (HR) data as a biometric parameter from athletes participating in sports events. This can be broadcast in real-time to viewers that have various social relationships with the participants.

In this paper, we report emerging findings from a pilot study and a small user study which we conducted using HeartLink. The pilot study was conducted with athletes during a triathlon and focused on testing the system itself. The user study was conducted during a charity run. It delved into the impact that real-time biometric data visualization can have upon the social network. Throughout this paper the term 'participants' refers to the athletes wearing the biometric sensors and the term 'viewers' refers to the individuals remotely observing the data.

The results from the pilot study highlighted a number of challenges that are encountered when building systems that broadcast real-time biometric data in the wild. These include issues such as system latency and interface design. The results from the user study showed that the broadcasting of real-time biometric data made viewers feel closer to each other even though they were geographically far away from the participants. On the other hand, the participants were more motivated in the event due to a feeling of 'being followed'.

2.3 Related Work

2.3.1 Personal data sharing

In the last decade, there has been the emergence of a number of social media applications such as Twitter, Facebook and Tumbler that allow citizens to share personal information with family, friends and the wider social network. These have created a new phenomenon where millions of people share personal data on a scale that has never happened before. Studies showed various positive effects that such personal data sharing can have on aspects like social support [155,169,175], self-representation [137,186] and the social connectedness that is created across friends [9,137,197].

2.3.2 Autonomous data collection and sharing

While the vast majority of these applications depend on the user to manually input the data being shared with friends [35,111,134], some recent applications are able to autonomously collect and transmit data on behalf of the user in real-time. This data is then used for sharing with friends or to interface with other passive or active datasets with minimal or no intervention from the user [132]. Mueller et al.'s research [132], for example, involved two joggers jogging at the same time in different places and communicating together via speech and ambient sound. To increase the social experience, each jogger heard the sound of the other jogger as if the other jogger was present. The spatial direction of the sound was depended on the heart rate of each jogger. Similar research applications used real-time GPS data for communicating the participants' locations as in the case of Comob [179] or Miluzzo's CenceMe [126] application. CenceMe looked into the effects of broadcasting data from sensor-enabled mobile phones to social networks like Facebook and MySpace. Using the sensors, activities such as walking, standing, dancing or talking were automatically identified and shared over the individual's social network in addition to randomly taken photos. In all of the three above-mentioned studies [126,132,179], the results showed that sharing of personal information could be helpful in creating engagement. They also generate curiosity and an urge to know more about what social network members are doing.

2.3.3 Sharing biometric data

The relatively few biometric data sharing applications that exist are predominantly from areas related to health [98,113] (see [97] for a recent literature review) and sport

[147,198]. In sports, mobile applications have been designed to help athletes monitor their performance through the collection of biometric data. For example Runkeeper and Endomondo, two popular mobile apps used by athletes to track their performance, allow the user to share bio data such as heart rate with selected friends. Related work explored the possibilities of augmenting interest in televised sport events by sharing the participants bio data (see [76,168,183]). We are similarly interested in exploring opportunities that arise when this very personal data is shared openly with everyone. In addition to this, we are interested in giving the viewers the possibility to cheer the data-sharing user in real-time thus proposing a real-time feedback loop.

2.3.4 Real-time broadcast and crowd feedback

Incentive theory states that when the positive reinforcing action closely follows the action that needs to be reinforced, the motivation is greater then otherwise [92]. Yet, with the exception of [132], in the above-mentioned studies which share bio data to gain encouragement from the social network, the motivation does not happen instantly. For example in [35] and [111] data is uploaded and shared only daily. In [132] while such feedback is instant, it is only shared with one co-participant and does not involve an online crowd. In our preliminary research we found that studies that combine both the sharing of biometric data with an online community and the aggregation of support from the same community in real-time, are hard to find.

2.4 System Design

To explore this, we needed a system that captures biometric data, such as HR data, from participants and broadcasts this data online in real-time. The system would then allow us to control the way the data is presented to the viewers and also log the interactions that the viewers have with the interface. While a few applications that share bio data in real-time do exist, these could not be used for this study as they do not allow 1) customization such as changing the way the data is presented 2) logging of interactions with the system and 3) instant feedback from viewers. In this light, HeartLink was designed as a research tool with these design needs. To gather informal feedback and preliminary ideas, system design started with informal discussions with amateur athletes. This was followed by idea generation using the Scamper technique [55] and Brainstorming exercises with a group of PhD students at Lancaster University. An online survey then assessed the readiness of the respondents to share personal data. This survey also analysed the current levels of use of sports-related mobile applications.

A pilot study and a main user study were conducted using HeartLink. The pilot study was primarily intended to test the reliability of the HeartLink system and gather feedback on ways in which the system could be improved. This study was conducted with three participants taking part as a team in the Windermere Triathlon and nine viewers (three viewers per athlete). These viewers were selected in such a way that there was diversity in the relationship of the viewers to the athletes. The user study was conducted during a Race For Life Event in aid of Cancer Research at Lancaster UK. In this event, one participant and eight viewers were recruited. Table 2 shows the social relationship between the participants prior to this event. In-depth interviews were carried out after the event.

	2A	2B	2C	2D	2E	2F	2G	2H	2I
2A		3	3	3	1	2	2	4	2
2B	3		3	3	1	4	2	1	2
2C	3	3		3	1	2	2	1	2
2D	3	3	3		1	1	1	1	1
2E	1	1	1	1		1	1	1	1
2F	2	4	2	1	1		1	1	1
2G	2	2	2	1	1	1		1	1
2H	4	1	1	1	1	1	1		1
2I	2	2	2	1	1	1	1	1	

Table 2: Social relations of the participants prior to the user study. '2A' is the athlete, '2B-2I' are the viewers, '1' represents participants that did not know each other, '2' if the participants were friends, '3' if they are work colleagues and '4' if relatives

In the initial design stages, HeartLink had a number of design constraints. These included the need to have a low cost per participant and the need to be fast to implement and replicate. It was also important for the system to be unobtrusive and reliable such that it could be used in a wide range of environments like walking, cycling and swimming. This approach made HeartLink applicable to different research settings. Ultimately, HeartLink was designed to be highly modular such that existing third party hardware and software applications could be used where possible. This methodology shortened the time of implementation, since the system did not need to be built from scratch. This included using off-the-shelf HR sensors, mobile applications, point-to-point data links and data storage services.

The specific selection of the third party modules that were used was grounded on 1) a survey that analysed the adoption of existing mobile applications among potential users, 2) the cost of using the system and 3) a decision matrix based on the features that were offered. We then coded the software to collect the data from the selected applications and display this data in a dynamic graphical visualization that we could design as needed. This rapid prototyping approach made it possible to design and implement the entire system in less than four weeks with a total of 164 coding hours. Most of the coding was done in PHP, Javascript and JQuery with data storage in a MySQL database. We also used Google Chart Tools (developers.google.com/chart/) to handle the chart visualizations in the interface. These provided a rapid way of implementing charts, thus making it easier to experiment with alternative representations of the same data. Figure 6 represents the flow of data in HeartLink.

Survey: The primary objective of the survey was to compile a list of the most commonly used mobile applications for tracking sports activities. Information regarding the eagerness of the participants to have their personal data shared with

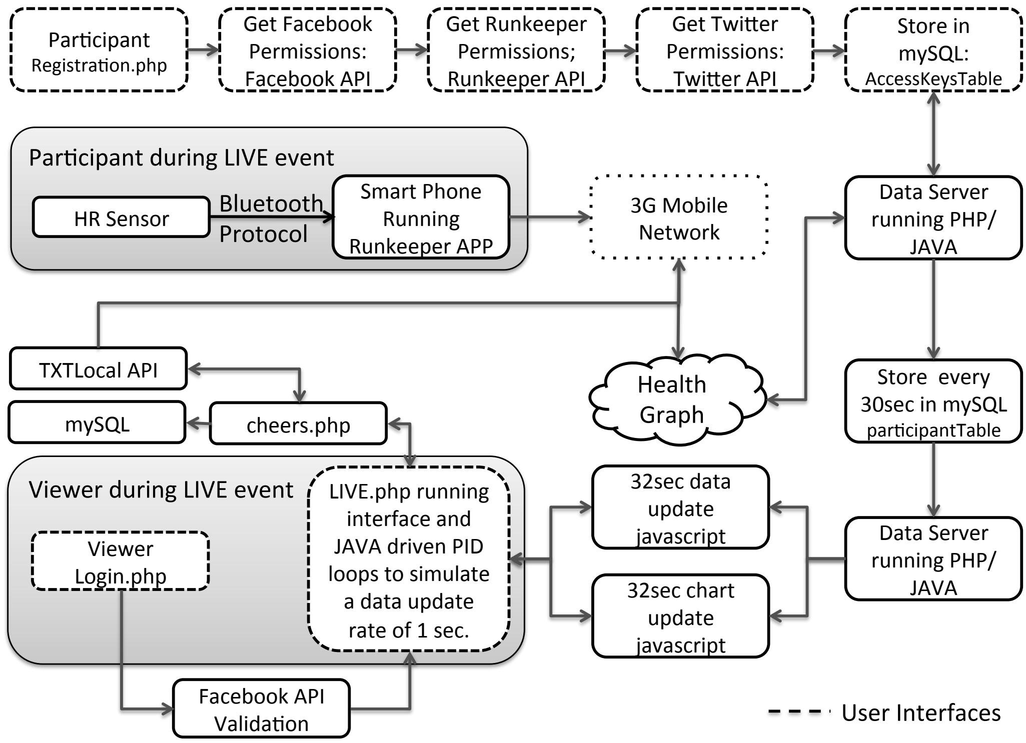

Figure 6: System dataflow of HeartLink

others was also collected. The survey asked participants if they tracked any personal information during sports activities and whether they were ready to share this data. Those who did track activities were asked how often they did this, the types of applications they used, if any, and if they were willing to participate in future experiments that involved interviews.

The following are sample questions from the survey:

- Do you share personal data from these applications with friends?
- What made you select this mobile application?

The participants were postgraduate students of Lancaster University. An email was sent to all postgraduate students asking them to volunteer in an online survey: http://goo.gl/mz9CU

We had 52 valid responses returned with a participants' average age of 26.3 years. 25 of these were female, while 27 were male. 75% of the participants claimed to practice sports at least once a month. Running, swimming and cycling were the most popular sport with 32%, 30%, 24% respectively (respondents could select more than one option). A total of 17 different sports-related mobile applications were mentioned by the participants with Runkeeper and Nike+ being the most common applications (3 participants each). When asked what type of friends' data they would be interested to follow in real time during a sport event, Geographical Position (20) was the most popular, followed by Distance Covered (17) and HR (14). 10 of the 52 respondents were willing to share personal data while 20 respondents were interested in observing other's data.

App	WEIGHTING 1-10	Runkeeper	Runkeeper ELITE	Runmeter GPS	Nike+ GPS	C25K	C25K Pro	Ghost Race	Gazelle GPS Workout Tracker	OutFront: MapMyTracks	Endomondo Lite	Endomondo Pro	iMapMyRun+	Adidas miCoach	Runstar	Runstar Pro	CardioTrainer Lite	CardioTrainer Pro	Sporty Pal Pro	Runtastic	Runstatic Pro	Sports TrackerLive	Sports TrackerLive Pro	My Tracks	Dailymile
Android	5	5	5	-5	-5	5	5	5	-5	-5	5	5	5	-5	5	5	-5	-5	5	5	5	5	5	5	5
Iphone	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	-5	-5	-5	5
*Cost	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Windows Mobile	1	-1	-1	-1	-1	-1	-1	-1	-1	-1	1	1	-1	1	-1	-1	-1	-1	1	1	1	-1	-1	-1	-1
GPS Log	2	2	2	2	2	2	2	2	2	2	-2	2	2	2	2	2	2	2	2	2	2	-2	2	2	2
Heart Rate Log	10	10	10	-10	-10	-10	-10	-10	-10	-10	-10	10	10	10	-10	-10	10	10	10	-10	10	10	10	10	-10
Realtime data broadcast	10	-10	10	-10	-10	-10	-10	-10	-10	10	10	10	10	-10	-10	-10	-10	-10	-10	-10	10	10	10	-10	10
API interface	10	-10	10	-10	-10	-10	-10	-10	-10	10	-10	-10	10	-10	-10	-10	-10	-10	-10	-10	-10	10	10	-10	10
Open source	2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	2	-2
Cloud/data storage and retrieval	2	-2	2	-2	-2	-2	-2	2	2	2	2	2	2	2	-2	-2	2	2	2	2	2	2	2	2	2
Automatic email to family and friends at end of run	2	2	2	2	2	-2	2	2	-2	2	-2	2	2	-2	-2	-2	2	2	2	2	2	-2	2	-2	2
Facebook and/or Twitter Integration	2	2	2	2	2	-2	2	2	-2	2	2	2	2	-2	-2	-2	2	2	2	2	2	-2	2	-2	2
Friends send motivation messages/Audio Feedback	2	-2	-2	-2	-2	-2	-2	-2	-2	-2	-2	2	-2	-2	-2	-2	-2	-2	2	-2	2	2	2	-2	-2
Weighted Total		-1	43	-31	-31	-29	-21	-17	-35	13	-3	29	43	-13	-29	-29	-7	-7	9	-15	29	25	37	-11	23

Scale:																					
	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9	10

Figure 7: Decision Matrix for existing mobile applications with weighted criteria

Decision Matrix: We used a decision matrix [138] to identify which application out of the 17 mentioned by the participants in the survey would be the best one to use as part of the prototype. Some of the mobile applications mentioned had multiple versions (for example, Runkeeper and RunKeeper Elite). In such cases the different versions were included separately in the compiled list for a total of 24 smartphone applications. These were plotted on the x-axis of the decision matrix as shown in Figure 7.

In parallel to producing this list, we compiled a list of criteria that were listed on the y-axis. These varied from essential criteria to others that were 'nice to have'. Essential criteria that were needed to answer the research questions included, the ability to broadcast data in real-time, the ability to capture biometric data reliably and that of having an application interface with which to access the data. We did not immediately eliminate the applications that did not have the essential criteria so that all options were kept open during the design stages. A weighting value from one to ten was then given based on an estimation of how many programming hours were need should we have to implement the non/existing features ourselves. It should be noted that these weighing numbers are nominal values and a value of 10 compared to 5 does not mean that an application is twice as good. The decision matrix was a useful tool to visualize and differentiate between the various options available in the set of mobile applications. Ultimately, each application was allotted the weighting score of the criteria: if that criteria was satisfied by the features offered and the negative value of the weighting if otherwise. This data was inputted in Microsoft Excel and color visualizations were added to highlight the strongest and weakest solutions. The operating system of the mobile phones that we had access to (Android 2.2) determined the selection of the Polar (www.polar.fi) HR sensors.

2.5 Wireless Infrastructure

The wireless infrastructure was based on three different protocols. The Polar HR sensors captured data and transmitted this data using Bluetooth technology to smartphones that were carried by the participants. The smartphones added additional data such as location through the GPS sensor and timestamp. This data was captured via RunKeeper (www.runkeeper.com), a third-party smartphone application, and was broadcast in real-time over mobile networks to the Health Graph (http://developer.runkeeper.com/healthgraph/home). The latter is an open database that stores personal health-related data together with social network relations.

Online hosted servers then synchronized the data through the Health Graph Application Programming Interface (API) every 30 seconds. Other APIs besides Runkeeper were used to interact with participants and social networks such as Facebook, Twitter and Text Messaging. Moreover, the designed infrastructure supported the possibility of capturing data in different situations such as walking, running, cycling and swimming (Figure 8). The rapid prototyping approach decreased the cost of building the system, particularly since the number of devices needed was small. By using our own smartphones for capturing the data, the total expense we had for broadcasting each participant was £65. This excludes the coding time. All the code we developed however is open source and can be accessed at http://highwire-dtc.com/franco/heartlink

Figure 8: Sealing a smartphone in preparation for transmitting under water during the triathlon in the pilot study

2.6 Interface

Two separate interfaces were designed. One allowed participants to register for broadcasting their biometric data. This consisted of a sequence of screens that asked the participants for permission to access Runkeeper, Facebook and Twitter accounts through the OAuth 2.0 protocol [172]. The second interface allowed the viewers to visualize the live data. This visualization showed the HR and the 'Distance Covered' by the participants in real-time. Additional parameters such as pace, average HR and total heartbeats were computed on the server and were also presented to the viewers. The selection of these parameters was based on the respondents' interest, as shown in the survey. Geographical Positioning was also mentioned by the respondents; however, we opted not to include this as this area has already been researched in other studies of coproxmity [132,179].

Before accessing this data, viewers were asked to optionally log in using their Facebook account details. A separate link to bypass the login stage was provided for users who wanted to remain anonymous. Interaction with the interface was then time stamped, logged and linked to the viewers' Facebook public data. The collected dataset was later analysed for relationships between interface interactions and the changes in the biometric data of the participants.

In addition, in the user study, the viewers could click on a Cheer button to motivate the runner. The 'Cheer' button was inspired from the Facebook 'Like' button. For every five cheers the runner would receive an alert through a vibration in the smartphone. The vibrations were limited to every five cheers since it was assumed that a constant clicking of cheers would ultimately annoy the runner. The number of cheers that the user could generate was also limited by making a 'page refresh' within the browser when the cheer button was pressed. In this way, the user would not be able to do successive clicking, such as double or triple clicking. The viewers however had immediate feedback on the total number of Cheers that the athlete accumulated.

The interface was developed around standard web browsers rather than designing for proprietary applications on specific mobile devices. With this approach, anyone having an internet-enabled device could follow the data in real-time. From an implementation perspective this methodology streamlined the development in one standardized format for all devices. For example we did not need to develop separate software for Windows, OS X and Android users. The use of a standard browser also shortened the learning curve needed by the users since most users are already familiar with such interfaces. Besides, this approach does not necessitate any installations, as would have been required had the system been implemented using a new custom-made smartphone application.

2.6.1 Instructions to viewers

The viewers had different relationships with the participants. These varied from family members to persons who they did not know. An informal briefing was given to the viewers some days before the events when they were contacted individually. Two days before the event, they were sent reminders together with instructions via email. These instructions directed the viewers to the appropriate website for logging in a few minutes before the event started. They were told that the event would last around thirty minutes but they could follow for as long as they wanted to. It was possible to send motivational ‘Cheers’ to the participants when they felt like it. For our data collection purposes, the instructions also asked the viewers to take notes of their experience when watching the event or post comments on the site. These notes were later collected.

2.7 Insights From the Pilot Study and the Main User Study

In both the pilot study and the main user study, data was collected from five sources: 1) the interface presented to the viewers had an embedded Facebook frame in which the viewers posted comments during the events (see Figure 9), 2) the viewers were asked to write down notes during the events. These were later collected and analysed and included reflections that the viewers felt it was not appropriate to share online, 3) our observations of the viewers' interaction with the system during the event, 4) time stamped data logged by the servers. This data included interactions with the interface, posting of comments online and the time when viewers logged in and out, and 5) a total of 12 semi-structured interviews conducted with the viewers and the participants. The following are sample questions from the semi-structured interviews:

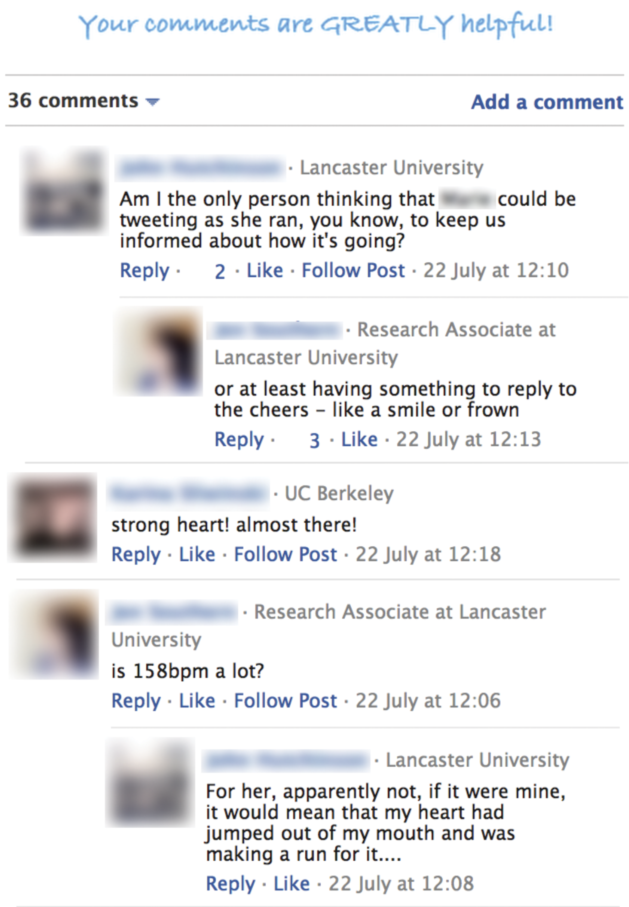

Figure 9: Embedded Facebook frame in the interface with selected comments posted by the viewers during the user study

- How long did you watch the event for? Did you do any other activities in between?
- What did you find most interesting and why?
- Would you use this system again and why?

The qualitative data in the study was transcribed using InqSribe and analysed using Atlas.ti. The analysis was based on inductive coding from both the transcriptions and online comments together with group discussions among the authors to identify links between the research objective and the data.

2.7.1 Insights from the pilot study

The data broadcast in the technical trial was intermittent. This happened because Health Graph was not functioning well on that particular day. This seemed to be a consequence of disruptions on Amazon's Cloud Computing service. This chain of dependent services has shown how vulnerable such a live broadcast system is. The Internet may give a perception of high reliability due to its networked configuration in comparison to traditional point-to-point broadcasting. Yet what happened in the pilot study showed that failure in the provision of one service disrupts the whole system. It is difficult to have redundancy on such services due to their scale and ubiquity. HeartLink integrates multiple large-scale third party systems such as RunKeeper, Amazon Web Services, Facebook, Health Graph, Mobile Networks and Global Positioning Systems (GPS). The pilot study also showed that when integrating multiple large-scale infrastructures, it is difficult to have control of the entire system. This makes the user exposed to unforeseen disruptions should one part fail. The reliability of HeartLink was also challenged by the unpredictability of the GPS and mobile phone coverage when performing live experiments 'in the wild' [31] and by numerous participants using similar wireless technologies and radio frequencies. In

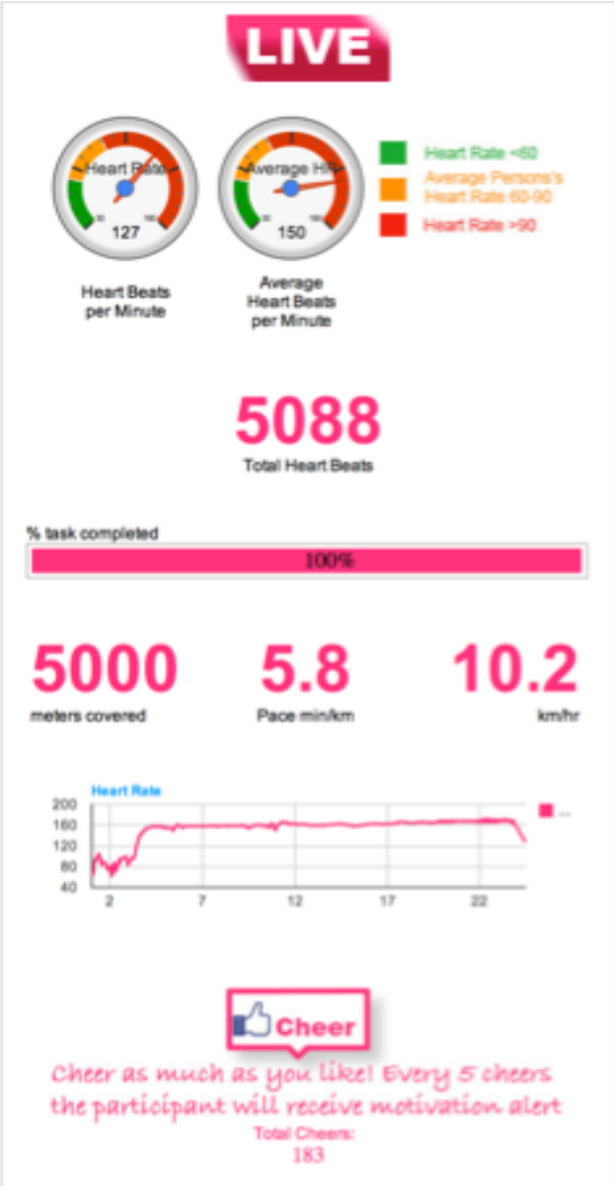

Figure 10: Part of the interface presented in the user study

addition, the Bluetooth transmission between the HR sensors and the smartphone was very weak so the participants had to keep the phones close to the respective HR sensors. Similar difficulties have been commonly encountered when doing live experiments with biometric data [76,168,183,184].

The pilot study provided insight also through the interviews particularly on the graphical visualizations used. The data in the visualization presented to the users was too detailed thus making it difficult to follow the changes that were happening. The data presentation was thus adapted for the user study. Where possible HeartLink presented the real-time data using charts instead of text. The most relevant parts in the visualization were highlighted by contrasting colours, distinct fonts and larger font sizes (see Figure 10). Three of the interviewees also pointed out the fact that it was awkward to have page refreshes in the browser each time the data was updated. This resets any personalization that the user would have made, for example the sorting of social network comments. Moreover, having updates every 30 seconds was too long and this did not give the perception of the data being updated in ‘real-time’.

2.7.1.1 Generating nearest real-time data

The data from the smartphone was transmitted to the Health Graph whenever there was any change in the data such as change of heart rate or GPS position. On average this occurred every 4.3 seconds. The dataset on the server was then updated from the Health Graph every 30 seconds due to limitations in the number of updates that we could technically do. The interface of each viewer within the browser would then refresh every 31 seconds. The extra second was to ensure that the data at the server had been refreshed. This approach created a number of issues. First, there was the awkwardness of having an entire page refresh within a web browser each time the data is updated. The viewers in the pilot study remarked on this. In most browsers, page refreshes are not done in a seamless fashion. This page refresh also resets any personalization that the viewers might have carried out. Secondly, updating data every 31 seconds reduced the possibility of giving the users a ‘real-time’ experience.

It was crucial for the scope of this research to have the viewers feel that the data was in real-time. For the user study some parts in the HeartLink system were redesigned in ways that minimized the time between each update. This involved using JQuery instead of simple HTML. Using JQuery, the system updated the visualization of every user each second. The data at the server however was still updating every thirty seconds. To solve this issue from a visualization perspective, we used algorithms to calculate intermediate values. Thus each viewer’s interface predicted the current real-time biometric values of the runner based on past trends that were extrapolated from previous data samples. Using this technique, the 30 second updates were distributed and presented to the viewers with one-second intervals rather then every thirty seconds. This approach made a tremendous improvement to the interface. This can be seen in the viewers’ comments during the user study when compared with those in the pilot study.

There is still room for improvement in this ‘near real-time’ approach. The system was estimating current values based on past actual values. Thus, when the runner slowed down during a thirty seconds timeframe, the data would show a decrease in value upon update. In the case of the ‘distance covered’, for example, the value would have decreased when this was updated to the actual value. This caused a paradox each time it happened. In fact, the viewers’ comments reflected this. In future, simply using past values rather then predicting current values could solve this. This solution however will increment the latency by thirty seconds so that the data would be further away from the ‘true’ real-time than the one used in this user study; yet this would avoid having backward jumps in the data upon update. An intermediate option could be that of using the same predictive PID loop technique but targeting for example, 85% of the predictive rate such that the probability of having an update with negative increments would be significantly decreased. Further research and experimentation will be needed to design and tune the algorithm that compensates for latency in the broadcasting infrastructure while still providing a true account of the data. Handling latency is very important particularly if there are viewers that are at the same event as the runner and are following the data on their smartphone device. Having a delay of 30 plus seconds will not be reasonable for most sports.

2.7.2 Insights from the user study

Visualizations: Figure 10 shows part of the visualization presented to the viewers in the user study. In the semi-structured interviews the viewers were asked to identify which part of this visualization they were most interested in during the event. All respondents stated that the percentage bar representing the 'distance covered' and the graph representing the heart rate were the most interesting followed by the 'actual distance covered' (numeric text), the 'heart rate' and the 'average heart rate'. The 'pace' and the 'speed' seemed only relevant to the viewers that were familiar with running. This was probably due to the fact that they could give more meaning to the data than others. The total heartbeats seemed the least interesting as reported by the viewers in the same interviews. There also appears to be a learning curve that the viewers go through when seeing the visualization for the first time. The duration of this learning curve is dependent on the number of parameters presented and the viewer's past experience of using biometric data.

Technical Challenges - sense making from bio data: On the day of the event, data broadcasting from the runner to the servers started thirty minutes before the race began. This allowed us to make sure that all the data links were working fine before starting the event. This pre-event broadcast gave us the opportunity to see whether or not the viewers were interested in the changes that took place before the race started.

When the participant started broadcasting data, this data was collected in a continuous incrementing dataset from which parameters such as average heart rate were calculated. However, it was difficult to know from simply observing the data, when the race started, as there was no marker that showed the point at which the race had actually started. This was needed for some algorithms, such as the one that computes the average heart rate in the race. These algorithms were averaging the whole data in the dataset including the time before the race had started. To display the average heart rate for the race, additional coding of the data had to be done while the event was taking place. The averaging algorithms then ignored the data that had been received prior to the start of the race.

A similar issue was encountered at the end of the race. Since the infrastructure was controlled from another geographical location over the net, the operator had no indication whether the race was completed or not. In the future this issue needs to be studied and catered for. It would be nice if there was no human interaction with the system and the broadcast was fully automated with precise understanding of the surroundings. An optional solution for example would be to have the system autonomously understand the precise timing (to the nearest heartbeat) of when the race started. This is essential for the data to be computed accurately. While it is very easy for a human, who is on location, to understand when the race would have started, it is not at all easy for a machine to do the same simple task on behalf of the user.

In future work, we plan to design ways of handling such issues by developing algorithms that detect 'a race start' based on say, an increase in the participant's heart rate. While this is still to be tested, the hypothesis is that it will be highly difficult to differentiate between an increase in HR due to a warm-up exercise or the emotional stress when the run is about to start or the actual start. A different approach for a machine to understand the precise moment when the race started is to use the GPS data. This approach also seems challenging, as current off-the-shelf GPS technology tends to be considerably noisy. For example, the GPS updates prior to the start of the race had an average error margin of five meters on each sample. Thus the unfiltered GPS dataset that was received by the server in the 30 minutes before the start of the race wrongly stated that 514 meters had been covered even though the runner was for most of the time in the same spot. The incremented GPS errors from each sample created a virtual motion that did not entirely exist. Moreover, understanding if the race started from changes in the GPS position is also tricky as in the case of the HR analysis, the runner might be warming up. The real-time factor increases the difficulty of the task compared to say analysing the dataset after the event took place. For example, detecting a change in speed would only generate the trigger some time after the start, once the data classifiers have been processed; not in 'real-time'.

2.8 Emerging Results

The results of the semi-structured interviews indicated that visualizing biometric data does influence social network ties. Various viewers have remarked that they felt more connected with the participant when viewing the real-time data. These remarks are found in both the comments sent during the event through the social network interface as well as in the follow-up semi-structured interviews. All the participants also felt this increase in connectedness even though they were not visualizing their own data.

The real-time broadcast of their data to their social network made them feel as if they are being observed:

"…it feels like a crowd is following you… in all three disciplines [swimming, cycling and running] you are quite on your own but with swimming you are really on your own with the water splashing around you and no one else… so [in this case] though you are on your own there is an environment where there are people around" [Participant 1A – from interview]

Two of the participants also stated that this real-time observation from their social network increases their motivation during the event. This is consistent with existing literature on sharing personal data on social networks [161,187]. The interest in visualizing biometric data is also shown in the comments left by the viewers on the social network interface. A particular case is highlighted by the frustration shown when the live data was not available due to technical faults at certain instances in the pilot study:

"☹ such a shame – hopefully it will come back up soon! Good luck to all" [Viewer 1G – Facebook comment]

"I was following while the event was running. It was kind of frustrating because it was not working… I could not see exactly what they were doing because there was no bio data…" [Viewer 1D – from interview]

Prior to the user study we were unsure if visualizing the data would be interesting enough to generate some degree of engagement or not. In the recruitment process the participants were not asked to follow the live event through to the end. Most viewers however, after the events, commented that they ended up watching the entire event even though they initially were not planning to do so. This was confirmed by the data on the server logs and shows that there is a level of engagement generated by the dynamic real-time data:

"I found it more engaging than I thought I would … I expected to watch for 5 minutes then go away; ended up staying there most of the time though" [Viewer 2B – from interview]

Our observations suggest that the degree of interest, which the viewer has, is related to the strength of the relationship between the participant and the viewer prior to visualizing the biometric data (Table 2). This indication however will need a larger sample of participants to determine with certainty. A large sample would make it possible to have enough subgroups of different network tie strengths for comparison.

A common suggestion from the viewers was to have additional data like the precise total timing of the race and the final placing of the participant in the race. Participants stated that the interest in following the event was due to the HR being presented with other data such as the percentage completion of the event. Other combinations should be tested in the future such as GPS location and live video. We intend to experiment with live video streaming in combination with bio data. The runner would transmit this in order to augment the sense making of the viewers for the biometric visualization they see. The camera may face in the same direction as the runner such that the live video shows the surrounding environment. It would also be interesting to experiment with other biometric data besides the HR such as heart rate variability, electro-encephalography and electro-dermal activity.

During follow up interviews, viewers were asked how and when they cheered. Two of the viewers stated that they cheered five times in a row whenever they wanted to cheer. They wanted to send feedback to the runner (through vibration). We found that other participants commonly carried out this pattern of clicking five successive cheers when we analysed the data logged by the server during the event. These punctuated clusters are visible in Figure 11 where the accumulative cheers submitted are plotted across time. This shows the eagerness of the viewers to have real communication with the runner not simple virtual cheers. In fact, in both follow-up interviews and online comments, viewers strongly requested the possibility of being able to interact with the runner during the race.

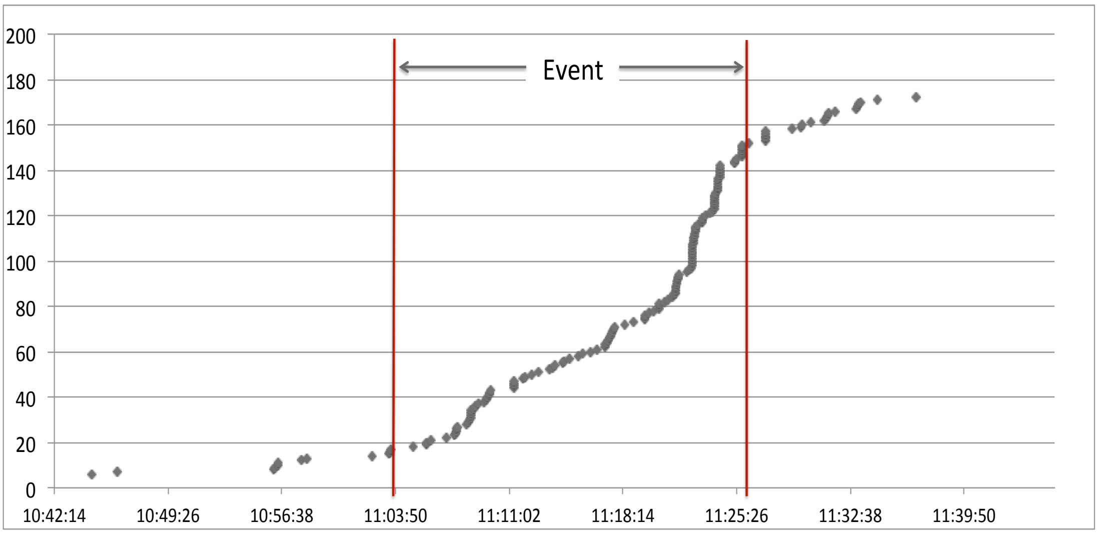

Figure 11: Accumulative number of cheers submitted during the event. The data was collected from time-stamped server logs. Red markers represent the start and end of the race.

Three respondents suggested the possibility of having some feedback from the runner or having the system itself telling them when motivation is most needed so they could send more cheers. An interesting area to explore in this regard is to have the system to automatically highlight 'requests for cheers' from the viewers, based on algorithmic analysis of the biometric patterns. If for example the pace is decreasing and the heart rate is increasing, the system will interpret this as the runner needing more motivation. Hence, it would highlight this information in the visualization presented to the viewers. In the study, the participants were also very keen to know what was being said online during their performance:

"I was so interested to know what my friends were chatting about [online] when I was running especially if there are not many people you know around you when you arrive at the finish line" [Participant B1: from interview].

Although the user study was conducted during a charity run, the interface used did not offer the viewers any options to donate. This was done intentionally so the study would focus on the biometric data visualizations. Yet participants still donated to the charity for which the event was being organized. Two viewers reported they donated prior to the start of the event. They felt that they should donate irrespective of the performance of the participant.

"I gave a donation on JustGiving before the race even started… I want to donate the money; I'm just going to do it… I donated what I can donate and I'm unlikely to donate more weather you [the participant] do it fast or slow… if you were walking I would have probably donated the same amount" [Viewer 11 – from interview]

Two other viewers made their donations during the event. In the interviews, they stated that the comments of the community within the website was what reminded them to donate more then visualizing the biometric data. Although this indicates that the influence generated by the biometric data would not directly effect donations, in the study, there is not enough data with which one could determine whether visualizing the biometric data had any significant influence on the viewers donating money. The study was not designed to measure this however it would be interesting to have another study that is designed in this regard.

2.9 Future Work

Based on the insights gained, HeartLink will be improved as follows: 1) Ways in which the online crowd can motivate the runner in real-time with the least interventions needed from the participant should be identified. We have used vibration modality but other methods like text to voice and augmented reality glasses are being considered. 2) HeartLink is able to automatically broadcast data on behalf of the user to keep the online community updated when the user is not in a position to manually input data. This automation will be increased as much as possible by for example automatically detecting the start or end of a race through real-time biometric data analysis 3) For research purposes the sample rate of the data logged on the server will be increased to 32Hz. This will allow detailed post-analysis of the relation between the cheers and the data changes. 4) Up until now HR was used as the only biometric parameter. Different types of biometric data will be used in future to see which type generates the most engagement between the viewers and the participants.

2.9.1 Research on biodata with real-time feedback from crowds

During this study, three promising research directions emerged. 1) We would first like to do the same study with more participants. This will let us analyse in detail the effects of sharing biometric data in real-time with different subgroups. For example we could differentiate between different social relations, participant-viewer age, gender, race and professional level of athletes. Existing studies show that these groups differ in the way they perceive different types of information and motivation [161,187]. 2) Determining that visualizing biometric data influences human behaviour opens up diverse possibilities for human-computer interaction. New business models may be designed around price variations that are determined by real-time biometric data. One example could be that where the donations made during charity runs are based on the heart rate of the runner. Our hypothesis, following the results from this study, is that since visualizing biometric data increases the connectedness between the donor and the runner, this will be reflected in an increase in donations when compared to donating passively at a fixed amount. Conducting experiments during, say, charity runs and using control groups could test this hypothesis. Both qualitative and quantitative analysis could then be used to measure the influence, if any, that the biometric data has on participants in such an economic decision-making situation. 3) We are looking into further developing HeartLink as a tool for crowdsourcing real-time motivation from a crowd. In particular this work will focus on situations where the user has a high cognitive and/or physical workload, as was the case in our user studies. In such situations it is not possible for users to share data on social networks through traditional methods like texting. Automatic sharing of bio and locative data can generate engagement with an online crowd in real-time. It will be interesting to look if the framework used in HeartLink could be generalized outside the sports activities that are here presented. Applications to research might involve situations were the users are conducting fell running competitions, team-based sports like football or competitive quizzes.

2.10 Conclusion

In this study we have presented our experience of designing and implementing HeartLink in a rapid prototyping approach to wirelessly share biometric data online and receive feedback from the online community in real-time. The key novelty of HeartLink was the analysis of changes in social connectedness through bio data sharing and the proposed two-way communication between the runner and the viewer. The design process went through a number of stages among which were the use of idea generation techniques, the use of strategic decision making tools, a pilot study and a user study. Through the data collected in the pilot study we have highlighted a number of issues that should be considered in the design of such systems. These include issues of system reliability, human interaction with the system and effect of system latency on the viewers. Using HeartLink in a user study has shown that visualizing biometric data can influence the relationship between the participants and the viewers. The participants in the study reported feeling close to the viewers due to a sensation of being followed by a crowd and the viewers also felt being part of the same community during the live broadcast.

Further work needs to be done to minimize manual human interaction within such systems by further developing algorithms that understand the environment through real-time analysis of the biometric data. This would minimize the interrupts that these systems give to each user, through tactile or visual feedback, by filtering the exact data that is needed, when needed. Having determined that visualizing biometric data does influence human relations, there is the need for further exploration in order to find out how this could be applied within different areas such as new types of business models or community building.

Chapter 3
SYSTEM DESIGN

Published as:

Curmi, F., Ferrario, M.A. & Whittle, J. Sharing Real-Time Biometric Data Across Social Networks: Requirements for Research Experiments, in *DIS'14: Proceedings of the SIGCHI Conference on Designing Interactive Systems*, ACM Press (2014), pp. 657-666.

3.1 Abstract

There is growing research interest in exploring how biometric data is and can be shared across online social networks. However, most existing tools for sharing biometric data lock researchers into vendor-specific solutions that cannot be easily adapted to the specific researchers' requirements, users' needs and ethical considerations.

To mitigate this, we investigate the requirements for open source researcher-oriented biometric data sharing systems. Requirements were captured using: first-hand insights from two prototype deployments, a systematic review of the literature, and interviews with HCI researchers who have built such tools. The requirements thus captured were implemented in the BioShare system and insights from implementing these requirements are presented. BioShare allows users both to share data but also receive inputs from remote viewers of the data in real-time. Concurrently it provides logging capabilities for researchers to analyse system interactions.

3.2 Introduction

This paper focuses on the requirements for researcher-oriented tools for biometric data sharing across online social networks. In recent years, technology has made it easier to capture biometric data such as heart rate, body temperature and skin response unobtrusively in diverse day-to-day situations. This, in combination with the diffusion of social networks, encouraged many individuals to quantify [180] and share [21] such data with others. This effect is echoed in the implementation of biometric data sharing features on many commercial products such as RunKeeper, Endomondo and Azumio that allow users to share this type of personal data over social networks. On the research side, there is a steady increase in studies that investigate the effects of sharing biometric data on both the person sharing the data [176] and the data viewer [42]. In practice, however, it can be very challenging to run such experiments because of the lack of systems that allow researchers to define their own configurations, data visualizations and data logging for hypotheses testing.

Most applications that allow sharing of biometric data over social networks have not been designed for research and are not open source. This makes it difficult for researchers to adapt these applications outside the scope for which they were designed as shown in [42]. For example, changing the data visualizations or logging a specific class of user interactions may at best require programming workarounds or at worst may be impossible. On the other hand, the open-source applications that share biometric data tend to work only for specific sensor brands and therefore lock the researcher into a particular vendor.

The study builds on prior critical design work by Curmi et al. [42]. This involved the development of two prototypes for this specific area of study with outcomes pointing out that in order to better support researchers working in this area, a robust open-source, configurable tool is required. We note that the approach presented here is not the only design approach possible for this scope: the design of a meta-research prototype that specifically focuses on the social network component of sharing biometric data. Specific issues such as energy consumption of the device, data security and integrity are kept outside the scope of this paper as better settings exist for these themes. However, we do not filter insights from the data collection and all the key observations that were gained through the critical design methodology are presented.

We also emphasize that this paper is not about evaluating one instance of the tool but that of showing the feasibility of the approach by instantiating it in multiple cases. As discussed in the paper, there are few academic papers discussing this rapidly evolving area. These give little insight on the 'design approach' for developing the data-sharing tools used. Consequently we have undertaken quite an in-depth evaluation in this regard.

The requirements were captured based on a multi-method approach. Firstly, we revisited two prior studies and made a systematic analysis of what is required for such experiments. Secondly, we carried out a systematic review of the literature, looking specifically at issues and challenges researchers had in building their own biometric data sharing tools. Finally, we carried out a series of semi-structured interviews with researchers in the area. The resulting set of requirements for researcher-oriented biometric data sharing tools is based on direct, first-hand experience in the field as well as secondary data from the wider research community.

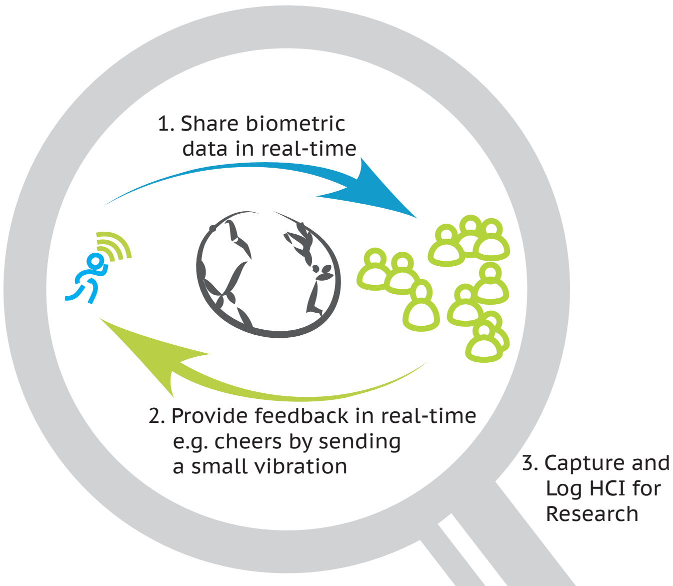

Figure 12: Core requirements: sharing biometric data, support for real-time feedback and logging of interactions.

This paper thus describes both the requirements captured and the insights gained from implementing these requirements in a prototype: BioShare. BioShare was designed as an open source tool for research: 1) it allows participants to share biometric data online unobtrusively in real-time, 2) it allows remote data viewers to send feedback to data-sharing participants in real-time and 3) it logs the interactions of participants and viewers for research purposes (Figure 12). The design looked into making the system as easy as possible for other researchers to use and adapt by using widely diffused coding languages such as HTML5. BioShare is also designed to be as configurable as possible: the researcher may define his/her own data visualizations, can define multiple feedback modalities to the participants, and can define his/her own data logging behaviour. Crucially, we identified divergent views from researchers about the ethical concerns of biometric data sharing. Thus, researchers can define different levels of control over the data ranging from sharing data openly with anyone online up to controlled sharing by registered participants only.

BioShare users are researchers. The design focuses on researchers' requirements but allows flexibility for the researcher to adapt the system to meet their users' (participants') needs on a case-by-case basis (e.g. open vs. controlled experiments). Adaptability was a key factor in the design process, as we cannot cater to all users in all possible experiments and contexts. For example researchers using BioShare should adapt the system to meet their national and organizational ethical requirements when sharing this data.

In the literature, we observe that the term 'biometric data' is very loaded with different applications in different fields. In this paper, we use the term 'biometric data' to refer to measurable and dynamic physiological data such as heart rate, skin conductance or body temperature. Throughout the design and development of BioShare heart rate was used as a test parameter.

3.3 The Context

In the last two decades, with the invention of social networks, communities started collecting and sharing very personal information at a scale that would have been difficult to predict. There are plenty of studies showing the positive [128,175] and negative [155,201] effects that sharing personal information can have. For example, Young et al. [201] shows the issues involved in sharing personal data on social networks due to risks when publicly sharing confidential information. On the other hand, when using Huston [37], social support through sharing has been a source of motivation for people trying to become more physically active. Similar positive outcomes are reported in sports [103] and in health [175]. Had someone 50 years ago mentioned that there will be a time where people will openly broadcast their personal data, such as when they have coffee, how they look and even express their emotions publicly, it would have been difficult to believe. Yet this has happened and in some communities it has become a daily norm.

Existing freely available mobile applications such as Runkeeper, Azumio and Nike+ allow users to share data as personal as biometric data, such as heart rate, over social networks. As the technology behind capturing biometric data is becoming increasingly unobtrusive, this type of data sharing is likely to increase. Some athletes, aware of how fit they are, might be interested in sharing their biometric data with friends as part of their real-time 'curated' [60] Facebook profile and Goffman's innate 'management of impression' [68]. Another example worth mentioning is that of insurance companies; these would be interested in having biometric data of customers as this influences their risk assessment. Innovation that drives early adopters in this regard may encourage customers to share their biometric data for a significant discount on their health insurance policy. In these scenarios we expect that research looking into the effects of sharing biometric data with others is likely to increase. Ideally this increase happens before such implementations take place. This motivates the need of research tools to analyse the benefits and drawbacks of sharing such personal information.

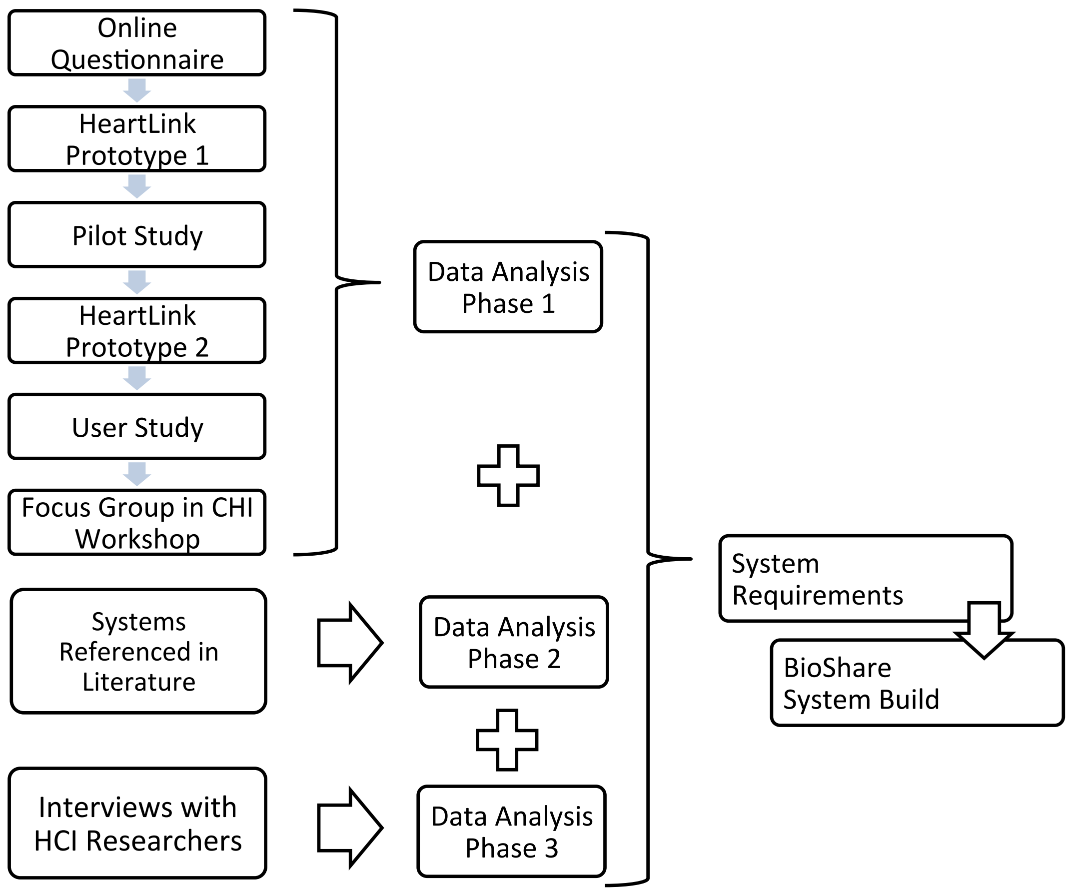

Figure 13: Methodology for requirements identification

3.4 Methodology

A multi-method approach was used to capture the researcher-requirements as shown in Figure 13 and discussed below.

3.4.1 Phase 1

The authors had first-hand experience of building and applying prototypes in two specific studies that involved the sharing of biometric data during sport events. This determined the design approach adopted. These prototypes and studies were originally intended for analysing the effects of sharing biometric data on the person viewing the data. Consequently, the data that was collected in this work was reanalysed through a new lens; that of capturing insights for building research tools that share biometric data.

Data was collected from: 1) an online survey that analysed the readiness of participants to share personal data, 2) the development of a first prototype, 3) a pilot study which tested this prototype during a triathlon, 4) this informed the development of a second prototype and, 5) a user study conducted during a charity run. Items 3 and 5 above included 12 interviews, quantitative data from server logs and the researchers' observations of the users' interaction with the system. (For details on items 1 to 4 see [42]).

3.4.2 Phase 2

To make the new tool as widely applicable as possible and to analyse if the insights gained from the authors' experience match those of other researchers with different design approaches, we systematically reviewed literature in which biometric data sharing systems were referenced. We identified and grouped common requirements that researchers have when using such tools. These will be discussed in the requirements section.

3.4.3 Phase 3

A limitation in the data collected in phase 2 was the fact that most of the published studies (particularly in HCI) focus their published contribution on the insights gained from sharing biometric data. Typically, limited information is given about the approaches taken in designing the data sharing tools that are used. To better understand the approach that different researchers adopted, we additionally carried out six interviews with HCI researchers. The sample size was determined by the limited number of HCI researchers active in this area. Although in the last decade there has been an increase in the number of publications involving biometric data sharing over social networks, the number of HCI researchers in this area is still small. We asked ten HCI researchers who have shared biometric data in their work for an interview and six accepted. Each interview session was video and audio recorded, and transcribed.

The questions asked during the interviews were intended to 1) understand the researcher's experience in sharing biometric data for research applications, 2) understand the tools that were used and how they were developed, 3) identify challenges encountered in the process, if any, and 4) collect the ethical issues faced before and during the sharing of biometric data.

The design of the open-ended questions used in the semi-structured interviews ensured that the questions were not contaminated with the data that was collected from phase 1 and 2. However, the preparation of the questions did take into account the publications of the interviewee such that apparently relevant aspects in their publications could be expanded upon. Sample questions included: What do you remember from building the system? What technical and non-technical challenges were encountered, if any?

3.5 Requirements

The data from these phases were translated into requirements as shown in Table 3. The functions that were implemented in the default configuration to match these requirements are listed in the first row. The table differentiates between functions that meet the specified requirements and functions which partially support a requirement i.e. individually they do not satisfy the requirement. Insights from each phase are discussed below.

	Features Implemented in the Default Configuration / Requirements	Source from where the requrement was identified: P=Prototypes, L=Literature, I=Interviews	Free open source distribution	Development via free open source tools	Use of android smartphones for data broadcast and presentation of feedback	Biometric data sharing & storage is self contained (not dependent on 3rd party applications)	Modular design	Provide online discussion facility for qualitative data collection on viewers'in interface	Prompt questions using lightboxes	Provide a viewer control & login system	Documentation for researchers with examples	Visualisations presented within a web browser using widely diffused code: HTML5 and JavaScript	Use data encription	Allow unrestricted data sharing	Use existing mobile networks for broadcast	Post data on social network	Periodically log viewer's browser settings and clicks	Ability to gene rate random data
Core requiremnets	Share Bio-Data in Real-time	P,L,I			🟢										🟢			
	Send Real-time Feedback e.g. cheers through device vibration	P,L,I			🟢										🟢			
	Log User Interactions	P,L,I						🟢	🟢	🟢		🟢				🟢	🟢	
	Researchers can use one or all of the above features	P,L,I					🟢											
	Compare biometric data to non-biometric data (i.e. the ability to share multiple types of data)	P			🟡							🟢					🟡	🟢
	Present different visualizations to different viewer-population	P								🟢								
	Data capturing system is minimally obtrusive (i.e. can be used for example in running, swimming and office work)	P,L,I			🟢													
	No additional cost for each participant sharing or viewing data	P,I	🟢	🟢														
	Low data broadcast latency	P				🟡												
Adaptation	Visualizations can be modified	P,L,I	🟢	🟢			🟢				🟡							
	The tool is adaptable to other researchers' needs	P,L,I	🟢	🟢			🟢				🟡							
	No lock-in in specific hardware brands	P	🟢	🟢			🟢				🟡							
Interaction	Log interaction from the data sharing participants	P,L,I				🟢												
	Log data viewers' interaction with the visualization	P,L,I														🟡	🟡	
	Log broadcasted data	P,L,I				🟢												
	Collect information from viewers like social relation with data sharing user	P							🟢									
Ethics	Participants' broadcasts could be viewed by researcher-selected viewers	P,I								🟢								
	Data collected can be shared openly	P,I												🟢				
	Data storage and processing is done on researchers-controlled server	P,I				🟢												
	Researchers can validate the code	P	🟢			🟢												
	Secure data broadcast	P,I											🟢					

Table 3: Key requirements captured and features implemented to meet 🟢 or support 🟡 the requirement

3.5.1 Phase 1: Requirements from the development of prototypes and respective studies

3.5.1.1 The context

Prior to the work presented in this paper, we revisited the design and built of two biometric data-sharing prototypes from the HeartLink project. These were developed using a rapid prototyping approach by combining a number of existing systems such as RunKeeper, cloud computing services and Messaging APIs. A pilot study was conducted to test HeartLink during a triathlon and a user study was then conducted with a second version of HeartLink during a charity run. In these events, athletes were able to share data in real-time using mobile phones and existing mobile networks to anyone online. To minimize interrupting the user, all the data was automatically broadcast with no intervention needed from the user. The data broadcast in both cases included the heart rate, the average heart rate during the event, the percentage of the task completed, the total number of heart beats, distance covered, pace, speed and a line chart with the heart rate data. With this set of data and when knowing the context of what the event is about, the viewers could gain an understanding of what was happening during the event. In addition, remote viewers following the athletes online were able to click on a ‘Cheer’ button. Clicking this button sent a small vibration to the athlete as a way of crowdsourcing real-time social support. Viewers were also able to share comments on the interface thus forming a community around the athlete. The online comments and the cheering data were then used to analyse the viewers’ understanding and engagement with the presented visualizations. The viewers’ interactions with the system together with the system’s status, such as timestamps, were recorded for research purposes.

3.5.1.2 Informing design from issues identification

Most of the challenges faced when sharing biometric data using HeartLink could be attributed to the fact that the tools used to share biometric data were not designed for HCI research purposes. While the plugging together of existing systems facilitated the rapid development of the solution (an approach commonly used in the literature [133]), it also raised a number of questions.

We observe that using off-the-shelf mobile applications for capturing data **limited the type of data** that could be used for research. It also **locked the researchers** into using specific hardware devices for capturing the data based on what is offered by the system chosen. For example, the solution supported capturing of heart-rate data but it was not possible to embed respiration unless additional systems or major customizations were added.

In addition, using commercial closed-source applications made it **difficult to adapt** the applications outside the scope for which they were designed. If the application does not allow the viewers to communicate with the athlete, it would be very unlikely that the company would adapt the proprietary mobile application that is used by thousands of users to suit a researcher's needs. At the same time, the researcher cannot adapt the system because the code is locked. HeartLink studies required that the system would allow the viewers to motivate the athletes while they are conducting an activity by pressing a 'Cheer' button. In this case, additional commercial applications were added to the system at the expense of increased system complexity.

The lengthy chain of modules that was needed to adapt the existing systems and meet the researchers' needs, made the system highly **prone to disruptions**. In addition, **depending on multiple large-scale infrastructures** such as cloud computing services, third party mobile apps and one's own infrastructure increased the risk of failure. In HeartLink, the system was as strong as the weakest link and should one part fail, the entire system would fail. An example of this was the disruption to one of the closed 3rd party applications that used cloud services. Although the study was being carried out in the UK, the disruption occurred due to severe weather conditions in the United States.

In addition, existing mobile applications that share biometric data such as RunKeeper and Endomondo do not **allow customization of the visualizations** that are presented to the users. Customization is imperative in a research setting to, for example, analyse the effect of how different presentations of biometric parameters influence the engagement of the viewers. When using existing mobile apps that are not designed for research it is difficult to **log the interactions** of remote participants. This is an essential feature in most HCI studies.

3.5.1.3 Ethics-related issues

The approach adopted in HeartLink raised a number of ethical issues. The fact that the system used multiple large-scale applications challenged the researchers' ability to manage the data in terms of data integrity. For example, when using RunKeeper as a communication tool, we had no **control over the data** that was broadcast, where this data was going, and which cloud services were being used. While this may be true of any communication over the Internet, should the system have been open source, one could validate the way the system works and personalize any encryption mechanisms and communication channels. In this way, the researchers need not rely on the 'Terms and Conditions' of all the different closed systems used in the solution [39]. Such 'Terms and Conditions' often offload any responsibility of the brand onto the user. In this case, the user is the researcher, who in turn, needs to embed (and cascade) conditions in the participants' 'Consent Forms' accordingly. This complexity could be highly simplified if the communication chain is simpler: for example, if the data is sent directly from a mobile app to a centralized server. This would simplify participant 'Consent Forms' and give the researcher more authority over the claims made within.

3.5.2 Phase 2: Common core requirements from the literature review

To make the design applicable beyond the HeartLink case, a review of the literature in this area was conducted. This identified common system requirements of tools that were used to share biometric data. In this work, we notice that academic studies that involve biometric data sharing with others were used for 1) health [181,182], 2) game control [118,132,183], 3) analysing social engagement [42,103,146,176] and 4) augmenting the viewers' experience [76,183]. Studies that specifically focused on sharing biometric data as a form of social engagement include the work of Perttula et al. [146], Kurvinen et al. [103] and Slovák et al. [176], all of which showed that data sharing can be a relevant tool for increasing social engagement. The use of biometric data to augment the experience of remote viewers seems to be the most widespread motivation among HCI researchers for sharing biometric data. Hallberg et al. [76] successfully broadcast biometric and location data of contestants in a skiing event to remote viewers as a way of enriching their experience. Similar approaches are found in [168], where the biometric data of participants on an amusement ride is shared with spectators, while in [183], actors exploring a haunted basement shared their physiological data with spectators who watched the event unfold from a nearby cinema. All the above-mentioned research used systems that at a minimum allowed one or more users to **share biometric data with remote viewers**. In addition, other cases ([42] and [132]) required a two-way communication system that allowed viewers to also **send feedback.** In [132], pairs of joggers running at a distance listened to each other's ambient sound and the direction of the sound varied according to the biometric data of the athletes. Similarly, in [45], social support from remote spectators was communicated through haptic feedback.

A common requirement in all the above-mentioned research is the **logging of user-interaction** related data. In some cases this was done manually through interviews and observations [118,167] while in others [42,168,184], the data sharing system itself logged part or all of the user-interaction data for analysis.

We observed that the area of biometric data sharing is limited by the shortage of open systems that provide the researcher with the core biometric data sharing functions and allow for customization. One existing system is ECT[1] (Equator Component Toolkit). This generic open-source data-sharing tool was designed for the rapid deployment of ubicomp environments [71]. Although it has been used for experiments that involve biometric data sharing [168], most of the core modules were designed and built for technology that is now a decade old. A more recent solution is the Vicarious architecture[2]. Its design, however, is focused on aggregating data from various biosensors rather than the real-time data sharing to social networks. We also note that commercial solutions such as Polar Team[2] Pro or Zypher's OmniSense technology are not designed to **integrate the three main requirements** in one system: i.e., the sharing of data openly over social networks, the provision of feedback to the user in real-time and the logging of participants' interaction with the visualized data. In addition, commercial products, as earlier mentioned, **lock the researcher** into having to use specific sensor brands.

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[1] http://equip.sourceforge.net
[2] https://github.com/horizon-institute/vicarious

3.5.3 Phase 3: Interviews with researchers on biometric data sharing

The results of this phase confirmed those from phases 1 and 2, namely:

- There is a lack of open source tools to research the sharing of biometric data. This forces the researcher to dedicate substantial resources (human and/or financial) for system development,
- The HCI community has limited knowledge on the effects of sharing biometric data. This is driving a demand for more research in this field,
- There are divergent views among researchers around ethical concerns that necessitate both controlled and open data broadcasts.

One interviewee remarked that the key challenge that she faces in this area is the limited sensemaking that the researcher can create out of biometric data due to the newness of using biometric data for storytelling. For example, in a non-digital scenario, spectators at the sidelines of a running event would easily understand fatigue through facial expressions, sweat, body kinematics, if the track is uphill, and *"they will say things like 'oh it is not that far', 'you look like you're doing good'... and the challenge is to replicate this remotely through physiological sensors and visualizations*"*... "and [in terms of research] we don't really have any sense into that yet"* [P3]. Participant 3 requires the systems to be easily adaptable, as experiments need to look into multiple variations of data sharing and visualizations. This calls for a design that is **simple to use** to encourage more research in this area.

All the researchers interviewed claimed that the **financial or human resource costs** were considered high in their first attempt to build biometric data sharing systems when compared to later attempts as the learning curve would initially be steep. Participants 1 and 5 remarked that usually they first buy the equipment that they need in their research and then build the systems around the software that is provided with the hardware. As expected, we noticed that while for computer-science oriented labs, building the systems is not of great concern, for others, the resources needed to build the data sharing system are a major barrier.

Surprisingly, the interviewees had diverse views regarding the **ethical issues** involved. This was true both as regards the sharing of biometric data per se and also as regards the influence this had on their system design. For participants 1 and 6, ethical issues were the cause of great '*concern and debates'*. Participant 1 mentioned a number of cases where his participants raised ethical concerns during the events. There was one particular case *"which could have had serious consequences"* due to a lack of provision in the system that allowed the participants to stop the biometric data broadcast. "*I think we were a bit naive with realizing the concerns that might have come after, I think we learnt these through that work."* [P1]. Participant 4 points out that *"there will always be ethical concerns, but putting the control of where the data goes, with the participants, is most important."*

On the other hand, participants 3, 5 and 6 are not concerned about any particular ethical issues around sharing biometric data. For participant 3 it is because the biometric data is not being shared in a medical context. "*I think that if you do sports, you are in the upper 10% so people imagine you're healthy and that is just [by] doing sport; its a plus right? But for the medical data, just being to the doctor is a minus."* [P3]

"as far as we can tell no one really cared about … heart rate or what happens with their data" [P5]

These differing opinions on ethics show both the naivety in the area and also that further debate is needed within the community. In terms of the requirements this necessitates systems that allow configurable ethical protocols e.g. giving the researcher the possibility of sharing the data publicly or privately.

All the interviewees believed that there is a need for **an open source system**. "I think it would be a great use …[particularly] if it is open source and others can plug in their own solutions...." [P3].

Only one interviewee has built both hardware and software for sharing biometric data from scratch. However, he stated that if he had to rebuild the system today, he would use smartphones as a data transceiver. This would greatly simplify implementation. The other researchers interviewed bought the biometric sensors and created customized software.

3.6 The BioShare System

In this section, we describe how the BioShare system was designed and implemented based on the requirements captured. Table 3 lists the features that were implemented in BioShare and identifies which user requirements are satisfied by the implemented features in the default configuration. BioShare is configurable to include different (versions of) features. Table 3 therefore focuses on the features available in the default configuration. The complete BioShare system, its documentation and instructions for researchers can be downloaded from www.heartlink.co.uk/bioshare

Simplicity as a design feature was given a significant amount of importance so that new variations to BioShare could be made for different experimental conditions. Moreover, HCI researchers who might not be expert computer programmers could also use and adapt the tool to their needs. Understanding that cost may be of an issue for other researchers BioShare was implemented using development tools that are available for free, such as generic text editors and integrated development environments. The modular design approach adopted makes it possible to change different parts of the system while reusing others. For example, the mobile application for collecting biometric data and broadcasting it to the server can be used standalone when one-way data communication is needed.

3.6.1 Infrastructure

BioShare collects and shares data through smartphones and broadcasts this data over WIFI or mobile networks. The data is broadcast by using generic phones that run Android OS and a custom made mobile application: the BioShare Mobile App. Android was selected because it is widely used and open source. In addition, Android does not lock the researcher into a specific hardware brand. Tests used Polar HR sensors; however, since all the code is open source any Bluetooth sensors with an open protocol such as Zypher or Simmer sensors can be used. The application was developed in JAVA using Eclipse IDE and Android SDK.

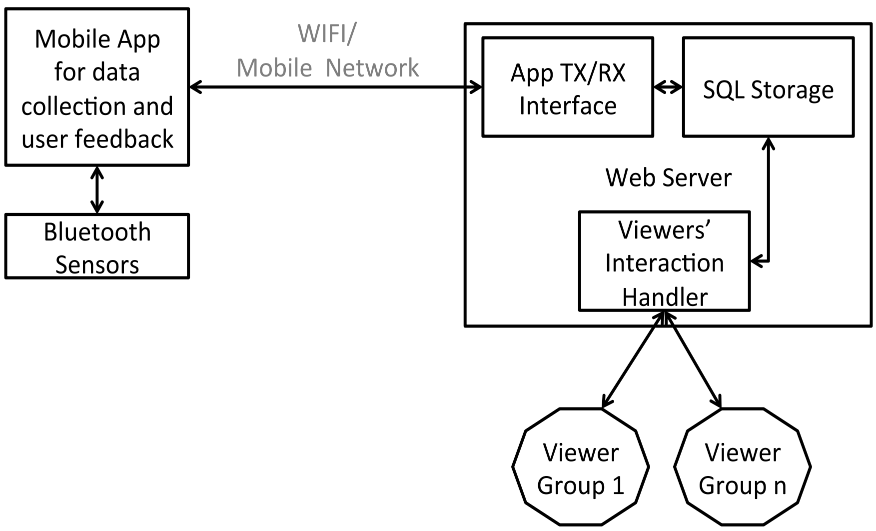

Figure 14: Architecture diagram of BioShare

The values collected from the sensors are broadcast to an HTTP server in real-time as shown in Figure 14. The data-receiving server stores the data in a SQL database and returns any feedback-related data from the viewers back to the device (Figure 15).

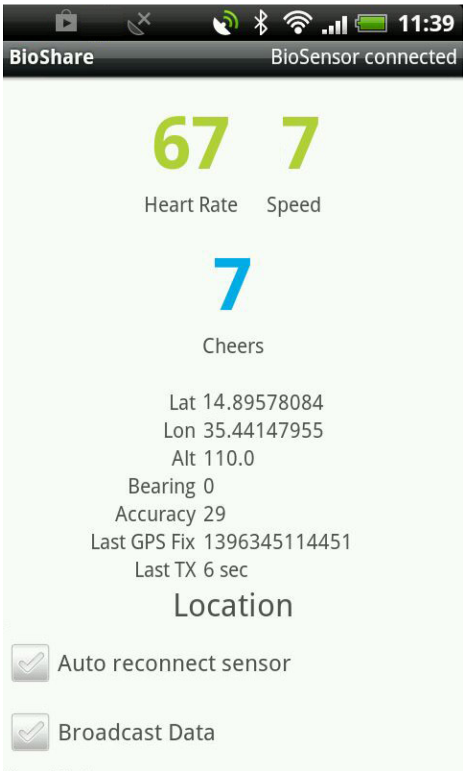

Figure 15: The default configuration in the BioShare mobile research app presenting the raw values that are broadcast and those returned from the server.

Separate code running on the same server is then used to share the received data with online viewers. The design handles different experimental conditions such as presenting different visualizations to control groups and experimental groups. For example, each alternate viewer logging on to the website can be presented with a different visualization. This allows for cross comparison of different data visualizations. The interaction data is then collected and stored in records that are tagged by the type of visualization that the user was presented with. This supports the researcher in understanding how different viewers interact with different type of visualizations. SQL was selected over noSQL primarily because BioShare is not intended for commercial / large-scale applications. We decided to keep the application as simple as possible understanding that small controlled experiments are most common in this area (see ref. [1, 4, 8, 10, 12]).

3.6.2 Data

The server-side code runs on an SSL secure server. However, since the interviewed researchers had conflicting views on the need to conduct experiments using open vs. closed data, BioShare handles both options. Researchers can give participants a hyperlink that gives open access to the real-time data broadcasts. In this case anyone online can view the live data. Alternatively, the researcher can control participants through an enforced login system. The instructions for these customizations can be found in the system documentation. In addition the server-side code is open source and can be installed on the researcher's own server such that the researcher has full control over the data without the need to access the data from 3rd party APIs. This approach contrasts with the HeartLink prototypes where data broadcast by existing mobile applications were then accessed through proprietary APIs from unknown storage infrastructures. The use of APIs is commonly used in commercial applications; however, it creates ethical concerns when used for research. In our experience and that of two of the interviewed researchers, this approach severely limits the authority that the researchers have over such sensitive personal data and the related claims that could be made in the consent forms. With the realized solution, all the data from the participants' app communicates directly with the researchers' infrastructure thus giving the researcher more authority over what can be guaranteed in the consent forms.

3.6.3 Visualizations

The visualization presented to the remote viewers (Figure 16) runs in a web browser. This approach makes it possible to view the data on any Internet connected device irrespective of the device's operating system.

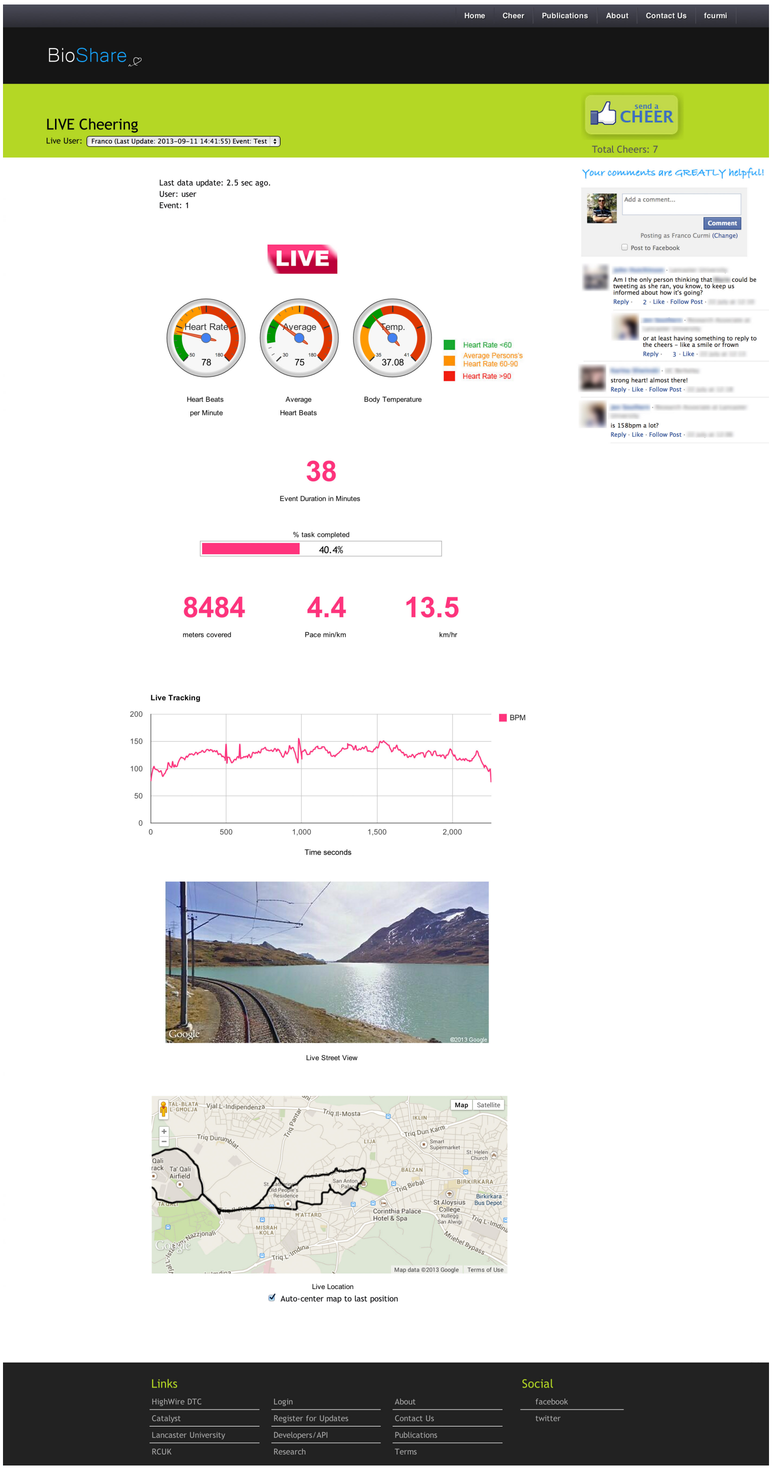

Figure 16: Part of the default visualization in BioShare with both biometric and non-biometric data. The tool allows participants to comment during the live events and logs the interaction of athletes and spectators

The visualizations are based on PHP, JavaScript and the Google Charts library. By using Google Charts, no participant data is shared with Google or any other 3rd party and all the data processing is done locally. Current default charts include numeric representation of the live data for biometric, temporal or locative data, line charts with the live heart rate data, maps augmented with the paths covered by the participant and an orientation-corrected street view of the current participant location. By default the data is updated every five seconds, though this can be modified based on the researcher's requirements and data sources.

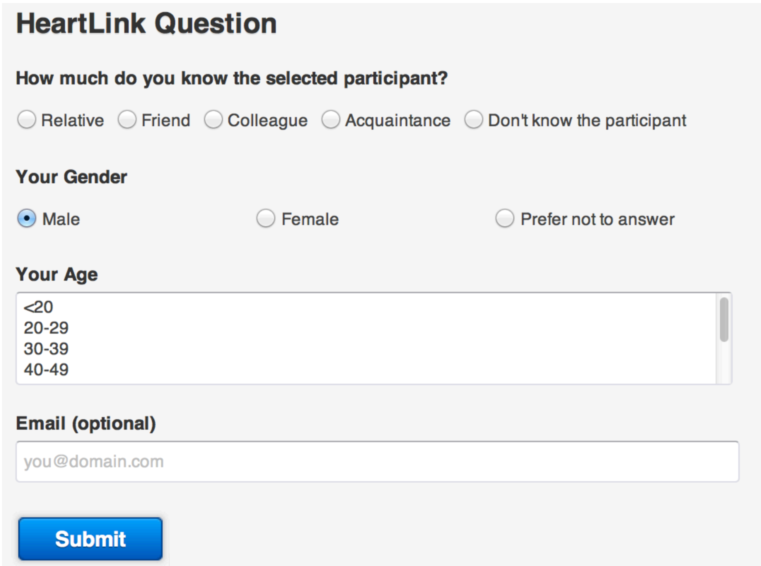

Figure 17: Sample questionnaire displayed as a lightbox on predefined events, for example, when a viewer selects a new participant to follow.

3.6.4 Logging of interactions and broadcasted data

BioShare logs all the data that is broadcast from the data-sharing participant. The system also logs remote data-viewers' interactions including the visualizations being viewed, viewing duration, time stamped comments written by the viewer during the event, time stamped feedback submitted by the viewer, viewer location and scrollbar position. The researchers can also enable a form-containing lightbox that is activated on predefined events. The lightbox is a small window and when displayed, the background is darkened. For example, a researcher may display Figure 17 whenever the participant being followed is changed. This form collects data related to the social connectedness of the viewer with the participant being watched. The data collected is used for social network analysis.

	System Features	1: Comparing viewers' interest in following different types of biometric and non biometric data	2: Comparing participants' response to different data presentations	3: Analyze the effect of live biometric data visualisations on different social ties
Core Features	Distribution is open source and free	✓	✓	✓
	Use free open source tools for development	✓	✓	✓
	Use of android smartphones for data broadcast and feedback	✓	✓	✓
	Present visualisations within a web browser using widely diffused code: HTML and JavaScript	✓	✓	✓
	Biometric data sharing is self contained (not dependent on 3rd party applications)	✓	✓	✓
	Modular design	✓	✓	✓
	Use existing mobile networks for broadcast	✓	✓	✓
	Use encryption in data broadcast	✓		
Viewers Control	Present online form to viewers to collect data on specific events			✓
	Viewers controlled through login system			✓
	Open data broadcast (no login needed for viewing data)	✓	✓	
	Randomly route viewers to different visualizations		✓	
Data Collection	Provide online discussion facility for qualitative data collection on viewers' interface	✓	✓	✓
	Provide a cheer button for viewers: this sends a vibration to the data sharing user		✓	✓
	Periodically log viewer's browser settings, clicks, and compute time spend on each visualization	✓	✓	✓
Control	Create random generated data for comparision with live data			✓
	Generate Random Cheering			✓

Table 4: Sample configuration possibilities for the three research studies detailed in the 'Configuration for Research'

3.7 Configuration for Research

To highlight different uses of BioShare, we briefly present three different configurations that were produced by adapting the default BioShare configuration. The system features used in each configuration are shown in Table 4.

3.7.1 Configuration 1

Case: Comparing biometric and non-biometric data type representations to identify which data type remote spectators of a running event would be most interested in watching.

Approach: The default HTML5-based visualization is adapted such that each of the default data types presented (heart rate as a numeric representation, heart rate as a line chart representation, % distance covered, speed, map with current participant's location and Google street view at the same location) are displayed vertically along the page within the web browser in such a way that the viewer needs to scroll the page to view the different data types. The system by default logs the scrollbar position of the viewers' interface together with timestamps; thus the researcher learns which data representation was most watched during the live event. The collected data can then be analysed using offline statistical analysis tools.

3.7.2 Configuration 2

Case: The research question for the second case looks into whether presenting real-time biometric and non-biometric data to remote viewers watching an event makes them more engaged than presenting non-biometric data only.

Approach: The experiment involves sharing data from four athletes to two randomly assigned groups. One group visualizes all the data available in the default version of BioShare (both biometric and non-biometric data) and the other group is presented with all the data except the biometric data. The researchers would then analyse the cheering and social network posts to identify if the group visualizing the biometric data is more engaged in the event and how.

3.7.3 Configuration 3

Case: What effect visualizing live biometric data has on different social ties during a specific event. For example how does viewing live biometric heart rate data in a specific activity influence the athlete's mother compared to Amazon Mechanical Turk recruited participants?

Approach: In this case, the researchers modified the default data visualization file such that it displays only the live biometric data representations. During the live broadcast, the data viewers are asked to state their social relationship with the data-sharing participants by using the (default) lightbox. Researchers can then analyse the data collected for patterns between the viewer engagement and the social network tie-strengths.

3.8 Limitations and Future work

We do not expect these requirements to be enough for every specific application by HCI researchers. These should be considered as a starting framework for an area where research needs to catch up with the rapidly moving industry as discussed earlier. HCI researchers using BioShare are expected to configure the tool to meet their users' needs after that they conduct their own requirements analysis with their users. In this light further work needs to be done on issues such as ethical concerns, data security, energy management and data coverage. A known issue is the dependency on WIFI or mobile networks. This is of concern particularly if the system is used in the wild where mobile reception may be weak or non-existent. However, having an open source system makes it possible to modify the code and create backup solutions. BioShare may be adapted to make use of emerging satellite communication, such as 'SPOT Connect', as a backup service to the terrestrial mobile network service.

SPOT Connect is a small device that, via Bluetooth, connects a standard smartphone to satellite systems for global communication.

In the near future the number of data visualization modules available by default in BioShare will increase together with the number of biosensors that can be connected to the mobile app and the type of data broadcasted. This includes live video broadcast from the app such that the storytelling ability of biometric data and live streaming video can be compared and contrasted. Moreover, the visualizations currently present the raw data received. Algorithms that generate inferences from the live biometric data and present the outcomes to the viewer could be implemented. For example, if the elevation is constant and the heart rate increases, we might infer that the participant is getting tired. This inference may be used for triggering events such as encouraging viewers to provide social support through the implemented feedback system.

3.9 Conclusion

This paper focuses on the requirements and design methodology adopted to develop a tool that shares biometric data for HCI research. To date, tools that have been used in HCI research where biometric data is shared, have raised a number of issues. Most of the existing tools are not designed for research and the few that are, tend to be difficult to adapt for research that falls outside the scope for which the tool was designed. A number of ethical issues such as the limited control the researcher has over the data were also been raised. These issues were identified following the building of two prototypes with which two studies were conducted. This data was then compared and contrasted with similar cases in the literature and with data that was collected from interviewing HCI researchers whose research involves the sharing of biometric data.

We hope that the requirements identified and the insights gained from implementing these requirements will alleviate the technical burden that researchers who need to share biometric data in this context face. This is expected to encourage more research that involves this data sharing thus contributing to the limited knowledge we currently have on the effects of interacting through biometric data.

Chapter 4
CROWDSOURCING SYNCHRONOUS SPECTATOR SUPPORT

Published as:

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4.1 Abstract

Many studies have shown that crowd-support, such as cheering during sport events, can have a positive impact on athletes' performance. However, up until recently this support was only possible if the supporters and the athletes were geographically co-located. Can cheering be done remotely and would this be effective? In this paper we investigate the effect and possibilities of live remote cheering on co-located athletes and online supporting crowds that have a weak social tie and no social tie with the athlete. We recruit 140 online spectators and 5 athletes for an ad-hoc 5km road race. Results indicate that crowds socially closer to the athletes are significantly more engaged in the support. The athletes were excited by live remote cheering from friendsourced spectators and cheering from unknown crowdsourced participants indicating that remote friends and outsourced spectators could be an important source of support.

4.2 Introduction

The Facebook 'Like' button was a revolutionary tool in digitizing a tiny yet significant piece of human communication within social networks. Receiving 'Likes' can have a positive effect on the emotions of the social network user receiving them and in the context of behavior change, this is often used as a source of motivation for people trying to attain new goals [89]. However while this type of support is very applicable in scenarios of behavior change that have longitudinal measures [134,175], such as in motivating persons who are trying to become more physically fit [37] or cease smoking [148], it might not be as practical for situations where motivation is needed in real-time and in sync with the activity that is being conducted such as cheering athletes during a race. Current social networks were primarily designed for asynchronous communication. While this has many advantages, for instance, the message receivers do not need to be online to receive the messages, it may be inapt for situations where support from one's network needs to be in sync with its demand. Currently, athletes who share information about their events through online social networks, often receive encouraging 'Likes' and posts in support. However, athletes typically see these posts only when the activity is completed. Consequently, any motivation created through the perceived social value of accumulating 'Likes', does not translate into support during the activity and has no influence on the outcome.

To start exploring synchronous social network support we use sports. Sports was chosen because many studies have already showed that cheering co-located spectators (e.g. on a race course) can have a direct impact on the performance of the athletes [28,59]; but can this be done remotely? This could have a huge impact yet there has been negligible HCI or CSCW work that explores ways of digitizing synchronous crowd support in this context. Possible benefits may include 1) allowing fans that don't afford to be physically present at the event's location to support the athlete, 2) allowing non-famous athletes to recruit support from their personal social networks or 3) potentially harnessing the support from globally crowdsourced participants through platforms like Amazon Mechanical Turk. Is this support possible and does the nature of the online crowd matter? Put in another way, are athletes more motivated by friends or is the support of strangers just as effective, if any?

We implement a system where long distance runners broadcast location and heart rate data to online spectators. The spectators can then cheer the athletes by pressing a 'Cheer' button. This sends an immediate alert to the selected athletes thus making the athletes aware that a crowd is following their activity. In the study we use a crowd made up of two groups. 1) Friendsourced volunteers. Based on Bernstein et al.'s proposition, we express friendsourcing as "collecting resources from a socially-connected group of individuals" [18]. 2) A paid crowd that was recruited through Crowdflower; a crowdsourcing platform. We then analysed the effects on both spectator groups and the athletes (being cheered on).

The data showed that friendsourced participants were more engaged with the system than outsourced spectators. We found that the athletes showed mild excitement when receiving real-time haptic and audible cheers but were particularly excited by knowing the number of cheers submitted and the number of people following the activity (logged in and not necessarily cheering) during the event.

4.3 Related Work

Up until a few years ago an athlete's performance was often broadcast only if the athlete was famous enough to merit television broadcast. In recent years as social networks became increasingly ubiquitous it became possible for almost any athlete with Internet access, to broadcast their participation in sport events. Freely available mobile applications like Runkeeper, Runtastic and Azumio allow users to share locative and physiological data, with selected friends or even publicly. These commercial implementations were preceded by a number of studies within academia that studied the effect on the athletes and spectators when sharing real-time data during sport events [76,103,131]. Sport applications such as Runtastic more recently implemented feedback features by which athletes can not only share live data but also receive live cheers from friends during the activity. After the event, the athletes can then look into who sent them cheers over a web interface. These commercial applications however do not provide much scientific insight on the social network effect of sharing live data and the impact that real-time spectator-support may have on athletes, if any.

Curmi et al. explored work in the area of real-time spectator support in 2012 through the HeartLink project [42]. In this work athletes shared heart rate data online and friends encouraged the athletes remotely. The HeartLink project consisted of two pilot studies and focused on the design and implementation of such systems. The study presented here follows the recommendations for future work that was suggested in this work namely: A) A need to validate results with a larger population. Thus spectator population was increased from 9 to 140. B) Test a new fully independent system (BioShare) and observe whether HeartLink's outcomes were influenced by issues raised from relying on distributed 3rd party systems. C) More importantly, compare and contrast the engagement of friends vs. unknown crowds by having different groups under observation concurrently. Additionally, we observe whether spectators are influenced by the social connectedness between the person cheering and the participant receiving the cheers. We also explore the effect on the athletes from being remotely cheered and whether the nature of the online cheering crowd matters - are athletes more motivated when supported by known crowds in contrast to unknown crowds?

Supporting crowds that are made up of unknown spectators are typical in sport events. On the other hand, the use of crowdsourced participants for user support is also not new and in recent years, through online crowdsourcing platforms, many innovative applications were developed such as summarizing academic papers [17] or deciphering blurred text [112]. But can crowd support and crowdsourcing be combined effectively in a real-time context?

4.3.1 Real-Time Factor

The real-time context is particularly challenging in crowdsourcing. Most crowdsourcing platforms are not designed for recruiting workers as a just-in-time workforce. Typical crowdsourced jobs, such as online surveys, are posted on crowdsourcing platforms and workers would complete the tasks when they please. In the cheering case however, the support has to happen at a specific time and workers have to 'sync' with the event rather then vice versa. Related work is found in studies on crowd-powered interfaces with highly innovative techniques for crowdsourcing just-in-time work such as VizWiz - a system for crowdsourcing near real-time support for vision impaired [20], Lasecki et al.'s ingenious work for captioning live speech [105] and Bernstein et al.'s work on queuing workers using multiple queuing models [16]. However, with the exception of Morris et al.'s work on 'Crowdsourcing Collective Emotional Intelligence' [128], there is very little knowledge on crowdsourcing spectator support.

4.4 Study Design

In the initial stages of the study that is presented in this paper, two design approaches for digitizing cheering during sport event were considered. The first was that of studying current cheering practices ethnographically and then finding ways to replicate as best as we can the cheering process digitally. The second was that of identifying radically new ways by focusing on the core objective (i.e. motivating the athletes) and designing new systems around this. While both approaches are pertinent, the second approach was adopted. In the first approach it is more likely to omit possible radical new ways of reaching equal or better outcomes for supporting the athletes. Through emerging digital tools, new approaches to cheering might now be possible but are not present in the 'traditional' co-located cheering processes. Consequently design started with a bottom up approach and a series of tests with different prototype configurations.

The preliminary tests were conducted during a range of events that included running, mountain running and cycling, and were intended to 1) test the data broadcasting system, 2) explore the study dynamics within simpler scenarios than those described in this paper and 3) gather insights on the user experience of both the athlete and the spectators. The insights gained from these pre-tests were then used to develop the research questions and the design of the exploratory deployment here described.

For this study we organized an ad-hoc 5 km race with co-located athletes and an online crowd of spectators. The race selection was based such that there will be enough time for the spectators to log in and understand the interface while at the same time make sure the race was not too long, so as not to increase the complexity of managing the online crowd. Additionally, the selection of the racecourse ensured that the event would have mobile network coverage on a selected service provider for at least 70% of the course.

4.4.1 Data sharing infrastructure

The data broadcast system was implemented using BioShare [41]. BioShare is an open source application that was designed for broadcasting data during day-to-day activities through a smartphone app and a web portal for visualizing the broadcasted data in real-time. The mobile application runs on Android devices and allows users to collect data through Bluetooth-connected sensors. This data is then shared with an online crowd that can interact with the data-sharing users through multiple modalities.

BioShare was specifically designed for researchers and as such, it also logs user interaction for post event analysis. The system was configured as illustrated in Figure 18. We re-configured the default settings in BioShare such that data is broadcast to those who log through a login process that will be described in the next sections.

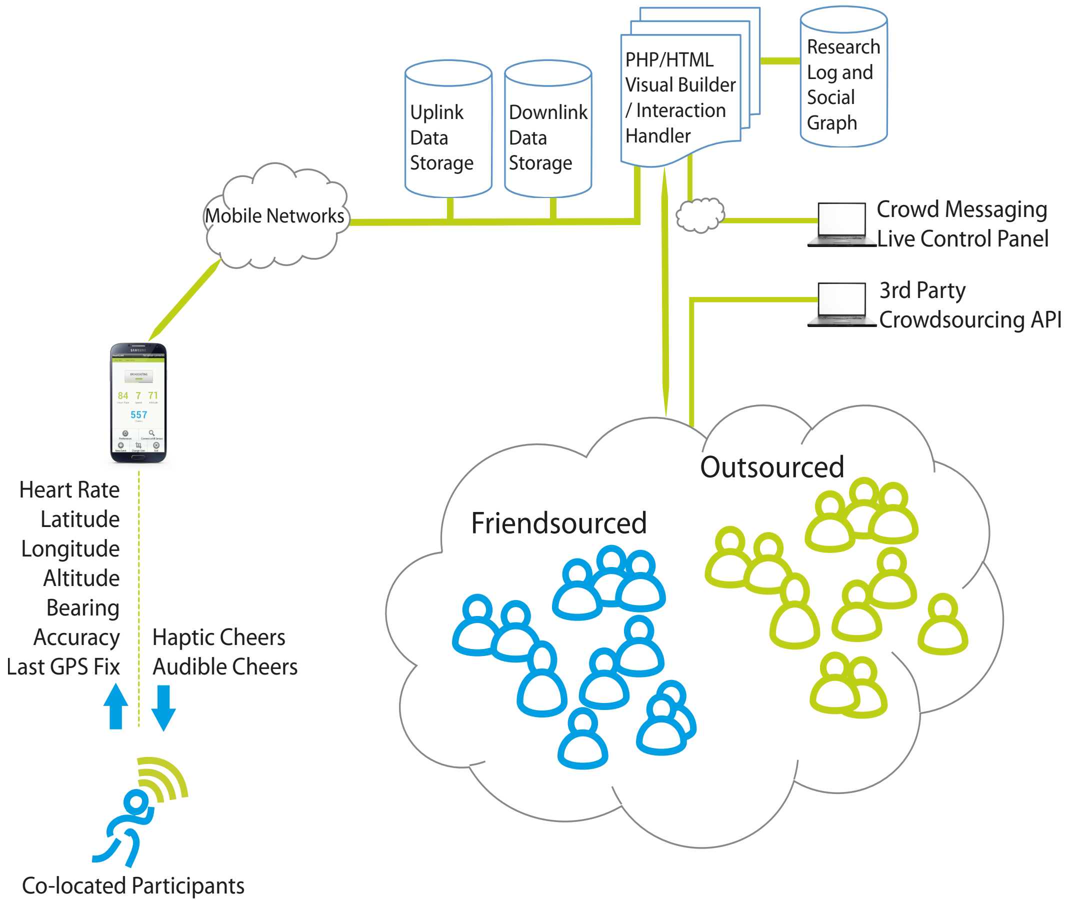

Figure 18: The system infrastructure.

In the pre-event tests we found that during synchronous studies that involve online crowds, a communication channel between the researchers and the crowd is essential. The real-time factor makes this work challenging particularly because it is difficult to predict all possible failure modes in such live activities at design stage. Additionally, unlike an in-the-lab study, the researchers have very limited feedback on what is happening within the distributed crowd (and no feedback from facial expressions and body language that may help in adjusting the study accordingly). In this light, a feature that allowed the researchers to broadcast messages on the spectators' interface was also implemented. This was used to inform the spectators of any technical issues that might occur during the live event.

4.4.2 Athlete participants

We recruited 5 athletes form a university running club who 1) were happy to participate in the study, 2) train regularly for competitive running and 3) had a detailed log of performance records in 5k races. In return of participating, a donation was given to the running club. The researchers did not know the athletes prior to this work and met them for the first time just before the race. None of the participants had used smart phones or any other device to track their performance during previous races so the participants had little predefined expectations of the technology or the user experience of carrying extra devices during the event.

Before starting the race the athletes were each given a Nexus 5 phone that was preconfigured with the customized BioShare application, an armband, a mobile data connection and a Polar WearLink heart rate chest strap that was connected to the phones via Bluetooth. The heart rate data type was used as it is a physiological parameter that is easy to measure in unobtrusive ways and because heart-rate measuring sensors are becoming very popular in emerging smartphones and wearable devices. Additionally the heart rate can indicate the fitness levels of individuals and the effort exerted during an activity. To ensure consistency, the phones were preconfigured and positioned by the researchers. The armbands were color-coded and this coding was used for identification of the participants on location.

4.4.3 Crowd participants

In parallel with recruiting the athletes, 140 online spectators were recruited for the live event. 76 of these participants were recruited from CrowdFlower - an online crowd-sourcing platform with a global distribution of active workers. Unlike Amazon Mechanical Turk, CrowdFlower supports European requestors at the time of writing. Crowdsourcing through an independent platform minimized the probability of having participants within this group that are socially connected with the athletes. These spectators were first introduced to the interface. They were then asked to follow the running athletes online for as long as they wish to and support them in the best way they could. At the end, they were presented with an 8-question survey.

A second group of spectators (n=64) were recruited through social networks at the athletes' university. Communication requesting participants to support the athletes was sent to the athlete's running club Facebook group and their departments' mailing lists. In this paper we refer to this group as 'Friendsourced'.

4.4.4 Procedure

During the event each of the devices carried by the participants collected and broadcasted live data as shown in Figure 19. Online spectators could visualize the live data through any Internet connected web browser after logging in through a Facebook app. The participants were also given the option to log in anonymously.

Following this, spectators were presented with live data visuals from each athlete consisting of heart rate, average heart rate during the event, a line chart with the heart rate, event duration in minutes, percentage of the task completed, meters covered, speed, pace and a chart with the running course overlaid on a map. All the data was dynamically updated every 2 seconds, on average, thus giving a "real-time" feel.

Spectators in both groups could change the athlete that was being followed at any time. This was done to observe how the crowd reacts to different athletes' performance. Just before the race the athletes were assigned as Participant 1 to 5 and this naming was used in the spectators' interface. Thus during the live event, none of the spectators knew who is, say, 'Participant 1'. However, the friendsourced crowd

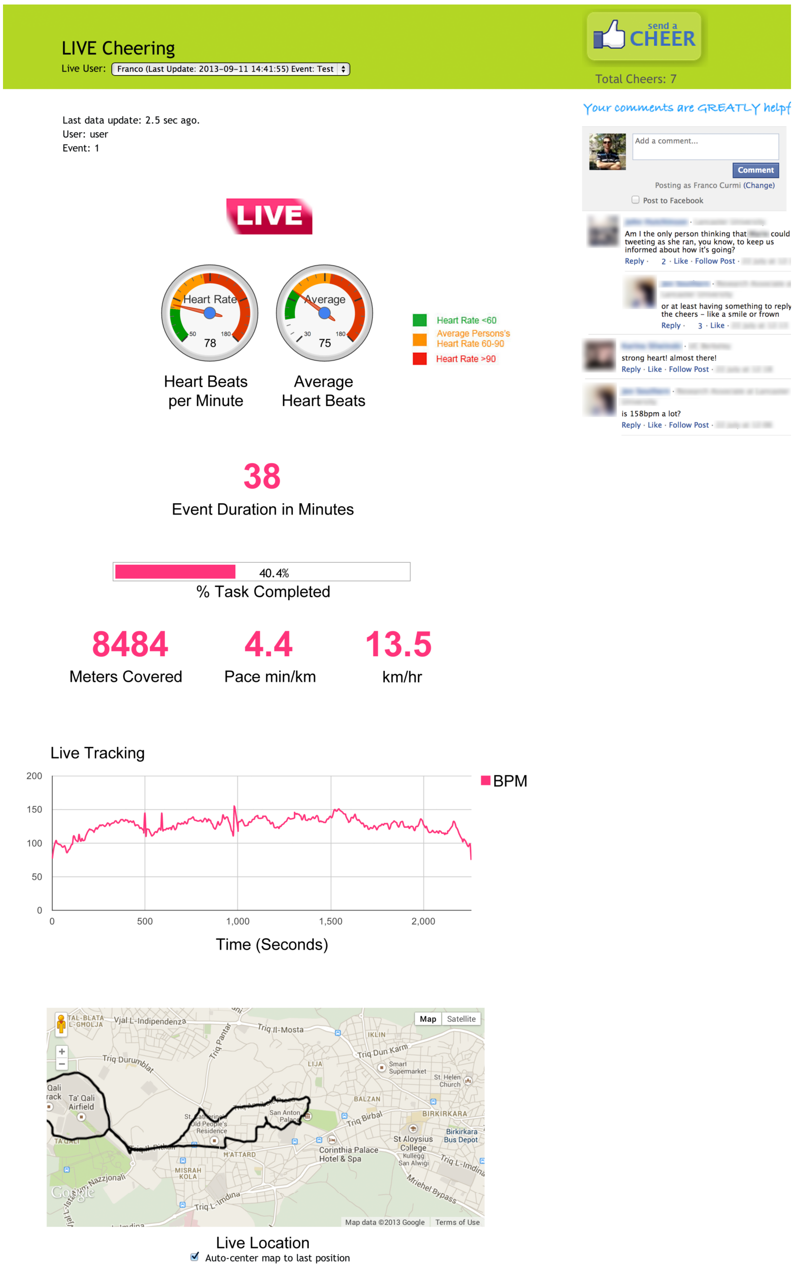

Figure 19: Sample spectator interface.

knew that the athletes were from their same department or running club. This approach was adopted to limit the range of tie strength within the group and ethical data sharing issues. In this study we consider these actors as having weak ties [70] with the athletes. The participants who were outsourced through the global crowdsourcing platform were considered as having no ties.

4.4.4.1 Interaction modality

Spectators could 'Cheer' the selected athlete by clicking a Cheer button. This button sent a small vibration to the device carried by the selected athlete. If the cheering spectator logged in through the Facebook application, then the athlete also heard the name of the person who cheered through the device's speaker and a speech synthesizer; otherwise the athlete heard 'Guest'. The interface presented also allowed all the spectators to post comments through a Facebook frame. By default the posts submitted by the spectators did not go on their personal Facebook profile but were only visible on the spectators' interface. To ensure that the data is not contaminated with crosstalk between the groups, each spectator only saw comments that were posted by those in the same group and following the same athlete.

The data broadcasting app (Figure 20) was designed in such a way that the users do not need to interact with it through touch during the activity. Before starting the event, the athletes were briefed on how the system works and what the haptic and audible feedback represents. The pre-event tests showed that the sound level is a key part of the user experience and a too low volume makes understanding difficult while a too high volume, particularly in public areas, makes the system awkward. For health and safety reasons the design intentionally avoided any use of headphones to hear the audible feedback so sound was generated through the device's speaker. At an ambient noise of 70db, the loudness of the devices was set to produce 76db at 30cm for 6db above ambient. 30cm was calculated as the average distance between the sound output of the device inside the armband and the nearest participant's ear. The ambient noise was calculated in pre-event trials using a Phonic audio analyser PAA3.

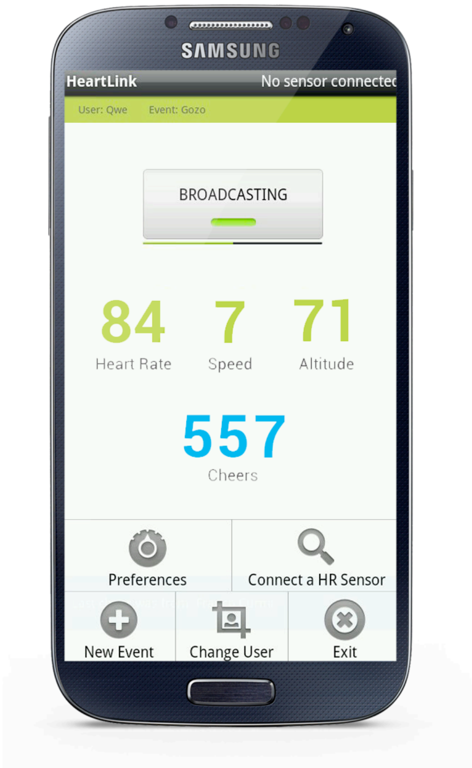

Figure 20: Customized BioShare research application running on athlete's devices.

4.4.5 Data collection

During the race data was intermittent for 40% of the race due to lack of mobile reception coverage and interference on the Bluetooth communication channels. Any intermitted data was identical for all conditions. The broadcast was time stamped and logged together with the interaction that spectators had with their interface including the cheers submitted, the comments posted and the duration of each participant following the data.

Additionally, when a spectator changed the athlete that was being followed, a modal form containing four questions was presented after 5 seconds. The 5 seconds delay was set to filter out any quick changes in athlete selection. This form collected information on the social network ties among participants, the spectator's age and allowed the spectators to leave comments. Qualitative data was collected from the athletes immediately after the race through a focus group. We felt that a focus group would generate more ideas through cross-pollination among the group in contrast to one-to-one interviews. This post-event focus group was made up of the 5 participating athletes, 3 co-located spectators (2 of these were also members of the running club but were injured on the day) and 1 interviewer. In the next section we present insights collected from the study, focusing particularly on the athletes' reactions to the spectator support and the spectators' interaction with the system in terms of the cheers submitted, posts submitted and spectator duration.

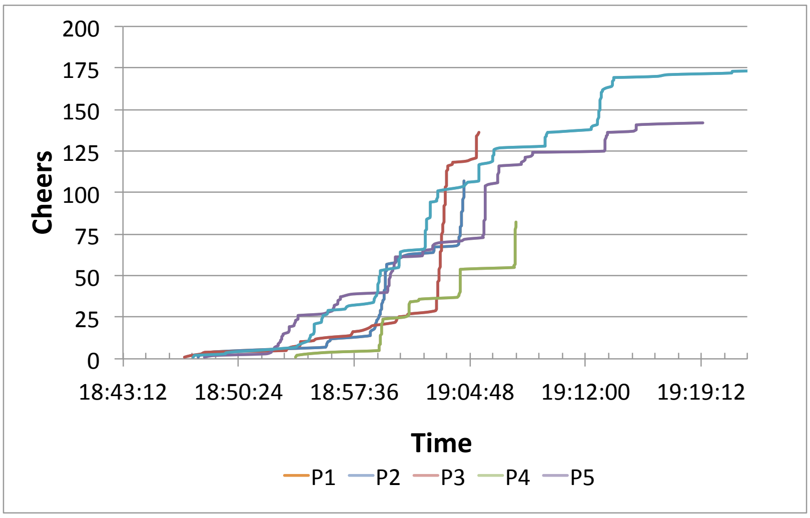

Figure 21: Cumulative live cheers submitted to the athletes.

4.5 Findings

4.5.1 Cheers submitted and crowd duration

The athletes (A) received a total of 727 cheers (A1: 118, A2: 150, A3: 155, A4: 85, A5: 219). Figure 21 represents the distribution of the cheers submitted for each participant. This data shows similar results to previous work [42] where spectators devised strategies to maximize the effectiveness of their cheers. This included holding back from submitting cheers at the beginning to then use the cheers when they feel the athletes need them most. Post event analysis showed that this repetitively resulted in an s-curve cumulative cheering distribution both for individual athletes as well as in aggregate. We note that the spectators had no limit on the number of cheers submitted.

Only cheers that were submitted from five minutes before the start of the activity and up to five minutes after the completion of the activity for individual participants are represented in Figure 21. The aggregate number of cheers represented is 645.

Figure 22 shows the time spent online by distribution density for each spectator group. Participants who were friendsourced spent significantly more time on the site (mean 14min. 24sec.; SD 21min. 45sec.) than paid outsourced spectators (mean 7min. 26sec.; SD 8min 48sec). They were also more diverse in engagement then the outsourced spectators.

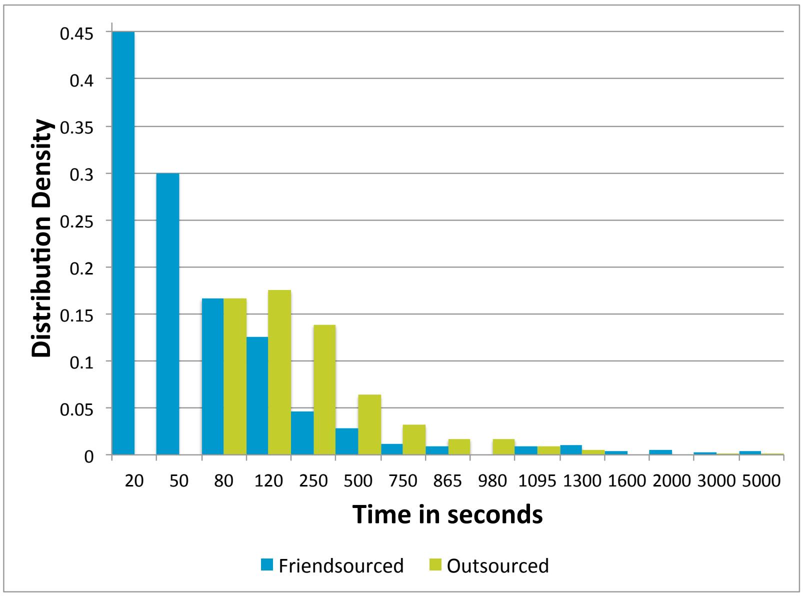

Figure 22: Friendsourced and outsourced crowd duration.

4.5.2 Post-event focus group with athletes

The insights gained from the post-event focus group complemented this data and contributed to contrast 1) the type of support that was provided (e.g. cheering modalities and motivators wrapping the live cheers), 2) the source of support (e.g. the contrast between the support from friendsourced and outsourced crowds on the participants), and 3) directions for future work in system design. These will be discussed next.

4.5.2.1 Type of support provided

We found that the participants were excited when they received live cheers during the race however other motivational factors that were not intentionally designed emerged during these interviews. Namely, the total number of cheers that each athlete receives and the number of spectators that are currently following their performance live on the portal (even though they might not necessarily cheer) could be a source of motivation. Whenever an athlete (A) arrived at the finish line, the interviewer (I) collected the devices and sensors. The interviewer then informed the arriving athlete the total number of cheers that the athlete received up until then and this resulted in high excitement from the athletes receiving the information. During the race, the athletes were only receiving aggregate cheers at a minimum of one vibration every 10 seconds (if cheers were sent within those 10 seconds) but they were not aware of the actual total number of cheers up until that point.

I: yours is 137 cheers.
A2: 137 cheers? all for one persons! 137? [excitement/laughing] quite a lot.
[A2 some time later; asking A1] Is that the most cheers?
A1 what's the cheer count you've got?...
[later] Co-located spectator 1: how much have you got?
A2: a 137 cheers apparently
Non participating athlete: you're a popular man.
A2: 137? that can't be right; a 137 in all? in total?
I: no no, just for you
A2: just for me? What!
Race Organizer [teasingly]: oh we're getting insane there. I don't know who said I don't want my arm to be cheered (before the race).

Not only receiving the cheers during the race excited the athletes but even simply getting to know the total number of cheers that were submitted. This, become a matter of competitive comparison more than the race timings themselves. All the participants agreed that the 10 seconds interval was fine otherwise "it might become a bit annoying." [A5]

Asked about the sound level of the devices, during the race the participants felt it was *"all right actually, I could hear the names and that was an all right noise, you don't want it really loud. If there were a lot of people on the way then you might need it a bit louder."* [A2] Three of the participants commented that they did not feel the vibrations. We found that the typical smartphone vibration is not a reliable communication modality when strapped on the arm in a running context. The strength of the haptic feedback was weak particularly since the armbands suppressed the vibrations. The audible feedback, calibrated as listed earlier, proofed to be more reliable in this context.

4.5.2.2 Source of the provided support

The athletes were asked a series of questions that were intended to identify whether the support from people they know was found more relevant then the support that was received from unknown crowds. Three of the athletes agree that both are relevant:

A3: …it's already nice to know people you know [are there]. A lot of numbers, is like when we go to big races and there are loads of crowds cheering you, and you don't know anyone… we always find this better - that is - with the volume of people there, cheering you on.

R5 partly agrees stating that sometimes it is "*better to have people you don't know cheering… you don't want your mum dominating*". The athletes were not bothered when they heard other athletes being cheered claiming that "*it is how it works in real-life, you hear all cheers around you*" A4.

4.5.2.3 Considerations for future designs

We observe that the athletes' suggestions for future design were particularly focused around new cheering modalities and means of aggregating the collective support. A3 suggests having features that allow the spectators to "*record their name"* as this is expected to communicate emotions better then a text to speech synthesizer. In this case, the athletes are likely to recognize the voices even if names are not narrated. A2 agrees: *"I don't think there is much more you could feel, because anything longer than that could be annoying. … we though of if people online could record something, say it would come up with their voice, say 'go on go on, you're the best' [clapping - excited] and it is in their voice."* Similar remarks were made by A4 and A5. When we aggregate the suggestions that emerged from the athletes we observe that, unknowingly and indirectly, the athletes were encouraging more synchronous social interaction within the system and from the crowd.

The modality of aggregating and communicating the support seems key for motivating the athletes. During the event the athletes received a haptic and audible cheer at most every 10 seconds if there were any cheers submitted in the previous 10 seconds – irrespective of the number of cheers submitted. The athletes, as quoted in previous sections, positively commented on this as a way of limiting the number of 'alerts'. However, this approach tells the athletes nothing about the number of spectators that are actually cheering. Non-participating athlete A7 suggested varying the sound level of the cheers based on the size of the cheering crowd, *"…say, every 10 seconds if there are more cheers than the previous [10 seconds] you get a louder noise."* This approach would be congruent to the s-curve cheering distribution presented earlier.

A major issue for all the participants except for one was the device form factor, claiming that they would not carry the device during competitive races due to the size and weight that they would have to carry. A3 states *"it has to be a less clunky device for me. I could never run with something as big as that on my arm. I know that you can't at the moment but if you could put it into your Garmin [watch]…".* A4 suggest that a device on the waist would be less annoying than on the arm. Similarly A3 comments: *...people that are racing wouldn't do it; they want as little weight as* *possible… I really don't like it [carrying that device]*. The only athlete who did not mind carrying the device had significantly bigger arms then the other athletes. This suggests that if such technology is designed for mass diffusion, then the size and weight of the device are critical design factors and that the current smartphone form factor is still not small enough for using it during competitive races.

From a spectator-support perspective, all the (competitive) athletes agreed that cheering would be more effective for non-competitive athletes such as the occasional amateur marathon runners "*because they are struggling to finish the race unlike people who train regularly*" and "*knowing that people are supporting you at that moment in time could be a source of encouragement*".

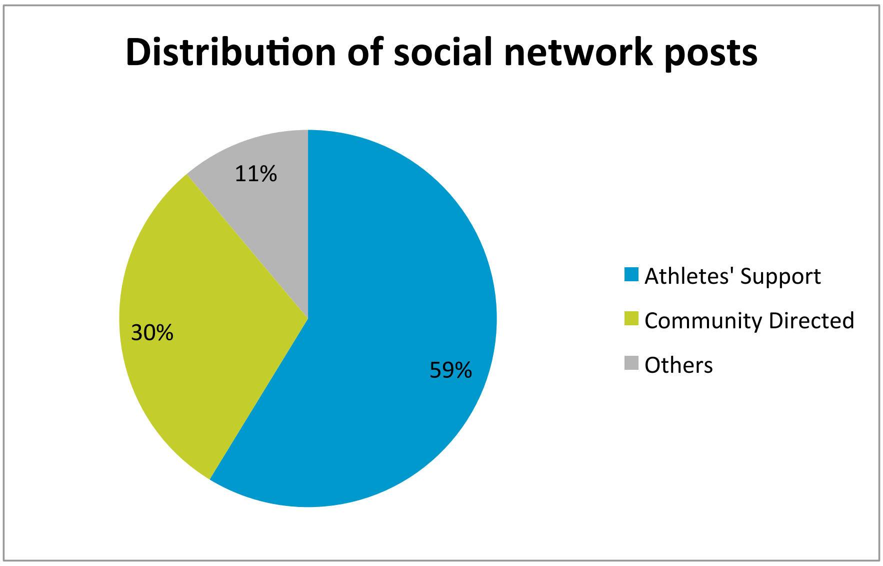

Figure 23: Distribution of social network posts submitted by the spectators.

4.5.3 Facebook comments

Figure 23 shows the distribution of posts send by the spectators during the event. Posts can be grouped into those that were directed to the athletes and those directed to the community on the site. The latter were instigated either because of intermittent data or because one or more spectators wanted clarifications on the system itself. The spectators posted a total of 60 comments. 28 comments were posted in the landing page and 32 were posted in the athlete's respective visualizations.

The athletes' demands for increase in social interaction that were exhibited during the focus group were also reflected in the comments posted by the crowd. For example, as athletes proposed that future implementations should allow spectators to send them live or recorded voice messages, many of the spectators were already posting text formatted as if the athlete would hear them, even though the spectators knew that the text messages will not be received by the athletes up until after the race. Posts like "Keep going (you aren't running as fast as you can)!" and "ALMOST THERE!" were typical. We observe that these are quite distinctive from the classical social network posts where athlete's friends often congratulate the athlete upon successfully completing an event - thus using the past tense rather then the present.

4.6 Discussion and Lessons Learnt

These results have both academic and commercial implications. The design of real-time systems for supporting athletes from remote crowds received negligible attention up until now as little research was done around real-time interaction between co-located and distributed crowds in sport events. We expect that similar studies that involve complex real-time structures will increase in the near future. With the rapidly advancing social networking and communication technologies, the implementation of such systems is becoming more feasible. These results also indicate that real-time spectator support could have high impact for many stakeholders that are directly and indirectly involved in the cheering process. Athletes feel more supported and the cheering process can increase spectator engagement. This process could be very attractive for indirect stakeholders such as marketing strategists who seek tools that facilitate social network diffusion through innovative sports-based communication channels. Additionally, having spectator support that is received 'just-in-time' when it is needed, is expected to augment the social support models that are used on existing social networks. Next we summarize the key lessons learnt around the effect of synchronous spectator support on the athletes, the spectators, and the limitations in the tested design.

4.6.1 Athletes' motivation

The motivation instilled in the athletes through live cheering could be explained through theories of expectations management [1] and self-determination theory (SDT) [49]. In the work presented in this paper, the participants had more online supporters then they expected. This difference between their 'expectations' and 'actual' support, created the excitement that was reported earlier. It will be interesting to analyse if the inverse effect would happen should the athletes not receive any cheering when they are expecting to be cheered. We believe that this would have a negative effect on the athletes that translates into a demotivating factor with similar effect to that of receiving jeers rather then cheers [59].

As regards motivation, sport athletes' 'intrinsic motivation' arises from values within the activity itself - for example, they may enjoy running, or satisfy a need to seek attention, or simply feel physiologically better. The motivators that are not intrinsically part of the activity such as receiving medals or as in the case of this study, receiving 'digital cheers', are 'extrinsic motivators'. Based on the motivational synergy model [3], these can fall in one of two states: 'synergistic' (in which case these support the intrinsic motivators thus augmenting the satisfaction and performance improvement from the intrinsic motivators) or 'non-synergistic' (in which case they undermine the intrinsic motivation). For example an athlete's intrinsic motivation for participating in running events may be attention seeking. In this case, the cheering process presented, is expected to increase the athlete's motivation should this make the athlete aware that an even larger crowd is following the performance. Inversely, the cheering becomes non-synergistic should this distract the athlete from the core intrinsic motivators, say, when the cheering device makes a bothering loud noise in public.

Deci and Ryan provide a more detailed approach to classifying extrinsic motivation over five classifications in the organismic integration theory as a subclass of SDT [160]. In this regard, our observations of the athletes' reactions brings us to highlight the psychological need of '*relatedness*' where through remote cheering the athletes feel connected to others and build a sense of belonging. Further research that looks into how the cheering process can be designed in ways that make this support synergistic to the athlete's intrinsic motivators is needed. Such design must take into account individual personalities and traits as different athletes have different motivators individually, which are different across time.

While paying crowds might not pertain to an applied research perspective, in hindsight, the predicted effectiveness went beyond our expectations. Both groups motivated the athletes (including paid participants) particularly because paid participants could freely cheer any athlete, so the athletes were motivated by the fact that the crowd was cheering 'them' vs. 'others' (rather than whether it was a friend or a paid supporter). It seems that in the proposed model, supporters' pay did not distract the intrinsic motivation of the athletes [51].

4.6.2 Spectators' engagement

The results confirm that the spectators' engagement is influenced by **1) the social tie strength** between the supporter and the athlete. This is not all encompassing and other unaccounted factors may be present. **2)** The **type of data visualized** is also expected to influence engagement as shown in Figure 21. Additionally, when comparing the event discussed in this paper to the work done in the HeartLink pilot studies [42], through content analysis of the spectators' posts in the two settings, we observe that the cheering crowd was much more enthusiastic in HeartLink. We believe that this effect was due to the 'charity' nature of the HeartLink event; the charity element seems to inject an obligation of making social good and encourage athlete-support. Thus another influencing factor is expected to be **3) the perceived athlete's motivation to do the activity** as in the theory of mind [10] – this perceived motivation ranges from self-centred (e.g. a competitive event) to altruistic (e.g. supporting the charity run's cause through the perceived value of supporting the athlete). In this light, the fact that the race in this study was specifically organized for a research purpose (in contrast to a public event) may have also influenced the intrinsic motivation of both the participating athletes and the spectators. Finally, **4) the spectator's incentive for recruitment** (e.g. being paid vs. voluntary support) is another influencing factor of spectator engagement that is worth further exploring through crowding theory [64].

In this work we did not account for the effect of paid vs. unpaid crowds. Future work is expected to single out these conditions across groups of equal social ties and pay. To decrease the workers' time-to-recruitment, we paid twice the value that was suggested by the platform for each worker thus making the task more compelling for the job-seeking workers. The job was posted 15 minutes before starting the event and any data from workers who started the 'task' after race completion were removed from the dataset. 0.20$ were paid to each worker for taking part in the task that was estimated to be fun and lasting few minutes on average. Participants were not instructed on how long they should watch the event for. They could spend just a minute but they were also free to stay online for longer if they wished to do so. Thus, a payment strategy was set such that pay was large enough to trigger an initial engagement from participants but low enough to allow us to observe if the initial paid engagement becomes intrinsic once spectators log in (i.e. would spectators freely stay online beyond what they are paid for by current crowdsourcing norms?). Based on the crowdsourcing platform's independent post-activity survey, through this approach the assigned task scored high on "contributor satisfaction" (4.3/5 n=41) and "pay" (4.3/5; n=41).

4.6.3 Issues, limitations and critical reflection

In conducting this exploratory deployment the authors faced a number of challenges arising from the quite unusual combination of interaction contexts that were involved. Namely, 1) being in-the-wild, 2) having co-located participants in combination with 3) a geographically distributed crowd that was recruited through social networks, 4) an outsourced crowd and 5) all necessitating synchronous interaction. Each of these factors augmented the complexity of running the deployment. The intermittent data broadcast that was due to the lack of mobile reception in parts of the racecourse was equal to all conditions yet it may have impacted some of the results. When an athlete enters a temporary 'blind spot', spectators following that athlete seem prompted to switch and follow other athletes. In this light we refrained from reporting results that would have had direct influence from this. For example, it would have been interesting to link the cheering patterns of spectators to the athletes' positions in the race but further tests are needed. Data indicated that athletes who ran slower received most cheers however this was not due to social network effects but was likely due to broadcasting for a longer timeframe thus giving the spectators more time to cheer. We do encourage future research to look deeper into this interesting area of human behavior with questions such as: 'During a challenging task, do crowds support the weakest or the strongest, and how is the distribution effected by the social tie strength between the supporter and the supported?' Our generalized hypotheses, based on athlete's feedback in this study, is that while the supported might appreciate support from both strong and no tie, the weak ties might be the most effective.

4.6.4 Future work

In addition to the future work suggested above, experimenting with different cheering modalities is an avenue worth pursuing. This should look at 1) **ways to aggregate and communicate** the support (e.g. using spacialised audio, modulating the audio amplitude based on crowd size or using different haptic feedback positioning). Another important factor is 2) the **type of support** that is communicated (e.g. communicating the number of persons following online, number of cheers, or using a recommender system to compute and present the most motivating comments to the athletes in near real-time).

In hindsight, in future we would modify three key design decisions taken; 1) presenting the data of one participant at a time in the interface, 2) allowing users to switch athletes and 3) presenting anonymized participants:

1) *Presenting collective vs. individual athlete data*: Our observations of the event dynamics indicated that if the spectators were presented with athletes' aggregate data, like for example a map that represents the location of all the athletes, then the crowd might have taken different cheering strategies. Presenting the spectators with individual athlete's data was a research driven design decision. From pilot studies we learned that presenting the data of all the athletes in one interface makes it difficult to link spectator comments with the data that prompted those comments. However,

presenting multiple athletes in one interface would help spectators follow athletes' relative performance. This would let us observe the distribution of spectator-support from human crowds across the weakest and the strongest athlete.

2) *Switching athletes*: Additionally, if spectators were locked into selecting one athlete at the start of the event, rather than being allowed to change athletes throughout the event, we envisage that the spectators would have been more captivated in having 'their' athlete do better thus increasing engagement through gamification dynamics.

3) *Anonymizing participants*: We believe that there is significant room for improvement in terms of spectator engagement particularly by designing interaction around spectators' intrinsic motivation to follow such events. The increase in engagement of the friendsourced and outsourced spectators shows that the bond between the spectators and the athlete is a key element of spectators' engagement. The anonymization of athletes within the spectators' interface was a design decision taken to minimize ethical concerns when sharing data, however, if the athletes were presented with their real names, we believe that the spectators would have experienced a more 'personal' connection. The decision to anonymise athletes was driven by the researchers not the athletes. Since this work was a first deployment of its kind in a research setting that includes very personal data sharing such as heart rate, we felt that it would be appropriate to use anonymity in this case. This decision was also supported by earlier interviews conducted with experts in this area [41]. Although future deployments of the system will not anonymise athletes for reasons specified earlier, the anonymisation of athletes in this context had research benefits, namely, that the cheering decisions (as perceived by the athletes) were based on athletic performance.

As findings show, a few more years of technological advancements are needed until easier and less obtrusive solutions are widely available. The smartphones' form factor and the unpredictability of mobile-data communication infrastructures are key issues. The availability and quality of mobile data connections are dependent on the number of users using the system at one time and the (typically) unknown operator's data vs. voice bandwidth policies at the connected nodes. This nulls the relevance of testing the mobile data connection across the course before events since the actual scenario during the race, particularly if it involves more than a handful of participants, may change drastically during the event. Predictability is critical if such systems are scaled up for larger crowds during popular city marathons. Interestingly, technology has evolved in such a way that aggregating and broadcasting data from large crows that are distributed across the globe may be easier than aggregating data from co-located in-the-wild participants.

In the longer term, further studies could precisely indicate how humans seek spectator support and socially support others. In specific contexts of human behavior, would we cheer the best or the weakest? Having enough data for a specific scenario, can we build a model that takes into consideration the data presented to spectators, the real-time performance and the social connectedness, to predict cheering patterns? Having such a model, could we influence the cheering patterns and maximize the athletes' performance - for example by encouraging cheering just when the athletes need them most?

4.7 Conclusion

The innovativeness of the work presented in this paper is the crowdsourcing of real-time spectator support through friendsourced and outsourced crowds. In this paper we have presented the results and insights gained from the study with 5 co-located athletes and an online crowd of 140 distributed spectators that were recruited from community networks and a crowdsourcing platform. The results showed that the social ties between the spectators and the athletes influence the engagement of spectators. More importantly, as in co-located cheering, the athletes were excited with both the support received from known crowds as well as support that was received from unknown crowds. This indicates that in spectator support, within the context that is presented in this paper, outsourced spectators could be a valuable source of support. We hope that this first step in crowdsourcing just-in-time support will help other researchers and more importantly stimulate new research in this very promising area.

Chapter 5

SEEING THE HEART RATE OF REMOTE OTHERS: AN IN-THE-WILD INVESTIGATION IN REMOTE SPECTATOR BEHAVIOUR DURING A RUNNING EVENT

Submitted as:

Curmi, F., Ferrario, M.A. & Whittle, J. Seeing the Heart Rate of Remote Others: An In-The-Wild Investigation in Remote Spectator Behaviour during a Running Event, submitted to *International Journal of Human Computer Studies.*

5.1 Abstract

The market has seen a surge in offer and demand of health and fitness applications and sport wearables that come equipped with highly sophisticated biometric data capture functionalities. In this context, biometric data capture and sharing has recently become increasingly common practice. However, while research on the effect that sharing such data has on the individuals using the devices exists, little research exists on the social effects that sharing such data has on groups of remote spectators. Is there any value in sharing heart rate data within social applications and does this sharing influence the behaviour of those seeing this data? This paper investigates this by conducting an in-the-wild study where the location and heart rate data of 5 athletes running a 5k-road race is shared with 140 online spectators in real-time. Specifically we investigate the difference in behaviour between spectators who are presented with biometric and context data, and those who are only presented with context data (e.g. location). We also examine whether this difference is dependent on the social relation between the athletes and the spectators.

We find that spectators presented with the heart rate data of remote athletes, support the athletes more and rate the presented system more positively. These effects are more significant across spectators who know the athletes than those who have no social connection with them. This not only confirms earlier literature, but also presents new insights and research directions.

5.2 Introduction

The use of biometric data such as heart rate data is becoming increasingly popular outside the medical practice. As the number of communication channels increased throughout the digital era, so did the diffusion of biometric data. A number of socio-technical systems are embedding features that allow users to share their biometric data. For example, freely available sports applications such as RunKeeper, allow users to share their heart rate data over social networks in real-time. Open broadcasts such as the RedBull Stratos event superimposed heart rate data over live video streams. This was followed live by over 8 million online viewers [29]. However, questions on the effect that this data has on its viewers are still largely unclear. In this study, we are interested in understanding whether presenting the heart rate data of athletes to remote spectators influences the spectators' behaviour. The work of Janssen et al. [85] and Kurvinen et al. [103] suggested that the effect that heart rate data has on others might be depended on the social relationship between the data sharing athlete and the data viewers. Thus, in this work we also investigate whether the influence on behaviour from seeing others' heart rate is subjective to this relationship.

In the last four years, we explored how to design and develop systems that facilitate real-time remote crowd support during challenging sports events such as running marathons. To do this, we iteratively developed and tested HeartLink (heartlink.co.uk), a system that allows athletes to broadcast location and biometric data to online spectators as the event unfolds. With HeartLink, on-line spectators can support their favourite athletes by clicking a 'Cheer' button while following their performance live. This creates a small vibration and a sound on the athlete's device (e.g. mobile phone) thus creating a physical connection between the athlete and the remote supporters.

A key element that was identified in this process was the need of the supported person to convey the story as it happens. Results from an earlier pilot study and a user study [41,43] suggested that displaying the users' heart rate to remote others influences spectators' behaviour. In this light, we further investigate the effect that the sharing of heart rate data has on those seeing this data.

Through an in-the-wild study, we investigate the difference in behaviour between those seeing and not seeing the heart rate data. We recruit two groups of spectators. One group is made up of athletes' friends and was recruited from their social networks. We call this group 'Friendsourced' [19]. The second group was recruited from a crowdsourcing platform so these participants had no social connection with the athletes. We refer to this group as 'Outsourced'. We then compare and contrast behavioural difference between those presented with the heart rate and those who are not presented with the heart rate. Additionally, we investigate whether any difference is equally reflected among those who know the athletes and those who do not.

In this light, this paper's contributions are the following:

1. It provides a historical overview of how biometric data sharing evolved through the advancement of technology.
2. It reports on the on-line behavioural differences between spectators who are presented only with context data, and spectators who are presented with biometric and context data. We find that the presentation of biometric data is associated with increase in cheering.
3. It reports on the on-line behavioural differences between friendsourced and outsourced spectators. We find that friendsourced spectators show more engagement in terms of the quantity of cheers they submit and the duration of their cheering efforts.
4. We then compare disparities between the four groups in conditions 2 and 3 above with results indicating that the most engaged spectators are friendsourced spectators who are presented with the additional heart rate data.
5. Finally, through literature, we derive and propose justifications for these results.

The next section provides a brief historical review of how technology-mediated heart rate data sharing evolved from the emergence in early 1900 up until the widespread diffusion through digital communication channels. We then describe the procedure adopted in this study, the results and discuss the outcomes.

5.3 The State of the Art in Heart Rate Sharing

5.3.1 A brief history

Traditionally, medicine was the driving force for advances in biometric data capturing, processing and communicating. The history of biometric data in health dates back to the early 1900. Figure 24 presents an indicative trend in the use of the term "heart rate" within textbooks for the period between 1800 and 2008. This shows an emergence of the term in early 1900 with a rapid diffusion starting in the 1960's. This dataset[3] consists of a randomly selected 6000 English texts for each year and the selection reflects the subject distribution. In this chart, the y-axes represent the occurrence of the term as a percentage of all the sample words in the dataset [124].

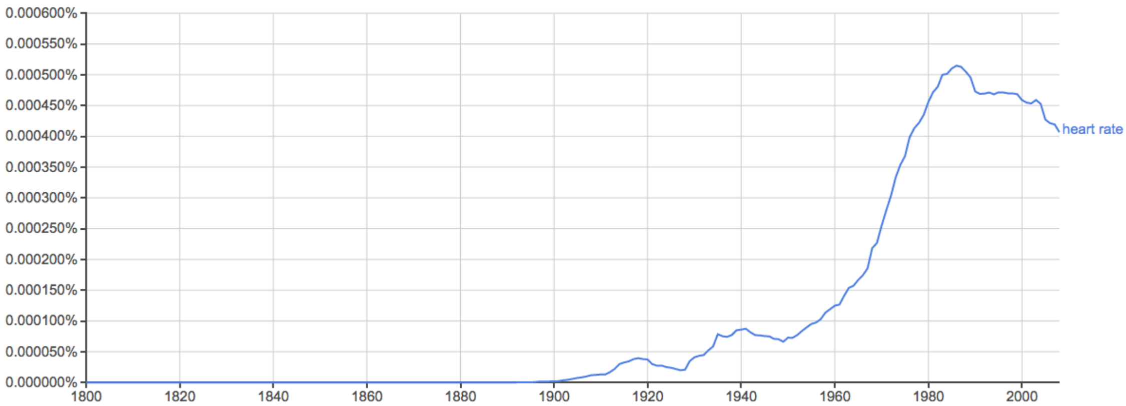

Figure 24: Google Ngram search for the terms "heart rate" from 1800-2008 in the corpus English one million as at 2015

The communication of biometric data, biotelemetry, was also subject to rapid evolution through a series of disruptive technologies. Figure 25 highlights key punctuations in this regard. Again, these advances were initially driven by demands in

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[3] By using the "English One Million" corpus as a dataset, the data on which this analysis is based takes into account the increase in published books in the later years.

health care [73]. However, more recently, the rise of ubiquitous computing, particularly smart phone technology, facilitated a rapid dissemination of biotelemetry-based applications outside the medical domain.

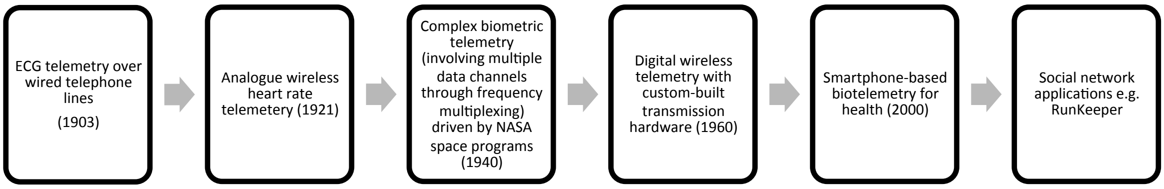

Figure 25: The evolution of biometric telemetry

The first reference to "biotelemetry" dates back to 1903 when Nobel prize winner Willem Einthoven transmitted electrocardiogram signals from hospital to his laboratory over telephone lines [139]. The next punctuated change occurred 18 years later with the first transmission of heartbeats over radio. Subsequently semiconductors opened up multiple possibilities for biotelemetry as equipment became more stable, smaller and more accurate. Today, the availability of off the shelf biometric sensors and mobile devices lets individuals who are not necessarily medical savvy, to capture, log and share this data. Applications like RunKeeper, Runtastic and Azumio, among many others, are free smartphone applications that allow users to capture and share their heart rate data over social networks in real-time with great simplicity. For example Azumio, a smartphone application reads the user's heart rate by placing the tip of a finger on the phone's camera thus avoiding the need of additional sensors. More recently, Poh et al. [149] develop a non-contact heart rate measurement application. Through a webcam, they analyses minute changes in facial skin colours to determine the cardiac pulse. However, while applications that allow the sharing of heart rate data are on the increase, little is known on the effect this sharing has on the persons who remotely see this very personal data. The results of a study that we conducted prior to this work and which involved the broadcast of athlete's heart rate data to a social network [32] suggested that relatives can become anxious when they perceive the heart rate of the athletes as being high or when the heart rate is unavailable due to technical system failure. In this work we investigate this further by looking into whether the presentation of the heart rate data influences the behaviour of those seeing the data and if this change in behaviour, if any, is dependent on the social relation between the data sharing user and the data viewer.

5.3.2 Biometric data sharing literature

Cases that involve biometric data sharing are quite common in HCI literature [76,85,100,103,130,146,168,176,193]. These studies can be clustered into two groups. First are those that focus on system design, such as the work of Konberg et al. [100]. A second group clusters those that look into the effectiveness or social impact that sharing biometric data can have on participants. An example of this is the work of Schnadelbach and Kurvinen [103,168]. By following upon this work, we will next look at the results that contribute in understanding the effect of biometric data sharing 1) as an information representation and 2) as a way to influence social connectedness between individuals.

5.3.2.1 Augmenting the experience of data viewers

Armstrong reports on a group of researchers at Lulea (Sweden) who presented two of the first attempts in which biometric data was used with the intention of augmenting the experience of spectators [7]. In their first project, the Arena project[4], Konberg, Ohult and Delsing built a system that collects breathing, heart rate and location based data of players during and ice hockey match. This data was then shared with

[4] The arena project was run in collaboration between Ericsson, Luleå University of Technology and the Centre for Distance Spanning Technology (CDT) through the years 1999-2002

spectators via custom-made handheld devices [7]. In this study, "*Measuring Breathing and Heart Rate Data with Distribution over Wireless IP Networks*", the work focuses primarily on the communication technology and less on the social impact that the system had. However, in a second project at the same centre, Hallberg and colleagues used similar custom-built technology to share data during the world's largest skiing event, the Vasaloppet week. Three participating athletes equipped with sensors took part in a 90-kilometer open-track non-competitive skiing marathon. The data collected included altitude, position, heart rate and speed. This data was connected through Bluetooth and GPRS technology to the Alipes platform [140]. This context-aware platform then presented the data to spectators who logged into the project's website through a Java applet [76]. By comparing both projects, we identify that Hallberg's study faced more challenging situations primarily due to the participants being 'in the wild' [31]. For example issues such as data loss were significant and amounted to 31% for the GPS data and 24% for the heart rate data across the ten-hour event. More importantly, the study reports that these interruptions in heart rate data seemed to influence the spectators' behaviour during the event. This suggests a link between the presented data and the spectators' behaviour.

Although this project was not specifically investigating the effect that the deployed system had on the spectators, the authors do however report from survey data that the solution did enrich the viewers' experience and that this approach could be valuable in augmenting television sports broadcast. Since then, the statistics presented through computer-generated graphics during television broadcasts, particularly in sports events, increased considerably. Additionally, capturing biometric data and presenting this to the television viewers is now technically possible. However, the use of biometric data, such as heart rate, in public television and online broadcasts is still negligible. The reason for this remains largely unknown.

However, a series of projects that explored this area were done in Nottingham. "*The Experiment Live*" was an artistic event in which Paul Tenant et al. looked at the possibility of using biometric data during television broadcasts [183]. They also look into whether television actors can fabricate biometric data during a live broadcast. Four participants were outfitted with sensors and were followed by cameras while they explored the basement of a presumed haunted house. The data was then broadcast live to a cinema where an audience followed the 40-minute event. The authors bring up the need to understand how to present visualizations that contain biometric data in ways that viewers can understand.

Schnädelbach et al. conducted similar work at the same university. They captured participants' data while riding amusement rides. Data visualizations that contained live video, audio, heart rate and acceleration data, were presented to spectators in a nearby location (n=90) [168,190]. The study reports that the data broadcast 'extends the experience for riders while also enhances the entertainment value for spectators'. The results do not single out individual data types that were presented and the effect these types had. This is an aspect we are interested in investigating.

5.3.2.2 Effect on social connectedness

Some early research investigated the effect of biometric data sharing between a football team and their families and coaches [103,177]. In this study, football players wore heart rate sensors and the data of each player was transmitted in real-time. This data could then be openly seen from mobile devices that were located around the pitch. They found that sharing heart rate data added an element of competition between the parents who expected their children to be the most fit in the group. They report that sharing the individual's heart rate motivated the participants to attend sports practice more frequently and become fitter. These discussions also highlighted the general lack of understanding of the heart rate data in the study population. However, the data sharing became a tool for generating social interaction as parents discussed and joked about the presented data during the games. Such interaction would not have happened without the data sharing activity.

A similar investigation but over a longer time period and with differing conclusions was conducted by Slovak et al. [176]. Slovak studied the effect of exchanging heart rate data in real-time between five couples over a two week period. In this case, the authors highlight the necessity of having contextual information. They report that viewing the heart rate data without any additional context was not very meaningful for the remote data viewers. For example, seeing remotely that your partner's current heart rate is 100, leaves room for multiple assumptions including, the person is running or stressed or excited. This emphasized the importance of context awareness that gives meaning to heart rate values. On the other hand, the 'mystery' of not knowing the precise context seems to have helped create the reported increase in "feeling of connectedness" between the participants. This contrasts with earlier referenced studies that involved specific sports contexts with shorter timeframes. In this case, the participant-pairs who were intimate couples report feeling an increase in emotional connectedness with the remote other when knowing that the data visualized represents a physical part of the other person. This suggests that sharing heart rate data generates different feelings to different individuals. This difference seems related to the relation between the participants, prior to sharing the data. Participants remark that sharing the heart rate data represents great openness, as unlike facial expression, it is something that you cannot intentionally control. This is particularly relevant when this data is shared in real-time.

The increase in social connectedness is also supported in the work of Janssen et al. In a lab-based experiment, Janssen and colleagues presented participants with sounds of real heartbeats from a known person, heartbeats of an unknown person and computer generated heartbeat sounds. Participants associated an increase in heart rate with an increase in emotional intensity [85]. However, when listening to heartbeats of unknown persons, the participants did not feel any increase in connectedness. They did feel an increase in social connectedness when the heartbeat they listened to was of a known participant thus indicating that the degree of connectedness between the participants affected how much influence heart rate data sharing creates and the state of the social relation between the participants before the experiment. These results are also held by O'Brien and Muller in 'Jogging over a distance' [132,141]. They developed and tested a context-aware system that shares ambient sound and heart rate data between two remotely located joggers. Each jogger was equipped with a heart rate sensor, a pair of headphones and a telemetry device. The telemetry device transmitted ambient sound and heart rate to the remote device and vice versa. The jogger with the highest exertion effort heard the other jogger as if he or she was behind. Again, the results, in this case, indicated that sharing heart rate data in real-time facilitated the social experience of the participants. The use of heart rate as an indication of effort provided a way in which athletes could interact and compare their performance in real-time.

In summary, the work reviewed suggests two key influencing factors in heart rate sharing, namely 1) the context in which the data is shared, and 2) the social relation between the person sharing the data and the data viewer.

Figure 26: Event environment (left) and positioning devices on participants (right)

5.4 Procedure

The work presented here is part of a larger study that looks into facilitating social support in real-time contexts. This work is composed of a number of in-the-wild study iterations that include 1) a pilot study that was conducted during a triathlon with 3 athletes and 9 online spectators. During this event, the athletes broadcast live data to the spectators. This data included locative and heart rate data. 2) A second study presented spectators with the live data of a single athlete. In this case, one athlete and 8 spectators followed the event online. Details of these preliminary studies can be found in [43]. 3) The insights collected were then used to develop an open source research tool, BioShare, for sharing personal data such as location and heart rate over social networks. The design of this tool was supported by additional interviews with researchers who published studies that involve personal data sharing. For further details on this work see [41]. 4) Following this, a specially configured version of BioShare, named HeartLink, was deployed in a 5-kilometer running event with 5 athletes and 140 online spectators (Figure 26). This deployment focuses on two aspects - the effect on the athletes from being supported by remote others and the effect on the spectators seeing live data. Details on the former can be found in [40]. This paper contributes to the latter, specifically, the effect on the spectators when seeing live heart rate of remote athletes.

5.4.1 System Design

For this investigation, we sent a group of 5 athletes on a 5k-road race. We recruited athletes who were willing to participate in the event and were ready to share personal data using HeartLink. The athletes were each given a heart rate sensor and a smartphone device that was running the HeartLink mobile app (Figure 27). HeartLink [41] was configured as shown in Figure 28. The app connected to a Polar WearLink heart rate sensor via Bluetooth computed geographical location and broadcast this data to a remote server via mobile network. The data broadcast included heart rate, latitude, longitude, altitude, bearing, data accuracy and the time of the last reliable data update (GPS Fix).

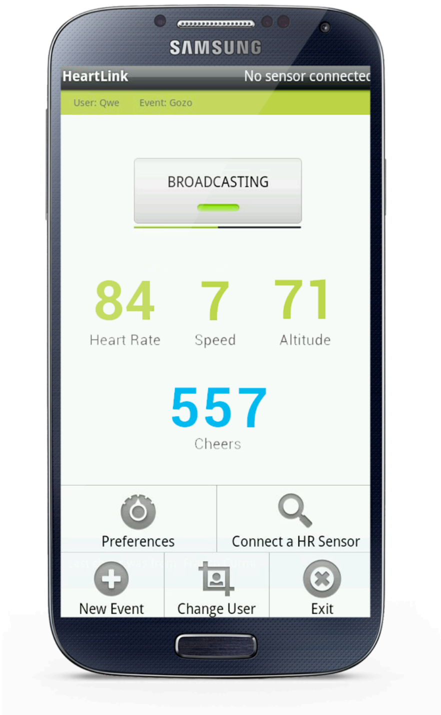

Figure 27: Customised HeartLink research application running on athlete's devices

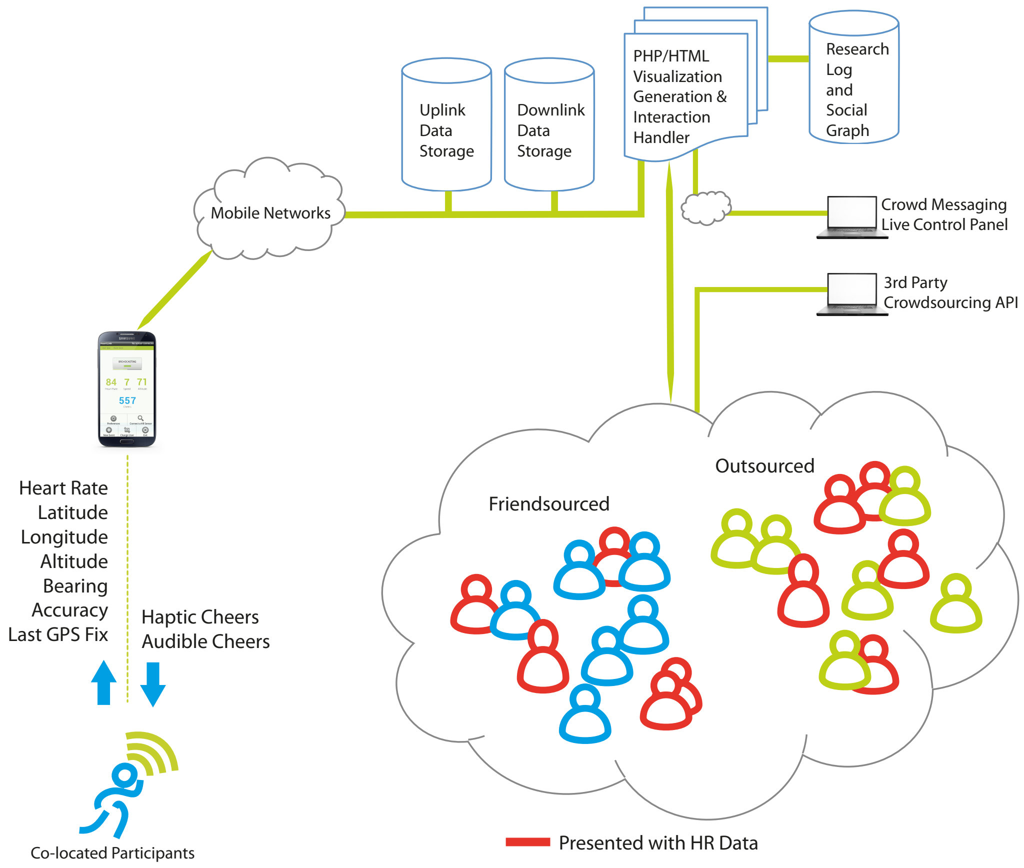

Figure 28: The system infrastructure

The server that received the data then generated and presented visuals to the spectators via their web browsers. These visuals were based on HTML, PHP scripts and CSS style sheets. All the data was dynamically updated at 2-second intervals thus giving a "real-time" feel. The 140 online spectators were asked to log in the event's web page through a custom-built Facebook app. They could select the athlete that they were interested in following and send live 'cheers' to the selected athlete by clicking a Cheer button. The Cheer button generates a small vibration on the device that is carried by the selected athlete and calls out the name of the person who sent the cheer. This makes the athlete aware that a crowd is following the performance. The 140 spectators that were recruited for the event were composed of two groups. 64 participants were recruited from the athletes' social networks. We recruited on-line participants through athlete Facebook requests. Thus, these spectators knew the participating athletes. 76 participants were recruited from CrowdFlower, a crowdsourcing platform that at the time of conducting the study accepted European requesters. These participants were socially distant from the athletes.

Figure 29: Spectator login sequence

At login, each spectator was randomly assigned to one of the two conditions (Figure 29). Participants in the control condition were presented with live data consisting of the distance covered by the athlete, the percentage of the race that was completed, speed, pace and a map with an overlay of the athlete's completed path. This was intended to make the spectators understand how the performance unfolded. The experimental group was presented with the same data plus the current heart rate of the selected athlete, the average heart rate and a chart with the heart rate. All spectators could also send posts through a Facebook frame within the interface as shown in Figure 30. To ensure that there was no cross contamination in the data between the control and experimental groups, each spectator only saw the posts sent by those following the same athlete and within the same experiment condition. By default, the posts sent were only visible on the HeartLink website and were not posted to the participants' Facebook profile. The spectators were briefed on how the system works, the function of the cheer button and the effect of submitting posts. In the next sections, we specifically focus on behaviour differences between those presented with live heart rate and those who were not presented with this data. For further details on the system's design and infrastructure, the readers are encouraged to see [41]. Additionally, results and detailed discussion on the cheering component of this work and its effect on the athletes may be found in [44].

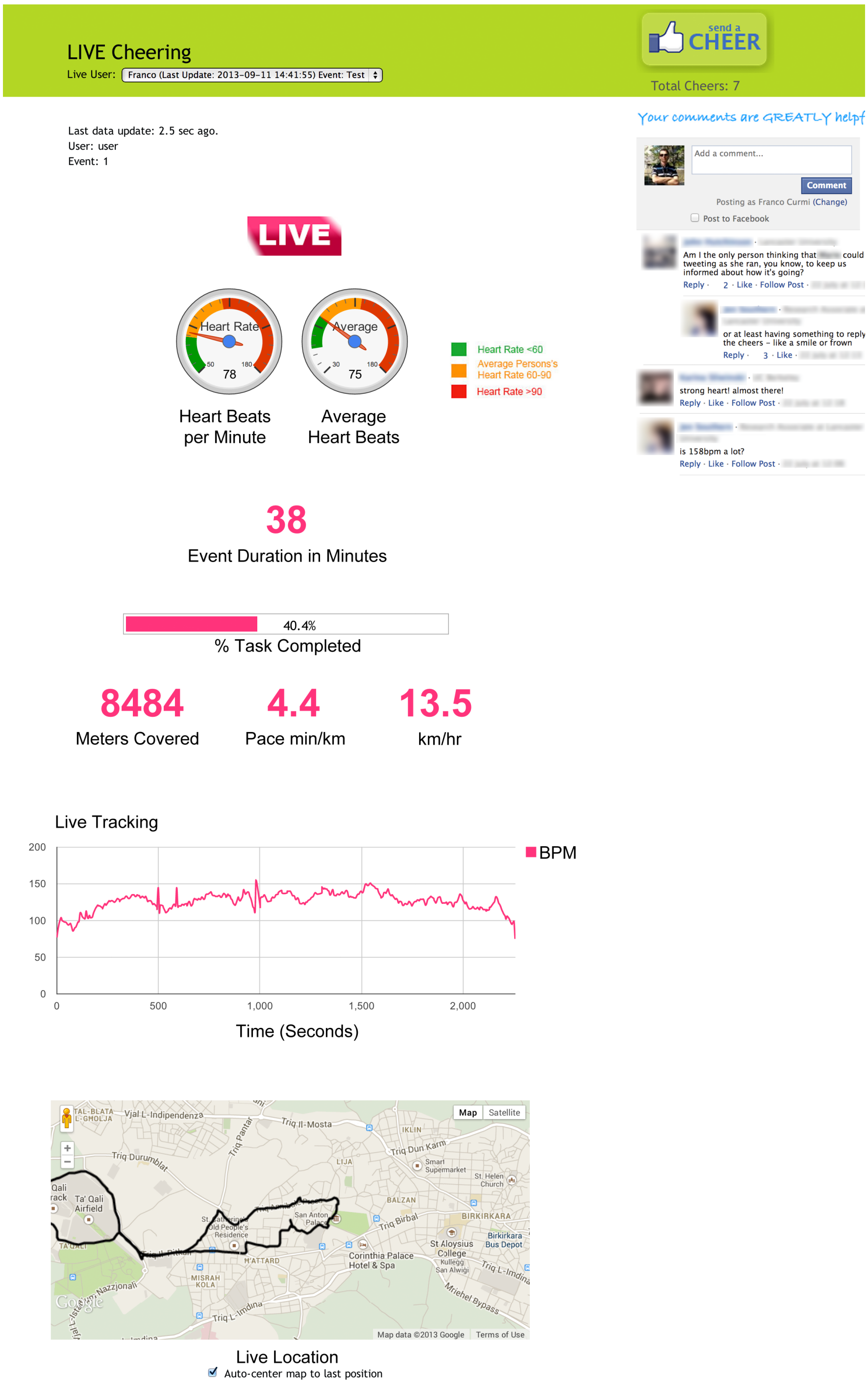

Figure 30: Sample spectator interface

5.5 Results

The findings reported in this section are derived by comparing and contrasting the number of cheers that different subgroup participants submitted, the time participants spent on the site and the cheering rate (cheers submitted per minute). Additionally, we substantiate these finding by reporting on behaviour differences in participant groups based on the messages posted during the event and the results of the post-event survey. In summary, we find that spectators presented with additional heart rate information show increased engagement in terms of the total number of cheers submitted and the self-reported ratings of the presented system. However, there was no significant difference between the spectator groups in the time spent supporting the athletes.

5.5.1 Cheers, duration on site and cheer rate

As common practice in experiments that involve unknown crowdsourced participants, we filtered out spammers from the outsourced spectator-crowd [127]. Additionally, during the event, data that was broadcast from the athletes' devices was occasionally interrupted. This was primarily due to loss of mobile connectivity in parts of the race. Thus occasionally, different spectators did not see the data as expected (for example momentarily had no heart rate data). This depended on which athlete the spectator was following at any moment in time and whether the selected athlete presented broadcast 'blind spots' while being followed. Thus, we analysed the athlete selection sequence of each spectator and filtered out spectators who during the event happened to switch to an athlete when the data was not displayed as expected. Based on this, from the total 140 spectators we select 41 participants who did not experience disruptions in the data (of these, 25 were presented with heart rate (HR) data, 16 were not presented with HR data, 20 were in the Friendsourced condition and 21 were in the Outsourced condition (21)).

We did not find any increase in the time spent on the site between those presented with the additional heart rate information and those who had no heart rate information. This, contrast with our expectations that heart rate viewers would spend extra time to familiarise with the additional biometric data.

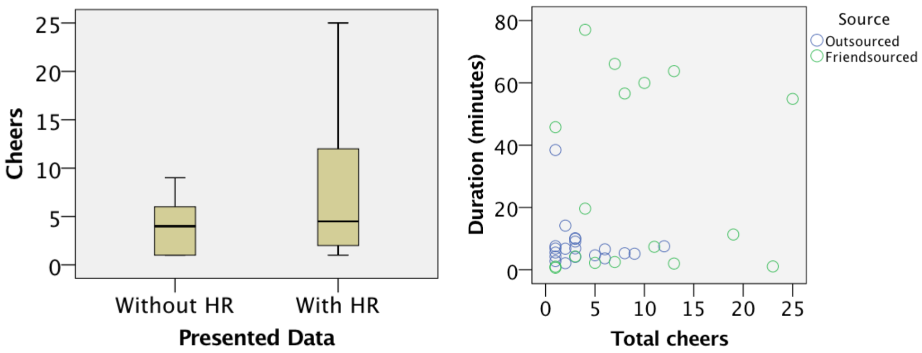

Figure 31: Left - Cheers submitted grouped by data presented, Right - Scatter plot for spectators' duration on site by the number of cheers submitted for the friendsourced and outsourced condition

Results show a significant difference in the total cheers submitted by the spectators that were presented with the heart rate data (M=15.83, SD=28.48) than those who where not presented with any heart rate data (M=3.93, SD=2.96); t(23.8)=2.029, p=0.05 (Figure 31: Left). On the other hand we encounter no significant difference in the time spent on the site by the spectators presented with the heart rate data (M=16.38, SD=20.73) and the spectators who were not presented with the heart rate data (M=21.44, SD= 25.91); t(27)= 6.58, p=0.52. The results also show that the cheer rate (cheers per minute) of the spectators who were presented with the heart rate data is more than three times that of the spectators who were not presented with this data. However, a t-test does not determine this as having any statistically significant value; t(38)=1.37, p=0.18.

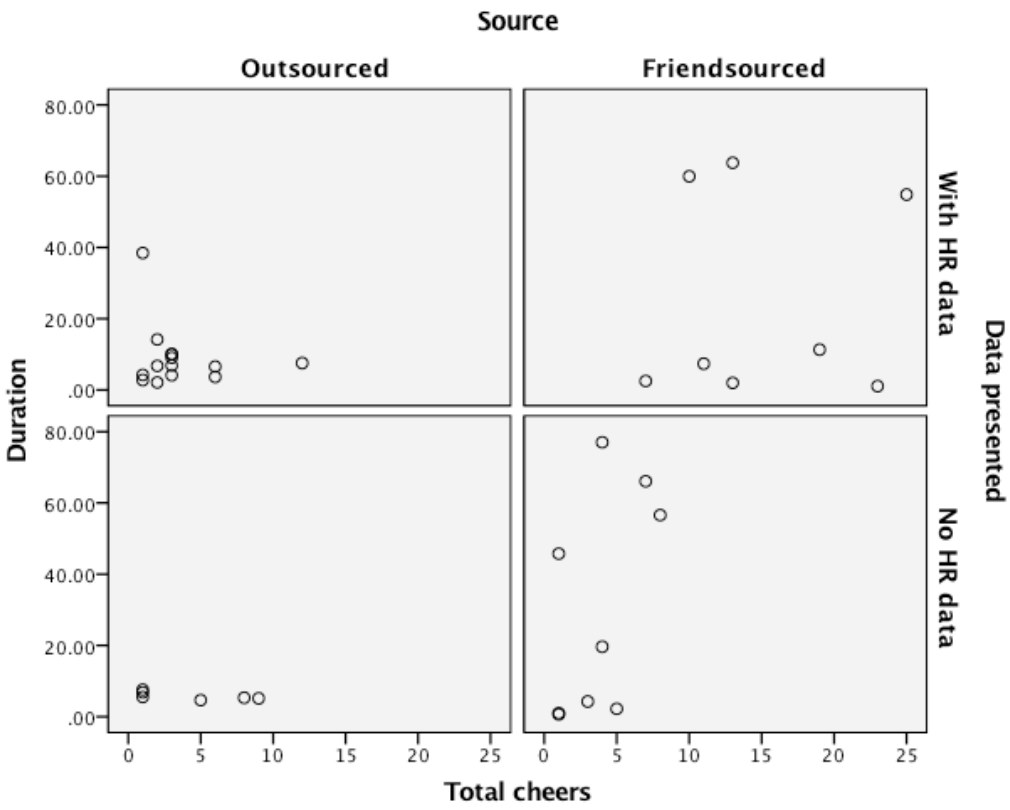

Figure 32: Scatter matrix plot of spectators' duration on site by cheers submitted for spectator recruitment source and data presented

This lack of statistical significance seems conditioned by the added time that friendsourced spectators spent on the site before and after the event (Figure 31: Right). During this time, the cheering rate was low or inexistent since the event would not have started. Yet some friendsourced spectators logged in the site early to ensure that they did not miss any part of the event. The matrix scatter plot in Figure 32 takes a deeper look into this by presenting the Cheers and Duration across Source groups and Data conditions. We find a significant difference in the scores for Cheers submitted by the friendsourced participants (M=19.26, SD=31.2) than the outsourced participants (M=3.65, SD=3.1); t(37)=2.23, p=0.03. There is also a significant difference in the time friendsourced spectators (M=29.1, SD=28.1) and outsourced spectators (M=8.12, SD=7.49) spent on the site; t(39)=3.3, p=0.02. However, the rate of cheers (cheers/min) did not reach the conventional statistically significant difference between these two groups; Friendsourced group (M=2.64, SD=5.07), Outsourced (M=0.65, SD=0.58); t(38)=1.74, p=0.09.

5.5.2 Social network posts

Table 5 shows the posts that the spectators posted on the interface. In total 60 posts were submitted by the 140 spectators. 28 were posted on the landing page while 32 were submitted to individual athletes. Across all athletes, the spectators who were presented with additional heart rate data submitted more posts than those who were not seeing any heart rate information. The participants visualizing the heart rate data were more engaged with the athletes based on the number of comments posted.

Table 5: Social network posts submitted by spectators

Athlete no.	Posts from spectators seeing heart rate data	Posts of spectators not seeing heart rate data
1	5	0
2	7	2
3	2	0
4	3	1
5	11	1
Total	28	4
Comments not attached to a specific athlete		28
Total comments submitted		60

5.5.3 Post event survey

Immediately after the event was completed, the spectators were presented with a survey that was intended to collect feedback on the system. Questions asked in the survey were intended to understand the respondent's readiness to use the presented system, the respondents' understanding of the live data, gather insights for next system iterations and identify any possible spammers among the respondents (e.g. users filling compulsory questions with random text).

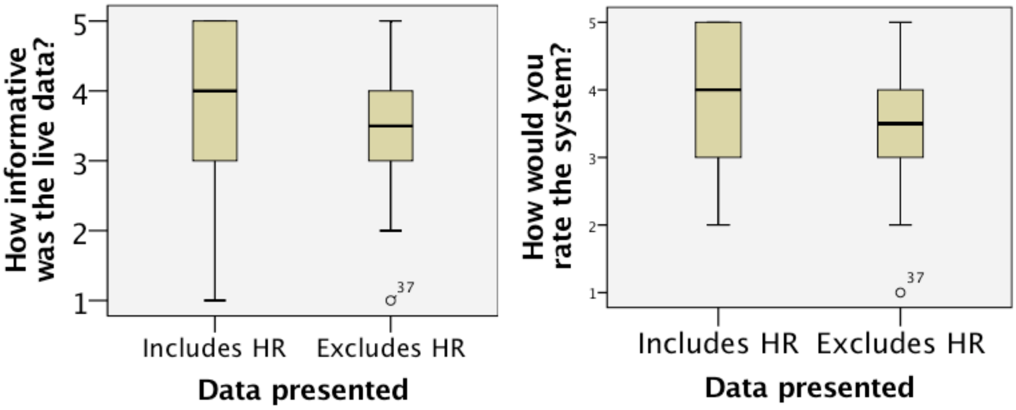

Figure 33: Left - How informative was the live data
(from 'Not Informative - 1' to 'Very Informative - 5" on a 5 point scale)? Right - How would you rate the system
(from 'Bad - 1' to 'Good - 5' on a 5 point scale)?

The results from this survey support earlier findings. Figure 33 represents responses by the different groups for two key questions, namely, 'How informative was the live data?' and 'How would you rate the system?' on a five point scale. Comparing the responses of the two groups in the first question with an independent sample's t-test indicates that spectators that were presented with heart rate data ($M=4.03$, $SD=1.03$), report finding the interface more informative ($M=3.5$, $SD=1.11$); $t(66)=2.03$, $p=0.05$. Those presented with the heart rate were also more positive when asked to rate the system ($M=4.08$, $SD=1.05$) in contrast with the control group ($M=3.50$, $SD=1.11$); $t(66)=2.22$, $p=0.03$.

In summary, results indicate that the live heart rate of athletes, effects remote spectators in the conditions described above, differently. Specifically, the cheers submitted suggest that online spectators of sports events are more engaged when presented with live heart rate data of the athletes. However, we did not find any increase in the time spent on the site between the two groups. We have expected that spectators presented with the heart rate would spend significantly more time on the site at least because of the added learning curve that the additional heart rate data presents.

5.6 Discussion

This study provides some interesting discoveries. Results indicate that the spectators who were presented with the heart rate data of the remote athletes were likely to be more positive about the system and cheered the athletes more. This suggests that by seeing heart rate visuals, supporters became more influenced by the effort exerted by the participants. Next we reflect on the results through existing theoretical perspectives and propose possible justifications for the spectator's behaviour that is shown in these results.

A: Biometric data visualisation improves understanding of athlete effort.

The spectators' mental interpretation of the heart rate is dependent on both their individual tacit knowledge and explicit knowledge [151]. To varying degree, spectators interpret the live heart rate visuals through their a priori knowledge of what, say, a value of 165 beats per minute represents. Should the spectator have the explicit knowledge from past experience, then this knowledge is likely to be applied in this context by relating the presented value to one's historic situations. On the other hand, those lacking any experience of a heart rate representation may either be put off by its representation or build a mental representation of the situation based on the context rather than the data per se. For example, by presenting the heart rate data in a dial graph where 150 beats per minute is represented in a red segment, than the visual may convey high exertion, not necessarily because of the data per se but because of the context. That is, the needle at the end of the dial scale is associated with a high value and this is reinforced with the red legend where red is typically associated with 'alerts' [152]. This would then contribute to the spectators' a priori experience for (future) post-priori cognition.

B: Spectators seeing the heart rate become more context-aware.

Information can be subjective or objective. Subjective information can be perceived in an interpretive manner while objective information is not the subject of interpretative information [10]. For example data captured from sensors, such as the geographical positioning of the participant on the map, is considered as objective information and leaves little room for ambiguity or self-interpretation about the position. However, different readers can interpret subjective data, such as a post on Facebook that says 'I'm struggling' differently and this can be very much influenced by the context. Knowing that the context of this post is that of a student studying at home, gives a completely different meaning than knowing that the person is a patient. The context influences how the participants interpret their environment [122]. The objective information, such as the data that is collected from mobile phone sensors, has a low level of expression of contextual information (in comparison to for example a descriptive narrative of the context). However, context contributes a significant impact to the cognitive understanding of a situation [10]. A change in context can retransform the interpretation that the user makes of the "mental representation of reality, even when reality has not changed" [22] p. 136.

Bae et al. [10] show that both subjective and objective context information can influence what other users understand of the context which in turn affects their social supportive behaviours. Different studies use different types of context information. Bae et al. use four context types [Activity, emotion, location and physical environment] [10]. Dey uses emotional, location, orientation, time and day information [43]. Our work uses activity, location, time, day and physiological state. We observe that although all the data is presented in an objective form using numbers that were generated through sensors, however, the heart rate still provides a strong element of speculation and self-interpretation. In other words, although all the spectators are concurrently seeing the same data and know the same context, individually, their understanding of what a 160 beats per minute represent differs.

Additionally, over time, this process helps spectators' learn what heart rate values represent. First, seeing others' heart rate helps in building a personal 'historical average' of what a typical heart rate in this context may be. This historic context, in combination with expectations management, may explain the spectators' reaction. For example, should spectators repetitively see the heart rate of participants in close proximity to 120 within successive similar events, than their expectations of the data are adjusted accordingly. Should then the spectators be presented with a heart rate of 175, than they are more likely to interpret this as the athlete is exerting extreme effort.

C: Real-time automated biometric data broadcast may be perceived less biased than manually input data that can be curated.

Heart rate data is widely considered as very personal data due to its ability to communicate feelings and emotions. This is particularly highlighted in Slovák's work where participants who shared their heart rate while playing poker were concerned that this will tell their strategy off [176]. Worthy et al. show that humans appreciate those who share personal information and sharing of such information creates more intimacy among individuals [199]. Self-disclosure can vary in breadth (variety of shared information), length (longitudinal time) and depth of information [125]. In this study, the heart rate data sharing seems to contribute to an increase in the 'depth' dimension of self-disclosure.

D: Those presented with additional heart rate information face a longer learning curve in data interpretation.

Our results did not show any significant indication in this regard yet it is still worth noting for future consideration. The participants in the heart rate condition were presented with data that may have necessitated a longer learning curve. This made us expect a longer duration spent by the participants on the site. On the other hand, participants who were not presented with the heart rate data may have found the interface less interesting, too simplistic and consequently less engaging. However, the increase in cheering and the more positive outlook on the system as reported by the spectators, suggests that this explanation alone is not sufficient. David Hoffman gives a detailed description of how visuals are interpreted by humans [77,78]. Visual stimuli are decoded by performing a probabilistic analysis of how the stimuli are related to previous experiences. Should we consider a random population of participants we may comfortably assume that few participants are likely to be familiar with the representation of a heart rate. However, in a study conducted by Slovak et al. participants who were unfamiliar with heart rate quickly got used to its representation when presented with heart rate feedback during day-to-day activities. Further studies are needed to explore this perspective further.

5.7 Limitations and Future Work

Results indicate that sharing heart rate data can have positive effects on spectators' engagement. However, we are short of pinpointing one specific reason as to why this happens. The spectators' behaviour seems dependent not only on the crowd itself but also on the individual personalities and experience, as discussed earlier.

Our data does not take into account the fact that the visuals presented to the supporters who were not presented with heart rate data could have been simpler and thus less visually engaging for the spectators. Our analysis also does not take into account the values that were actually presented to the spectators (e.g. a heart rate of 170 vs. 120).

This could have influenced the spectators. For example, research in psychology and social media shows that individuals are more reactive to negative information than positive information [47] and this is rationalized through the negativity bias [12]. In this light we expect that if viewers are aware that a higher heart rate value represents greater exertion effort, spectators are more likely to engage with the interface and provide support in ways that the spectators believe is most supportive. Future work should look into this assumption along with other data-representation variations, such as the current athlete's altitude, gradient, or the athlete's position in the race. Additionally, social support is influenced by how much the supporter perceives that the supported needs support, even when the supporter does not know the supported [10]. Biometric parameters such as the heart rate can increase the supporter's understanding of the effort exerted by the supported.

These results are congruent with existing research on heart rate data sharing. Janssen et al. showed that heart beat communication can be considered by others as an intimate cue [85] while Slovák et al. indicated that heart rate communication can improve social connections [176]. The increase in spectator engagement that is reported in this work could be particularly relevant not only for online social networks but also for traditional one-to-many broadcasters.

Presenting additional heart rate data during television broadcast promises an increase in viewer engagement. This is most relevant for sports broadcasts where athletes' performance is based on exertion [76]. For example, presenting the average heart rate of two teams playing in a televised soccer match could enhance the story being conveyed by the broadcast, it gives commentators more opportunity for discussion and makes televised graphics more dynamic. In recent years, television broadcast has increased the quantity of graphical information and statistics presented to viewers while studies showed that dynamic graphics have positive effects on viewer engagement [65]. On the other hand, heart rate data may enhance story telling because of the added detail that constructs the context. For example presenting the average heart rate of the two teams can help the spectators to better hypothesise which team is most tired and thus less likely to improve performance.

While technically doable, these implementations pose social challenges particularly due to the sensitivity of biometric data, ethical issues and different legislations on the topic. While these are very important issues that need to be factored in, in this paper we focused our attention on the impact that sharing heart rate data can have on remote online spectators.

5.8 Conclusion

In this paper, we compare the effects of sharing heart rate data and user engagement in a real-time feedback context. A number of studies looked into the effect of sharing heart rate, however, these were primarily focused on sharing data between individuals and without real-time feedback from remote crowds [86,132]. We recruited online spectators who followed athletes during a 5k-road race. Each of the spectators were randomly assigned to one of two conditions; in the control condition the spectators were presented with live locative data and in an experimental condition the spectators were presented with both live locative data and heart rate data. Spectators who were presented with additional heart rate visuals showed more attempts to support the athletes and submitted more comments to the site.

These results support existing literature, indicating that visualizing other's heart rate can increase engagement and the connectedness between the data sharing user and data viewer. We provided possible justifications by drawing insights from existing theoretical perspectives that support these results. In summary, we find that the heart rate representation may enhance the supporters' perception of the effort that is exerted by the athletes. Secondly, supporters may feel an increase in self-disclosure on behalf of the athlete sharing heart rate data. Thirdly, real-time data from sensors may be perceived as trustworthier than other traditional self-curated content such as text messages.

Chapter 6
EMBEDDING A DISTRIBUTED CROWD INSIDE A SMART DEVICE

Submitted as:

Curmi, F., Ferrario, M.A., & Whittle, J. Embedding a Distributed Crowd Inside a Smart Device, submitted to *CHI'16: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems.*

6.1 Abstract

This paper presents a digitally connected relay baton prototype that links long-distance runners with distributed online crowds. This context-aware baton broadcasts live locative data to social network and communicates back remote crowd support to the athletes through haptic and audible cheers. The work takes an exploratory design approach by building on prior research into biometric data broadcast and brings new insights in the space of designing real-time techno-mediated social support. This prototype was tested during a 170-mile charity relay race across the UK with 13 athletes and 261 on-line supporters. Based on the insights collected from the design process and the deployment, the study identifies user-motivation for implementing systems that facilitate real-time remote support in a sporting context. The work also identifies fundamental design considerations that designers should take into account in their decision-making process.

6.2 Introduction

Crowd support can contribute to the success of competing athletes during sporting events. However, up until recently this could only happen if the athletes and the spectators were in the same location, such as at the stadium or along the racecourse. There has been very little, if any, investment around interacting with remote spectators during sporting events even though they often consist of a much larger user population than co-located spectators. Most of the existing technology that allows remote spectators to show their support has been designed for post-race feedback with little or no effect during performance.

More recently, through a copycat strategy, several commercial mobile sports applications have implemented simple cheering modalities whereby online friends can send digital 'cheers' to athletes during the sports activity itself. These cheers are typically sent as sounds, vibrations or audible messages on the athlete's device. However, although commercial implementations have rapidly progressed, remote crowd support still remains an under-explored area of research within the HCI community. The objective of this paper is therefore to investigate this research area and draw a design space that provides a guide to designers of future real-time crowd support systems.

Figure 34: The long-distance relay baton type A during a test run

Related work [42,44] suggests that real-time remote support might be most effective during challenging sporting events – such as long distance running – during which the athletes are most likely to feel lonely. To further investigate this we designed a baton prototype (Figure 34) that can be carried by the athletes engaged in long distance running relays. We deployed this device in a 170-mile relay race across the UK with 13 athletes and 261 online spectators. The relay was a particularly challenging effort that involved running in remote parts of the country and at night.

The baton broadcasts locative and performance-related data to online spectators through mobile networks. Spectators can follow the live data through their browsers and by pressing a 'Cheer' button, they send a small vibration to the baton. Thus, the athlete becomes aware that his/her performance is followed by spectators around the globe. The baton also calls out the name of the 'cheering' spectator so that the athlete is informed where the support comes from. As we shall further elaborate upon later, in total, the work required 380 hours of product design and development in a co-design approach [163].

Through observations, a focus group and server-collected data, we identify key aspects that give bearing to technology-mediated crowd support systems. From these, we then isolate three fundamental design considerations for real-time crowd support: (1) the degree of spectator expressiveness, (2) the context applicability, and (3) the real-time data flow within the social network. Spectator expressiveness may range from a limited or 'low effort' Facebook-style 'like' to a more expressively-open fashion where spectators can cheer athletes live thorough microphones as an aggregate crowd.

6.3 Existing Work

The study of live distributed-crowd support is a relatively new area of research. There are however some applications whose function is based on 'crowd processing' which operates in real or near real-time. Most closely related is Bernstein et al. Soylent [17]. Soylent is a word processor that summarises documents on demand by harnessing the collective intelligence of Amazon Mechanical Turk workers. Similarly, TimeWarp [105] (an evolution of Legion:Scribe [106]) lets users transcribe live speech by efficiently segmenting the narration into manageable chunks and assigning different segments to online distributed operatives. A more empathic-based objective is presented by Morris et al. in their attempt to crowdsource collective emotional intelligence [128]. In this work, distributed online participants contribute emotional support through 'cognitive reappraisal' [72] of an individual's emotional state. These cases show that remote crowds can have positive effect on an individual's instant necessities not only through harnessing mental calculations but also in the more challenging social and emotional support applications. We are interested in investigating real-time crowd support in a sporting context.

A commonly cited work within a sporting context that is closely related is ‘Jogging Over a Distance’ [103]. Mueller et al. explored the effect of having two distant athletes communicate during jogs to support each other. Although this work did not involve crowds, the research outcomes indicated that providing the athlete with real-time feedback from a remote athlete enhances the social experience of the participating athlete.

On the other hand, research cases that involve multiple spectators within sport focus on either 1) augmenting the experience of remote spectators by for example broadcasting additional personal data (e.g. see [11,76,103]) or 2) on connecting spectators during events (e.g. [84,116]). For example, Hallberg’s study [76] presented the seminal work on sharing live telemetry data from athletes to remote online spectators through mobile networks. In this paper we augment the experience of spectators that are following the event remotely by allowing these spectators not just to follow but also to interact with the athletes by sending live cheers through the custom-designed digital relay baton.

Recently, Curmi et al. conducted a series of studies in which remote spectators supported athletes participating in a triathlon, a charity run and a competitive road race [42,44]. They conclude that supporting athletes remotely can have a positive impact on athletes. Additionally, results in this work suggest that remote-support may be most relevant when the task is challenging and in situations where the athletes feel lonely. Similar indications can be drawn from the commendable work of Wozniak et al. [200] where they deployed a similar crowd feedback system in a 10km externally organised event.

Based on these indications and with the intention of maximising the effect that remote crowd support may have on the athletes, we deploy real-time crowd support in a long distance relay race and a custom designed digital baton. Long distance relay races are typically non-competitive sporting events and often present an environment that is challenging and where athletes may feel lonely particularly during nighttime. They range in duration from a few hours up to a number of days. Popular races are the annual Great Britain Relay Race, the Olympic Torch Relay or the Queen's Baton Relay in the Commonwealth games.

Similarly, digital batons are not new. At the University of Bath, a group of students developed a baton that periodically records its position internally[5]. A more complex model is the Queen's Relay Baton[6]. In this case, the baton periodically logs its position and internally records a front facing and a rear facing video camera. Additionally, the baton broadcasts its position online such that spectators can follow its location.

We build on existing work, and implement a synchronous two-way communication by which the baton does not only collect and broadcast data from the athletes to spectators but can also collect distributed-crowd support and communicate this support in real-time back to the athletes that are carrying the baton.

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[5] http://www.theiet.org/students/you-and-iet/on-campus/2012/gps-enabled-baton.cfm
[6] http://www.thecgf.com/qbr/

6.4 Design Process

Figure 35 shows the key stages in the co-design process of the relay baton. This culminated in the 170-mile deployment. As mentioned earlier, the authors were interested in this event because of its challenging nature both in terms of mental effort (e.g. loneliness) and physical endurance. These factors were sought since earlier work suggests their relevance to the proposed system [35]. Moreover, conducting research 'in the wild' in an extreme 170-mile event promised design issues hardly to emerge in conventional / lab context [174].

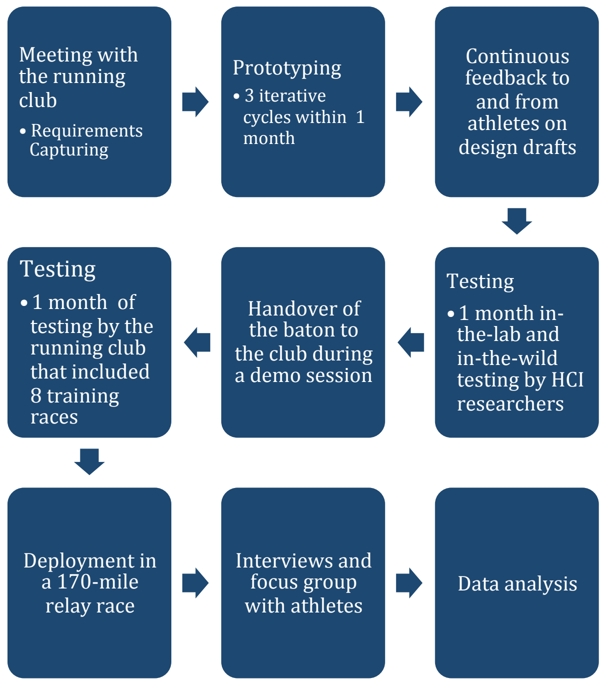

Figure 35: The design process

6.4.1 The event

The relay race was a charity event organised by a university running club. Before committing themselves to taking the event onto open public roads, the organisers considered conducting it as a 170-mile relay race around campus. However, this choice was discarded as deemed '*far too boring*' even with the promise of a larger co-located cheering crowd. "*We wanted the real thing [outside university] but then we* *realized that we would not have anyone able to support us in such long distance*” [event organiser].

In the end the event was oganised as a coast-to-coast race along an historic route known as ‘The Way of the Roses’. The route starts from Morecambe in Lancashire and ends in Bridlington in East Yorkshire. The course had varying altitude ranging from sea level to 400m. The race started at 0900hrs and was expected to last approximately 24 hours. The actual duration was particularly dependent on the athletes’ pace but also on the weather conditions and the athletes’ ability to follow the correct path. ‘The Way of the Roses’ is a cycle route that is part of the national cycle network and which most people cycle over two to three days. It goes along roads and cycle paths and is well marked along the route. However, the markings are not always easy to follow. For example, a marker may be hidden behind a parked car. This made the athletes’ task more challenging adding to their cognitive load during the event. Athletes passed the baton at predefined handover checkpoints of 5-mile intervals. To ensure that no athlete was alone at any point during the race, at least one cyclist accompanied the athletes throughout the course. Additionally, a support vehicle transported the runners from the previous and for the next relay leg so this vehicle was always waiting at the next handover checkpoint. Both athletes and organisers also felt that nighttime was going to be particularly challenging, as the countryside lanes would be dark and deserted.

6.4.2 The design process as a research process

The relay baton, the crowd-powered interface and the interaction design was co-designed with the event organisers as the end-users. This process was primarily user driven. The time from the initial meeting to deployment was three months. This co-design process was punctuated by five key stages as shown in Figure 35.

Figure 36: (a) early design sketches, (b) internal energy storage, (c-f) shell design and shaping tool, (g) the relay baton type B (with extended battery capacity)

First (1), an initial preliminary meeting with the organisers defined the scope of the event and the preliminary system desires. Second (2), three relay baton prototypes were iteratively developed (Figure 36a-g) along with the real-time data handling server and the crowd’s online interface. The organisers were engaged throughout this process and provided a regular contribution to the design decisions through face-to-face meetings and online correspondence. This prototyping process lasted one month. This was followed by another month of ‘in-the-lab’ and ‘in-the-wild’ testing by the researchers/developers. The objectives included reliability testing, user interaction evaluations and energy consumption testing in both city and rural conditions. A key concern when designing telemetry for extreme conditions is the ability of the baton to reliably handle mobile disconnections and reconnections in the wild while seamlessly transfer data to and from the crowd. Thus (3), the testing included transporting the baton in rural areas at the edge of mobile coverage and beyond. One month before the 170-mile event, the baton was handed over to the running club and a training session was conducted (4). This session included guidelines on correct handling, how the system works, information on spectators' recruitment process and presentation of the spectators' interface. As part of the briefing, we also informed the athletes that they were free to adapt the prototype in whatever way they felt appropriate. For example, they might have wanted to attach straps that will make it easier to carry the device over long distances. Finally (5), the athletes further tested the prototype during eight training races. Any feedback that was collected by the organisers was then implemented in the prototype. This feedback involved minor software changes regarding simplification of the logging in process for the spectators and aesthetical enhancements.

6.5 The Baton

The baton's outer shell (Figure 36) is made of Polyvinyl Chloride (PVC). A hollow cylindrical pipe was heated and reshaped into the required form factor with a custom-made tool (Figure 36d). This tool facilitated consistent reproduction of the required form factor thus minimising variations between test-iterations. In total three iterations were created and each successive iteration primarily improved ergonomics and dimensions. For an aesthetic finish, the baton was spray-painted and the 24mm-radius handgrip was covered with tennis racket grip tape. This decreased the likeliness of the baton slipping during handovers. The soft grip tape also made the baton more comfortable to carry over long distances and provided perspiration to sweat. Other design considerations included design for both rainy and sunny conditions (i.e. the interface needed to be appropriately visibly during the day), night-time visibility, energy autonomy, data updates (i.e. updates should be fast enough to give a real-time feel to the spectator) and aesthetic look and feel.

In line with the rapid prototyping approach adopted, an Android device was used as the main processing and display unit. This approach shortened the design cycles in contrast with developing a custom interface and telemetry hardware. In a second design iteration, a modified off the shelve 5400mAh power-bank was embedded within the device to provide enough energy storage for an autonomy of 24 hours of broadcast. In the third iteration, this form factor was adapted such that 12000mAh battery capacity could be stored inside the baton thus giving a continuous broadcast capacity of 96 hours (Figure 36g). The extra contingency in broadcast hours was implemented for any variances in power consumption when broadcasting within rural areas and for the effect that the crowd cheering could have during the real-life deployment.

Through a custom built native app, the baton collected and broadcast telemetry data every 10 seconds to a remote server using a RESTful API over HTTP protocol [14]. The process was managed as a background asynchronous thread in Android OS. When the mobile data network was available, this thread broadcast the data with a 4-second timeout and buffered the transmission data whenever the mobile data network dropped.

6.6 The Athlete's and Crowd's Interface

The remote server collected the data and presented the data in a browser interface as shown in Figure 38. Figure 37 shows the complete infrastructure. This infrastructure was based on BioShare [41] but the default configuration of BioShare was adapted to meet the needs of this investigation. BioShare is an open source tool that allows researchers to collect and share data over social networks in real-time.

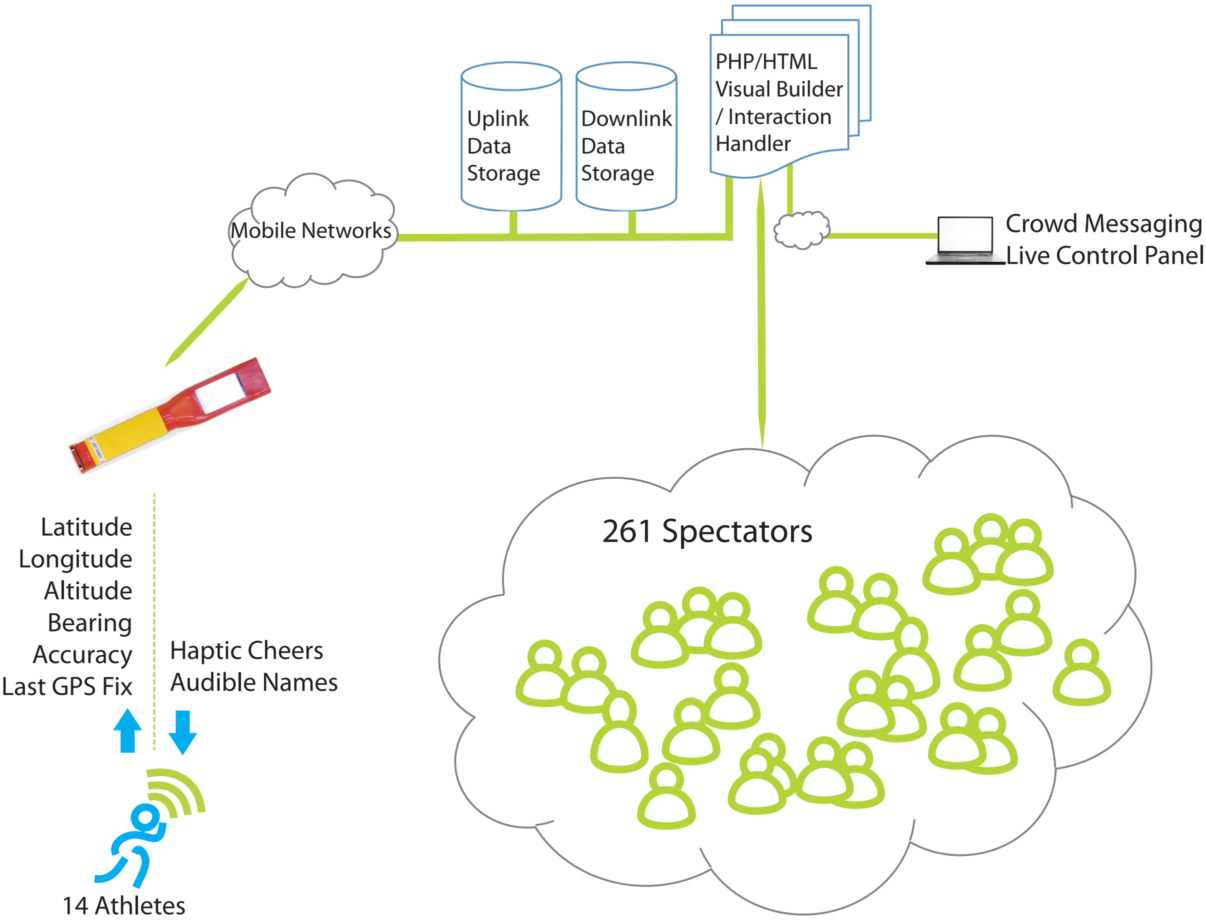

Figure 37: System configuration

It also allows data viewers to send instant feedback to the data sharing users. The baton's interface displayed the time, the current speed, the altitude and the total cheers that were received. When started, the native application presented a 'Start Broadcast' button. This button was hidden once the broadcast started and all user interaction through the display was disabled. This minimised the possibility of accidently turning off the broadcast during such a long event. Stopping the broadcast necessitated triggering a hard-to-press button that was within the baton.

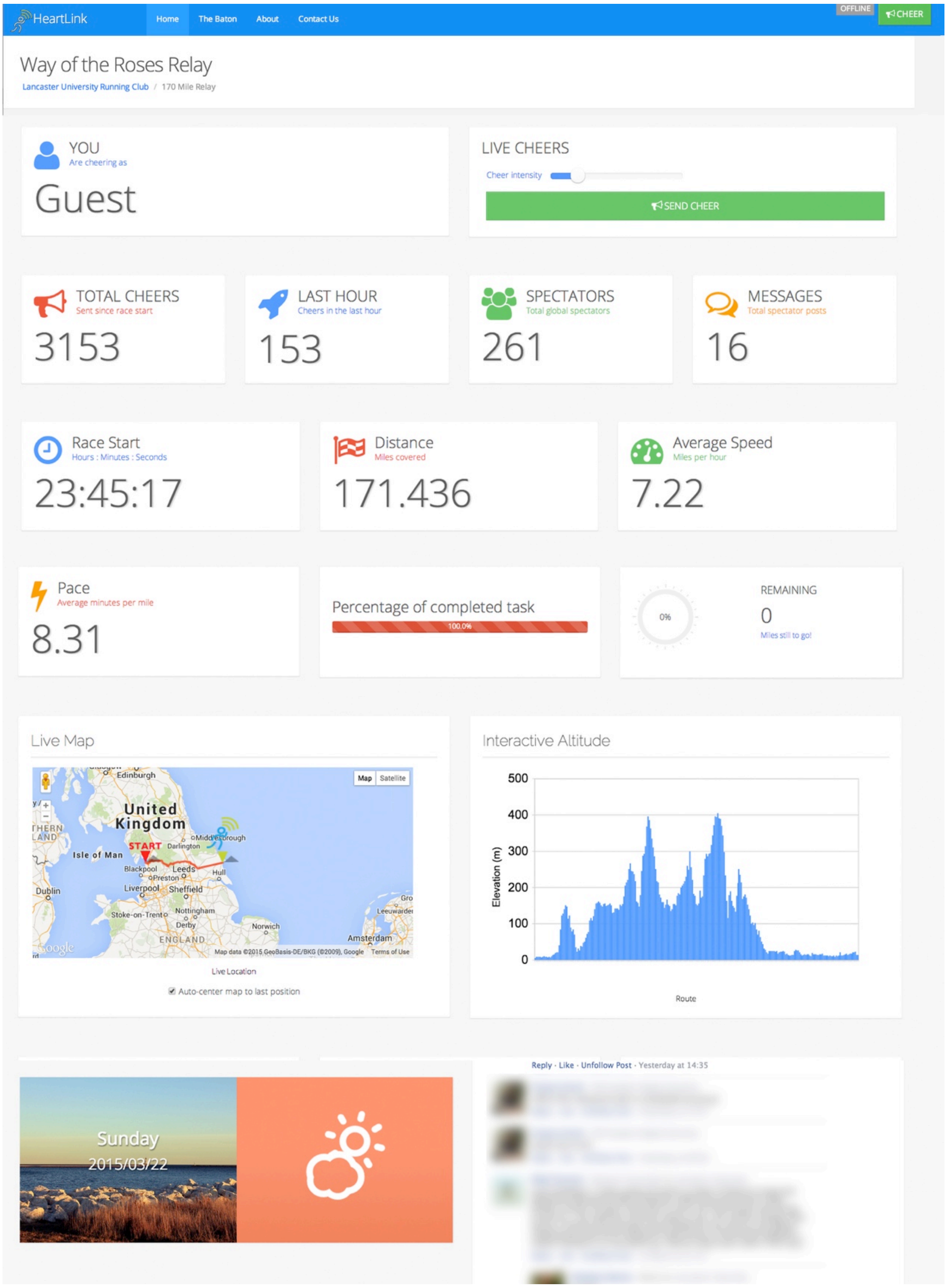

Figure 38: Distributed spectators' interface

6.7 Spectators' Interaction

When loading their interface, spectators could either sign in with Facebook or manually type in their name (Figure 39). During the 170-mile relay race, spectators could then follow the live data through any Internet-connected web browsers. The data presented by the server included the name of the spectator, the total cheers that the athletes received, the cheers sent in the last hour, the total number of spectators who have sent cheers, the total number of messages sent, the race duration, the distance covered, the average speed, an interactive chart that displays the covered altitude, the weather at the athlete's location, and a map with the covered path and position of the baton at that moment in time.

Figure 39: The login interface for spectators

The crowd's interface also displayed whether the baton was online or offline and the time the data was received from the baton. This was relevant particularly when the baton lost mobile data connection through remote rural areas. Additionally, a Facebook messaging frame was also embedded in the interface such that spectators could send and read messages. This was intended to build a community around the activity as the event was taking place. In this way, whenever the data broadcast from the baton was interrupted due to a loss of network coverage, the messaging interface provided a secondary source of engagement for the spectators and potentially alleviate the disconnection problem [33].

A system control panel allowed the organisers to send messages to the crowd in a persistent-positioned space on their screen. This approach followed insights gained in pervious research [44]. This manual message broadcast was intended for crowd coordination in unexpected circumstances that a live event occasions. From past events we noticed that, for example, a technical fault in the telemetry system could lead the spectators to multiple conjunctures; such as the system is not working, or the event stopped, or that there was an accident. Thus, the "online/offline" indicator on the spectators' interface could mitigate such potentially misleading situations. This information on mobile-awareness could also make the user value the effect of changes in connectivity on the system [32] and appreciate the athlete's environment.

Finally, the presented interface had an always-visible "Cheer" button and a "Cheer Intensity" slider. The Cheer Intensity slider had no effect on the cheering, and the spectators were not given any information about this element. On the other hand, pressing the Cheer button triggered a small vibration (400ms) on the baton that was carried by the athletes. Hence, the athlete carrying the baton builds awareness that a crowd is following the performance. The baton also calls out the name of the person who sent the last cheer so the athletes understand whether the live support is coming from known or unknown spectators. Both the athletes and the spectators were aware of these dynamics and the interaction effects.

6.8 Findings

13 athletes participated in the 170-mile relay race that lasted 23 hours 45 minutes. 261 spectators submitted cheers that totalled 3153. Unexpectedly, the biggest challenge for

the athletes during the race was to stay on track in country roads. On multiple occasions, athletes followed a wrong direction and had to run back. On one occasion, an athlete had gone three miles in the wrong direction. For this reason, the actual total distance covered by the athletes was 185 miles. Since the course markers are designed for cyclists, sometimes these are positioned at a distance from their respective turn. This distance may provide the right timing for a cyclist but less so for a runner. As these occasions happened, remote spectators could follow a ‘top view’ of these wrong turns and closed alleys entered, through their live map.

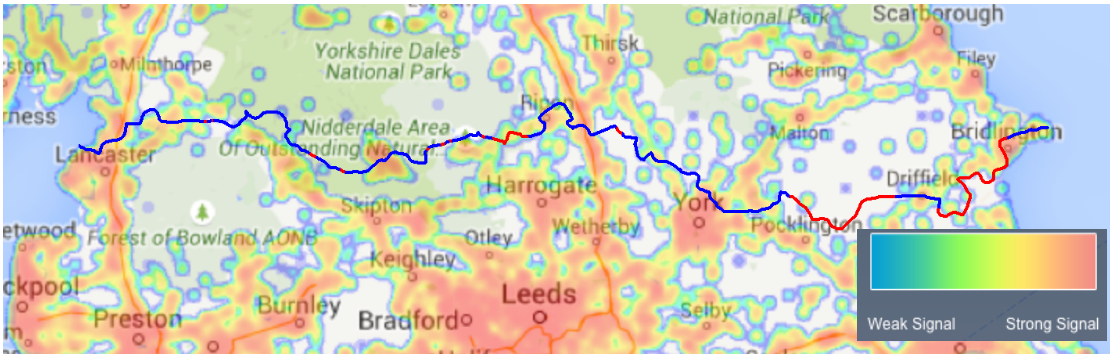

Figure 40: 2G and 3G-cell coverage based on OpenSignal coverage map as predicted on the day before the event. The blue path represents the actual data connections, and the red represents data disconnections

Another point of consideration was the weight of the baton. Upon carrying the baton for a long distance, some athletes felt the baton heavy so in some passages the cyclists had to carry the baton instead. The athletes could then still hear the cheers but saved on carrying the weight.

A major concern for such an extreme in-the-wild event was the mobile network coverage throughout the 170 miles, most of which, was in rural areas (Figure 40). The assigned server received data from the baton live during 74% of the race (17 hours 34 minutes). In total, there were 12 live data drops. Of these 11 were due to blind spots in the mobile network across the course and one due to a software liability. In this count, a blind spot is true whenever the data connection interval between the server and the baton is greater than 60 seconds. Although the total number of drops may seem high, during the event, small drops did not appear to distract the spectators. Post submitted during the event suggested that blind spots of short duration might increase the spectators' curiosity and their interest in knowing what is happening. These positive effects from data disconnection could be attributed to the design decision of giving connectivity feedback to the users [34].

6.9 System Relevance

From the design and deployment process, we extrapolate motivations for real-time crowd-support systems. Next we list these motivations. This list is not necessarily exhaustive and future evolutions of this and similar systems are likely to provide additional applications and contexts. All quotes within these results are athletes' statements unless stated otherwise.

6.9.1 Receiving live support

The most evident motivation for using the system is that of having a live supportive audience i.e. athletes become aware that others are sending their support:

"… we got frantic text messages [SMS] from X, someone else in the running club, who said, oh you just disappeared on the map. We said, 'it's fine, still alive, it's all good.' You definitely got the sense that people were tracking it for long periods".

The athletes refer to two distinct ways in which real-time support is effective. The first is in mitigating loneliness. *"In this sort of event, where it is a very lonely event because it is just you and the cyclist, it [remote support] is helpful. In a [competitive] race cheering does not massively help me."* Similar results were identified in earlier work [44]. The second way is in mitigating fatigue: "*You've done so many miles and you may be really struggling and that [the cheering] is just what you need."*

6.9.2 Having followers

Sharing data also provided a sense of prominence. In our investigation, we take into account the data sharing (i.e. knowing that others are following the event) and the crowds' feedback (i.e. receiving support), separately. During the event, the athletes were mindful both of having their effort followed (telemetry) and of receiving support from remote spectators (cheering). Interviewed athletes commented positively on both the sharing of data through telemetry such that spectators can follow the event and also on receiving live support.

"It is the mixture of the two… people had the data to know where we are, and they also followed it… I know that my mum followed it for a lot of the time because she had the cheering so it was like 'oh I am cheering them on!'."

The broadcasting of live data from athletes to spectators did not only initiate engagement but also opened up communication over secondary channels like traditional SMS texting.

"When this person from the running club was watching he would texts us [standby athletes] and we all cheer and we go 'ye this is another cheer to us'. It may be midnight and he probably should be in bed, but no he sat up there following and cheering us."

6.9.3 Using live telemetry as a proof of accomplishment

One of the most surprising findings is the use of live telemetry as a proof of accomplishment. The athletes report that the telemetry provides evidence of task completion. This supports existing literature [176] and earlier work [42,44] where the real-time sensor-captured data broadcast is reported to give the data viewer an increased perception of truthfulness than what otherwise may be considered as curated content. In this light, the live telemetry provides curiosity, suspense and expectation.

6.9.4 Democratisation of sport events

The charity event upon which this research is based was driven by university students with limited funding and resources. The cost of material for developing the relay baton was £15 excluding the Android phone while the cost of telemetry data for the whole event was less then 10p. Over the 24-hour event, the baton used a total telemetry data cost of 4.2Mbs. This created a method of democratising the endeavour at a widely accessible cost. The organisers could broadcast the activity live in a way that remote spectators can follow and interact with the athletes with similarities to commercially driven broadcast events. In this way, non-famous athletes become less dependent on traditional broadcasters to broadcast themselves. Non-famous athletes can self-harness the power of their social media for spectator support irrespective of how famous they are.

6.9.5 Triggering support mindfulness

The athletes report perceiving an association between the altitude and the support they were receiving. Figure 41 shows the cheers submitted by the remote crowd across time. This shows that spectators cheered at different intensities, thus suggesting that spectators are interested in externalizing varying degrees of excitement and support. It also indicates that spectators do not cheer randomly but are influenced by the data and external dynamics such as the current altitude or the perceived exertion effort as suggested in [99]. This relationship is also reflected in the athletes' comments:

"We started the hill and at the top of the hill we got so many more cheers. It was quite remarkable".

"In the first hill they went up by about 500. Joe had a very hilly section".

These results support earlier work that shows that remote spectators are keen in building clear images of the remote context through data [176,179]. In this work, both locative and physiological data was shown to make the actors feel closer. Designers should thus seek ways to augment spectators' emotional experience of the remote environment and the effort exerted.

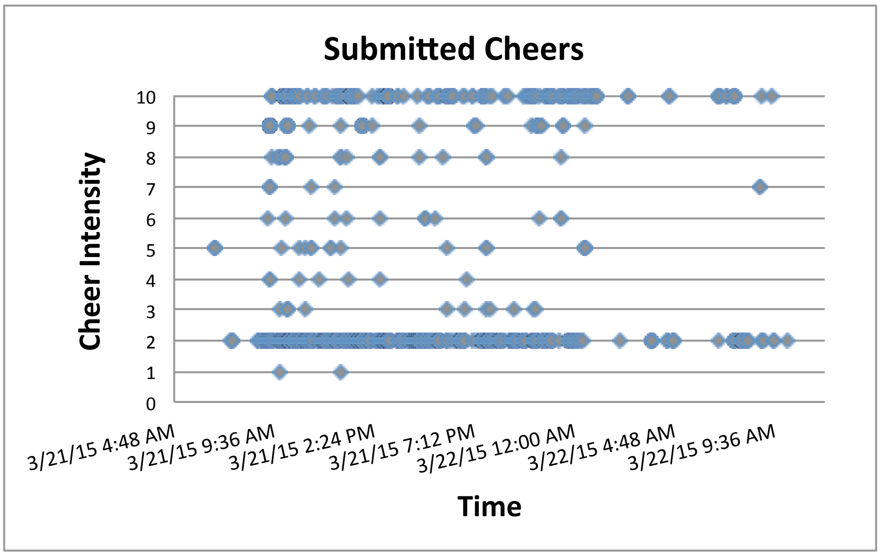

Figure 41: Cheers submitted during the event by cheer intensity. Cheer intensity has a default value of two.

6.9.6 Transposing social network edges

After the event, the athletes positively commented that: '*knowing who was supporting you [during the event] was really nice…* '. "*I really like being able to hear who it is who is cheering, especially if they know it is your section, so they are cheering you.*" In line with earlier work [44], we observe that the most effective live remote support seems to be that of acquaintances. "*People I know best are effective, however, if you had someone who is around the other side of the world supporting you, [excited] they must have logged on especially to help, it is not something which I feel I was duty bound to do, so that could be quite nice.*"

6.9.7 Satisfy a social need to connect, just-in-time

Allowing spectators to login through either Facebook or by manually inputting their name opened up room for fake names. Some of the names used by friends were not particularly suitable, such as, 'We hate Pete', which, in general, is not a good thing. The fake names issue can be minimised by enforcing login through a social media app like Facebook. However, issues such as lack of anonymization and a need of having a social media account would then arise. Most of the cheers (69.8%) were sent by spectators who logged in as 'Guests' (i.e. remained anonymous). On the other hand, the fact that the baton synthesised the log in name, prompted some of the spectators to re-log into the system and insert complex messages in their name field. In this way, they could send customised messages, like *"go Mike"* (rephrased), to the athlete carrying the baton. This highlights the spectators' interest in communicating with the athlete during the event with more expressive tools than binary cheers.

6.9.8 Reaching a new audience

For the event organisers, the proposed cheering system facilitated reaching a new audience that was otherwise not connected with the event during the event. This 'audience' is likely to be different and in addition to the spectators who would be on the course cheering. After the event the organiser highlights, through reflection, key engagement values:

'We used it [the system] more to let people know how we were going because we knew that people would not be able to come and see it [the race] very easily as we went past. So we wanted people to still be involved.'

This is likely to increase event awareness and web traffic to the charity event's webpage both of which are important marketing affordances. Additionally, having an innovative system where spectators could interact with the athletes live, facilitated event advertising through social networks before the event.

The organiser believes that the cheering is most effective because it gives the audience a feeling of contribution, 'they feel they are participating'. This, irrespective of whether the cheering has any effect on the athletes or otherwise.

6.9.9 Tracking and event control for organisers

An unintended consequence of carrying the baton was the ability of the organiser to track where the athletes are and immediately detect wrong turns. On two occasions, this helped in guiding athletes (remotely via the cyclist) back on the course. Additionally, through the live telemetry, the spectators present on the course could know when the athletes are coming up towards them and where and when they should be ready to cheer.

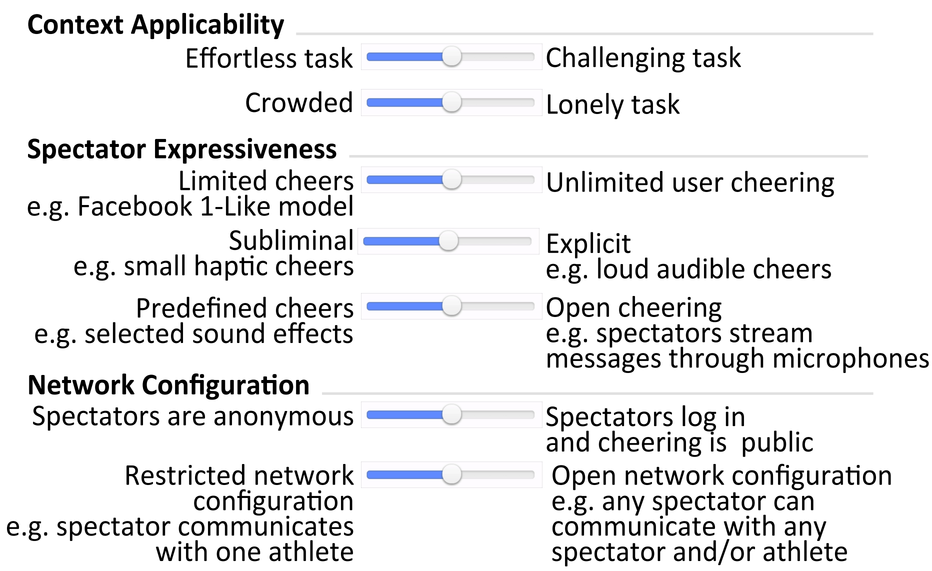

Figure 42: Design considerations

6.10 Design Considerations for Remote Crowd Support

These results encourage the design of smart devices that facilitate real-time remote crowd support. These social support systems bring in a unique combination of design decisions that designers need to take into consideration. Figure 42 lists the key design variables that designers may draw upon. We group these in three: spectator expressiveness, context applicability and network configuration.

6.10.1 Spectator expressiveness

"I loved the cheer intensity…! Aaaa ok I am not going to cheer them very much!" [Athlete - Laughing]

A design consideration is the degree of expressiveness that spectators are allowed to show. This brings in play considerations such as the number of cheers that spectators are allowed to send, the cheering modality and whether spectators are allowed to generate customized cheering themselves (e.g. record their own messages) or use pre-defined modalities (e.g. system sound effects).

A common question in the design process was - should spectators be allowed to cheer unlimitedly? In hindsight, an unlimited option as deployed in the presented case may better express human emotions. When this feature was discussed during design meetings, some athletes showed surprise in having unlimited cheers. Existing social networks deeply nurtured an expectation of one '*Like'* per actor. Originally, this approach may have been driven by a technical need of social network simplification. However, in a real-life situation, there are no such restrictions and emotions are expressed in varying degrees by different users with diverse social ties.

This leads in a second design decision; deciding the explicitness of the cheers, ranging from very subtle feedback to explicit feedback. At the end of the scale, explicit feedback may consist of audible cheers that are loud enough for nearby athletes to hear.

A third design decision is the degree of openness in cheer expressiveness. In this case at the lower end of the scale is having predefined cheers such as haptic cheers. The other end of the scale one could allow spectators to send self-generated support. An example of this may be that of allowing spectators to stream live voice comments to the selected athlete while the spectator's spacebar is pressed. More open approaches are likely to increase spectator expressiveness but are also expected to increase ethical and security concerns.

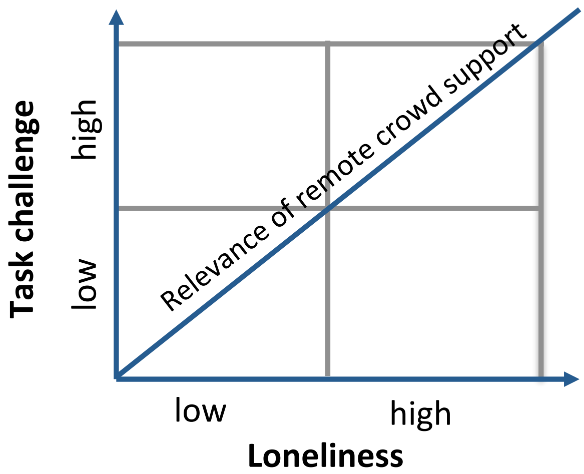

Figure 43: Crowd cheering effectiveness in relation to task design

6.10.2 Context applicability

In which conditions are the cheers most effective? The results highlight two key factors that influence the effectiveness of remote support; 1) the challenge-intensity that is provided by the task and 2) the loneliness (or otherwise) of the event. This is depicted in a 2x2 matrix in Figure 43. Earlier work suggested that support is most effective during a 'challenging' task. However, upon comparing the loneliness arising from the long-distance relay event with earlier work, it seems that the awareness that a remote crowd is following the performance is more impactful when the athlete is feeling lonely rather than otherwise (e.g. when there is already a crowd of cheering spectators along the course).

6.10.3 Network configuration

The above design considerations operate within a set network configuration that may connect some or all of the athletes, spectators and organisers; through unidirectional, bidirectional or omnidirectional communication. For example, designers may support communication in between spectators or limit communication to in between the individual spectators and single athletes.

Designers should seek to integrate together the requirements of all the stakeholders with a single system. Unlike traditional broadcasting, online crowd-support during sports events creates an ecosystem with multiple stakeholders in which the action or lack of action of one actor influences the other actors. For example, athletes' performance may influence the spectators' engagement (e.g. send more cheers) and this may influence the athletes' performance (e.g. motivate them to perform harder). As such, researchers should seek to analyse these systems both at a micro level (e.g. analyse spectators' reaction to different visual) but also at a macro level (i.e. as complete ecosystems).

Future work should continue to find ways of decreasing the obtrusiveness of the data capturing and broadcast devices by looking into infinitely small and lightweight devices. This is expected to shift attention away from the distractions that physical devices create and allow athletes to better focus on the performance and social interaction. We might never reach the point of infinity or technology invisibility, but technology is projected in this direction. More importantly, in future work, interaction design should seek to 1) increase the emotional engagement of the spectators by sharing live data that best narrates the effort that is invested by the athlete. 2) Expand the cheering modalities to allow spectators to express their support with a variable degree of expressiveness. The hypothesis that if given the option to cheer with different 'strength' levels, spectators would always use the highest scale is wrong. Research shows that spectators plan their cheers in ways they believe would individually and collectively maximise the effect that the cheering may have on the athlete [45].

6.11 Conclusion

In this paper, we presented a connected baton for long-distance relays. The baton keeps the social network informed on how the event unfolds by broadcasting sensor-captured data through mobile network. Concurrently, remote spectators communicate their support through remote cheering.

Systems that are designed to facilitate real-time feedback from remote crowds have not been widely developed. The reason may be due to the social barriers (e.g. the pressure that such systems place on the social network actors to support the event in sync) as well as technical challenges. A technical challenge, particularly in such a large-scale in-the-wild event, is the perceived unreliability of the mobile network connectivity. Upon deployment, however, short network disconnections seemed to minimally interfere with the spectators' engagement. For example, cheers submitted by the spectators were relatively constant even when data coverage at the athletes' position momentarily limited the data updates.

In this regard, social capital seemed to compensate for the lack in precision. This reflection suggests that we may need to reframe our focus on 'visual perfection' when designing such socio-dependent support systems. In the last century, the broadcast industry exposed viewers to a constant increase of '*visual perfection'* and *'systems perfection'*. We expect that broadcasted content is perfect, stable, with exceptional lighting and excellent picture composition. Viral video sharing on social networks brought in an inverse perspective to this [54]. In our case, small dropouts in data updates had little influence on spectator engagement, particularly when spectators were in some way socially related to the athletes.

In preliminary spectators-interface designs we considered live video broadcasts from forward-facing cameras that are strapped to the athletes' chests. At the time, this design track was abolished as tests indicated that shots would be too shaky for spectators who are typically used to the centralized broadcasts from leading broadcasters. However, after having now deployed a number of trials, we observe that democratic broadcasts like the one deployed in this study, provide additional motivators that compensate for a loss in traditional 'quality'. In a situation where athletes are running alone, spectators with a social connection are keen to see a live picture and get a glimpse on what the environment looks like. Is it raining? Is it dark? Is the terrain rough? How does the breathing sound? This, irrespective of whether the media is jittery or compressed. In this regard, designers may want to consider balancing resources not only in 'designing for system perfection' but also factor in the value of 'designing for real-time social dynamics'. In this light, we hope that this work also contributes in brining to discussion the making of more humane social networks. In this case, the focus is not in making affective machines, but more importantly, in making machines that facilitate collective human support, just when this is needed.

Chapter 7
DISCUSSION

In the previous sections, we presented the studies within individual chapters. In this chapter, we reflect on the themes that emerged through the entire design process. We bring forward key themes that have arisen in hindsight and future work that we believe promises thought-provoking investigations.

7.1 Emerging Themes

Three key themes that emerged from the chapters that were presented up until now are the following. 1) The value that real-time crowd support provides for the users. 2) The value that crowd-engagement features such as cheering bring to commercial organisations that adopt them. 3) The power dynamics that the system, that was investigated within different contexts, create.

7.1.1 Value for users

Each of the papers that are presented in this dissertation brought up the value of democratisation that remote-crowd support systems seem to enable. Traditionally, only famous athletes had the clout of attracting broadcasters to follow their performances. Being broadcasted, makes famous athletes even more famous and likely to become even more popular with broadcasters. The democratisation that technology creates (predominantly through the dissemination of social networking) attracted the attention of many researchers particularly in Science and Technology Studies (STS). Using the systems that were deployed in the study, athletes who might not be famous, do away without having broadcasters to disseminate their performance. They can broadcast themselves at a global reach with negligible costs. Athletes, who might not be famous, may have, say, 400 friends on Facebook, who might be interested in supporting them. In this case, engagement of supporters is more likely to occur because of the social affinity between the athlete and the spectator rather then because of how famous the athlete is. One may argue that being cheered on because of a social affinity has a higher value than being cheered on by unknown spectators. Understandably some might disagree. Personal traits and ethical positioning are likely to bias different individuals to internalise sources of extrinsic motivation differently [49]. In parallel to this, the spectators' motivations to support the athletes remotely vary. Spectators may find value in associating oneself with a good cause such as a charity run. As data in Chapter 2 showed, spectators may feel associated with the athlete, gain a sense of belonging, or both.

On the other hand, the democratisation that open systems, such as HeartLink, provide could be challenged. Social networks brought about a face value that everyone is equal. Everyone has access to information and that, seemingly, the information belongs to everyone. This is partly true and is reflected in the deployed designs. As mentioned earlier, non-famous athletes who might not have anyone supporting them on the course can how harness the power of social media and recruit supporters with minimum costs. However, this seemingly level playing field is still spikey [62]. Should famous athletes adopt a remote support system such as HeartLink, they are expected to receive a larger number of followers then an armature non-famous athlete. This effect is seen across all social media ecosystems from simple twitter feeds to areas as far away as high frequency trading (HFT) [136,69]. While everyone can have a twitter account and can tweet, the diffusion and the impact of messaging is different for social actors with different power values. Similarly, computerization of investment instruments changed the playing field of trading stocks, bonds and investments. This highlighted the political effects that technology presents. "Despite the widespread rhetoric that computerization inherently democratizes, the consequences of the introduction of HFT are widely acknowledged to be new concentrations of wealth and power, opacity rather than transparency of information flows, and structural resistance to democratic oversight and control.” [69] p.278.

7.1.2 Value for Commercial Applications

To the best of our knowledge, at the time of writing, cheering features are not the main objective of any of the existing commercial mobile apps. In most cases, the main objective of existing mobile applications that are designed for athletes, is the quantified-self, that is, the collection of athlete-centred performance data. Commercial mobile applications that embed cheering features, such as Runtastic or RunKeeper, provide a cheering facility as an additional feature that was embedded at a non-initial stage in the lifetime of the application. In hindsight we observe that the cheering features present three key values to the quantified-self application. First, when spectators use the cheering feature, the application profits from network effects and network externalities. The application is not any longer solely a data-logger that connects the athlete with his or her data. By allowing data sharing over social networks, the application creates a broadcast. By allowing cheers to be sent back, the application creates a network with unidirectional edges. Network effects, coined by Robert Metcalf, are nicely exemplified by Shapiro and Varian in “Information Rules” [171]. An example of network effects is commonly brought up using the telephone as a case. The telephone set has negligible purpose for the first and only person to buy a telephone set (A). The second person buying a telephone set (B) increases the value of telephone set A even though telephone set A did not physically change in any way. Telephone A can now call Telephone B. The value of the network increases the more phones connect to it and while the cost of each phone may be equal, the number of connections increase exponentially. By providing cheering features, the mobile application further motivates its integration with existing social network thus becoming a network rather then an individual isolated application.

Secondly, the cheering features motivate the users (athletes) to share data. In existing commercial mobile applications that are designed for athletes, the data is shared through Facebook posts that include the name of the app within the data visuals. This sharing of data diffuses information about the brand through the social network actors (athletes) who effectively advertise the application's brand. The application users become the advertisers and themselves generate brand awareness, diffusion and propagation. In this way, the brand has as many information dissemination sources as its number of users.

Thirdly, such user-driven information diffusion is likely to be more effective than information that is disseminated by the brand as explicit advertising. While the algorithm that social networks such as Facebook use to select which content should be disseminated is kept under wraps, it is widely acknowledged that information that is posted by commercial entities on Facebook are less likely to be diffused then posts from personal accounts, save for paid adverts. This diffusion of information through the users' accounts such as the one described above, mitigates this within an ethical framework.

7.1.3 Power Dynamics

The work presented in this study brings to attention the interplay of power among the actors within the network and how each actor is susceptible to influence and influences others in the network. In hindsight, the live cheering system here presented can be looked at as an ecosystem, in which athletes tell their story live by sharing data with an online community of spectators. The spectators may be influenced by the data they are presented and may interact with the athlete by sending cheers. In turn, this support may influence the athlete's performance and hence the data shared by the athlete may be affected. This complex ecosystem is not merely influenced by the main actors, that is, the athletes and the cheering spectators, but is also influenced by the environment in which these actors are performing, the co-located supporting spectators, the organisers and the system itself. For example, in Chapter 6, we have seen how the engagement of the spectators varies when presented with different interfaces and when the relationship between the spectators and the athletes varies. We have also seen, particularly in Chapters 4 and 5, that the cheering process could bring elements of gamification for both the athletes and the spectators.

7.2 Reflection

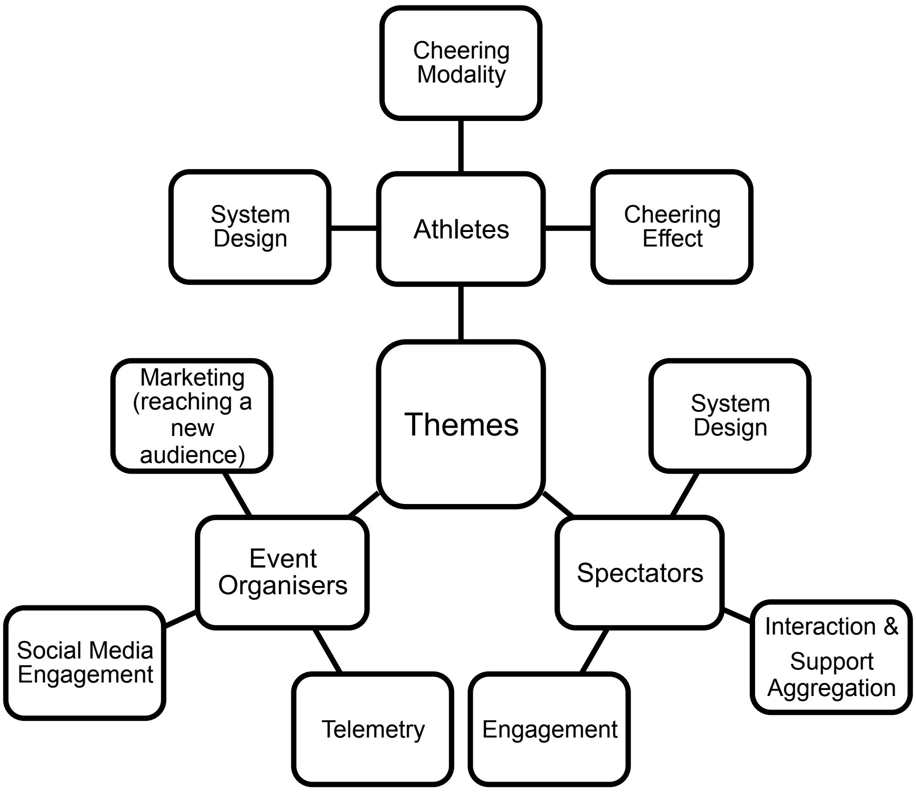

Figure 44: Key Themes

Figure 44 shows the themes around the key stakeholders that have emerged across the deployments. The primary stakeholders are the athletes and the spectators. However, the qualitative data that was collected in this work brought to light a third stakeholder, the event organisers. Through the presented papers, we started understanding 1) how to design the systems around the athlete, 2) the effect of the cheering modalities that were used and 3) the effect of the cheering on the athletes. Additionally, from the spectators' perspective, we started understanding 4) how to design systems that facilitate support from remote crowds, 5) aggregate the support and 6) encourage engagement from the spectators. Finally, the event organisers stressed the value of the deployed systems 7) as a way of reaching new audiences, 8) as a data gathering tool and 9) for social media engagement.

7.2.1 Spectator and user interfaces

We found that the interfaces there were deployed are driven by two main sources: The athletes and the spectators. In their work, "Designing the Spectator Experience", Reeves et al. classify these interfaces as public interfaces. These are public interfaces not because the interfaces are out in the wild but rather because of the "extent to which [the] performer's manipulations of an interface and their resulting effects are hidden, partially revealed, fully revealed or even amplified for spectators." p.741 [153]. In recent years, there have been numerous discussions within related communities, such the SIGCHI, on interfaces that are moving away from providing an individual dialogue but rather are *designed for a crowd* [23,24,104] and *driven by a crowd* [16,19,20]. In most of these cases, as it is the case in this study, the crowd is distributed. In some cases the interaction happens in real-time [105] or near real-time [20].

In a real-life cheering context, within a open sporting event, the human interaction is intended to be public. Spectators cheer from the sides of a racecourse or from the stands at a stadium. On the other hand, in the digital world, there is by far more human-human communication that is designed for a private setting rather then a public one. Public telephones for example are enclosed in boxes or photo kiosks [153]. There are also multiple levels of engagement. There are spectators who follow the data through the crowd-powered interface, hence they can follow the data of the athletes and also the data that is driven by the crowd (i.e. the live cheering, the spectators live comments as the event unfolds and the number of spectators that join and leave the event, during the event). There are also the supporters, that is, those spectators who do not simply follow the data but also interact with the interface and the athletes by cheering and commenting, hence contributing to the live discussion. Finally there are the athletes whose interaction is highly automated, both the sharing of data, and in receiving feedback from the crowd. In a way, the interface of the athletes is hidden and inexistent. It is an extension of the crowd's interface. For example, the relay baton that was presented in Chapter 6, opens up a channel to the crowd. The athletes do not interact with the baton but the baton automates the communication from the athlete to the crowd. The baton captures the data and sends it to the crowd without any interaction from the user (the athlete). There is also the co-located spectators, who, although they might not interact with the cheering system or the online crowd, they may also influence the online environment through the athlete's environment. In this regard, Reeves et al. add another dimension to *public* vs. *private* dichotomy; *manipulations* and *effects,* where manipulations are the actions of the 'performer' (in our case these are the actions of the athlete). On the other hand, effect is the impact of the manipulations; a click on a cheer button triggers a vibration (direct effect) and may make the athlete aware of the support being sent. The athlete may perform better and his or her exertion may influence the gradient of the chart representing the live heart rate (indirect effect).

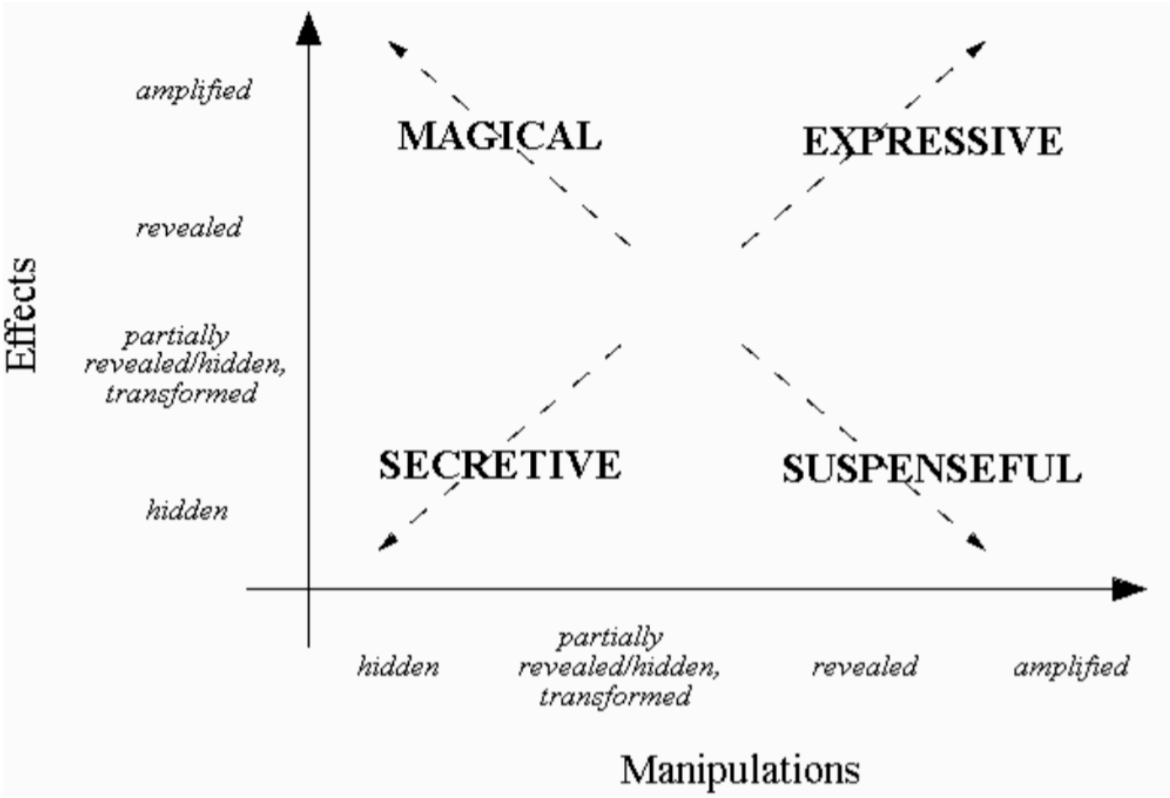

Figure 45: Secretive, expressive, magical and suspenseful approaches to designing the spectator's view from [153]

The work of Reeves et al. helps us position our interface within the spectrum of interfaces that is presented in Figure 45. Interface categories include 1) Magical, this refers to interfaces that hide the manipulations but the effects are revealed (e.g. wizard of oz interface [46]), 2) Secretive, where both the effects and the manipulations are hidden (e.g. within a competitive game), 3) Suspenseful, where manipulations are hidden but the effects are revealed and finally 4) Expressive, where both the manipulations and the effects are revealed or amplified (Figure 45). Within this taxonomy, the proposed cheering system positions itself in the expressive quadrant. Spectators' actions are channelled to the athletes and amplified through haptic and sound synthesisers. The athletes' performance is sensed and amplified to all connected spectators within the spectators' interfaces.

The cheering system associates another dimension to this. The interface is not only generated and interacted with by the individual and displayed to the spectators as a crowd, but this crowd also drives the interface. In other words, the interface (including the cheers, the number of online spectators and the live comments that make up the interface) is generated from the crowd. These become, as Michael Bernstein coined, crowd-powered interfaces [19]. Crowd-powered interfaces are "interfaces that rely on human activity traces or human computation to provide benefits to the end user." [19] p.347. Undoubtedly, the cheering process is explicitly conducted for the benefit of an end user, the athlete. We argue that this process relies on both 'human activity traces' and 'human computation'. They rely on human activity traces as the distributed individuals trigger the cheers, and each has his or her intentions and motivations to cheer. The human computation component is highlighted in the interviews of the user study whose findings are presented in Chapter 3. Upon interview, the spectators showed interest in maximising the positive impact that the cheers could have on the athlete. In this regard, spectators devised strategies such as leaving more cheers towards the end of the race, 'such that the cheered athletes do not get used to the cheering'. These strategies are reflected in the cumulative cheering plots that are derived from logs.

7.2.2 Communication Modalities

Across the papers, we looked at primarily two communication flows. Informing the spectators and informing the athletes. The athletes' awareness of spectators' behaviour and their support, can contribute to build a sense of 'liveness' [153]. However, it can also generate pressure on the athlete. The sense of 'being observed' that real-time remote support systems create, may make the athlete feel obliged to perform or feel embarrassed for mistakes since spectators are following the performance. The modality that is adopted to communicate the crowd's support to the athlete is an influential factor in the design of the athletes' experience. The deployments explored tactile and sound alerts to communicate the cheering crowd. Results showed that the effect of the communication modality is dependent on different externalities over and above the modality itself. These include the context (e.g. the background noise within the environment), the trustworthiness of the cheering crowd (e.g. whether there are spammers among the cheering crowd who might misuse the modality, say, send inappropriate messages) and the individual personalities of the athletes that the set modality is communicating with. For example when the modalities where calibrated to generate the same intensity of tactile feedback, some athletes did not feel the set vibration. This seemed related to the athlete's body mass and athletes with larger arms were more likely not to feel the vibrations that were triggered by the telemetry device. Similarly, the participants' responses on the appropriateness of the connected-baton's size also varied in relation to body mass and size. Bigger persons were predominantly happy with its ergonomics while smaller-sized athletes brought up the theme of improving the design by presenting smaller handgrips. These highlight the need of personalisation in both the devises and the communication modalities.

7.2.3 Conducting RIW deployments with synchronous interaction between distributed participants

In all the presented papers, all the deployments were conducted in the wild. Planning, organising and deploying this research proofed to be challenging. Moreover, each study involved multiple user groups that were not only in the wild but also distributed across different locations. Additionally, the interaction under investigation was a synchronous one. Thus, the participants needed to synchronize themselves to the study rather than the study synchronises to the participants. The need for participants to synchronise with the study limits the number of participants that can take part in the study as their participation is not only conditioned by their willingness and appropriateness to the sample group but also by their personal schedule. This restriction is particularly visible when the user group is friendsourced, that is, the participants have a social tie with the athletes. On the other hand, this is less restricting for outsourced participants, that is, where participants have no social connection with the athletes as the sample frame may be larger. These issues are shown in Chapter 5 where participants were recruited from CrowdFlower, a crowdsourcing platform. Crowdsourcing platforms provide a large enough pool of participants (crowd workers) who are seeking work that matches their expected enjoyment and financial return. The enjoyment value is a major factor in the recruitment process. Many studies show that crowdsourced participants value the pleasantness of a given task [93,94,159]. This impacts both the engagement of participants in the task and also the reputation on the platform (through post-task-completion feedback) of the researcher who issued the study.

Each of the influencing factors depicted in Figure 46 augments the complexity that conducting such a study entails. Throughout this study, we gain insights into designing systems and deploying them in different contexts in the wild. Other research methods have been considered in the early design stages of this study. A method that was considered but never adopted was an in the lab study in which researchers observe how different user groups react to different stimuli within the lab while they are presented with controlled data. For example, one study could have been that of showing interfaces that contain play-backed data as if an athlete was running at that moment in time to then observe how spectators react to the presented data. We could have then repeated the experiment with variations in data and spectator groups. Concurrently, we also considered studying the athletes experience of being cheered on while using a treadmill within the lab and having different cheering models and patterns being played back at various phases of the study.

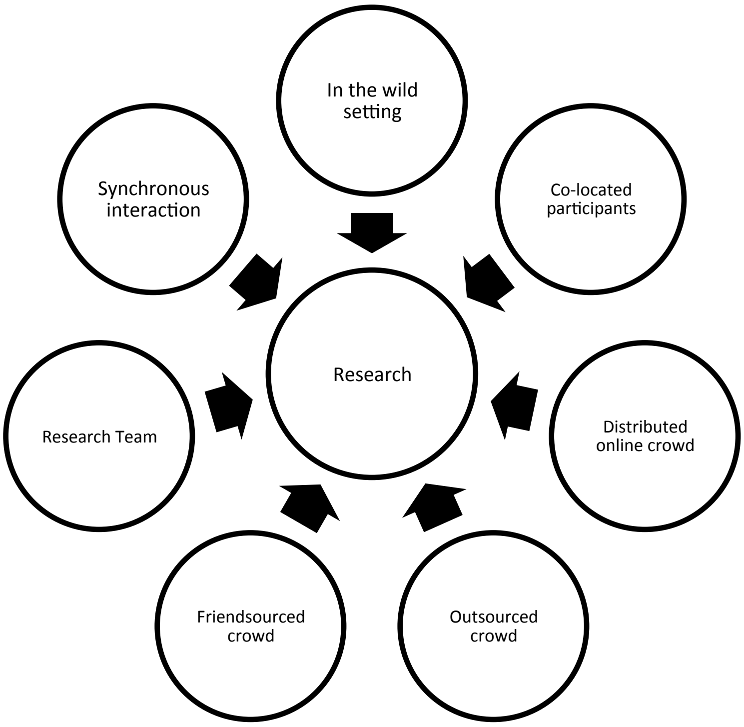

Figure 46: Methodological influencing contexts

Such a study would have been different. 1) The researchers would not have been bound with recruiting a large group of participants to perform at one specific global time. 2) The researchers would have had more control over the environment and confounding variables would have been limited. For example, weather conditions would have been minimally influential on the study, if any. Windows would have been closed and a treadmill could be kept at the same gradient for all participants such that all the participants would have been presented with an identical controlled experience. Similarly, cheers could have been computer generated from predefined patterns that would simulate remote cheering crowds. 3) Running such an experiment would have been easier because the researcher would be in the comfort of the well-known, tried and tested, "lab". The researcher could have wired, handled and observed one participant at a time.

However, no matter how controlled this environment would have been, it would have never been anything close to the real thing; the in-the-wild environment with real crowds sending self-initiated cheers at that moment in time. Hence, an in-the-wild investigation was adopted [158].

In hindsight, an in the wild deployment that involves distributed crowds, like the four deployments in this study, are more unforgiving then an in the lab approach where single participants sequentially conduct offline sessions. For example, if there is an issue with the system, such as what happened in the pilot study due to downtime on Amazon Web Services, the researcher needs to coordinate a crowd that is distributed. This is challenging, not only because the investigation involves a crowd but also because the data is live and distributed. In this case, the research event is likely to fail or at a minimum, the research objectives would change. Moreover, a new event would require coordinating a new crowd. Should that have been in the lab, a participant would have been ranked as an outlier or replaced with an additional lab session. Finally, in a lab version, systems can be tested, and researchers can pose as dummies. In an in-the-wild version where crowds operate synchronously, the systems are difficult to test fully. For example, collecting enough participants to simulate a crowd to test a system in situ is often impractical. Furthermore, if the researcher does manage to do this, in most cases, the in-the-wild environment is likely to change over time. Hence, reliability cannot be guaranteed across all variables. For example, data telemetry that is dependent on mobile network coverage (reception) may be influenced by the density of users that happen to be in that area and of which the researchers has little or no control.

These challenges that RIW brings to the table further highlight the differences of RIW over an in lab study. These differences emphasise the distinct values that both approaches present the researcher with. Based on the above considerations, we recommend the following to researchers who intend conduct research on the lines of this work:

1. The researcher should seek to control any variable that can be controlled but plan contingencies for unexpected events.
2. Conduct meticulous planning can minimize unexpected outcomes.
3. Observations during the event are very important and should be documented during or immediately after the event.
4. The researcher should have a communication channel with the remote participants. This can be used for ad-hoc coordination should unplanned phenomena occur.
5. Keeping documenting and coordinating roles separate. Due to the complexity that such tasks entail, we recommend that researchers build a research team where each member is assigned a pre-designed role. Different studies and conditions would necessitate different roles for supporting staff. In the case of the study that was presented in Chapter 4, the 5k-roadrace, the recommended roles for the event so that the researchers can focus on core areas are as follows: 1) A person may be assigned to coordinate the online crowd. This person would, for example, message the crowd should there be a need to do so during the live event and answer any queries that online participants may have. 2) A person needs to coordinate the co-located athletes. 3) An experienced researcher journals the event. 4) A videographer and/or photographer may provide grounded content for post-event analysis or in support of post-event publications.

7.3 Future work and implications.

7.3.1 Synchronous and Asynchronous Interaction

In the course of the study, we have designed and implemented other prototypes that were not presented in this document. These prototypes were not included in this text because they were never evaluated within an event. This happened either because the exploration methodology that was elaborated upon earlier indicated that other tracks promised more interesting outcomes within the early phase of a possible innovation lifecycle. In other cases, we did not have the right participants, events or infrastructure to run the prototypes within the complexities that the methodology entailed. In some cases, these prototypes were tested in the lab but were not deployed in the wild. Among these, we prototyped multiple versions of the BioShare App using online app development tools such as AppInventor. We found these tools excellent for developing functional prototypes rapidly at early stages of the design process. However, their simplicity is balanced by a limitation in flexibility that the designer has when developing applications such as HeartLink and BioShare. This is most felt when interfacing with, for example, biometric sensing devices, customising graphics and embedding responsive design. In the end, the deployed version was developed as a native application in JAVA.

An interesting design direction that is worth further exploring is that of asynchronous cheering. A design for asynchronous cheering was also implemented but never deployed. In this implementation, spectators log in a website anytime before the event and leave cheers by clicking on different visuals. These visuals include a map with the course and a chart with the altitude as shown in Figure 47. The cheers that are dropped on the map, are stored in a database and downloaded on the athletes' device before the event. The cheers are then triggered when set conditions are met. For example, if a cheer is ‘dropped’ on the digital course (map), then the athlete receives an alert when he or she physically passes in closest proximity to the location where the cheer was digitally dropped. Future work may consider other conditions. For example, a cheer can be triggered if the athlete reaches a certain altitude or when the athlete has been exerting a predefined level of effort for a set duration. In this case, the level of exertion may be calculated with the same methodology that was used in “Jogging over a distance”[131]. Such a system could be relevant for contexts in which an Internet connection is intermittent or inexistent. An example of an event where this could be applicable is the Ocean Floor race. The Ocean Floor race[7] is an ultra marathon non-stop footrace of 160 miles through the Egyptian western desert.

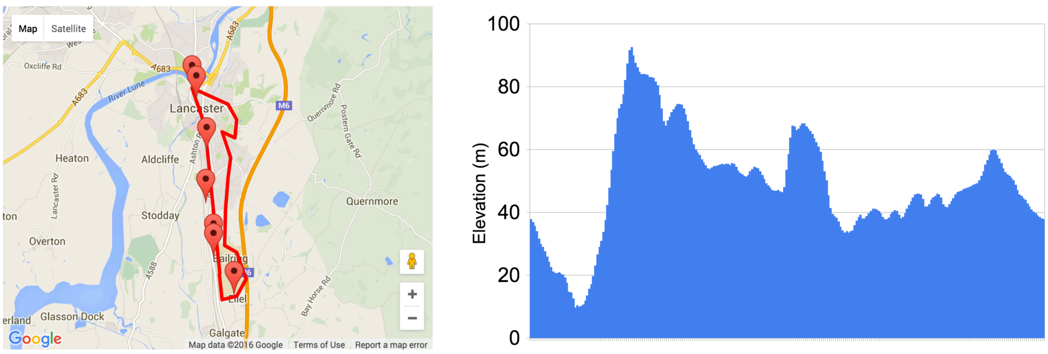

Figure 47: Spectators can place cheers on the course of a selected athlete before the event by clicking on the map (left) or altitude chart (right). The athletes are alerted when they pass from the location in which a cheer was placed.

Our primary objective when developing this system was not to study the design process, although that can be interesting. Rather, the research would have focused on comparing and contrasting how the impact of synchronous and asynchronous remote cheering differs on the athlete if any. Specifically, our interest is to find out whether receiving cheers in real-time presents added advantages than otherwise. This research, though interesting, would have taken us away from the research questions and hence

[7] http://www.oceanfloorrace.com/

this is being suggested as future work. We are happy to share the prototypes with researchers who are interested in following up research in this direction.

A methodology for comparing and contrasting synchronous and asynchronous cheering is challenging particularly if a large crowd is required for the study. An approach to conduct such a study is by randomly assigning participating athletes in two groups. One group will experience synchronous cheering, and the other group would experience asynchronous cheering within the same event.

A synchronous interaction system allows for immediate feedback. This feedback, in the form of cheers, is received by the athletes as the event unfolds. Our hypothesis is that a synchronous approach could provide added value due to the immediateness of the feedback. Many studies looked into the effect of having immediate feedback, particularly on motivation and education. For example, Epstein et al. found that performance of students who were given immediate feedback upon completion of multiple choice tests did not differ in performance in the short-term from students who were not given immediate feedback. However, when tested after a day or a week, the participants who received immediate feedback during tests showed higher scores thus indicating that immediate feedback promotes retention from the cognitive processing [58]. Similar outcomes are supported by Dihoff et al. [53] and Scheeler et al. [165]. In the latter, immediate feedback to teachers during their deliveries, increased course completion rates in all trials within the study. We find similar outcomes in literature on 'Motivation,' [92].

Hence, there are two beautiful research tracks that future work may look into. First, is to study whether athletes who are cheered on remotely perform differently from athletes who are not remotely cheered on. Secondly, is to study whether synchronous cheers differ in impact over asynchronous cheers. Based on the above literature our hypothesis is that receiving synchronous cheering presents a more positive impact on the athlete, but this is yet to be tested.

Another research direction that is worth further exploring is the effect that the remote cheering has on the athlete. More specifically, what is the social network effect on the athlete's performance? Such a study would preferably be a longitudinal one and involve a large number of participants. This number should be large enough to conduct reliable multivariate analysis that looks into the different social tie strengths within the network, the athlete's performance and the type of challenge that is presented (for example having different levels of loneliness, levels of exertion and athletes objectives for participating).

7.3.2 Advancements in Interaction Automation

One major challenge that was faced in the initial design stages, was the design of a system that allows the athletes to interact with the crowd without distracting the athlete from the challenging activity that he or she is conducting. This was partly solved by automating the data collection and sharing process through sensors. The sensors collect data and this data is communicated to the spectators in the hope that spectators construct a story. Although valid, the emotional value of the constructed story is not comparable with the story that a human narrator or professional television broadcast crew can enact. It primarily lacks the intelligence that builds context awareness within the story telling process. For example in Chapter 3, we have highlighted the difficulty for sensors to automatically distinguish between the start of the race and when the athlete started a warming up session. This created a context of ambiguity. Though one may argue that such ambiguity could be an interesting perspective for the researcher [67], this is not always the case. Another example could be that of identifying when the athletes are tired and in need of social support. In other words, the state of the system lacks the 'intelligence' that a human narrator can provide. We expect that advancements in sensing, processing and interaction technology will facilitate and increasingly allow users to interact with others while doing challenging tasks. These will also enrich the story telling process through better context awareness. Moreover, technology is increasingly hidden, unobtrusive and necessitating progressively less attention on the communication modality thus leaving more space for the communication itself. This applies both to the athlete's data sharing process (i.e. automated data sensing and broadcasting to inform the spectators on how the event is unfolding) and the athlete's feedback process (i.e. making the athlete build an understanding of the live feedback from the crowd and the surroundings). As regards, the latter, we expect that augmented reality devices could present an opportunity in which athletes augment their view with feedback from spectators thus enriching the feedback modalities that have been tested across the presented papers. At the same time, these minimise attention-expensive distractions such as looking at a phone while running. Similarly, small devices such as smart watches with embedded mobile network connectivity are expected to remove issues related with form-factor of the devices that were used in the deployments.

7.3.3 Social Marketing

A promising area for further research is that of analysing the influence that different social ties have on others. In other words, would a random athlete be more motivated in the event if his or her mum was on the side of the pitch supporting or would 1000 unknown spectators be more effective, if any? The understanding of social relations and the influence that the different relations have on each other, have received much attention in both academia and industry in recent years. Online social networks facilitated our probing of social dynamics to a level of detail that would have been impossible doing before. Sinan Aral and Dylan Walker [5] developed a method to identify the 'influence' and 'susceptibility to influence' of social network members. Through a randomised controlled experiment, they measured the influence and susceptibility to influence across a representative sample of 1.3 million Facebook users who share messages and recommendations on movies, directors and actors within the film industry [5] p.337. To avoid bias, they randomly manipulate who receives influence posts. They then use hazard modelling [82] to measure who is more or less influenced and susceptible to influence. This approach takes into consideration not only the adoption rate among the social network members but also the variations in time between the influence and its effect. Understanding how social network members influence each other has become increasingly important in many areas including viral marketing, product adoption, social contagion, peer influence and behaviour change. For example, you are more likely to select a holiday destination if a person you know recommends that destination rather then if you see an advert from a brand that you do not associate yourself with [6]. Similarly, in our case, different social ties are likely to influence the support that the athlete may receive through the cheering process. In Chapter 6 we have discussed and suggested differences that spectators with different social ties seemed to have on the athletes. This was done through a qualitative approach. The dataset was not large enough to justify a quantitative analysis. Future work may seek to collect a quantitative data set and use Aral's validated framework for measuring social influence [5]. Diffusing the HeartLink app or a similar app across a wider community could facilitate the collection of such a data set. With the users' consent, the app could then collect insights related to the athlete's performance, the cheers received and the relationship between the network members. A longitudinal analysis of the data could further explain cheering patterns among different social ties, the influence that cheering from different social ties has on the athletes, behaviour change[8] and contagion[9] that might emerge due to the social support that is received or sent.

7.4 Conclusion

In conclusion, we believe that through further innovation, real-time support systems that involve crowds will increasingly provide added value to the users. Systems that allow for real-time support from remote crowds now exit in both commercial and academic applications. Examples of these are the popular quantified-self applications that are designed for athletes or Morris et al. solution for crowdsourcing emotional support from Amazon Mechanical Turk workers [128]. The technology is still relatively young and there are still hurdles that need to be surpassed until we see a wider diffusion of products that are designed around engaging crowds in real-time. First, technology is expected to become more embedded in human life, less obtrusive and ubiquitous. We expect that the trend in devices becoming smaller will continue such that any device 'obtrusiveness-related' barriers are smoothed out. Secondly, technology is expected to become more context aware on both the environment and the user. This would help in further enhancing the automated story telling process about how the event is unfolding through sensors. Thirdly, the development and innovation in human-computer interaction devices such as smart watches, e-textiles and head-mounted displays for augmented vision are expected to facilitate the

[8] Such a study may, for example, indicate that athletes who are most supported are likely to increase the intensity of their training and hence perform better.

[9] For example after following and supporting the athletes, some spectators may become interested in participating as athletes and become more active.

presentation of crowd feedback to the athlete while at the same time minimise technology-related distractions for the athlete.

Through the work done, we started building a general understanding of the dynamics that are involved in systems that facilitate social support from remote crowds, in real-time. We find that there is value for the three key stakeholders, namely the athletes, the spectators and the event organisers. While specific motivations for each vary due to individual personality traits, in general, athletes seem to be motivated by the sense of belonging that is enacted when the athlete/s become aware that one or more remote others are dedicating their time to follow and support them. The spectators bring in a sense of altruism from supporting others. For the event organisers, the presented system draws attention to the event by engaging with a crowd whose members, in most cases, would otherwise not be present at the event.

Chapter 8
CONCLUSION

"...it feels like a crowd is following you... though you are on your own, there is an environment where there are people around" [Participant]

This work investigates real-time support from distributed online crowds. To do this we developed a series of mobile applications for athletes and online interfaces that allow crowds to externalize their support. Through four in-the-wild deployments we then broadcast sensor-data to spectators in custom-designed data visualisations. These visuals helped supporters build an understanding of the remote performance and supporters were prompted to externalise their support in the form of remote cheering.

We investigated four central questions to 1) understand the experience of the data-sharing athletes while receiving remote support, 2) identify factors that influence remote spectators' behaviour during live events, 3) identify motivations for using real-time spectator support systems, and 4) provide guidelines for researchers and designers that seeks to facilitate support from remote spectators during sports events.

8.1 Key Findings and Contributions

1. The first area of contribution is the cheering effect on the athletes [RQ1]. Athletes were excited when they were cheered on remotely during events. Results show that this effect is depended on multiple factors. These include 1) the athletes expectations of the quantity of cheers they will receive, 2) the difficulty of the task at hand, 3) how lonely the athletes feel during the specific event and also 4) the social tie between the athletes and the cheering spectator/s. Our findings indicate that remote cheering sent by spectators with weak ties (such as acquaintances) could be more impactful that the support sent by spectators with strong ties (relatives) or no ties (unknown supporters) [Chapter 4].

2. We provide insights on distributed crowd behaviour [RQ2]. We find that the behavior of the cheering crowd is dependent on both the social tie and the data that is presented. Spectators who are presented with additional athlete's heart-

rate data cheered the athletes significantly more than those who were not presented with this data. Findings also indicate that spectators with a closer social relation with the athletes were more engaged in the athletic performance [Chapter 5].

We also identify that given a range of supporting options, the spectators do not support at the most intense level constantly (as we might have expected), but plan cheer in ways that the spectators believe will maximise the affect on the athletes. These individual actions form the collective crowd behavior [Chapter 4, 6].

3. Empirically, we isolate and present nine key user motivations for using real-time crowd support systems [RQ 3]. Remote support systems in the presented context may be motivated to 1) receive live support, 2) build a community of followers, 3) to proof accomplishment, 4) as a way of democratising support in sporting events, 5) to trigger support mindfulness, 6) to create new social connections, 7) to satisfy a social need to connect, 8) to gather insights on the event and 9) to reach a new audience that may be different from the audience that is present at the event's location [Chapter 6].

   Through our experience of creating and deploying four iterations of HeartLink and after contrasting this experience with that of other HCI researchers, we provided insights on how to engineer real-time crowd support systems, [RQ 4]. In Chapter 6, we specifically classify three key areas that designers and researchers need to consider when looking into real-time crowd-support systems. Namely:

   1) 'Spectator Expressiveness': the design of how spectators express their emotions and the degree of expressiveness that the technology facilitates,
   2) 'Context Applicability': key contextual factors such as difficulty of the task in terms of terrain and remoteness of the location. These impact crowd-support appropriateness and relevance.
   3) 'Network Configuration': how the data flows within the social-support network.

Through these factors, this research has provided a robust proof of concept for the design of crowd support applications, its implications and theoretic framework.

8.1.1 Research challenges

In hindsight, system deployments were particularly challenging in contrast with other commonly used HCI research techniques, such as, an in the lab study. The research design had to face a number of unique challenges, each of which increased the complexity of the investigation. All the deployments took place in-the-wild. This brings in added challenges that are widely documented in literature [15,31]. In addition to this, the study involved coordinating co-located participants (athletes), coordinating an online distributed crowd (spectators) and all functioning through synchronous interaction i.e. all the actors need to be active at the same geographical time and operate collectively as one ecosystem. In future, a contribution on the design of such complex research deployments is worth considering.

8.2 Limitations and Future Work

These challenges together with the limited scope and resources of a PhD research study, capped the scale of deployments. For example, conducting in-the-wild longitudinal studies with the intention of observing long-term variations in athletes' performance and behaviour change, are beyond the scope of the study - though relevant.

Similarly, in future work, finer grade insights could be obtained by recruiting more participants to create additional subgroups. With a large enough dataset, a study could dissect the impact of cheer quantity, cheer intensity and cheers from different social ties, on the quantified performance of individual athletes.

We argue that our findings are just the beginning of this research area and we trust that other studies will follow. What is presented here may provide the preliminary groundwork for real-time remote crowd support. Our results indicate that this research domain promises high impact in many research fields, including social network theory, crowd psychology and commercial applications in sports.

Another area that needs further investigation is that of the cheering modality. We have tested haptic and audible cheers. Other modalities such as live streaming of spectators' microphone data is worth exploring. This is discussed in detail in Chapter 6.

Finally, a more challenging but equally interesting area is that of studying how these systems could be personalized for individual needs and expectations. The results in Chapter 4 indicated that different athletes react differently to cheering. Through a psychological framework, further work could indicated which traits determine the relevance or otherwise of remote cheering for individual personalities.

8.2.1 Ethical issues

This work also brought to light a number of ethical issues that need further investigation in future work. Key to this is the 'real-time factor' in data sharing. In systems such as HeartLink, the user's data is broadcast in real-time. Thus, the user has very limited control over the data that is shared. The user can stop the data sharing at any point but without any retroactive effect on the data already broadcast and viewed by the spectators. Another aspect that this research provoked is the sharing of biometric data across social networks. When the data shared is of biometric nature, such as the heart rate, the owner of the data cannot intentionally influence the data. For example, unlike curated content on Facebook, it is impossible for the user to intentionally change the heart-rate with the purpose of looking fitter [87,150,176].

Thirdly, the crowdsourcing of social support also opens up new questions. For example, if participants in a specific context perform better when remotely supported, can we crowdsource 'cheerers' through platforms like Amazon Mechanical Turk during real-life competitive events? While this can be easily implemented with existing technology as we have shown in this work, questions emerge around social adequacy of such an approach outside a research scope.

By using off-the-shelf technology and rapid-prototyping design, HeartLink allowed users to share biometric data openly, ubiquitously and in real-time. This was facilitated by a development that is relatively low-cost and open-source. The ethical issues and implications of this potentially disruptive innovation however are many and hence further research is needed.

8.3 Impact and Implications

From a social perspective, the presented work has the potential to further broaden spectator support that was traditionally limited to famous athletes. Using systems like HeartLink non-famous athletes can harness the power of their social media presence with relatively no added cost.

On the other hand, from a marketing standpoint, systems that allow large-scale remote spectator support could have huge commercial value. Although globally sport spectators make up an enormous market sector, there have yet been little, if any, attempts to technologically facilitate remote spectator interaction during major sporting events. Television broadcasts are the leading source of information for remote spectators and up until now, these still provide one-way communication. Designing further evolutions of crowd-support systems as those presented in this work could create disruptive innovation. These applications have the potential to diffuse in an enormous technologically untapped market.

This research gave us valuable insights on how to design technology-based systems to crowd-support users when they are conducting challenging tasks. This is expected to lead us into applications that go beyond sports, such as health, where remote social support is most effective if delivered in sync with when it is needed.

Ultimately, through this work, we proposed a new function for social networks - social networks as a tool for crowdsourcing motivation in real-time during physically or cognitively challenging tasks. Since our first publication on the topic, all the leading commercial jogging-related smartphone applications implemented real-time cheering facilities. We cannot claim that these implementations were inspired by our academic work [42]. However, seeing applied cases in line with our then foresight, fills us with satisfaction. We hope that this work will contribute in making social networks more humane, perhaps, not by making affective machines, but more importantly, by making machines that facilitate collective human support – in real-time. Seeing how technology evolved over the last years, the future looks promising.

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PUBLICATIONS AND CONTRIBUTIONS

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- Curmi, F., Ferrario, M.A., Southern. J. & Whittle, J., HeartLink: Open Broadcast of Live Biometric Data to Social Network, *Proc. CHI'13 EA [Video Showcase],* ACM Press (2013), 2793.
- Curmi, F., Ferrario, M.A., & Whittle, J., Crowdsourcing 'Motivation' in Real-time through Social Media, *in CHI'13 Workshop: Designing Social Media for Change*, (2013).
- Curmi, F., Ferrario, M.A., & Whittle, J., Sharing the Quantified Self as an Economic Transaction: Social Capital pro Spectator Support, *in CHI'15 Workshop: Beyond Personal Informatics: Designing for Experiences with Data,* (2015).
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- Curmi, F., Ferrario, M.A., & Whittle, J., Bioshare: A Research Tool for Analysing Social Network Effects when Sharing Biometric Data, *Proc. DIS'14 EA*, ACM Press (2014), 101-104.

Work Under Review

- Curmi, F., Ferrario, M.A. & Whittle, J. Seeing the Heart Rate of Remote Others: An In-The-Wild Investigation in Remote Spectator Behaviour during a Running Event, submitted to *International Journal of Human Computer Studies*, [Chapter 5]
- Curmi, F., Ferrario, M.A., & Whittle, J. Embedding a Distributed Crowd Inside a Smart Device, submitted to *CHI'16* [Chapter 6]
- Case, O., Curmi, F., Weise, S., Blair, G. & Quick, A., Together in Electric Dreams: Towards a User-generate Cinema, [in progress]
- Curmi, F., Ferrario, M.A., & Whittle, J. Aggregating Just-in-time Social Support from Online Distributed Crowds, to be submitted for *CHI'16 EA* [Video Showcase]

- Curmi, F. & Whittle, J. An Epistemology of the Peer Reviewer: a Satirical Reviews' Analysis, to be submitted for *CHI'16 EA* [Video Showcase]

Published Book Articles

- Curmi, F., Sammut-Bonnici, T. Innovation Strategy, in *Wiley-Blackwell Encyclopaedia of Management* - John Wiley & Sons; 3rd Edition (2015)

Related Artefacts and Media Content In Chronological Order

- HeartLink Software - an open source crowdsourcing application that integrates RunKeeper API, TextMessaging API and Facebook API
- BioShare Web Crowdsourcing Interface
- BioShare Android Data Broadcasting App
- 30'' Video for CHI'13 Paper Preview
- 120'' Video for CHI'13 Video Showcase
- Relay Baton (version A): A Context-aware Relay Baton for Crowdsourcing Support in Real-time
- Relay Baton (version B): A Context-aware Relay Baton with a 48-hour Broadcast Autonomy

Knowledge Dissemination Through Dialogue

Invited talks, presentations and conferences attended

- Making Data: Lancaster University 2014, *Eliciting Empathy through Biometric Data Sharing*
- Synergize, Making Collaborative Research Happen: Lancaster University 2014 *HeartLink Review*
- *Designing Digital Tools for Crowdsourcing Social Support in Real-time,* Mixed Reality Lab, Nottingham June 2013
- Paper Presentation at CHI'13 Paris, France 2013
- Workshop Presentation at CHI'13 Paris, France 2013
- Interactive Demo at CHI'13 Paris, France 2013
- Paper Presentation at DIS'14 Vancouver, Canada 2014
- Interactive Demo at DIS'14 Vancouver, Canada 2014
- Paper Presentation at CHI'15 Seoul, South Korea 2015
- Workshop Presentation at CHI'15 Seoul, South Korea 2015
- A Review of CI'12 at HighWire Breakfast Club 2012
- HighWire Breakfast Club 2013: A sneak preview of HeartLink at CHI'13
- Organising Workshop: *Collective Intelligence in the Digital Economy,* Nottingham DTC Doc Fest 2012
- Networking Event at Collective Intelligence 2012, M.I.T. Boston, U.S.