Mobile Decision Support and Data Provisioning for Low Back Pain

Simo Hosio\textsuperscript{1}, Jaro Karppinen\textsuperscript{2}, Niels van Berkel\textsuperscript{3}, Jonas Oppenlaender\textsuperscript{1}, Jorge Goncalves\textsuperscript{3}

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\textsuperscript{1}University of Oulu, Finland \\
\textsuperscript{2}The Finnish Institute of Occupational Health, Oulu University Hospital \\
\textsuperscript{3}The University of Melbourne, Australia
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\textbf{ABSTRACT.} The smartphone is an impressive scientific tool due to its increasingly powerful sensing capabilities. We present a mobile application, Back Pain Buddy, that offers decision support and coaching for people with low back pain (LBP). The application encompasses 1) a crowd-powered decision support system for discovering treatments and 2) a mobile sensing solution for producing information to scientists about users’ lifestyle ingredients that are considered crucial in LBP research. We report the results of two user studies aimed at validating the decision support system and understanding issues in the sensing solution. We find the decision support feature as highly valuable for experts and non-experts alike. The sensing approach, on the other hand, was perceived positively especially by tech-savvy people who personally struggle with LBP. Finally, we discuss our future plans for this research endeavour.

Keywords: low back pain, crowdsourcing, decision support, mobile sensing
Figure 1. Screenshots of the “Back Pain Buddy” mobile application. Top row from left: 1) start screen, 2) decision support system to discover back pain treatments, and 3) example list of retrieved treatments. Bottom row from left: 1) intro screen to data collection and 2) on/off toggles to control the collection of a given type of contextual data.
INTRODUCTION

Low Back Pain (LBP) is the leading cause of activity limitations and work absence throughout much of the world. LBP is a complex issue with several factors affecting the condition. There are no silver bullet solutions to LBP, and its global economic ramifications and negative impact on the quality of countless lives, communities, and families are massive [1]. LBP ranked as the sixth most burdensome condition in the U.S. concerning poor health in 1990, and only two decades later it was found to cause more disability globally than any other medical condition [2].

The rise of personal and affordable health trackers has enabled studying, tracking and even proactively preventing several types of health issues. In particular, the so-called “medicalized smartphone” [3] is revolutionizing several aspects of medicine. Surprisingly, and despite its massive global burden, LBP is one of the few major medical research areas where not much work has been conducted with smartphones. Thus, exploring their potential role in LBP research yields a fascinating research avenue. Our work is highly exploratory by nature, and our overarching aims are to build toward exploiting people’s personal smartphones in addressing two issues specific to the LBP research field:

- While LBP is extensively documented, the lack of clear therapeutic consensus causes a plethora of treatments being advocated by clinicians and commercial operators [4]. This absence of agreement causes a practical problem in choosing a treatment, especially for people with poor access to clinicians (due to e.g., lower socioeconomic status [1]) or for the majority of ordinary citizens who first turn to the Internet for seeking help [5].
- Poor or non-existent knowledge of LBP-relevant contextual information and lifestyle ingredients (e.g., activity levels, physical environments, ambient noise, subjective and lived experience of LBP) of patients and pre-patients [2].

We present Back Pain Buddy – a mobile application that provides crowdsourced and trustworthy decision support to address issue #1 and incorporates a powerful mobile sensing solution to address issue #2. Back Pain Buddy is being developed together with the University of Oulu in Finland, the University of Melbourne in Australia, the Finnish Institute of Occupational Health, and Oulu University Hospital. It is the end user's entry point to a larger scheme to start collecting – among the first in the world – LBP-relevant contextual information using people's mobile devices in large-scale, longitudinal cohort studies. As an academic venture, we aim for openness of data and free use of the developed technologies. This is crucial, as for-profit corporations are increasingly dominating the personal user data market and pose a direct threat to science and equality (see e.g. a recent alarming opinion piece in Nature [6]). Indeed, we predicate our work on legacy and foundation for future value creation instead of immediately seeking answers to sharply formulated research questions.

The results from our user studies show that the decision support system provides value to its users and that the potential end users of Back Pain Buddy also find the mobile sensing solution as feasible. However, they have reservations regarding privacy, ethics, and harmful commercial use of the data, which all need addressing before we can proceed to larger international trials.
BACK PAIN BUDDY

Overview

The application consists of two components: decision support and mobile sensing. The first prototype of the application contained only the sensing component. We quickly learned, however, that it was challenging to recruit participants to a study where they would not receive any immediate value with the application but instead were “just” donating data. Our best efforts with a medical collaborator organization (Oulu University hospital) resulted in only a handful of LBP-patients installing the application. This was simply not a sustainable long-term approach toward our goals (outlined in Figure 2). While this pre-study was encouraging in the sense that the participants did fill in self-reports about their LBP condition for several weeks, and we also managed to collect sensor data, we needed to offer better incentives to scale up participation. To this end, we decided to include the decision support system as an added feature that provides immediate value for end users which we could then ask to donate their contextual data.

![Diagram](image)

Figure 2. Conceptual diagram of our data exploitation plans. Users get decision support in the form of ideal back pain treatments. They can also contrast their lifestyle ingredients to clinicians' and national recommendations. Researchers, on the other hand, benefit from contextual information about the lives of people suffering from LBP.

Crowdsourced Decision Support to Discover LBP Treatments

Crowdsourcing decision support via digital applications is a relatively young but inherently
powerful concept: people trust other people with experience on the topic at hands. Consider customer reviews on Amazon, for example. The same principle helps to offer decision support for any arbitrary multi-answer question, as we have explored in our own previous work [7]. The decision support system we developed uses the crowds to first break down a question into sets of candidate answers and possible criteria that can be used to assess the answers. Then, the crowds assess every answer in light of every criterion, using a "goodness" scale from 1-100. The collected knowledge base encapsulates wisdom of the crowd that can be used to compute a list of answers that best match the user's ideal solution to the question. For more information on the concept and examples of different computational means to obtain decision support from the knowledge bases, we refer to [7].

LBP presents an excellent example of a multi-answer problem that is suitable to be used with our decision-support concept. Here, we are interested in assisting users to find solutions to the question “What is a good way to treat low back pain?” To this end, we redesigned the system introduced in [7] into a mobile-first back-pain themed decision support component, embeddable in a mobile application. We upgraded the back-end to support multiple knowledge sources (crowds), to let end users choose if they want decision support from LBP-experts (doctors, physiotherapists), others than experts (non-experts), or union of both. The decision support interface is simple and only asks the user to define her ideal back pain treatment using any or all of the criteria available in the system. To achieve this, the user defines ideal criteria for a treatment using slider input elements (Figure 1, upper row, middle). The interface also contains radio buttons to choose the source of the retrieved treatments (experts, non-experts, combination). After setting the ideal criteria, the decision support system fetches the best-matching LBP treatments from the underlying knowledge base (Figure 1, upper row, right).

**Mobile Sensing Component**

Smartphones have emerged as powerful research tools for studying human behaviour and conditions, thanks to their ubiquity and increasing sensing capabilities. Mobile sensing has risen as a research domain that refers to acquiring and understanding data captured using the array or onboard sensors. Due to a fragmented device (and even OS) base, this is far from trivial, however, and several mobile sensing platforms have been built to ease the data harvesting and aggregation processes.

Especially in the context of LBP, accurate contextual information of patients and pre-patients is a key challenge to tackle [8]. Back Pain Buddy sets to fill this gap. To do this, we exploit the AWARE mobile sensing platform [9]. While others exist, AWARE is an open source, secure, extensible mobile sensing platform that enables us to collect and provide access to data on our own servers. It supports plugins, i.e., we can implement and run any custom native code – a crucial feature for our custom data collection needs. This way, we can also allow the user to be in full control of what data is collected, as can be seen in Figure 1 (bottom row, right). Using AWARE as a library in Back Pain Buddy, we are preparing to capture the following ten types of contextual data that have all been identified as highly relevant to LBP research [8]:

1. Employment (documenting type of work, effects caused by LBP in the workplace, effects of LBP to employment situation)
2. Environment (ambient information, weather, wind, temperature)
3. Pain Characteristics (type, intensity, speed, level of recovery)
4. Demographics (age, gender, height, weight, country, etc.)
5. Disability (type, extent)
6. Physical (current activity levels, maintenance, body function)
7. Psychological (effort of living, feelings of loss, disempowerment, worry)
8. Social (psychosocial challenges, negative reactions by friends and relatives)
9. Treatment (treatment burden, treatments being attended to)
10. Medical History (records, past treatments)

We note that not all of these can be harvested passively but require repeated self-reporting by the user to complement sensing-based data collection [10]. For this, AWARE provides the Experience Sampling Method, offered via a query builder and questionnaire scheduler. Together, the ten factors encompass internal and external influences, factors about current activities, and other relevant information that could be useful for LBP research and can be used to provide coaching in the form of lifestyle recommendations and encouragements. For instance, the comparison of a user's activity levels to those recommended by the user’s personal doctor transparently provides useful information to both parties. Yet we emphasize that the user is in control: each of the data types is an optional feature in the application, users can simply turn the said collection feature on or off (Figure 1, bottom row, right).

STUDIES

Study 1: Opinions on Decision Support Component
To collect the LBP knowledge bases (potential treatments, criteria, and their relations), we bootstrapped the system together with both clinical experts (doctors, physiotherapists) and non-experts (everyone else). This was conducted online, using a custom 1-page web application. On the site, users could contribute new treatments and rate others’ treatment suggestions to the question “What is a good way to treat low back pain?”. Inputting new treatments was enabled by standard HTML form input fields, and rating values happened with slider inputs (1 slider per 1 criterion), very similar to the UI depicted in Figure 1 (top row, middle) for obtaining decision support. For more information on the implemented system, we refer the reader to [11].

Instead of tapping into an existing labour market (which would not provide us with the needed expertise), as is the case in a typical crowdsourced system, we had to use a great deal of imagination to reach medical doctors and physiotherapists. We contacted a local back pain researcher (senior professor at a university hospital), who was able to provide us with access to a national back pain organization for doctors and physiotherapists. Before initiating any contact to their mailing lists, we used the local collaborators to define the four criteria that back pain patients typically find as important when looking for treatments. We did not want to have a dynamic list of criteria in the system, as the data collection needs rise linearly each time a new criterion is included. Nevertheless, the four most important ones, as judged by real practitioners, seemed like a reasonable compromise.

Using the email list of the national organization, we promoted the system to medical doctors and physiotherapists. Then, our local expert collaborators curated the list into a "gold standard" LBP treatment collection, and we sent this collection to the same mailing list for assessment. Then, to collect non-expert knowledge on LBP, the system was promoted publicly online in back pain related Facebook groups and several relevant social media profiles. As a reward, we raffled one $100 gift card to a health-themed online market.
Then, for the actual DSS evaluation, we invited those who had contributed data to the knowledge base to use the now-bootstrapped decision support system. Their task was to "play" with it, get decision support, and simply see what it can do and what thoughts arise when using such crowdsourced knowledge on LBP. Everyone using the system was invited to complete an online survey, evaluating the value proposition, perceived trustworthiness, and overall usefulness. Second, Back Pain Buddy (the mobile application embedding the DSS component) was featured for a full day at a technology fair / exhibition of a local prototype “future hospital”, managed by the local university hospital’s research division. There, we interviewed final-year medical doctors and physiotherapists touring the fair as part of a course on future medical technologies.

Study 2: Acceptability of Contextual Data Collection

To study the acceptability and future issues of the contextual data collection component, we deployed surveys online to people with self-interest in LBP. We used mainly the list of our already-devoted participants from the previous user study. We listed the ten contextual elements we are preparing to include in our data model as a Likert-scale, requesting users to consider their willingness to donate this data type for each item. Each item was ranked on a scale from 1-7 as "not at all willing" to "extremely willing". We clarified in the survey that not all data types can be collected passively using sensors but would require manual input from time to time. Another purpose of introducing the data types to the user was to make them think about the concept more deeply. We reasoned this would help them provide better open-ended commentary. We also included items about general acceptability of the concept, demographic data, mobile tech savviness, past personal experience with LBP, and open-ended items to provide feedback.

To further stimulate the participants’ thinking, we adopted elements from the Expectation Disconfirmation Theory (EDT) that is used in marketing sciences to predict consumer satisfaction with future products and that has been recently extended to predict technology trust and usage continuance intentions of technological products [12]. We adopted and described the following four items to the participants:

1. **Ease of use**; the degree to which the sensing solution will require little mental effort to use.
2. **Functionality**; the degree to which the solution will have the capability, functions, or features needed to accomplish its tasks.
3. **Reliability**; the degree to which the solution will continually operate properly, or will operate in a consistent, flawless manner.
4. **Usefulness**; the degree to which the user trusts that the solution is beneficial for its purpose.

Again, the items were presented as a Likert-scale where each item was ranked from 1-7 as “not at all” to “extremely” (e.g., "Not at all easy to use - extremely easy to use"). This section was also complemented with open-ended item to provide feedback. Together with information on users' technology savviness, these items help predict issues in the system's future acceptability [12].
RESULTS

**Active Decision Support System: Value for All Stakeholders (Study 1)**

Through the mailing lists that we got access to via our collaborators, we were able to recruit 65 experts (37 m, 28 f, age range 29 to 76 years, $M = 53.0, SD = 11.4$) to contribute 39 back pain treatments to bootstrap the decision support system. These were curated to 12 "gold standard" expert-solutions that were then re-evaluated by the same expert pool. The experts inserted 610 unique ratings for the 12 treatments and four criteria that were already bootstrapped in the system by our collaborators.

288 participants (63 m, 225 f, age range 23 to 75, $M = 47.2, SD = 11.8$) contributed to the non-expert knowledge base. This crowd had an evident self-interest in the topic, as only 18 of them had never experienced back pain in their lives. The non-expert crowd contributed 69 new treatment ideas, out of which 56 were valid (we moderated away entries that were gibberish, such as "asdf" or empty submissions). Non-experts contributed 8391 ratings for the available treatments.

46 people (9 experts, 37 non-experts) helped evaluate the actual decision support system after using it to discover treatments. In general, users perceived the DSS as highly useful in discovering back pain treatments (average 4.6, on a scale from 1 to 7). For an in-depth look into the collected data, we ask the reader to turn to [11]. We also conducted a lightweight qualitative analysis to the results. First, we loaded all the results in to a shared Google Spreadsheet, where two of the paper’s authors reduced the result set to items that we deemed as useful. Then, the same authors identified larger common themes independently, and finally again collaboratively discussed to finalise the themes and the items belonging to them. The usefulness of the system was supported by the qualitative findings:

P1, Female, 34: “The clinical care personnel get information of treatments that they do now know about, while the one with the pain learns about new options by others with pain”

The inclusion of non-expert knowledge in the tool was seen as highly crucial for the system to be interesting: 30 respondents found the combined knowledge of experts and non-experts to be the most interesting knowledge source. The same sentiment was surprisingly shared between the experts as well:

P19, Male, 53, Expert: “Academic expertise alone does not provide a holistic view to the situation. It is good to understand what people in general think and how they experience the treatments to learn new viewpoints”

However, critical viewpoints were also brought forward, especially regarding the ambiguity of the sliders used for indicating the desired criteria:

P11, Female, 50, Non-expert: “I would develop a better input mechanism than the slider. It is difficult. Traditional written scale works, as then there is no interpretation involved in giving the score.”
Mobile Sensing: Generally Acceptable but with Reservations (Study 2)

We collected 192 survey responses (participants' age from 21 to 75, mean 46.1, SD = 12.2) to our survey on the mobile sensing concept. Of these, 88 respondents identified themselves as highly mobile tech savvy (scores 6 and seven on a scale from 1-7 to the question "In your own assessment, how familiar are you with novel mobile technologies and their future potential?"). 87 identified as moderately savvy (scores 3-5), and 17 as little or not savvy (scores 1-2). We also asked about participants' personal experience with back pain, and 61 identified themselves as heavily affected by back pain, 90 as moderately affected, and 41 as little or not at all affected.

Figure 3 plots people's response on the willingness to allow data collection per each of the contextual data element and the enthusiasm to allow data collection in general. Below that, we plot respondent's future expectations toward the system's characteristics.

![Figure 3](image)

Figure 3. Top: data types plotted in order of willingness to donate. The arrow denotes overall acceptance of data collection. Bottom: expected characteristics of the final deployed system. X-axes in the plots corresponds to the percentage of responses.

We observe that respondents were overall quite positive in allowing data collection, but that there were significant differences in the allowance of different data types (confirmed by a Kruskal-Wallis Test, p<0.05). More specifically, participants were more willing to donate pain characteristics and treatment data than data on psychological or social elements (Wilcoxon Rank-Sum Test for each four pairs, p<0.05). Interestingly, prior experiences with LBP, i.e. the pain that people had personally suffered, did not significantly affect data donation willingness. We discovered, however, that respondents’ tech savviness affected the overall willingness to donate data (the item marked with an arrow in Figure 3). Those in the low-tech savviness category scored an average of 4.3, whereas those in the moderate category scored 4.7, and those with high savviness scored 5.5. People with high savviness scored significantly higher than those with low or those with moderate savviness (Wilcoxon Rank-Sum Test for both, p<0.05).

Tech savviness also played a major role in the future expectations. In all of the probed expected system characteristics (ease of use, functionality, reliability, usefulness), there were statistically significant differences between the tech savviness categories, as
confirmed with Kruskal-Wallis tests (p<0.05). People with low tech savviness expected the future system to be less easy to use (average 3.8, on a scale from 1 to 7) than moderately or highly tech savvy people (5.4 and 6.1). As for functionality, the scores per savviness categories were 4.1, 5.1 and 5.7 (low-moderate-high tech savviness). Reliability scores were 3.9, 4.6, and 5.1 (low-moderate-high) and finally the usefulness of the system was anticipated as 4.6, 5.5, and 5.9 (low-moderate-high).

The overall response provided in the open-ended items toward the concept was excited and welcoming. Some of the more optimistic comments included such as:

P12, Female, 29: “I think it’s only great if I can help others!” and

P97, Female, 39: “I’m willing to help in any kind of venture that aims for alleviating pains – and not just by giving more and more painkillers”

45 of the 192 respondents expressed three types of major reservations toward the mobile sensing component: the idea of the collected data accidentally being leaked to wrong parties; the system trying to exploit the data commercially; and ethics of the data collection in general. The following responses exemplify some of these concerns:

P109, Male, 28: “As long as the data stays only within the scientific or healthcare domains, I would donate my data”, or

P114, Male, 64: “Only a strictly sandboxed application has any chance to survive in the future “cyber jungle”

DISCUSSION

In Finland, 80-90% of all people have been estimated to suffer from back pain during their lifetimes. This highlights pain’s evergreen nature as the subject of empirical studies [1]. Our exploratory approach builds on harvesting people's contextual data and using that to shed more light on the age-old and globally massively burdensome problem of LBP. The long-term plan contributes to creating yet unforeseeable well-being assets that a greater understanding of people's lifestyles will yield. All this depends on not privately vaulting the data and offering it free to the scientific community [6].

Back Pain Buddy is our contribution to the ongoing trend of leveraging the smartphone in the health domain [3]. It is a mobile end user application that encompasses a powerful and trustworthy decision support system and a component to harvest crucial contextual information is our entry point to a system that will provide data and insights to researchers and users alike on a global scale. While we have a promising start, open questions remain. How to reward contributing? How to make sure all the incoming data is of equally high quality? While long-term field studies with real subjects in their authentic everyday environments are not easy or cheap to conduct, they are well worth it in this case: LBP is a global problem. To this end, we also note that while the knowledge base collected by medical doctors should generalize relatively well outside Finland, there are a lot of open questions on how to scale up the system to accommodate different countries, regions, and cultures. Here, we explore options such as prioritising local data (national) or allowing users to filter data only from certain countries.
On the Uses of Contextual Knowledge

Our initial plans to exploit the collected contextual span beyond just offering it to the LBP research community. First, when enough data exists on a Back Pain Buddy user, we can explore passive decision support in an attempt to nudge and coach the user toward healthier life choices. For instance, different countries have differing national recommendations on e.g. minimum exercise and activity levels or other lifestyle ingredients that people should optimally follow in their life. Especially with LBP, informing about the benefits regarding activity and keeping up a "normal" life rhythm is beneficial [4]. Thus, we will build an automated solution to inform users when their activity levels drop below personalised recommendations and if their activity patterns start to decline over time. Second, when we introduce the personal clinicians into the loop, for example by adding a field to the application where the clinician would simply enter her unique identification code to gain access to user data, we are able to provide patient data to the people who most need it, and care keepers can also start adding e.g. activity level recommendations. All this, naturally, leads to a situation where we must be highly considerate about e.g., data management issues imposed by GDPR. Here, we rely on a modified back end of the AWARE mobile sensing toolkit [9], an open source project that has been recently updated for GDPR as well.

Limitations

We also acknowledge limitations in this first exploration. First, the participants in Study 1 were mostly female, highlighting the challenge of studies where we simply recruit users online – there is no easy way to guarantee an even sample of all genders. Further, Study 2 participants were recruited mostly from the same people who participated in Study 1. While this reduces the findings’ generalizability, we argue that most of our system’s end users are people interested in LBP in the first place. Recruiting among people who have already expressed interest in the topic is a suitable approach in this case (indeed, the two studies are very different, so there is no carryover effect).

A Roadmap Toward Open LBP Context Data

As our plan progresses, we keep coming across worries by end-users that introduce new design suggestions. For instance, we need to emphasize the fact that the decision support feature is a way to discover treatment suggestions and not a replacement for visiting a doctor tends to cause confusion. The user is always responsible for her choices: Back Pain Buddy simply helps to discover treatments that can then e.g. be discussed with medical professionals. To this end, we also plan to tweak the UI to subtly steer the user to the treatments articulated by medical professionals and show an additional warning dialog when the user wishes to discover treatments by non-professionals. The treatment knowledge base is indeed community-managed, and there are always quality issues involved in user generated content.

However, we argue that the biggest upcoming challenge is a strategic one rather than a technical or design one. We must think long term, and not focus solely on immediate academic output. We are actively applying funding and looking for collaborators to focus on the following obstacles:

1. Unified definitions on how to describe the contextual data elements. Building a standard data collection scheme/language for storing the ten contextual elements [8] will enable
other research units to start contributing data and use other platforms and devices than our initial setup (Android + AWARE).

2. Securing and designing the data storage/sharing facilities. As a starting point, we are using the open source AWARE server, modified to our needs. Here, crucial first issues to solve are how to ensure all contributed data adheres to the unified definition, and how to ensure automatic data quality checks? How can we allow clinicians access to certain identified person's data vault while keeping it closed to the rest of the world?

3. Passive decision support based on sensed contextual data. We must investigate, in a series of studies, how to use the collected data so that it encourages the user to make better choices. Here, we also investigate how to best visualize users' activity levels and other lifestyle ingredients in contrast to national recommendations and other users.

4. Scale up, initiate meaningful collaborations. Our collaborators at the Finnish Institute of Occupational Health can help us scale up the research, but before this, we need to run additional studies to validate the concept with real patients and people suffering from LBP.

CONCLUSION

Back Pain Buddy is a mobile application for providing decision support and collecting contextual data – both recognized gaps in LBP research and practice. Our results show that people are willing to donate their data, and that especially tech-savvy individuals expect no problems with adopting the application. This article introduces the idea, communicates promising first results to the community, and hopes to spark interest among interested international collaborators.

BIOS

Simo Hosio (simo.hosio@oulu.fi), Ph.D., is an Adjunct Professor and a member of the Center for Ubiquitous Computing research unit at the University of Oulu, Finland. His research interests include social computing, crowdsourcing, public displays, and mobile sensing. Hosio is a member of the ACM.

Jaro Karppinen (jaro.karppinen@ttl.fi), MD, Ph.D., is a Professor of Physiatry at the University of Oulu, Finland and Finnish Institute of Occupational Health. His research interests include back pain and its regional care models, remote rehabilitation, imaging, and measuring pain on the basis of the autonomic nervous system, voice and facial expressions.

Niels van Berkel (niels.van@unimelb.edu.au) is a Ph.D. candidate at the Interaction Design Lab at The University of Melbourne, Australia. His research interests include ubicomp, HCI, mobile sensing, and social computing. Van Berkel is a member of the ACM.

Jonas Oppenlaender (jonas.oppenlaender@oulu.fi) is a Ph.D. candidate at the Center for Ubiquitous Computing research unit at the University of Oulu, Finland. His research interests include human computation, crowdsourcing, social computing and leveraging social machines for engaging citizens in research.

Jorge Goncalves (jorge.goncalves@unimelb.edu.au), Ph.D., is a Lecturer at the Interaction Design Lab at The University of Melbourne, Australia. His research interests include
ubicomp, HCI, crowdsourcing, public displays, and social computing. Goncalves is a member of the ACM.

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