Smarter Software Engineering Methods for Smart Environments

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Abstract. Wearable technology and improved processing of streaming data have contributed to the advancement of the Internet of Things (IoT) and its applications such as smart living and working environments. The development of use-cases for such solutions continue to evolve and are supported by research into security, privacy and UX, which are all seen as central to developing appropriate and acceptable solutions. Development of IoT systems may also follow best-practice engineering principles (model-driven development and testing, formal methods etc.) to ensure they will meet all requirements and perform as expected in (often) uncontrolled environments. We argue, however, that there are two key concepts that are still overlooked. We define these as 'Data Sovereignty Management' (DSM) and 'Quality of Life' measurements (QoL). In this paper we present examples of how and why DSM and QoL should be considered central within the development of IoT systems, and propose that software engineering methods be extended to include these.

1 Introduction

The increase in the availability of cheap, lightweight sensors and wearable technology, alongside the development of smarter processing methods using edge and fog computing, has helped to move Internet of Things (IoT) solutions into the mainstream [5, 18]. Although the idea of IoT-enabled "smart cities" (where interconnected devices, people and infrastructure can be used to make everyday living easier) has been around for many years, there is an increasing desire to scale this down to specialised "smart living" environments [19, 4]. These are typically envisaged to provide support to enable groups such as the elderly, or those with specialist medical needs, to live in their own homes (rather than moving into care homes or hospital settings). They aim to use IoT solutions to ensure that the people the technology is focussed on are safe (for example are following medication protocols or maintaining routine behaviours).

The development of such solutions leads to research questions based around key considerations such as privacy and security of data collection [1, 8, 20]; optimising cloud computing via techniques such as fog and edge computing [6, 2]; the usability of the technologies that will surround people in their every day lives [17, 15]. These, and similar topics, are at the heart of much of the research that is undertaken when IoT solutions are developed. These often devolve into specialist research areas such as: Cyber-Security; network architecture; artificial intelligence; HCI or UX, which are then used as the basis for supporting new solutions of the use of IoT in various domains.

There are, of course, other considerations which we need to take into account when developing these 'smart' environments. One of these is understanding the effect that living in a smart environment has on the people who inhabit them. This is different from UX and usability considerations as it needs to take into account the long-term effects of reduced autonomy (due to being forced into a routine that is deemed safe by the system) or constant monitoring in peoples' everyday lives. While this may be studied as a part of traditional HCI evaluation studies (e.g. [9]) there is not a well-defined approach for doing this or understanding how to capture and use such data in general. This leads to fundamental questions of how can we effectively reason about these effects during the design process and, subsequently, in evaluation studies?

Alongside these direct effects of living in a smart environment there is also the consideration of data, and more specifically data ownership. IoT solutions based around the monitoring of individuals or groups of inhabitants generate large amounts of data which is both heterogenous and, in many cases, constantly streaming (big data) much of which can be considered personal data. Initiatives such as the EU General Data protection Regulation (GDPR) [10] have highlighted the need to ensure users have control over how their data is used, and by whom. While these regulations mandate greater transparency, they do not necessarily address all of the relevant issues pertaining to personal data. This is particularly relevant now that data has become a form of 'currency'. There is currently no guidance on how to assist developers in tracking all of the necessary data sovereignty requirements throughout all parts of a development process.

In this paper we contend that both the engineering principles we use to design and develop IoT systems and smart environments, as well as the evaluation and testing techniques we use to ensure they are usable and error-free, must be able to include these more detailed considerations of the effect on a user's quality of life (QoL) as well as data sovereignty management (DSM) principles. We define QoL to include not just the everyday experience of using (or living within) the technologies, but the longer term implications on users' way of life from the use of technology in this way as well as the management and ownership of data collected by such technologies. DSM affects the complete life-cycle of data from sensing, communication, pattern analysis to long-term storage and access.

We will argue in Section 3 that both software engineering methods and model-driven development techniques are lacking consideration for user quality of life as well as data sovereignty management.

In order to demonstrate how these problems may manifest we provide two real-world examples of IoT solutions which highlight the issues identified, and then suggest an approach to begin to address this.

2 Examples

2.1 Monitoring Workers in Hazardous Environments

Since 2014 the Hakituri project[1] has been investigating solutions based around the use of wearable technology for workers in hazardous environments. The initial aims of the project were to identify appropriate data that could be gathered from workers in-situ that could be analysed and used to identify fatigue. This was done with the goal of helping with accident prevention in high-risk work environments, such as forestry [3].

In the initial stages of the project a wide variety of personal and contextual data types were considered and/or experimented with, for example: worker activity levels based on step counts, role, heart-rate, heart-rate variability (HRV); worker well-being based on hydration, sleep patterns; contextual factors such as ambient temperature; humidity; terrain type.

It was clear early on that while the workers who participated in our studies were keen to be involved in research that may have potentially life-saving benefits, they were also uncomfortable with the nature of some of the data being collected and how it might be used. For example, if a wearable solution identifies a worker as being fatigued and his boss is notified what is the result? Is the worker given time to rest before continuing with his work, or sent home for the rest of the day and not paid? These started to create ethical questions around the type of data collection we wanted to do which related to the intended use of the data vs. its actual use (worker safety vs. management tool). It also led us to reconsider the use of off-the-shelf wearable solutions due to lack of data ownership associated with such tools.

The issues around data collection in this project are further complicated by the fact that a large proportion of the workers in the target industry are Māori. This means that, as we collect large amounts of data (numerous workers on a daily basis), we are creating a large personal dataset, and therefore our DSM needs to include the principles of indigenous data sovereignty [11–13].

From these we identify our first problem statement:
How can we ensure that data collected in IoT solutions is always treated in accordance with the system requirements and the end-user wishes?

Our proposed solution to this is that data must be treated as a first-class citizen in all parts of the development process. This means that at the requirements stage we must identify and describe all aspects relating to: what data is collected, how will it be used in all parts of the system, how/where is it stored, who owns the data, who has access to the data etc. Then as we begin to develop our system, we must continue to include DSM in whatever engineering process we follow. So if we are using a model-based development process the models must include the DSM and enable us to reason about it (e.g., to ensure the requirements are met) in the same way that we reason about functional behaviour and user interaction. Testing and evaluation methods must also be extended

[1] https://isdb.cms.waikato.ac.nz/research-projects/hakituri/

to similarly include the DSM and ensure that the developed solution correctly manages the data in accordance with the requirements.

Including the data as a component in our software models will help to ensure that we can reason about it within our development process. However, we also need to consider DSM as a component with our human centred approaches. That is, not only do we need to find ways of gathering requirements about the data from the stakeholders, but also ensure that our usability testing includes this aspect. For example, we must ensure that if the user requirements are that they should be able to specify different parts of the data and who has access to these (in our forestry context this may be the supervisors of work teams or family members who can see some, but not all, of the data) then we should provide usable methods for users to define this personalisation. DSM, therefore, includes both determining how the data should be managed as well as all aspects of controlling that management both within the system and by the users.

2.2 Developing Smart Home Environments for Elderly Care

An increasingly common use-case proposed for smart-home environments is a supportive environment for the elderly which enables them to continue to live in their own home safely, see [7, 16, 21, 22] for just a few examples of this. Such systems may be designed to monitor behaviour of those living in the environment to ensure that they are 'safe' which may be based on behaviour patterns, adherence to medication protocols, identifying potential danger through fall analysis etc. Depending on the complexity of such systems there are a number of technical challenges that are typically identified that need to be addressed which may include things like how the sensors are used to collect data and then make predictions (AI and machine learning challenges), privacy and security of the networks and data (cyber-security), structure of the system and its dataflow to ensure accuracy and coverage criteria (architecture) ability of the end-users to interact safely and successfully with the systems (usability).

What is typically missing from explorations about how to satisfactorily develop such systems is an understanding of the impact on the quality of life of those who are living in the environment. In 2015 the Superflux lab created the "Uninvited Guests" short video[2] for the ThingTank project[3] which explored the tensions between embedded technology designed to assist an elderly man living alone and his desire for autonomy in his daily life. This has become part of an ongoing dialogue which seeks to understand the real implications and impacts of these smart environments on those who inhabit them. However, this has not yet translated into any systematic development and evaluation methods which allow us to understand such quality of life metrics during the development lifecycle.

While usability and UX can consider the user's interactions with the system, and to some extent how it makes them feel during that interaction, it does not capture the longer term implications of having technology incorporated into our

[2] http://superflux.in/index.php/work/uninvited-guests/
[3] http://thingtank.org/

everyday lives. A small example of this can be seen in the way fitness trackers are use. A study by Endeavour Partners found that a third of U.S. consumers who purchased a particular brand of fitness tracker stopped using it entirely within six months [14]. Initially there is a novelty which leads to enjoyment and good UX, the positive feedback and motivational aspects can both be appealing and seem supportive to users. However, over time use typically drops off (and is abandoned) as the intrusiveness of reminders, or the feeling of failure that may be engendered if daily targets are not met degrades the user experience with increased use.

This leads to our second problem statement:
How can we measure the impact of IoT solutions on the quality of life of end users to ensure that the solutions we propose and build are not just usable but also acceptable?
This goes beyond traditional UX measures and requires us to find tangible ways of both measuring, and including the measurements of, QoL into all stages of a development process. This requires the development of an evaluation framework that can be used to predict the outcome of envisaged scenarios, as well as measure them during traditional user evaluation. We also need to be able to measure the potential impact of subversion (alongside traditional problems such as loss of connectivity, data corruption etc.) that may occur with data collection to understand the trustworthiness of the data before using it (e.g., following the approach described in [23]).

3 Conclusion

The QoL and DSM we have described are not distinct, but rather interconnected. If the users' quality of life is negatively affected by living within a smart environment they may act to subvert the system or avoid using it, which then has an impact on the quality of data being collected and ultimately the utility of the system. Similarly if it is not transparent to users how their rights and interests in the collected data are being managed and protected this may directly affect how they feel about the system and impact their quality of life.

If we consider state-of-the-art software engineering methods, and in particular model-driven development techniques, two dimensions are currently missing. The first is a reliable method for measuring and evaluating quality of life impact (QoL), the second is a way of recording data management processes as a first class citizen in the model-driven engineering process. While we recognise both of these concepts as important, the problem of developing engineering practices that address these concerns during development, testing and evaluation has not yet been addressed.

Furthermore, while IoT technology is often considered as if it were providing solitary solutions, most smart living environments will be a combination of technology solutions, thus further complicating issues of long term impact on QoL and increased complexity of DSM.

The answer to the discussed problems will be to ensure that both QoL metrics and DSM are included as first-class citizens in robust software engineering processes. In this way they can be reasoned about along with all other parts of the systems being developed.

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