A HUMAN CENTRIC

APPROACH TO THE INTERNET OF THINGS

by

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ABSTRACT

This research focuses on human interaction with the IoT, not only from the perspective of the user, but also considering the requirements that smart objects should meet to support human activities.

It analyses how the IoT was originally conceived from a technology and data driven approach, and why there is a need to provide an IoT framework that considers humans' tasks and goals. As such, the nature of the actions and interactions found in a human-based IoT are discussed in the context of social-like collaborations, where actors are in pursue of a common goal.

This thesis reframes Human-IoT interaction as a social, collaborative system, described in terms of its capacity to support the activities of the involved social actors in pursuit of a common goal. An structure is proposed to describe the nature of these interactions, and a methodology to model user behaviour based on the tasks and goals supporting a theme is proposed. The methodology is used to analyse the requirements of a domestic IoT system, leading to the implementation of a demonstrator system, and a study to validate the method.

This research posits that user experience should inform IoT system design to prevent misunderstanding of its purpose.

To Jimena and Regina,

for they are the stars of my universe.

Love you,

always.

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PUBLICATIONS

Concepts, figures and some material used in this thesis has been previously published in the following papers. Where appropriate, chapter and sections where material from these papers is used, is identified.

Conference Papers

Cervantes-Solis, J. W., Baber, C., Khattab, A., & Mitch, R. (2015). Rule and Theme Discovery in Human Interactions with an 'Internet of Things.' *Proceedings of the British HCI 2015 Conference* (pp. 222–227).

Cervantes-Solis, J. W., & Baber, C. (2016). Towards Theme Discovery Paradigm in the Internet of Things. In P. Waterson, R. Sims, & E.-M. Hubbard (Eds.), *Contemporary Ergonomics and Human Factors 2016* (pp. 335–340). Chartered Institute of Ergonomics & Human Factors.

Cervantes-Solis, J. W., & Baber, C. (2017). Towards the definition of a modelling framework for meaningful human-IoT interactions. *Proceedings of the 31st British Computer Society Human Computer Interaction Conference* (p. 28).

Cervantes-Solis, J. W., & Baber, C. (2018). Modelling user interactions in the IoT. *Proceedings of the Ergonomics and Human Factors Conference 2018*. Chartered Institute of Ergonomics & Human Factors.

GLOSSARY OF TERMS

6LowPAN: IPv6 over Low Power Wireless Personal Area Network, a communications protocol for constrained devices.

AP: Wireless Access point.

API: Application Programming Interface.

BLE: Bluetooth Low Energy, a wireless Personal Area Network communication protocol with low power profile.

Bluetooth: A wireless Personal Area Network communication protocol.

CoAP: Constrained Application Protocol, a communications protocol suited for constrained devices.

CSV: Comma Separated Values file format; data are formatted in columns and rows.

DHCP: Dynamic Host Configuration Protocol, a network management protocol to dynamically assign network addressed to network nodes.

Ecology: In biology, the study of relations and interactions of organisms and their environment.

Ecosystem: In biology, a group of interconnected organisms.

HCI: Human-Computer Interaction.

HII: Human-IoT Interaction.

HTA: Hierarchical Task Analysis

HTTP: Hypertext Transfer Protocol, a structured data format allowing for the creation of links to other data.

HTTP GET: An HTTP request to obtain information from a linked resource.

HTTP POST: An HTTP request to publish information to a linked resource.

IoT: Internet of Things.

IP: Internet Protocol.

MQQT: Message Queuing Telemetry Transport, a message based protocol for low bandwidth communications.

NAT: Network Address Translation

RFID: Radio Frequency Identification

SPC: Sensing, Processing and Communications, the enabling characteristics for the IoT

TAFEI: Task Analysis for Error Identification.

TCP/IP: Transfer Control Protocol/Internet Protocol. Suite of communication protocols underlying Internet and computer networks connectivity.

URI: Unique Resource Identifier, a code to identify resources in a network.

Wi-Fi: IP based wireless communication.

ZigBee: A wireless communication protocol for Low Power, Low Bandwidth Personal Area Networks.

Contents

List of Figures

List of Tables

1 Introduction

The number of things embedded with electronics, software, sensors, actuators and network connectivity has distinctly increased in recent years. These items can connect to with each other and exchange data, including mobile phones, vehicles, home appliances, health kits, industrial devices and city infrastructure to name a few, which are now collectively known as the Internet of Things (IoT).

The Internet of Things has gained interest from the industrial, commercial and research sectors. Examples are found in applications ranging from industrial automation, city infrastructure monitoring and management, to healthcare and consumer electronics. In the latter, human interaction becomes a predominant feature. Specifically, home automation presents challenges for research in terms of how humans interact with these systems, and this thesis focuses in the 'Domestic' Internet of Things, to frame its research questions.

For Human-IoT Interaction (HII), Stankovic (2014) defined three main challenges:

- *Understanding how humans can exert control in the IoT*

- *Identifying models of human behaviour*
- *Determining how to introduce human behaviour into control methodologies*

In this regard, this thesis aims to explore aspects of humans integrating into a system with the IoT in pursue of common goals.

1.1 Research Questions

IoT research has been framed under a technology-centred approach in which data and communication strategies take the forefront. This paradigm often leaves human users in a second plane, even in those applications that are closely related to their human users, such as domestic applications. As such, this thesis looks to answer the following research questions:

- Why is there a requirement for a human based view of the IoT over a 'tech-centred' paradigm?
    - What is the nature of the Human-IoT Interactions (HII)?
    - How humans make sense of interactions with the IoT?
- How can the IoT be characterised to support human activities?
    - How are activities described in the IoT?
    - Can Interaction design strategies be applied to model and develop a human-centred IoT?

A commonly accepted definition of the IoT establishes it as a "*network of devices with sensing and processing capabilities*" (Atzori et al., 2010). Nodes in a network share information, infrastructure and resources, which as will be discussed in the following chapters, allow objects to possess autonomic behaviour.

The IoT autonomous paradigm described above, assumes that *things*[1] are organized into networks that can perform tasks to allow humans to offload some activities to the system (Kortuem et al., 2010), to improve quality of life (Wilson et al., 2015). This implies that the IoT requires interaction with human users in order to establish specific goals (Gaglio, 2014). As such, one can envisage exchanges between users and *things* which have social-like attributes (Atzori et al., 2014), to imbue this interactions with meaning (Barthel et al., 2010).

From this perspective this relationship between humans and *things* becomes a 'socio-technical assembly' which *things* become meaningful to their users through their functionality or their relatedness (Barthel et al., 2010). Farooq and Grudin (2016) argue that a symbiotic relationship exists between users and objects, moving forward from interaction to integration into a system in terms of their relationships, implying that meaning is built upon negotiation of activities between each humans and *things*. As such, the design and development of IoT systems should consider agency of *things* and humans, to understand *"interdependence of human and non-human actors, and crafting meaningful interactions between the relevant actors in a context"* (Cila et al., 2017). It is plausible, in this context, that 'agency' is not simply a matter of the human being in control and the things following the orders from the human, but rather than different stages of the interaction will see either human or *things* taking the lead. This means that, in new designs for IoT, *"product designers are faced with new forms of material affordances"* (Cila et al., 2017), and these affordances are often distributed across platforms and technologies. Moreover, these new affordances will go beyond their original conception (Baber, 2018). As such

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[1] In this thesis, *things* is italicised when referring to an object part of the Internet of Things.

"*the designer is also responsible for considering the multiple overlapping relationships with other products and contexts while giving form and ascribing behaviour to a product*" (Cila et al., 2017).

In The Design of Future Things, Norman (2007) argues that *"as we start giving objects around us more initiative, more intelligence and more emotion and personality, we now have to worry about how we interact with our machines"*, highlighting a requirement for the definition of new design patterns for Human-Computer Interaction.

Arguably, many IoT applications have been developed with a heavier focus on the business case they aim to support, and less so on human factors. In a paradigm in which the IoT enables 'smart' objects, failure to consider people's expectations and experience in their design creates misunderstandings about the object's purpose, which potentially affects adoption.

For example, IoT devices such as a smart salt grinder (Figure 1.1), arguably fall flat due to being unnecessarily smart. Such devices might be interesting conceits, but they might not address a real problem that requires a technological solution or do not make their functionality completely transparent to the user. According to its marketing literature, the designers of the device aimed to conceal a digital hub centred on a dining table in a connected salt shaker, hypothesising that the salt shaker's ubiquity would aid in its adoption to fulfil a secondary goal. In this case, to be able to control different aspects of the household, such as lighting or ambient music. As such, it could be argued that, as intended by its designers, the device's and user's goals might differ.

Figure 1.1 A 'smart' salt shaker (source: mysmalt.com)

1.2 The Internet of Things

The term ‘Internet of Things’ (IoT) is widely attributed to Kevin Ashton (Ashton, 2009; Sarma et al., 2000), a founder of the *Auto-ID Center* in the Massachusetts Institute of Technology (MIT). The purpose of this research centre was to establish a way of tracking objects in the supply chain of retail and manufacturing industries, with the primary aid of radio-frequency identification (RFID) technology (Auto ID Labs, 2014). Since then, we have transitioned from simple, passive sensors that could track a device’s status, to active devices that can both receive and transmit data pertaining their location, status and environment, and take action to achieve a goal.

Zanella et al. (2014) describes the IoT as a:

“recent communication paradigm that envisions a near future, in which the objects of everyday life will be equipped with microcontrollers, transceivers for digital communication, and suitable protocol stacks that will make them able to communicate with one another and with the users, becoming an integral part of the Internet”.

Ultimately, the IoT will involve billions of devices are networked to collect and process information to provide insight and intelligence for its stakeholders (Rose et al., 2015). Today these devices include, for example, thermostats (Nest Labs, 2014); health monitoring scales (Withings, 2017) and light bulbs (Philips, 2014). It has been adopted in fields ranging from manufacturing (Bi et al., 2014); health (Islam et al., 2015); the home (Jie et al., 2013), and cities (Zanella et al., 2014) to name a few.

Gartner, a market research firm, has stated that:

"The Internet of Things, which excludes PCs, tablets and smartphones, will grow to 26 billion units installed in 2020, and will generate incremental revenue exceeding $300 billion" (Gartner Inc, 2013).

ARM Ltd., market leader and provider of the CPU cores running on 95% of smartphone devices and those found in close to 40% of IoT devices in 2016, forecasts that by 2035, over 1 trillion devices, will power the IoT (Sparks, 2017).

Moreover, the Internet of Things field has rapidly grown to encompass different areas interacting with each other, creating opportunities and challenges not only for technology, but also on how users interact and adopt IoT enabled devices.

This represents a rapidly expanding number of connected devices and use cases. Arguably the principal beneficiaries of the services provided by these networks have been the enterprises who are promoting these technologies as part of their business models (Fleisch, 2010; Makinen, 2014; Regalado, 2014). In this regard this field could be considered an attempt to create a new necessity to drive and increase the market dominance of the biggest Internet companies aiming to create new business models and revenue streams by providing new ways of gathering data and monitoring processes in real-time (Sterling, 2014; Butler, 2016).

1.3 IoT paradigms

From a research point of view, the IoT is not a novel concept, but a reorganisation and reutilisation of concepts in stablished areas of research including: embedded systems, wireless sensor networks, mobile, pervasive and ubiquitous computing, (Stankovic, 2014). Moreover, Bijker (2014) suggests that technology analysis can be framed within four units of study: the singular artefact, the technological system, the sociotechnical ensemble, and the technological culture. As such, we could derive different visions for the IoT, depending on the application and scope. From raw sensor data to the more complex interaction of devices, networks and users in these environments. Bijker framework posits that research on these units goes from the specific technological aspects (singular artefact), how they interact with others (technological systems), how they impact normative and cultural aspects (technological culture) and how they influence society (sociotechnical assembly). The latter vision focusing on the relationship between technology and users. As such, in contrast to the definition that considers the technical implementation aspects of the IoT Atzori et al., (2010) define three converging visions that also considers three types of interactions in the Internet of Things in terms of: the objects ('things'), the network ('internet') and the semantics that give meaning to the interconnection of networked devices in this environment to their human users. Thus, a broader view of the IoT should consider both the underlying technologies that drive it, the context of operation, the relationships amongst devices and users, and the purpose of these communication exchanges. This thesis focuses not only on the technical system, but on the 'ensemble' formed when humans interact with the IoT, as will be discussed in the following chapter.

1.3.1 Humans in the loop

This thesis considers IoT systems in which humans are the main stakeholders, and focuses in the human-computer aspects of the interactions between system, objects and human users.

Miorandi et al. (2012) argue that device interoperability is required for a system to be able to 'reason', postulating that 'reasoning' is a result of the distributed cooperation between the "*system's resources and the user's needs and expectations*".

In contrast to development in Industrial or Infrastructure IoT applications, the number of IoT systems that require direct human intervention has increased over time with the development of applications addressing the consumer electronics, health care and home automation areas (Stankovic, 2014). In some cases, these applications expect some kind of user input and in others, the human becomes the beneficiary of its services. Thus, the human becomes part of the IoT system, and could be considered as another node in the network (Nunes et al., 2015). As mentioned in later chapters, one characteristic of an intelligent agent is defined by their ability to interact with other agents to reach their delegated goals. Atzori et al. (2011) suggests that the interactions of human and things in the IoT could be considered a social organisation, producing mutually beneficial relations of agents that collectively create a 'society of smart objects'. Analogous to Minsky's (1988) definition of a 'society of mind', where agents interact with others, performing actions that could be described as cognitive, the interaction of 'things' and their users establish a relationship that gains meaning primarily through this collaboration. In this regard, when objects support user's activities in a proactive and positive manner, users attribute value and purpose to the device (Norman, 1993a).

In his research Grey Walter (1950) focuses on how a simple robot with a limited set of sensors and actuators could attain its goal and appeared to possess intelligence. Moreover, (Brooks, 1991) described how intelligence is built incrementally, upon the aggregation of different activities and by delegating perception to different elements in the system. The net effect, according to Brooks, is that the representation of models is decentralised to the various components of the society of objects, each enacting their own particular role.

Hence, in a system in which humans and users collaborate, it is worthwhile not only to analyse what the machine's roles are, but also what do the humans expect and as a consequence, the human's own roles in the system.

When taking into account applications that are aimed to human users, the notion of interaction between the IoT and these users becomes an important consideration in the system's functionality. For example, an automatic thermostat requires its user to provide a temperature set point in order to achieve its purpose of temperature control, and the human requires of the thermostat to achieve its desired comfort level. Actors take part of a collaborative endeavour to accomplish their tasks. Moreover, in the IoT there is an expectation of a degree of decision making or 'smartness' from its devices and platforms.

Current trends in technical development have enabled the Internet of Things (IoT) to shift from passive objects (Smith and Konsynski, 2003), to *things* that actively engage with their environment, other *things*, and human users (Kortuem et al., 2010). From the simple Radio Frequency Identification (RFID) enabled objects used in the IoT's origins, *things* have evolved into complex objects imbued with agency, intelligence and autonomy (Fortino, 2016). Commercial and enterprise marketing promises that between the IoT and the mobile Apps ecosystem, objects would be connected to each other, allowing for seamless service composition, effectively creating a 'blanket of smartness' that would make common activities easier for the users (Bojanova et al., 2014). Market leaders, such as Intel, have promised ecosystems that would improve efficiency, safety, providing a richer experience to users, so that, devices

"*will become smart enough to function on their own, making real-time decisions, learning from their environment, and using that learning to improve performance*" (Intel, 2017).

Gartner Research (Gartner Inc., 2014) identifies a 'hype cycle' curve to characterise how technology is generally adopted and utilized (Figure 1.2).

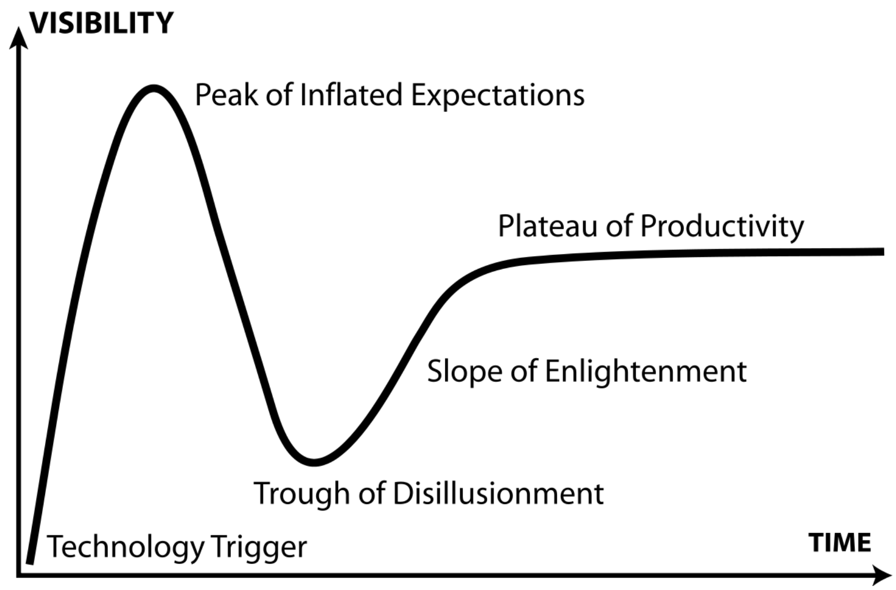

Figure 1.2 Gartner's hype cycle (Gartner Inc., 2014)

Although this hype cycle is not generally accepted as a rigorous, scientific methodology, it provides a reference frame to put technology expectations and requirements in perspective. The research firm puts the IoT on peak phase of the cycle, and arguably for IoT with humans in the loop, the involvement of the user often influences their adoption and engagement. Kuniavsky (2010) argues that a system's chances of getting through its hype phase is determined by how useful and meaningful its services are to its users.

1.3.2 Domestic IoT

One common area of application of IoT technologies is that of home automation or ‘smart home’, with devices ranging from automatic temperature controllers, connected refrigerators, and automatic kettles and coffee makers to name a few. According to market research firm Parks Associates, in the U.S., user’s intention to purchase at least one ‘smart home device’ has increased from less than 25% of households in 2014 to almost 50% by the end of 2017 (Parks Associates, 2018). Notwithstanding their adoption in consumer electronics, it is also found that the percentage of consumers that experience some kind of problem with their ‘smart home devices’ is close to 35%, with problems ranging from connectivity and energy management, but primarily to *“unresponsive or overly sensitive devices that create false alarms”*(Connected Thinking, 2017).

There are a number of established IoT commercial applications such as automatic thermostats and lighting that provide a range of opportunities to analyse how human users react to automation technologies, and on the other hand how these systems are implemented and how they are expected to support user’s activities (Wilson et al., 2015). Moreover, home automation aims to provide *“better living experiences”* (Gračanin et al., 2011), and as suggested by Mennicken et al. (2014) provide *“peace of mind”*, enabling social and environmental ‘good’ behaviour. In terms of complexity, domestic IoT provides multi-user environments such that different perspectives could be considered. Finally, domestic IoT provides a framework for emerging automation possibilities, as the tasks and activities that occur within the home environment are well defined, and in some cases, such as those tasks requiring extra effort or are tedious to the user (i.e. cleaning up), would be welcomed as candidates for automation, promoting adoption and meaningful experiences.

Rode et al., (2004) suggest that when using programmable home appliances (such as a heating system), the decisions on how and when to set them, is not done in isolation, but by considering the context of the appliance within the household dynamics. Takayama et al. (2012) found that satisfaction levels within home automation technologies were higher in systems that allow for clear and 'organic' connections to the home and to family members. Similarly, Bourgeois et al.(2014) proactively inform users of the impact of their washing machine routines and the best times to perform these activities to encourage engagement and participation. These studies suggest that users tend to think of the consequences of their decisions when interacting with these 'smart' appliances. Additionally, users consider them a collection of interconnected devices that affect each other. Providing information relating to the outcome of their goals also leads to a better understanding and engagement on these systems (Yang and Newman, 2013; Revell and Stanton, 2017). This thesis focuses on applications that fall within this domestic category, as it relates to a context in which humans are closer beneficiaries of the IoT's outcomes.

1.4 User's expectation of the IoT

The intelligent IoT vision is not a novel concept. Mark Weiser (1991) explored the scenario of ubiquitous computing available across all physical spaces, intermingling invisibly with our everyday activities, automating the most tedious, such as making coffee or toast, and supporting the more complex such as driving.

In this context Stankovic et al. (2005) extended the notion of ubiquitous computing to consider the inclusion of sensors and actuators integrated into real-world scenarios and devices providing the capability to focus on the "*physical, real time, and embedded aspects*" identifying the notion as *physical computing.* Moreover, Rajkumar et al. (2010) extend the notion as *cyber-physical systems* to consider the computing capabilities that "*transform how humans interact and* *control the physical world around us*". As such, this paradigm provides a foundation for a smart Internet of Things that suggests a networked organisation of agents performing automated tasks allowing humans to offload some activities to the system (Kortuem et al., 2010) to improve their quality of life (Wilson et al., 2015; Stankovic et al., 2005).

Like Weiser's, these definitions are focused on expectation's placed upon the system, and less so on considering aspects of the interaction with the objects and environments from the user's perspective and their role in completing goals. This *thesis* posits that users' requirements are to be considered as an aspect for IoT design that promotes proactive behaviour both from users and devices, as will be discussed in further chapters.

Norman (2014) observed that we have many things that make us smart, from writing to calculators and computers. However just because the technology allows for their 'smartification' through embedded sensing, processing and communication capabilities, it shouldn't necessarily imply that an object would benefit from it, nor that having the object do the thinking for us would make life easier for people. The problem might well be that intelligence without understanding can be frustrating to the user.

Norman (1993) argues that some technology has developed almost by accident, without much planning, allowing for an emergence of a machine centred view of technology, relegating users to a second plane and forcing them to behave in a machine-centred manner.

The disassociation between a system's and user's goals has been analysed from the point of view of common appliances such as smart thermostats in which users fail to understand the system's behaviour (Yang and Newman, 2013). Or in home automation in which systems often provide interfaces primarily aimed to technology early adopters, and less so to the 'common' user (Takayama et al., 2012).

In some applications it has been observed that the notion of ‘smartness’ is not necessarily used in the right context, nor completely well interpreted. Corporate marketing materials often make incorrect assumptions, such as the prevailing idea that

“…its smart because you can control it from your mobile”.(Nest Labs, 2017)

Similar quotes are usually found in advertising for internet enabled devices: smart coffee makers (Mr. Coffee, 2017), smart scales (Withings, 2017), or smart fitness trackers (Fitbit, 2015), just to name a few. In some cases, the devices add extra functionality by providing information such as the amount of water or coffee required to prepare a cup. However, relying on a software application on a smartphone as the main user interface, arguably moves any notion of intelligence from the *thing* to the mobile app. From an operational standpoint these systems could be considered devices with remotely accessed features with no autonomy that qualifies them as smart.

The current iteration and roadmap established for the development of autonomous cars, provides a vision of ‘smart systems’ closer to what is generally expected from the IoT. In autonomous vehicles development five stages of automation are defined, ranging from the most basic at level 1 to a fully autonomous operation at level 5 (Litman, 2014). Level 1 enables vehicle features such as cruise control, that is, only the speed of the vehicle is automatically controlled, whilst the operation of the vehicle is the driver’s responsibility. At level 5, full decision making of the vehicle is expected in all possible terrain and driving conditions, with no user input in regards to vehicle operation. Parameters such as energy management and engine integrity are optimised, providing the system with a notion of self-well-being in order to maintain adequate operational standards. On the other hand, from a user’s perspective it is expected that benefits such as safety, comfort and convenience are increased as a result of the device's autonomous operation (Atzori et al., 2014b; Chi et al., 2007).

Although the analysis of commercial applications is not the focus of this work, in order to provide a framework for a user centric IoT, it is important to consider how commercially available IoT solutions influence the perception that users have towards IoT systems. In this regard, Norman (1993) coins Grudin's law as "*When those who benefit are not those who do the work, then the technology is likely to fail or, at least, be subverted",* highlighting the problem that arises when the persons who design technology are not the same who use it.

In contrast to what the consumer electronics market suggests, a formal definition of intelligent systems implies that in order to consider that they have a degree of 'smartness' they must possess operational mechanisms that allow them to take the appropriate actions, given the right conditions, in order to achieve a goal (Sheth, 2016a). Humans expectation of autonomous systems has been identified in different research initiatives, characterising it as: reliable (Lee, 2008), transparent and understandable (Bellotti and Edwards, 2001), personalised and aware of their context (Perera et al., 2014) and will provide help when required (Augusto, 2007).

According to Chilana et al. (2015) user experience in HCI influences system adoption, highlighting the requirement for providing system design and evaluation that *"goes beyond-the-user market adoption".* When considering 'smart' objects, the question would be how usability promotes the notion of smartness. As discussed in Chapter 2, agents pursue their goals. As such, there is an opportunity to reframe development of IoT systems in the context of human involvement, considering machine's goals that relate or support the users'.

This thesis posits that the user's expectations and requirements should be at the forefront of IoT design, and that for it to be considered 'smart' there is a consideration to be made to approach it from the perspective of a human-centred vision. This would support the definition of design requirements for the IoT, by identifying relationships amongst its nodes, both human and machine. In chapter 4 this thesis explores a means of conceptualizing the interaction of humans and *things* in the IoT in a social context in terms of the notion of IoT conversations (in which humans and objects cooperate to pursue specific topics in terms of common themes).

1.5 Motivation for research

For the different stakeholder groups involved in IoT development, the focus of research generally shifts from 'things' to 'internet', to data analytics, depending on what they are expecting to gain (Atzori et al., 2010). It has been claimed that from a purely business model perspective, data which can be analysed to gain insight into consumer habits becomes valuable, and thus these technologies have been mainly driven by market forces relating to data harvesting (Sterling, 2014).

In (Aazam et al., 2014; Atzori et al., 2010; Gubbi et al., 2013; Ortiz et al., 2014; Stankovic, 2014) the principal challenges for the development and fulfilment of the IoT are:

"1. Standardisation and interoperability between networks

2. Data integrity

3. Privacy, security, trust and Quality of Service

4. Architectures

5. Accessibility (openness and decentralisation)

6. Energy and fault tolerance management

7. Human in the loop, interaction and interfaces

8. Thing and service discovery

9. Semantics and context management"

All these foci present opportunities for research and development.

Nonetheless, it has been argued that the main beneficiary of IoT systems ought to be the human user (Atzori et al., 2014a), who benefits from the insights the system provides. Notwithstanding, this is not always the case, as the focus of research and development has been on the technical aspects of the IoT such as communication protocols and frameworks, data collection and analysis and the application of these data in the context of machine learning solutions aimed to provide insights into aspects of the IoT solutions. Thus, this thesis focuses on Human-IoT interaction (HII) (Guo et al., 2012b), identifying how humans perceive and interact with 'smart' objects, and in how these *things* are able to convey their purpose. Given both their physical and data-centred characteristics, human interaction is defined and affected by these properties.

The IoT provides an opportunity for creating objects and environments that can be considered smart. If these objects have characteristics that allow them to behave in an intelligent fashion, by providing purposeful information to the user, a more transparent and meaningful user interaction could be achieved. As such, the research of a methodology for the creation of intelligent *things* could enable new opportunities towards creating the vision of the IoT in which the devices are intelligent enough to provide answers to questions that users require.

Current commercial IoT development usually follows the design and development route of data first then product, or product then data (Manyika et al., 2015). That is, development often aims to use data collected from a certain process or use an established product to collect data. Although this approach has produced successful systems, it can fail to consider the main goal of the product and what human activity is it supporting. In the case of human centred products and services, this approach often disregards user requirements over commercial functionality and data harvesting processes (Sterling, 2014). Thus, one of the fundamental aspects of *things* would be their ability to support and extend human activities. In this regard, this thesis aims to analyse how these activities are characterised in terms of the goals human users aim to achieve, and whether smart objects are capable of complementing these activities.

1.6 Contributions

This thesis will address challenges faced by humans interacting with an Internet of Things, its functionality and its implications on user's expectations. By framing the interactions as a collaborative endeavour, the relationship between IoT devices and their human users is explored by establishing a social-like communication, in which a common objective is expected, and how a negotiation occurs in this collaboration in terms of information exchange, akin to a conversation. By using this framework, a modelling methodology for meaningful interactions is developed and applied to demonstrator systems.

As such, this thesis presents the following contributions:

a) A vision of the Internet of Things in which humans are the main beneficiaries of the services it provides, and as a consequence, they are considered nodes in the network alongside *things*.

b) An exploration of the relationships found amongst actors in the IoT, analysing the system as a social-like infrastructure, in which nodes collaborate according to their own role towards the fulfilment of the system's purpose.

c) A reassessment of the interactions amongst IoT nodes as theme-framed conversations between social actors (that is, entities which can be described through their social-like characteristics such as their relationships and trustworthiness).

d) A method for analysis of interaction and design for a human-centred Internet of Things, leading to the repurposing of goal and task based methodology, showing how it is applied to the design of an IoT system, providing the basis for device and system augmentation in terms of its sensing, processing and communication capabilities.

1.7 Thesis outline

This thesis is comprised of ten chapters, including the introduction chapter and a discussion chapter. The following is intended to provide an overview of the organisation of this document.

Chapter 2 A Techno-centric IoT, presents the background and literature review on the fundamental concepts on which the Internet of Things its based, and the applications it enables. From a technology perspective, the actors involved in these networks are introduced. A vision of 'smart' systems is presented from the perspective of its enabling technologies and the notion of agency.

Chapter 3 Humans Interacting with IoT, showcases challenges faced in Human-IoT interaction and usability focusing on how the IoT presents its features in terms of its physical attributes and its data-enabled characteristics. This chapter provides a background in sense making and the mental models required to interact with devices in an IoT network, and the affordances they present to their users. The functionality of the IoT is described in terms of the tasks and goals, and how they are aligned to the user's expectations.

Chapter 4. A Social Internet of Things, explores the implications of analysing Human-IoT interactions with the aim of bringing together user requirements and the technology-centric

IoT, grounded by a common purpose or goal. By analysing the concept of purpose in terms of the system's goals and how they are achieved, this chapter establishes meaning in terms of the relationships and interactions between humans and *things*. The notion of a conversation is proposed as a paradigm for information exchange amongst participants in the IoT system,

Chapter 5. Designing for a Human-Centred IoT, focuses on proposing a framework to model Human-IoT interactions in the context of the previously defined social-like and collaborative environment. A modelling methodology that promotes a user-centred approach is presented, highlighting user requirements and goal support by analysing human tasks and machine actions.

Chapter 6. Understanding Topics and Themes in the IoT, aims to analyse the challenge that actors in an IoT system face in making sense of their interactions to achieve the expected goals. To conceptualise and explore these notions, an experiment was developed to study how humans understand and interact with a simple 'smart environment'.

Chapter 7. Modelling an experimental testbed, presents an application of the modelling methodology proposed in Chapter 6, providing an analysis of the tasks and goals in a controlled environment.

Chapter 8. Implementing an experimental testbed. Following the application of the modelling methodology, this chapters shows how an IoT system is developed based on requirements defined through the methodology, and the connectivity and middleware platform requirements.

Chapter 9. People using the experimental testbed, focuses on analysis of data collected with the demonstrator system and a group of participants. Results of this analysis are presented in terms of the statistical tools, and their relation to the previously discussed concepts of a theme-based collaborative IoT.

Chapter 10 Discussion, presents a summary of the thesis contributions and reframes the research questions in terms of the outcomes of the work presented, and finally, future work that this research could enable.

2 *A Techno-Centric Internet of Things*

2.1 Introduction

The IoT has been primarily aimed to commercial, industrial and infrastructure applications, in which human participation is minimal. This chapter provides an overview of the Internet of Things technology context to analyse its development and requirements definition with the aim of identifying the underlying technologies of the IoT. By applying a technology-centred vision of the IoT, that is, exclusively focusing on its enabling technologies, this chapter analyses how the IoT has been adopted to provide solutions that support activities ranging from infrastructure, manufacturing and health. In the context of this thesis research questions, in order to be able to acknowledge a human based vision of the IoT, a discussion of the underlying technologies of the IoT is required to highlight their influence on how humans interact with these systems.

2.2 A data-centric approach in the IoT

Some parts of this section are taken from the paper "*Towards Theme Discovery Paradigm in the Internet of Things*" by Cervantes-Solis, J. W., & Baber, C. (2016), published in the proceedings of the Contemporary Ergonomics and Human Factors 2016 conference. The author of this thesis developed the concepts presented in the work, conducted the research and wrote the paper with the support of Prof Baber.

Arguably, current commercial and industrial deployments of IoT systems are interested in the collection of data towards the fulfilment of specific business models (Sterling, 2014). Accordingly, it is not unusual for communication exchanges between *things* to occur at the data level, and for a digital representation of the object to be the main point of contact with the user, rather than the physical *thing* itself. In the Industrial IoT the concept of 'digital twin' has been adopted to express its data sharing properties through the use of APIs in contrast to interacting with the physical objects (Schroeder et al., 2016). Hence, *things* become extended digitised versions of themselves (Shin, 2014), presenting their features not only in terms of their physical attributes but also in of the data they collect and process, i.e., barometric pressure, temperature, power consumption; or by describing their function, i.e., altimeter, thermometer, electricity meter. As objects become smarter, so their functions become increasingly abstract (e.g., rather than monitoring temperature a digital thermostat might be making decisions about paying for electricity or saving energy). Thus, in a data-centric level of abstraction, where physical objects could disassociate from their data properties, information exchange might not be completely clear and straightforward to the user, leading to confusion and misunderstanding of the intended usage or expected outcome of the interactions (Yang & Newman, 2013).

In terms of research efforts and enterprise applications is a drive for *Things* to become smarter (Singh et al., 2014), more aware of their environment and to have the means of engaging in interactions with other *things*, and their human users, to provide services for the latter.

These devices are being increasingly adopted by humans into their everyday activities (Swan, 2012), for example as wearable health trackers (Figure 2.1) or in home automation (Figure 2.2).

Figure 2.1 Fitbit wearable health tracker (source: fitbit.com)

Figure 2.2 Nest Hello smart doorbell (Source: www.nest.com).

2.3 Things

Things in an Internet of Things environment are the most basic entity in these systems (Kortuem et al., 2010), and it is through their interactions with other things and their users that the IoT fulfils its purpose.

The International Telecommunications Union describes the Internet of Things as:

"a system comprised of devices with the capability of being able to communicate with other devices, in any given environment and regardless of its temporal situation" (Peña-López, 2005). These capabilities would be implemented through technologies that enables them to be tracked, always connected and to possess a degree of autonomy. Focusing on the prevailing concepts of ubiquitous and next generation networks, the ITU based its definition on the availability of enabling technologies that allow devices to exist within the three dimensions as shown in Figure 2.3.

The most basic representations of the IoT adhere to the possibility of everything connected into the internet, enabling the notion of immediate data sharing, communications protocols and relationships between nodes involved. *Things* in the IoT are defined by the IEEE as any physical object that is connected to the Internet, and capable of interacting with the physical world (Minerva et al., 2015). Thus, the concept of *thing* has been adopted to consider any physical object that can be networked, from kettles, plant pot monitors, toasters, and weight scales to industrial robots, cars and traffic lights.

Sterling (2005) extended the ITU definition by introducing an object's capacity of being tracked through space, defining the physical object as:

"…the protagonist of a documented process. It is an historical entity with an accessible, precise trajectory through space and time".

Sterling named this concept, SPIME, a contraction of 'space' and 'time'. Furthermore, Atzori et al. (2010) imbues this objects with a 'visibility' property, allowing them to be identified and addressed in the network, enabling the *"traceability and awareness of [their] status"*.

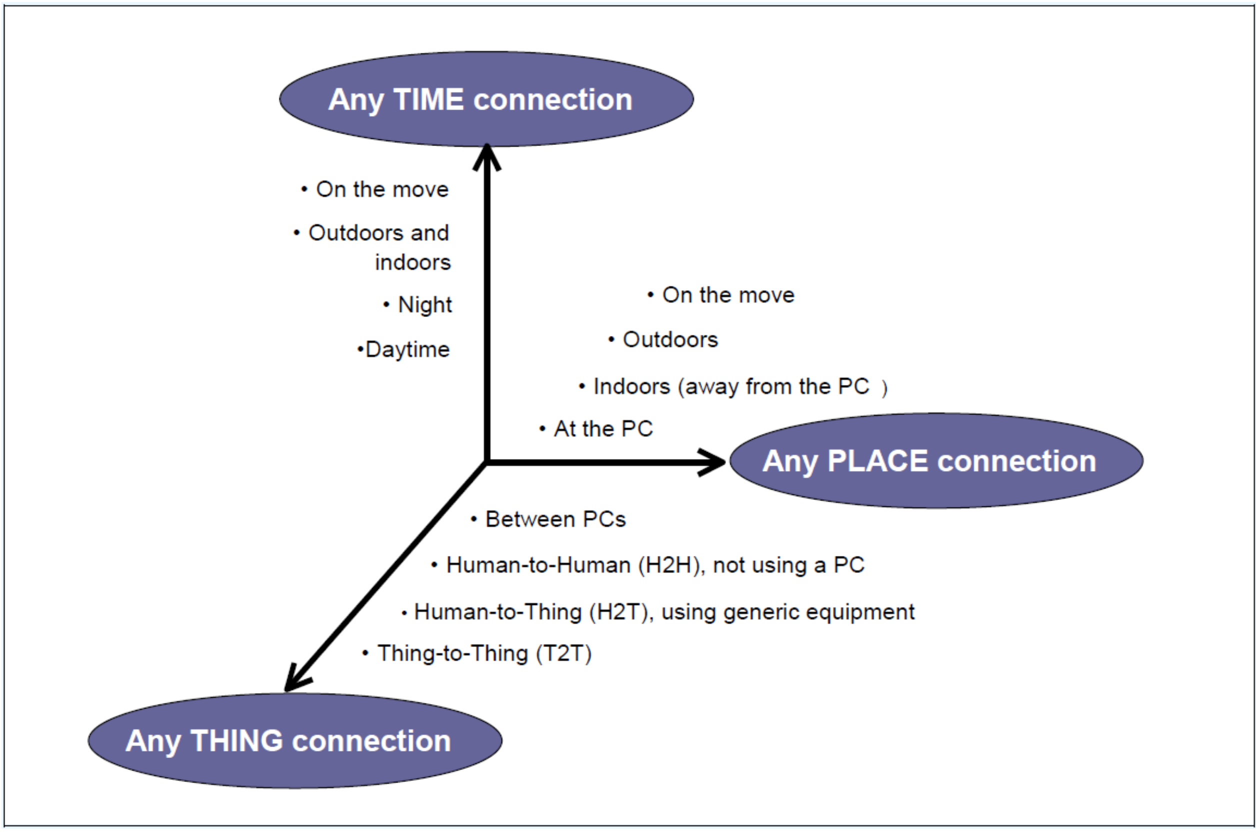

Figure 2.3 The ITU vision for the IoT (Strategy and Unit, 2005), considering three main dimensions for devices to exist: in any time, place and with other things.

As per the definitions, objects would be able to communicate with other similar objects, and keep a record of their activities. Notwithstanding, these descriptions fall short of defining the possibility of the *things* themselves being capable of tracking their own status, or in the context of the vision of a ‘smart’ IoT, to possess a degree of autonomy that allows them to make their own decisions to act upon their environment. In terms of computing, these traits are fulfilled when considering the possibility of embedding processors onto the objects to support state machine behaviours.

These definitions focus on analysing networked objects in terms of their functionality and how they connect to other objects, and less so on their relatedness to human activity. As posed by the research questions, the aim of this thesis is to frame *things* in terms of how they relate to humans, creating a social assembly.

2.4 Sensors, processors, and communications: enabling autonomous behaviour

The attributes that functionally define a *thing*, are implemented with embedded sensors, processors and communications.

Current technology capabilities in silicon development and manufacturing provide for technology ecosystems that facilitate the notion of 'embedded intelligence' for potentially any physical object, as mentioned in chapter 1. Thus, a kettle could conceivable become a 'smart kettle' that knows when it is used, decides when it is the best moment to be descaled, and communicates its goals and expectations to its user or manufacturer.

As with any modern computing device, embedding processors and effectors (sensors and actuators) enable the opportunity for the implementation of objects that follow a sequential state machine behaviour. This provides a system with a view of itself and the environment, represented through a set of states and its sequences, the conditions produce changes of state, and the actions that the system could take (Wagner et al., 2006). In contrast to combinatorial systems in which outputs are a direct and immediate result of the inputs, a sequential system has memory that allows it to keep track of previous and future states, in terms of the status of the internal inputs (instructions or conditions) and outputs (Mano, 2012) as shown in Figure 2.4.

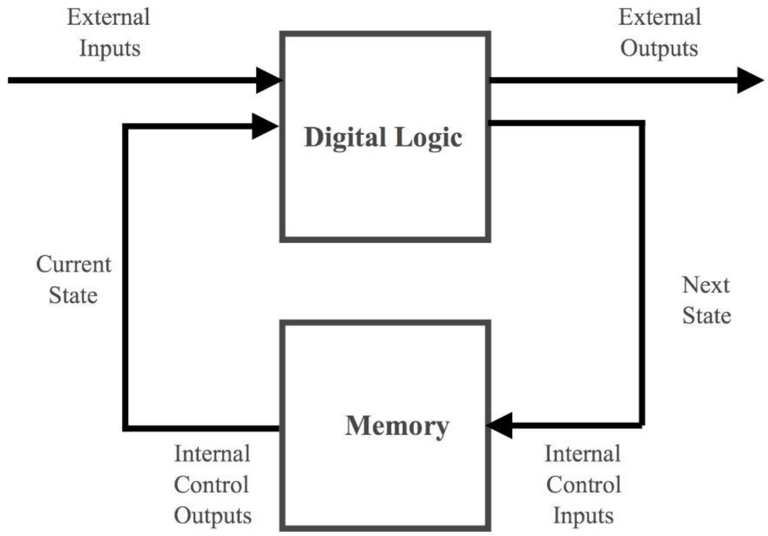

Figure 2.4 A Sequential Digital System

Providing a mechanism to determine states as per the internal and external conditions of the system, allows for behavioural modelling through the use of state diagrams, that highlight the state transitions, inputs and outputs. This state-based paradigm allows for the representation and implementation of systems that are capable of following algorithms and taking decisions on their own in order to attain their purpose, as observed in modern computing devices. Thus, state diagrams are commonly used to model the behaviour of event-driven computing and software systems in terms of its status as characterised by its inputs and outputs (Mano, 2012).

These computing capabilities found in *things*, allows them to make decisions according to external and internal stimuli, making them capable of reacting to other *things*. The scenario of interaction with other similar devices allows a ‘technological system’ analysis, based on the devices’ technical capabilities, such as those characterised by data-centric applications as discussed at the beginning of this chapter.

Clark et al. (1991) analyse human communication in terms of coordinated collaboration, taking place in turns, influenced by context and regulated by commonalities. As such, we could envision a 'sociotechnical' frame for the IoT in which things and humans could operate in a collaborative environment, as will be discussed in the following chapter.

2.5 Smart objects

The vision of the IoT is considered to allow for the creation of 'smart' environments where users benefit from systems that, by collecting, processing and sharing data from different sources, can learn and infer their actions and activities (Kortuem et al., 2010). It is generally considered that by the process of instrumenting objects, this imbues them with 'smartness'. As such, the concept gave rise to the adoption of terms such as 'smart manufacturing' or 'smart cities' (Miorandi et al., 2012). Arguably, the concept inherits a confusing connotation in the sense that it becomes a marketing term, in contrast to the system's real functionality. Other applications have also incorrectly applied the concept to devices that have some form of connectivity to a smart phone.

Modern IoT applications, such as those that enable the Smart Cities ecosystems (Ganchev and O'Droma, 2014) strive to provide a form of 'blanket' intelligence, with the ability to cover a multitude of aspects and in turn provide a sort of omnipresent intelligence derived from the collective intelligence of different IoT nodes (Anantharam et al., 2013).

Smart systems have been analysed through the notions of context aware computing (Schilit et al., 1994), pervasive systems (Satyanarayanan, 2001) and ambient intelligence (Augusto, 2007). These fields consider scenarios in which the system effectively is aware of user's requirements, depending on their context and needs and thus provide a more complete notion of what constitutes as intelligent.

2.5.1 Agents

As mentioned in section 2.4, the notion of silicon embedded into physical objects, not only provides the framework for the creation of 'augmented' versions of themselves through Sensing, Processing and Communication (SPC) capabilities, but could be considered to have some decision making abilities, and interact with the environment accordingly.

For Wooldridge (2009) an agent is an entity *"acting autonomously, in an environment to achieve its delegated goals",* operating continuously in a sense-decide-act loop, and becomes intelligent when extended with *"reactivity, proactiveness, and social ability"* traits. Hence, intelligence in these entities would require them to act upon dynamic environments responding to its changes; working in a "*goal directed behaviour*" that is systematically working to achieve their goals recognising opportunities; in cooperation and coordination with other agents, often requiring to negotiate diverging goals. The notion of agency provides a framework in which objects are imbued with the required properties to enable their capacity to capacity to act, physically and cognitively.

Kelly (2017) applies the term 'cognification' to devices when they are imbued with sensing, processing and communication capabilities (SPC). As suggested Wooldridge, this implies that 'cognified' could be considered to provide the attributes necessary to consider *things* as agents. Moreover, improvements on SPC characteristics enable technological properties that lead to more complex and richer data that allow for machine learning and AI solutions that arguably embed higher degrees of intelligence and decision making (Sezer et al., 2018)

In commercial applications it is often the case that IoT devices are referred to as 'smart' as a general description of their functionality. However, it is common to find that these objects' capabilities rely on their connectivity to a third party, such as an app or hub that provides a service such as data analytics, monitoring or control. That is, whatever notion of 'intelligence' the device possesses, it is provided by an intermediary platform known as middleware as discussed in section 2.9.

2.5.2 Goals

A system's goal is defined by what it needs to achieve and the processes and actions it takes to do so. Norman (2002) characterises a goal as a final state, reached by a set of actions, and suggests an analysis of the environment (or world) before and after the actions were taken. As such, this interpretation involves an understanding of the actions, the world's states, and a consideration of whether the expected goal was achieved by evaluating the changes in the world.

Consequently a notion of goal completion must be addressed. 'Utility' in agency literature refers to a metric representing how 'good' is the state in which the system is at any given moment (Wooldridge, 2009). It is used to provide a function to measure of how close the agent is to completing its delegated goal. Accordingly, an agent looks to optimise this function given its environment, its parameters, and other agents to complete its goals. If a utility function leans towards the expected value, it is said not only that it's reaching its goal, but also, that by acting according to its goal, it is providing a service of value to a user or other agent.

2.5.3 Multiagent systems in the IoT

Wooldridge (2009) considers intelligent agents when they can be *"reactive to respond to the environment in a timely fashion";"proactive, to take initiative to realise its goals"*; and show social traits such as "*cooperation and negotiation to satisfy these goals"*.

When considering networks of *things*, it is desirable to approach the problem of interaction and intelligence in the IoT from the perspective of how networked agents act in unison, and the processes by which they reach agreement.

Olfati-Saber et al. (2007) argue that a consensus protocol, or algorithm is required to provide the framework in which agents exchange information in order to reach agreement on what they are doing. In multiagent systems a utility function (Wooldridge, 2009) measures and ranks alternatives for the system and its agents, providing stopping parameters to determine that a goal has been reached, and no further action should be expected.

Jha and Lehnhoff (2014) posit how 'smart' devices can engage in a conversation with each other and learn from others, arguing that such a framework is required for the IoT. The authors stablish a set of challenges for the realisation of an 'intelligent' IoT that supports such conversations. Among those are:

- Realising an architecture for heterogeneous IoT, allowing for the cross communication of different devices under different protocols.
- Adaptive systems, allowing for reconfiguration of devices at a hardware and software level
- Network bandwidth
- Scalability
- Security
- Autonomy

2.6 Networks

Things in the IoT were originally conceived such that they were able to connect to each other using established internet protocols and infrastructure. Thus, for example, protocols like TCP/IP (Transmission Control Protocol/Internet Protocol) were used for data routing and device addressing, and Wi-Fi for wireless physical connectivity (Gubbi et al., 2013). As their development and adoption increased, these protocols evolved into specialized versions focusing on energy consumption, data bandwidth and signal range, such as 6LowPAN (Internet Protocol Version 6 over Low Power Personal Area Network) to name a few (Gaglio, 2014). Although these protocols address how devices connect to each other, they rely on a data-centric vision, and often don not provide a description of the nature of the connections. That is, how devices connect to each other in similar groups or clusters, where they connect, the context of the connection, and how tight or loose the connections. In the context of this thesis, network properties relating to the connections take precedence over their technical implementation. As will be discussed with more detail in chapter 3, the human-*things* system forms the basis of analysis of interaction in the IoT, and thus, this research considers the networking capabilities in its more broad sense, providing descriptions in terms of the IoT system's nodes, topology and links. Thus networks can be characterised by features such as the cliques they form or the structure of their data and connections, and measured by metrics such as their centrality (their distance from the centre of the network) or degree of membership (how tight or loose are nodes from the network) (Newman, 2010).

These metrics show how 'network-enabled' characteristics can be applied such as, homophily (a node's tendency to network with other similar nodes), membership or clique association or propinquity (a node's tendency to form networks with geographically close nodes) (Scott, 2012). Analysing the IoT from the point of view of these attributes support the view of the IoT as a collaborative endeavour amongst its nodes, as will be discussed with more detail in chapter 3.

2.7 Distributed systems

Van Steen and Tanenbaum (2016) have defined a distributed system as *"a collection of autonomous computing elements that appears to its users as a single coherent system"*. Nodes in the system connect to each other to form networks, each node acting autonomously, but collaborating to attain a common goal as a collective. Moreover, nodes are usually not limited in size, scope, complexity, topology and their hardware and software implementations. As defined in section 2.9 , in these networks a layer on top of devices is in charge of organising and managing nodes in the form of middleware applications. Nodes collaborate exchanging messages to coordinate and synchronise, and to manage group membership, authentication and security.

Distributed systems allow for service composition (Ikram et al., 2015; van Steen and Tanenbaum, 2016) that can be distributed across different nodes, regardless of their physical location. Given their complexity, distributed system design often adheres to the following principles (Coulouris et al., 2005):

- resource sharing to take advantage of each device's capabilities in a networked environment;
- distribution transparency to appear to the end user as a single, coherent system;
- openness, to allow for interoperability, portability and extensibility,
- scalability, addressing size, communications, resource distribution, and replication.

Distributed computing has been applied to high performance computing, information systems, and pervasive systems, of which the IoT is a derivation. In IoT ecosystems, computing and physical resources (sensors and actuators, as introduced in chapter 1 for cyber-physical systems) are distributed across the environment in pursuit of a common goal (Tracey and Sreenan, 2013).

As mentioned above, Internet of Things development has benefited from the guidelines found in distributed system development. Notwithstanding, in terms of resource allocation not much has been explored, as many applications focus on providing a single, rigid service (Colistra et al., 2014). As such, nodes remain fixed on their same task contributing to a larger application.

Colistra et al. (2014) analyse the problem of resource allocation in the IoT, exploring the possibilities for opportunistic networking, enabling new services and applications through the redistribution of idle resources. In this context Colistra et al. introduce the notion of 'task groups' in which different *things* perform similar tasks, and a server manages their allocation and functionality. These *things* would be identified in the server in terms of their digital counterparts, or virtual objects (VO). As such, if a particular signal needs to be measured (i.e. barometric pressure) and more than one node can provide such data, the server would issue a command to the relevant node, in the appropriate location and 'task group" as shown in Figure 2.5. More importantly, the middleware layer provided by the server must negotiate how and which of the nodes are used to make sure that the system goal is achieved. This concept posits the possibility of defining an object's purpose in terms of what is capable of doing (tasks) in contribution to the completion of a purpose (goal), as will be explored in the following sections.

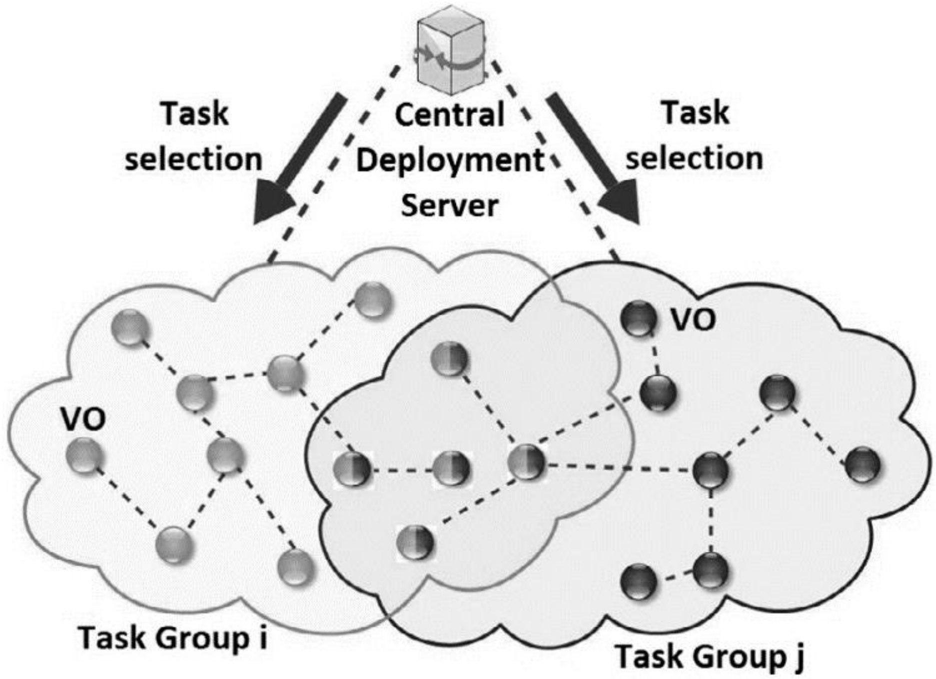

Figure 2.5 'Task groups' reference model (Colistra et al., 2014).

2.8 Centralised and decentralised topologies

In some cases the nodes within the same network might not be aware of the functionality provided by members of the same system and due to a highly heterogeneous IoT development in terms of protocols an technologies, different networks (and nodes) exist without being aware of each other (Khalil et al., 2014).

Moreover, these devices would collect data about their environment or their users without the latter being aware of it. This creates a notion of an invisible and opaque system that might be following its own agenda, without the user's participation, preventing them from building the required mental models to properly engage with the IoT system (Schmitt et al., 2011).

In the context a single solution IoT applications, such as smart fitness trackers, it is common that their main interface is through a built-for-purpose *app*, usually within a mobile device. The use of mobile apps as one of the main methods for UI in the IoT has been attributed to:

- The market penetration of mobile devices (Kleiner et al., 2015),
- Technology adoption cycles (early adopters as drivers of technology) (Kleiner et al., 2015; Gartner Inc., 2014),
- The availability of sensors on board mobile devices (Mayer et al., 2014; Carlson & Pagel, 2014).

The effect is that current IoT architectures are often considered isolated solutions (Atzori et al., 2014b) that fulfil one particular use case aligning to a company's value chain or business model. In some cases, the network has a communications hub in charge of ensuring the interoperability of its sensors and actuators (nodes). For example, the nodes in such a topology could be implemented with Zigbee or BLE (Blueetooth Low Energy) standards, whilst the main user interface could be implemented as a smartphone application, as illustrated in Figure 2.6. Additionally, to provide access to other Internet enabled services such as data storage or data analytics, an IP (Internet Protocol) interface is required. In applications that rely on mobile phone applications as user interfaces, it is common that a centralised node acting as a hub is required to handle communications with nodes and when required, to the Internet.

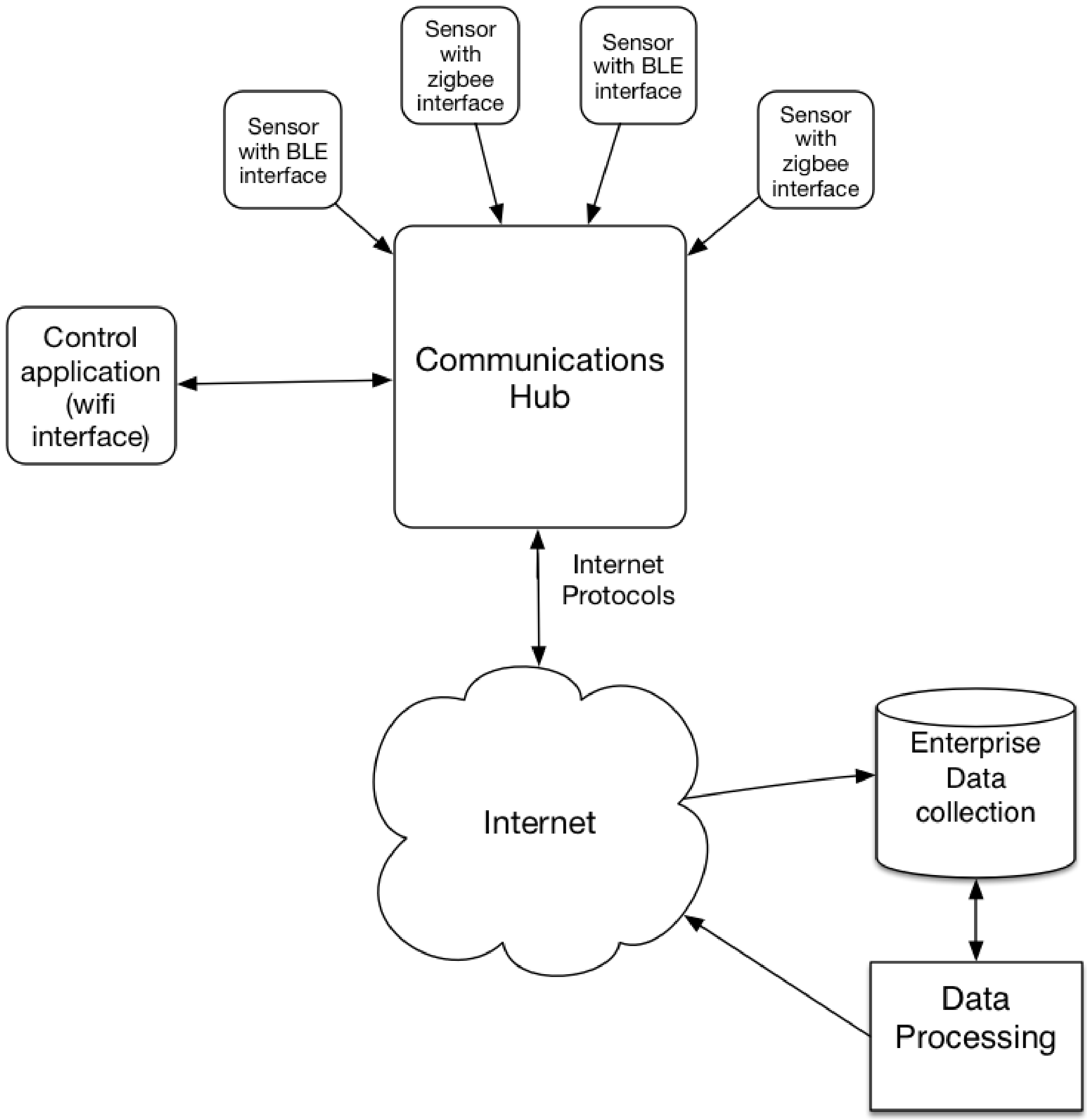

Figure 2.6 A common architecture for the IoT.

An example of such a system is the Philips Hue lighting solution (Wang, 2013; Philips, 2014), a wireless lighting system, comprised of connected lightbulbs and a smartphone-based controller app. Both lightbulbs and application connect to each other through a hub in charge of connectivity, and receiving and issuing commands. Other commercially available products exist that use a similar approach, including health (Withings,2014; iHealth, 2015), home automation

(Nest Labs, 2014; Apple, 2015), retail (OnyxBeacon, 2015), and logistics (Welbourne et al., 2009). The centralised topology illustrated by Figure 2.6 has been previously analysed (Jara et al., 2011; Ur et al., 2013; Mennicken et al., 2014; Xu et al., 2010; Zanella & Bui, 2014). This approach facilitates connectivity by means of well tested technologies, such as IP (Mainetti et al., 2011) and therefore, allows the realisation of the combined technologies that comprise the IoT, providing an interface to middleware solutions that manage interactions within the network. However, the technical interpretation of the IoT often leaves users out of the development process, disregarding their own goals and expectations from the system, diverting from the notion of a collaborative environment (Yang and Newman, 2013). Moreover ecosystem fragmentation is preponderant, and it seems that for every new IoT related product or services, the common approach is to build its own architectures and interfaces, maintaining the trend of isolation amongst IoT systems (McKinsey & Company, 2015).

In terms of 'smart' objects, the central node arrangement seems to contradict the notion of autonomous objects that perform 'smart' activities on their own accord, relegating them to passive entities that fulfil their functions as assigned by another object, or central node (Ding and Jin, 2013). Figure 2.7 shows a an IoT in which a central node has the responsibilities of enforcing rules, collect data from IoT devices, issue commands to the system's actuators, and interfaces with the user. Arguably, this arrangement places a barrier between users and devices, which often creates a disassociation of the object's functionality from the user's perspective.

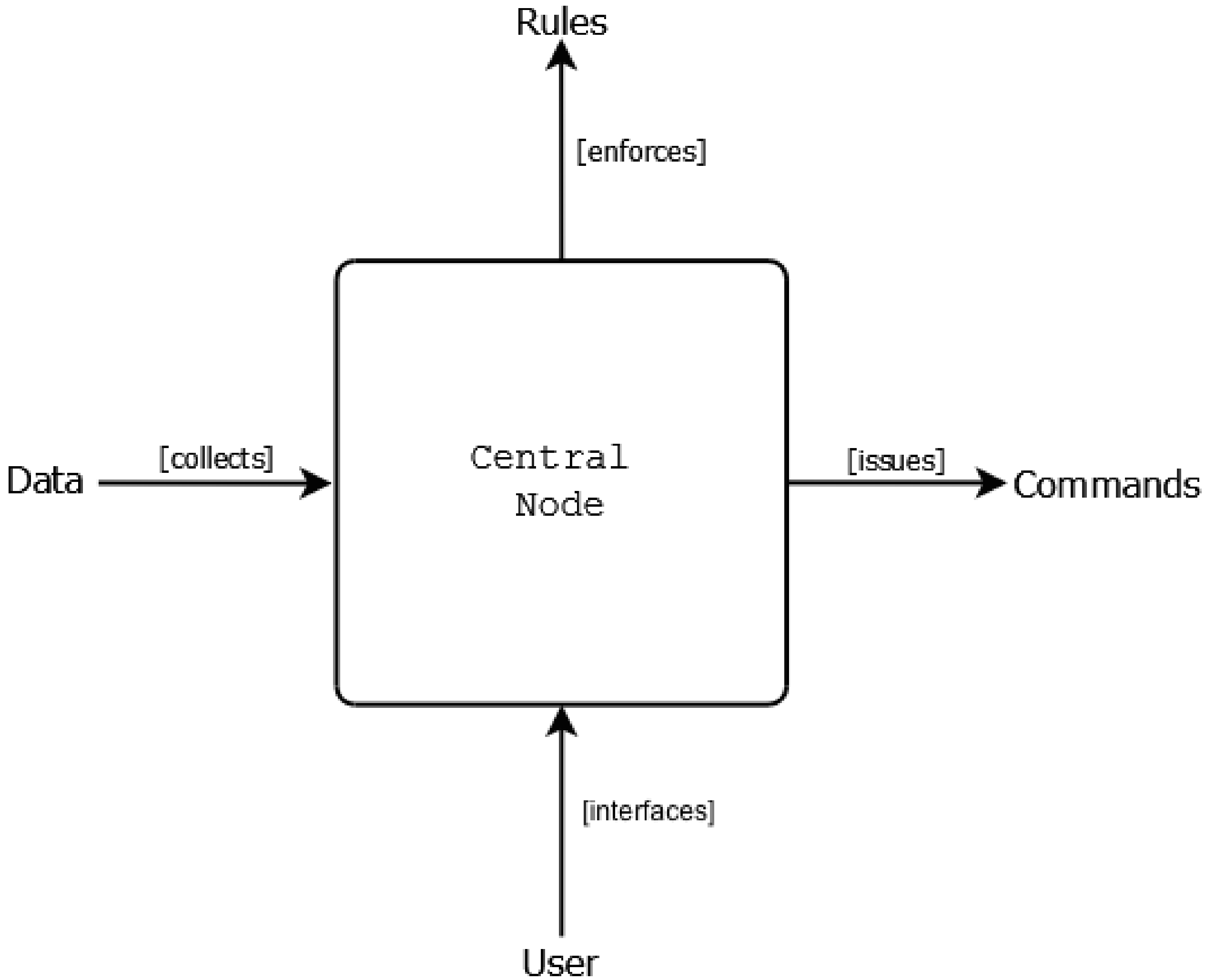

Figure 2.7 A centralised node architecture for the IoT (Cervantes-Solis et al. 2015).

Moreover, these centralised topologies rely on the existence of *things* that are in charge of processing data, but one drawback of centralised networks is the possibility of bottleneck problems in terms of data, and it has been shown that switching data processing to other parts of the network provides advantages in terms of resource utilization, communication overheads (Yue et al., 2012) and offloading of processing power (Satyanarayanan, 2014) , whilst communicating only what is more relevant to the application at hand. For this research the perspective of approaching the IoT at a device level as opposed to a system wide vision, allows for the consideration of more direct relationship of users and automation, without an intermediary such as hub.

Shifting data processing from the centre of the network (data centres or hubs) to the *Edge of the Network*, with the addition of making the data available to all individuals, would open very interesting interaction and behaviour opportunities (Shi et al., 2016). For example, sensors which might be in an inactive state or idle, could activate to pursue the system's utility function. In this fashion, a node could be repurposed according to the particular task.

These challenges have been analysed in terms of *Task Allocation* and how consensus is reached (Colistra et al., 2014), by means of the semantics involved in message and action communication. However, it is still dependant on the particular function and technical implementation of each node, and this model is not fully realised in current IoT systems.

The concept of an IoT system capable to provide meaning, not from the centre of the network, but by partially shifting this process to the node, enables the notion of systems in which humans could interact with this nodes to obtain knowledge from the system, whilst minimising the obfuscation present in current systems due data communication channels invisible to the user.

As such, a decentralised IoT topology can be proposed, where the system's function would be distributed amongst nodes in order to accomplish the network´s main goal, enabling a direct relationship with users (Figure 2.8).

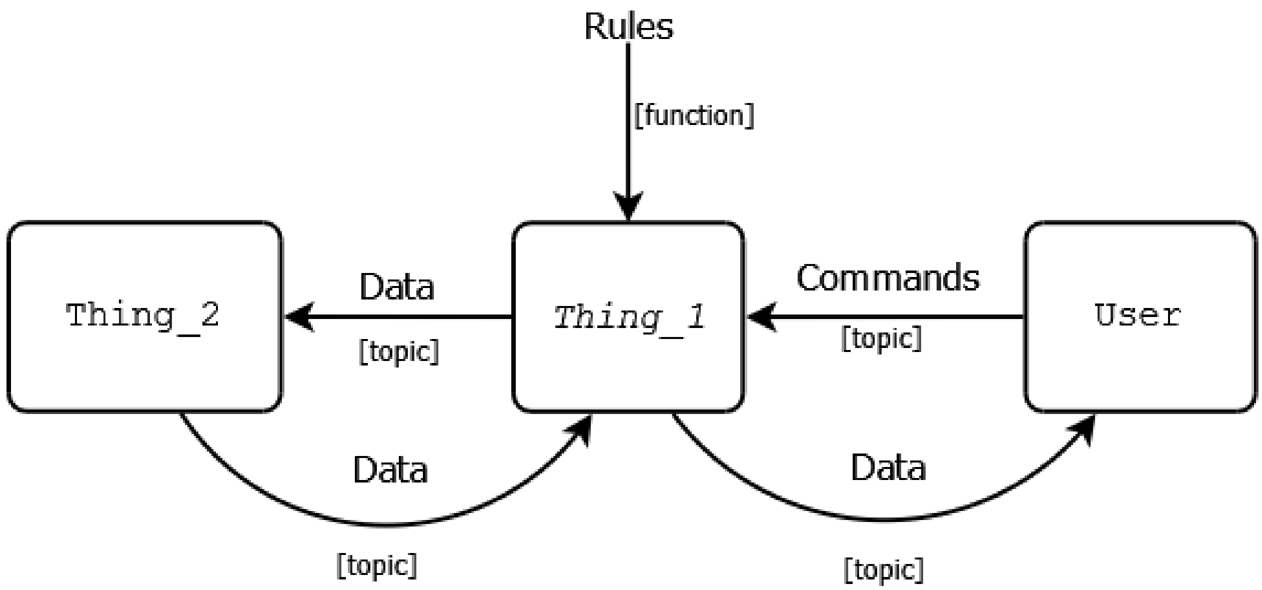

Figure 2.8 A Decentralised architecture for the IoT.

This model could be extended to pursue the investigation of scenarios in which each individual of the network enforces their own rules and the system's according to the application's context, and its overarching purpose.

To illustrate this concept, let us consider three different example IoT systems:

- A fully instrumented coffee mug, fitted with a 3-axis accelerometer and a force sensitive sensor. Thus, it is able to detect when it's lifted, how it's lifted, and whether it's full or empty.
- Room ambient monitoring. Fitted with light, temperature and humidity sensors, and connected to the heating system to determine and act upon optimal living conditions
- A sleep monitoring system made up of accelerometer and gyroscope sensors attached to the user's pillow.

Each of these systems would only be focused on solving a particular need, but if their services could be unified, new functionality could emerge, such as:

- Correlate coffee consumption to sleep patterns
- Correlate sleep patterns to a room's ambient conditions
- Modify heating or lighting conditions when its user is about to wake up
- Using the mug´s accelerometer to detect its user propensity to motor diseases
- Using the ambient monitoring system´s humidity and temperatures sensor to infer on the room's occupancy status

In effect, the individual sensors and actuators, with their corresponding data and actions could be combined and correlated for new meanings and purposes.

As observed in Figure 2.7 and Figure 2.8, the relationships between the system's participants can be characterised in terms of type of interaction expected and information shared. This semantical characterisation will be explored with more detail in Chapter 3, however it posits how roles are defined in terms of interactions, and how are those roles allocated to determine what each of the participants 'responsibilities'.

In terms of distributed architectures such as the one found in the IoT, Tracey and Sreenan, (2013) propose a data model aiming to provide service level abstractions, highlighting the nature of the data exchange provided by each node. Thus, nodes have roles according to their resources. For example, some nodes are capable of sending their own sensor data, whilst others have the function of relaying or storing those data. Nodes with more advanced computing resources could provide results from data processing or aggregation.

Moreover, (Colistra et al., 2014) present a semantic description aimed to provide a mechanism for resource allocation, making a differentiation between sensor parameters, resources and services, and introduces them as modules supported by the application's middleware. Thus, node roles are characterised in terms of their capabilities and their involvement in fulfilling the system's purpose, which can be described as the tasks required to complete goals.

2.9 Middleware

Often, *things* in the same physical or logical networks belong to the same application, forming an ecosystem (Fortino, 2016). Accordingly, infrastructure to support this Ecosystem of Things (EoT) needs to be in implemented (Mineraud et al., 2016). Usually known as 'middleware' or 'IoT Platform' this refers to the collection of software and hardware used to manage all elements of an EoT. Network topology tends to be heterogeneous, with devices distributed across different domains, or even physical locations. Thus, Razzaque et al. (2016) define middleware as the platform that provides *"common or generic services to different application domains"*, providing a software layer easing development through common programing interfaces such as APIs (Application Programming Interface). Although this allows for organised and well-defined interpretation of interactions (Fersi, 2015), the concept implies a rigid approach network activity by hardcoding the interaction of devices or platforms, arguably hindering the possibilities for agentic behaviour from the IoT.

To provide more flexibility on application development and insights from IoT data, middleware platforms have been developed to provide an 'intelligent' approach, in which data interactions would be able to provide insights on user or device behaviour. As such, machine learning, semantic and cognitive based platforms (Perera et al., 2014; Sheth, 2016b; Sabou et al., 2005) provide a 'smart' approach to the IoT, a notion that will be explored in the following section.

Aazam et al. (2014) propose different layers in an IoT architecture differentiating between the 'perception' layer (where sensors, or *things*, reside), to the 'Network and Middleware' layers that manage and connect devices. This identifies both the infrastructure required to communicate and gather "knowledge" from the *things* or technical implementations of the Data Link, Network, and Transport layers of the Open Systems Interconnection (OSI) model; and the control structures to mediate and process the collected data (OSI model's Application layer) (Tanenbaum, 2002). From a human centric perspective, middleware applications have focused on how the information obtained through these networks could provide 'smarter' applications that support the association of information to enable decision making capabilities (Gyrard et al., 2016).

Nevertheless, middleware often focus on providing infrastructure services for the EoT in a 'technical system' framework as defined by Bijker (2014), at best enabling data-driven user interfaces that provide information to users, but do not address usability issues.

2.9.1 Messaging

In order for distributed system to coordinate and manage its resources, messaging strategies are required. Data frames are passed between devices and routed sources to the appropriate destinations by a managing module (van Steen and Tanenbaum, 2016). A common messaging architecture is that of 'publish-subscribe' in which objects are only messaged if the subscribe to a particular type of data stream.

MQQT (Message Queuing Telemetry Platform) (MQTT.org, 2017) is a messaging protocol commonly used for the IoT, and it uses the concept of 'topic' to identify messages that are available to objects' according to their subscription status. In this way, objects can only acknowledge and respond to messages belonging to their subscribed topics. Moreover, the protocol ensures that messages are delivered by queuing incoming messages in a buffer, handling possible connectivity issues. As will be discussed in following chapters the notion of topics to communicate commonly agreed messages provides the basis for a collaborative IoT.

2.9.2 Flow based programming

As discussed, middleware platforms are in charge not only of managing devices, but also on coordinating distributed resources across physical and virtual locations. The status of these resources provide a description on the network's state, linking objects and their services.

Data flow platforms have been used to model the connections in network's resources (Blackstock and Lea, 2014). Originally developed to handle programming logic for parallel processors (Johnston et al., 2004), they provide a graphical approach to represent "*data inputs, outputs and functions…connected with arcs that define the data flow between components*" (Blackstock and Lea, 2014).

This paradigm supports a simple and intuitive approach to programming multi-resource systems, modelling these systems as a series of asynchronous processes that react to events, providing. As such, this vision provides a state-based system description of inputs and outputs, and the event driven processes that describe their behaviour (Johnston, 2004).

For the IoT, the Web of Things Kit (WoTKit) (Blackstock and Lea, 2012) and IBM's Node-RED (O'Leary and Conway-Jones, 2017) have been developed to provide connectivity between hardware based devices and software APIs in a simple web based, graphical drag-and-drop interface. Building blocks are known as 'nodes', the connections are 'wires' and the algorithm is referred to as a 'flow'. Thus, components and their relationships are clearly identified in the system in terms of nodes and wires, and the graphical flow diagrams can be converted into code by an appropriate parser describing the list of objects and their connections.

Both WoTKit and Node-RED are built on javascript engines, and provide system descriptions as JSON (JavaScript Object Notation) objects.

Figure 2.9 shows a generalised view of a flow based program. Input nodes are able to gather data coming from different sources such as devices (including sensor and actuators) or services through their APIs. These data could be processed by functionality provided by a separate node. Finally, a system control logic node aggregates and process data from the different sources through using the system's rules and control logic, providing system services through output nodes. This final node is often used as the input for the system user interface in IoT *things*, or to provide API connectivity to other software applications.

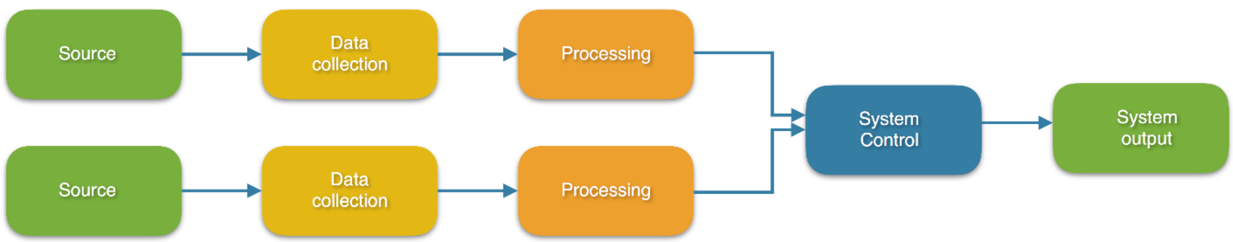

Figure 2.9 A generalised view of a data-flow program.

Although flow-based program structure seems to emulate a sequential process, as noted earlier in this section, different nodes often operate concurrently, distributing tasks and processes in terms of passing data to the appropriate devices (both internal and external to the flow).

2.10 Service discovery

Parts of this section were adapted from the paper "*Towards Theme Discovery Paradigm in the Internet of Things*" by, Cervantes-Solis, J. W., & Baber, C. (2016), presented in the Contemporary Ergonomics and Human Factors 2016 conference. The author of this thesis developed the concepts presented in the work, conducted the research and wrote the paper with the support of Prof Baber.

Things are able to share aspects on where they are situated, status of their surroundings, and how or when they were used. As such, these devices generate data that can be broadly categorized by three types: location, environmental and social. In the context of HCI, Jara et al. (2014) argue that the "*cyber social integration is being promoted through the evolution of the communication mediums and the new capabilities to retrieve and discover knowledge*". By introducing human users, Human-IoT Interaction falls within the realm of social data, where associations between objects and humans are heavily influenced by the user's requirement to obtain a purposeful result (Nunes et al., 2015), while negotiating their role in this association. Much like any other relationship, the users' expectations are to obtain some benefit from it. Particularly in the case of the human user, the anticipation would be to obtain services from the 'smart' device, allowing users to offload physical and cognitive tasks, and procuring knowledge and insights related to their use (such as calories burnt in a wearable fitness tracker, or energy consumed in a smart electric meter) (Nunes et al., 2015).

Nitti et al. (2016) propose that Service Discovery is one of the challenges faced by IoT development, allowing devices to register their services to the network and make their resources available to nodes. In the semantic web, Service Discovery has been categorised by (Fayyad et al., 2005) as "*the process of locating web services that can be used to request a service that fulfils a user's needs*". To do so, the 'user's needs' must be defined in terms of goals, and the IoT's functionality aligned to those goals.

Human-*thing* interactions imply that there is a common interest in reaching such goals, analogous to a mutually beneficial social relationship. It has been suggested that these conversations are required in order to establish a collaborative sense-making process (Preece et al., 2015), and that these 'IoT actors' participate towards common aims and achieving rules through an emphasis and understanding of the system's purpose, as opposed to hard-coded rules (Cervantes-Solis et al., 2015a). Moreover, it has been argued that in order for physical objects to have any value or meaning to users, they must hold an instance of social data attached to them (Speed, 2011). This implies that objects must be used and appropriated in order to become meaningful for a person. In fact, it has been argued that the most important requirement for interaction is not the ability to use an object, but the engagement they support with the user (Golightly, 1996).

Chapter 5 will explore the concept of Theme Discovery, where the service an IoT system provides is achieved through cooperation of its nodes, including the human user included. The concept of Theme Discovery is proposed as a mean of interpreting the outcomes or goals of the system, and assumes that, in any given collaboration, it can be framed as a conversation with exists a central guiding. Thus, a theme provides a means for grounding a conversation, as described in section 4.7.3 Akin to the development of the Semantic Web (Berners-Lee et al., 2001), these approaches look to establish semantics (Manat, 2014) and ontologies (Wang et al., 2012) that describe Human-IoT interactions in a conversation like exchange. The conversational IoT approach enables the opportunity to support modelling and design methodologies that are characterised by states, transitions, turn-based and contextual, as will be discussed in chapter 5.

2.11 Conclusion

The literature review points to a lack of IoT system models that include the experience that people have when interacting with *things*. Devices such as those found in the IoT often rely on data exchanges between the objects and supporting applications, usually through communication channels undisclosed to the user.

In this regard, this chapter has provided an overview of the underlying technologies found in the IoT in order to frame the requirements to analyse how the IoT would need to be addressed in order to accommodate human users.

Data are commonly used by IoT objects to achieve the purpose defined by their makers or by the company that wants to mine the data they produce, and in some cases baffling users, hindering their engagement with the system. A well-researched example is that of the smart thermostat, which commonly has the basic goal of controlling temperature settings within a household. However, they often also provide energy optimisation by analysing patterns on room occupancy, comfort settings, energy tariffs, energy consumption, etc., whilst collecting data from many households to profile energy usage. When setting a temperature level, someone would expect an immediate reaction by the system but they might receive no apparent response because the system is optimising for a parameter of which they are unaware, so the system appears to be malfunctioning.

As such, the technological approaches described in this chapter provide a frame of reference of how the IoT operates, and how users relate to its components. For example, as has been discussed middleware platforms have been developed to provide a way of managing things in the IoT. However, as will be discussed in chapter 3, human could take the role of managing these objects, not necessarily to be in charge of controlling or operating them, but in the sense that some *things* require set points to be configured by the human users. Correspondently, this posits the question of whether a human user could be capable of handling interacting with the diverse number of *things* in a network. As such, this allows the consideration of an IoT in which the number of devices is not at the forefront of the system requirements, but that it supports user's expectations and needs.

For these reasons, a human factors-based analysis of how to identify and support user's requirements should be considered. The following chapter will aim to provide a human-based overview of how the IoT has been used to approach the issue of combining their physical and digital traits, and how users identify and react to *things'* features.

3 Humans interacting with the IoT

3.1 Introduction

As discussed in the previous chapter, in a techno-centric IoT the focus of research lies on the data or function of the collection of *things* that constitute the network. For human users, this could create problems in the separation of the digital form of the *things* from their physical form, influencing the nature of Human-IoT interactions and how humans make sense of the IoT. One assumption might be that the presentation of the collected data, or parameters being managed ought to be sufficient to allow the user to guess what the *things* are seeking to achieve. In terms of the smart objects found in the IoT, their 'agency' arises from their sensing and processing ability. In other words, one might assume that these objects have a purpose because they have been programmed to perform in a specific manner, but it is not always easy for the human participant in an IoT to discern what purpose the *things* (or network of *things*) are seeking to achieve. This misses the more fundamental issue that we tend to ascribe agency on the basis of the ongoing behaviour of objects. As, for example, Malafouris, (2013) points out *"agency is the relational and emergent product of material engagement*" by which physical interaction (material engagement) between people and things leads to the recognition of 'agency' . Thus, as users interact with *things,* they recognise when they are in charge, and vice versa, shaping their actions. Baber (2014) illustrates this with the work of Michotte (1963), in which people were asked to describe what they saw when a moving object (a 'launcher') hit a stationary object (a 'target') which then started moving. If the target moved in the same direction and with the same velocity as the launcher, people spoke of the launcher *causing* the target to move (providing the time between contact and motion was negligible). This launcher effect suggests that people interpret the behaviour of objects *as if* they were capable of autonomy and *as if* they possessed sufficient agency to act. The explanations do not seem to involve predictive theories of causality so much as ad hoc responses to changes in state in which objects cause events to occur. This suggests that indicating the state of an object (or network of objects) might not support people's understanding of the operation of that object, but a description in terms of 'intentions' or 'personality traits' that the *things* are assumed to possess. The question then is not simply how to present data or parameters to the users of IoT but also how best to help them make and understand valid inferences about agency.

3.2 Human Computer Interaction with the IoT

One of Human-Computer Interaction's (HCI) main research topics is to examine how humans interact with computers with the objective of providing novel and potentially better forms of collaboration between computer systems and users (Dix et al., 2004).

HCI evaluates a system from the perspective not only of its own goals, but also places the human user at the forefront of those goals as its main beneficiary. By doing so, HCI aims to provide the means for a harmonious relationship between the computing system and its user. As such, HCI's objects of study focus on the cognitive models of the interactions, its socio-technical issues, models of communication and collaboration, task analysis, and system modelling and design (Dix et al., 2004).

The implication of an IoT that has been developed from different technologies (Stankovic, 2014), presents a shift of HCI analysis, ranging from the purely technical operation of the IoT such as hardware specifications and protocols, to the observation of meaning and knowledge-based interactions (Atzori et al., 2010). Once ordinary objects become cognified, they can be considered to possess agentic behaviour, with their own goals and utility functions, interacting with human users accordingly (Jia et al., 2012). Ma (2011) suggests that the pervasive and cognified nature of things working alongside other things, enables an autonomous information flow that is considered intelligent in terms of the services it enables.

It is common for 'smart' objects to interact not only with their users, but also with other objects, each possessing their own goals, and even co-dependent goals between some devices.

Referring back to the previously discussed heating example, modern automatic systems usually require users to set the desired temperature, but will also consider optimal operating times, according to variable energy rates (Scott et al., 2011). For example, the NEST thermostat is comprised of not only temperature sensors, but also detects movement, humidity and proximity (Hernandez et al., 2014). By learning user's operating habits, and the ambient conditions, the thermostat's functionality adapts to operate under the best possible conditions (Nest Labs, 2014). However, a human user could supersede the device's control logic, resulting in conflicting goals between machine and human. When considering goals that are shared between *things*, we could posit on the nature of human's role in the interactions, as will be discussed in section 3.3.

Arguably, the purpose of IoT systems would be to offload activities from the user. Users should be aware of the system's intentions and behaviour with limited interfaces, and how they become part of the operation loop.

Often devices look to fulfil their own goals, sometimes relegating the user's to a secondary position, and obfuscating what it is trying to achieve, as analysed by Yang and Newman (2013) in the context of smart heating, where the system's goals are not necessarily aligned to users expectations.

3.2.1 Affordances in the IoT

As discussed in the Introduction, for simple, non-cognified objects, the notion of affordances has been applied in regards to an object's "*fundamental properties that determine how it could be used*" (Norman, 2002). Baber (2018) extends this notion to the properties that allow for an interpretation of *"the object's functions in terms of specific features, and linking this interpretation to a goal that one wishes to achieve"*. As such, this characterisation not only relates to how the object can be used in terms of its physical affordances, but also to what it can be used for in the context of the user's needs and expectations.

Objects commonly have a designed purpose characterised by their physical attributes, defined by their supported tasks in context of their state (Kolios et al., 2016). For instance, the physical attributes of a mug affords a series of tasks dependant on the context of operation, and the object's state. That is, a mug full of water could be lifted and drunk from, whilst an empty mug could be stored in a cupboard. When objects are cognified, they are augmented, and their properties can be characterised beyond the physical aspect (Barthel et al., 2010), e.g., an augmented mug could show if its empty or full, or the temperature of its contents. In physical-computing and cyber-physical systems, such as the the IoT, *things'* status are defined by both their physical and digital features.

Giaccardi et al. (2014) posit that "*the relationship between the virtual object and the actual object is not always symmetrical*", arguing that data modifies the value of the physical object as perceived by the user. Giaccardi et al. point that not only data extends an object's nature, but it is also modified by their embedded computer code and algorithms that determine their behaviours.

Smart' objects often present limited user interfaces (UI), where user's perception and understanding of *things* is sometimes narrow and even inaccurate (Nazari Shirehjini and Semsar, 2017; Kortuem et al., 2010). Bellotti et al. (2002) note that *"without visible affordances users can unintentionally interact or fail to interact"*.

Norman (2007) notes that information related to an object can be conveyed by cues as provided by their own affordances, through *"implicit communications, sounds, events, calm, sensible signals, and the exploitation of natural mappings between display devices and our interpretations of the world"*. That is, *implicit* communication cues allow for their understanding without any "*specific learning or training, or transmission*" from the user's part, enabling information exchange *"without interruption, annoyance, or even the need for conscious attention*". An example can be found in voice conversations in which a silence can be implicitly signal the listening party's turn to speak. *Explicit* affordances contrast to an *implicit* communication in the sense that these have to be specifically designed. Using the previous example, such an interface might consider the implementation of visual cue to make the listening party aware of their turn to speak. The latter could be appropriate for some applications, nevertheless, Norman (2007) adds: "*Implicit communication can be a powerful tool for informing without annoying*".

As such, for cognified objects, an approach to interaction would be to consider the objects' *implicit* affordances as a property of the *thing* (or, for IoT, perhaps a collection of *things*) which can be naturally perceived by the user, enabling inference on the appropriate course of action. Affordances increase the 'perceived relatedness' to objects to "*highlight user involvement and control*" (Jia et al., 2012). In the context of the IoT, this concept has been also used to analyse how an object is understood (Barthel et al., 2010), and how objects relate to their digital representations (Coulton et al., 2014).

When analysing the implications of affordances in the context of smart objects, Baber (2018) identifies the requirement for models that provide a framework for the design of prompts and cues that enable users to identify how objects are used and what are they expected to achieve. Nevertheless, Baber notes that designing object's affordances is not possible, but that efforts should be focused on the design of 'affording situations" that show how "*Knowing how a person with given ability would interact with an object to achieve a given goal in a given context is central to ISO definitions of Human-Centred Design"*.

3.2.2 Sensemaking

Duffy and Baber (2013) address the notion of sensemaking as the process of coordinating actions given certain situations. As such it relates to "*interpreting a situation in terms of the 'meaning' that can be extracted from it...in a cognitive process of information collection and assimilation*".

For a human-centred IoT (Koreshoff et al., 2013) argue that the sensemaking process requires interaction methods that address collection and assimilation not only of the devices physical attributes, but also of data-enabled characteristics, highlighting the design requirements that must be put in place in order to allow for these process to occur within the system such that they allow for action on the user's behalf to take place.

In the IoT, this implies that sense-making processes should inform how humans create models of the IoT in terms of their interfaces and the services it presents, as will be discussed in the following section.

3.2.3 Mental models

As discussed in the previous Chapter, the IoT presents a view were data interactions often occurs in communication channels undisclosed to the users. This section analyses how humans make sense of technology, and in the context of this thesis, IoT applications.

Analysing how artefacts support human cognitive activities, Norman (1993) highlights the notion of 'representation' to provide a framework in which we make sense for *"objects, things and concepts"*. Representation provides a model that *"captures the essential elements of the event*", but also has the drawback of relying on how close is the model to what it is representing. If the representation omits aspects relevant to what it is expected to support it could become misleading and confusing to its users. Norman (1993) provides a guideline to develop representations as follows:

- *"They should capture important and critical features of the represented world"*
- *"They are appropriate for the person"*
- *"They are appropriate for the task, enhancing the ability to make judgements"*

Moreover, Norman (2014) extends his definition by differentiating amongst the stakeholders for a particular object. As such, these representations should include the user's conceptual model (the user's representation of the object), the user's mental model (its understanding or internal representation) and the designer's conceptual model

Schmitt et al. (2011) focus on user's abilities that must be supported by the conceptual model noting that they should provide a *description* of the system's working mechanisms; an *explanation* of the interactions of the systems, i.e., the system's reactions to its possible interfaces; and to provide *expectations* or anticipations of the system's behaviour under a particular context. Moreover, Schmitt et al. propose that the user's mental model is also of interest in light of the conceptual model as it will influence how the user creates its internal representation.

Yarosh and Zave (2017) approach smart object design from a perspective of mental models created by users in terms of the interactions with the most prominent features of the device. Their research provides different scenarios on the usability and users' expectation of a 'smart lock'. In particular, errors and biases are analysed as a way of understanding user's misconceptions with the system, and to highlight problems in device design. This methodology exploits the notion of a human-centred analysis of interactions in terms of usability depending on the context. This approach enables to provide responses for the mental models in different domains by encapsulating the object's features into particular functions.

For home automation, Kempton (1986) explores the mental models that define the constructs that explain human behaviour when interacting with autonomous heating, providing the groundwork for the research of how users perceive autonomous systems in home environments and how these often deviate from what was designed, as will be discussed in section 4.6.

Moreover, for context-aware ubiquitous computing, Schmitt et al. (2011) identify a requirement for systems that supports the users' mental model such that they "*enable people to describe a system's working mechanisms, to explain their interaction with the system and to anticipate future system behaviour*".

As such, for the purpose of this work mental models of IoT systems are defined as the representations that describe, explain and contextualise relevant, human-centred and support user-centred goals.

When considering the IoT as an autonomous, smart environment, this research aims to explore human behaviour when interacting with objects, providing both physical and data-based representations in interaction design.

3.3 Usability for the IoT

The Internet of Things has been adopted into applications which either requires the intervention of the human user, or provides information to the user. As such, interactions occur within a group of cognified objects and humans, establishing a society similar to that described by Marvin Minsky (1988) where simple processes and agents, operate alongside to fulfil tasks. In the context of Human Computer Interaction (HCI), the question then is how a human will become a participant in such a society. As described in Chapter 2, *things* often serve as data collection nodes in a network, and are managed by a central node. In this topology, user interaction occurs with the central, controlling node. Arguably the system's 'intelligence' would be considered to reside for the most part in this controlling node, in much the same way a server manages a range of client nodes in a computer network (Tanenbaum, 2002). In this paradigm, HCI for IoT would not be dissimilar to traditional approaches, with the user negotiating with the user interface of the central node to specify operation parameters or query information about the system. This conflicts with the vision of an IoT comprised of loosely connected devices that interact with others only when required to complete their tasks and goals. Moreover, nodes connected in a centralised topology have, at best, an incomplete view of their role in the operation of the network. If as mentioned earlier, the human user is to be considered to have a role in the IoT, they would also have a partial view of the networks functionality. As such, the challenge for HCI is to analyse how best to supplement the human user's role and interactions with the IoT.

One of the aims of usability has been to design clear interactions, that prevent users from being distracted or diverted from their goals (Norman, 2002). Digital devices have mostly followed these interaction principles. Nevertheless, cognification of *things* has also created scenarios in which much of the information exchanges occur in communication channels hidden or opaque to the users.

3.3.1 User experience in the IoT

Based on the previously introduced notion of physical-computing (Stankovic et al., 2005), Kuniavsky (2010) proposes that *thing* design encompasses many disciplines, focusing on:

- *The physical object*
- *The software interface*
- *The hardware interface*
- *Interactions with other devices in the network*
- *Representation to other objects and human users*

Based on work by Garrett (2002) focusing on web-based applications, Kuniavsky proposes different levels of user experience, ranging from the concrete to the abstract (Figure 3.1). In his framework, user experience focuses on the physical aspects (surface), to the functional (structure), requirements (scope) and the purpose of the system.

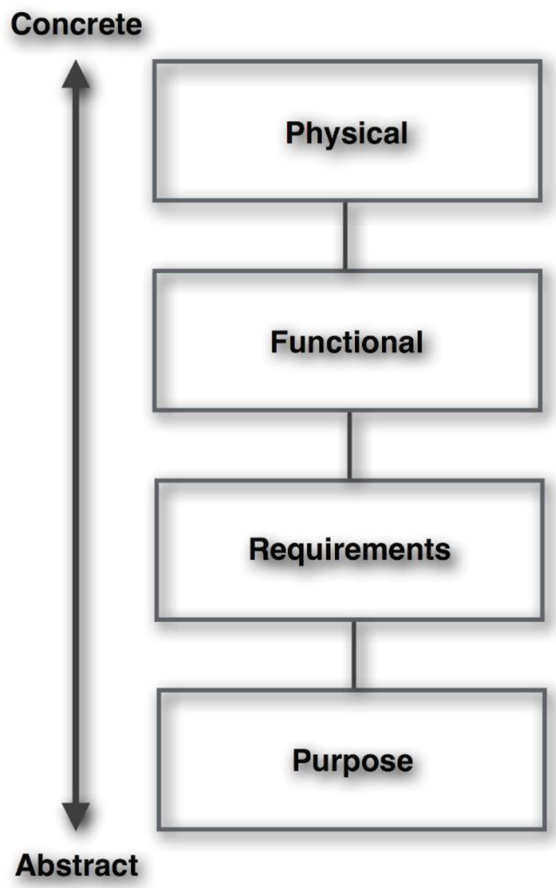

Figure 3.1 Planes of user experience in smart objects, adapted from (Kuniavsky, 2010).

Norman (2007) states that system designers *"tend to focus on the technology, attempting to automate whatever possible for safety and conveniences",* but notes that given some technological limitations not everything can be automated, with users needing to keep their attention on those tasks that are not. In these cases, it is imperative that both human and machine know what each is attempting. Thus Norman proposes that to provide meaningful experiences, system should designers focus on improving the coordination and cooperation of human and smart objects.

3.3.2 Data representations in IoT usability

As observed in Chapter 2, IoT development has focused on data. Thus, much like materials (plastic, metal, etc.) in physical objects, Kuniavsky (2010) argues that "*information becomes a design material*" for smart objects, providing its own set of constraints and capabilities.

Data-based approaches become useful when thinking about devices whose interfaces rely on displays (i.e. smartphones). Figure 3.2 shows the interface for a mobile app used to control a 'smart' lighting system. Users are able to change lighting intensity and colour in different zones in their household, looking to create ambient situations according to context, such as 'watching a movie' or 'dinnertime'.

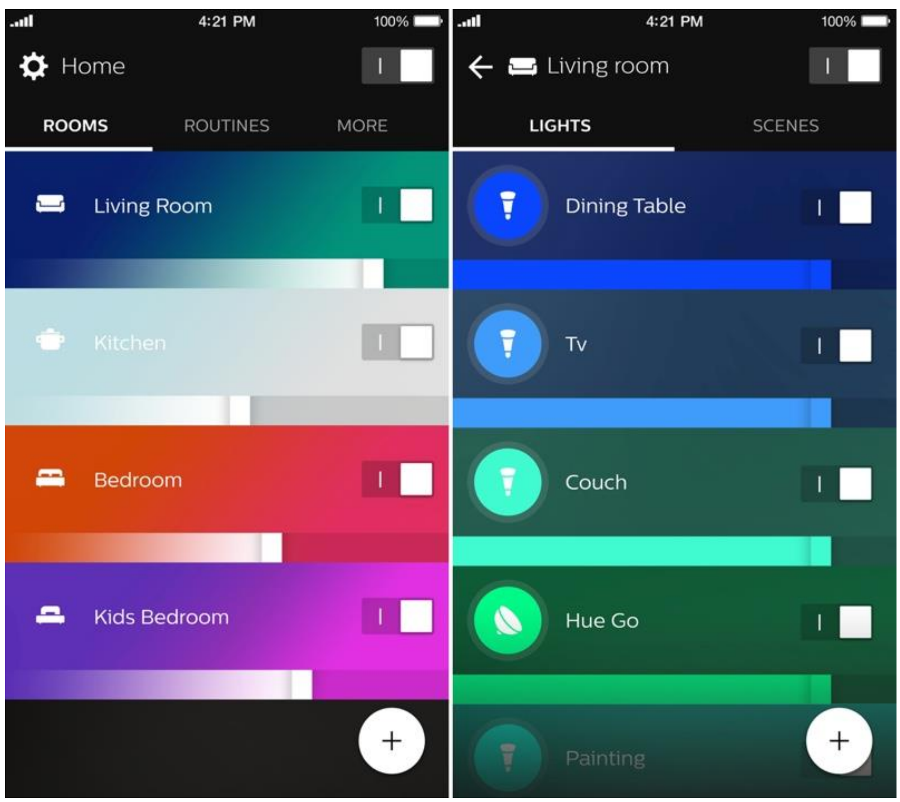

Figure 3.2 Smartphone based application to interface with the Hue Smart lightning solution (image: www.meethue.com)

In interfaces such as the Hue's, although there is a clear metaphor for switching lights on and off, for a more 'intelligent' and flexible behaviour, the system also provide a means of controlling and programming the operation of the lightbulbs. As such, for the latter example, the physical interaction through a screen dislocated from the physical object, produces opaque interactions.

3.3.3 Tangible interfaces

Ishii and Ullmer (1997) introduced the notion of tangible interfaces to consider computing devices that "*augment the real physical world by coupling digital information to everyday physical objects and environments*". These objects operate under the basic paradigm of "*user uses their hands to manipulate some physical object(s) via physical gestures; a computer system detects this, alters its state, and gives feedback accordingly*" (Fishkin, 2004).

In contrast to a data enabled paradigm (as described in the previous section) where users are often left wondering what the device is trying to accomplish, Pschetz et al. (2017) presents the Bitbarista IoT-enabled coffee machine, aimed to provide a way for users to reflect on the impact of data being used and produced by an 'intelligent' machine. Based on the notions of 'Reflective' and 'Critical' design, this device is explicitly designed not centred on efficiency, but on information and data processes, in contrast to what usability guidelines would traditionally suggest. By showing users the price of their cup of coffee and where the coffee is sourced (through a built in User Interface), this 'verbose' IoT device displays data instead of hiding it, relates the data to the process behind it, and allows users to decide how they participate in these data processes (Figure 3.3). The study found that users perceived the system to be a passive device in contrast to an autonomous object. Notwithstanding, users referred to be more at 'ease' with the system by knowing exactly which data transactions were occurring, and reflected on a positive relationship with the device. This study suggest that a dialogue approach with a smart object provides user with a sense of being in control, leading to less *"discomfort and anxiety"* (Pschetz et al., 2017).

Houben et al. (2016) analyse how users interpret, relate and organise data through a '*human-data design'* approach, arguing that 'hybrid' representations that consider both physical and data-based aspects are much better suited for these systems.

This relationship between users and things in the context of design, has been explored in terms of a *things* forming a "*socio material assembly*" in which objects share a "*physical effect in the world*"(Cila et al., 2017) in relation to their operation. According to Cila et al. (2017), these devices also need to be in *"a form that enables users to invite these products into their lives and makes an impact on people's life quality"*. As such, design efforts not only should look into the system's technical implementation, but also on the impact it has on users.

By using tangible interfaces in a controlled environment, Houben et al. (2016) posit that users engage with technology and appropriate it when they can directly relate to the effects it has on the operation of the device. By using tangible interactions participants in their study found that devices were *"doing what they were supposed to be doing"*.

3.3.4 Modelling Human Interaction with the IoT

Modelling is the *"process of matching the facilities that the system provides to the needs of the user"* and based on user needs, to specify guidelines for *"design decisions and make design choices explicit"* (Booth, 2014). IoT design and modelling has focused on a device and system perspective, highlighting technical implementations over usability (Sterling, 2005). Methodologies have been approached from a data centric perspective (Feinberg, 2017; Wolff, 2016) in which the modelling process is based on data flow, from their collection to their application, or how data is understood and appropriated by its users (Pschetz et al., 2017). It has also been addressed from an agent based perspective (Cila et al., 2017), in which actors in the network (both things and humans) are considered agents that are imbued with *"collector, actor, and creator"* roles that define how they interact with each other. From a device perspective domain specific ontologies and semantics have been identified (Derler et al., 2012). Kawsar et al. (2010b) explore how to implement object's profiles that allow for their extensibility through the addition of new, compatible sensors and actuators, highlighting the development efforts to the networks and its devices. Finally, research has been conducted on the adoption of middleware technologies that allow for modelling interactions through centralized entities (Dixon et al., 2010).

3.3.5 Interaction Design for the IoT

Cila et al. (2017) define four types of connected products as:

- *"Products that inform users of their status and expect instructions,*
- *Products that create connections with users to learn from the interactions,*
- *Products that form networks with other products to provide information and infer user activities,*
- *Non-networked products that can learn from user interaction"*

By placing users at the centre, this categorisation relates to the roles of the actors of the network also considering what type of interactions are expected, and the negotiation and delegation between user and smart objects.

Figure 3.3 Bitbarista, a 'verbose' IoT device (image: petrashub.org).

For intelligent machines, the challenge for HCI is to create engaging products such that they provide meaningful services to their human users. In 'The design of Future Things' (Norman, 2007) six rules for interaction design are provided:

1. *"Provide rich, complex and natural signals*
2. *Be predictable*
3. *Provide a good conceptual model*
4. *Make the output understandable*
5. *Provide continual awareness, without annoyance*
6. *Exploit natural mappings to make interaction understandable and effective"*

Norman’s framework implicitly considers human users in a harmonious relationship with smart objects.

3.4 Task and goal analysis

System usability has been approached by in ergonomics and HCI by a different range of methodologies, focusing on analysis of user actions. Hierarchical Task Analysis (HTA) (Stanton, 2006) has been used as a means of providing system requirements through a representation of the system’s sub goals, and used in different applications such as user interface design, workload design and assessment and error prediction. An extension of HTA was defined by Task Analysis for Error Identification (TAFEI) (Baber and Stanton, 1994), originally conceived as a tool to analyse a system’s usability through system actions, and the possible errors derived from them.

3.4.1 Hierarchical Task Analysis

Hierarchical Task Analysis (HTA) (Stanton, 2006) has been applied to different applications such as user interface design, workload design and assessment, and error prediction, acknowledging that tasks can be categorised as physical and cognitive, seeking to represent system goals and plans (Stanton, 2006).

Stanton (2006) states that there are three principles for analysis in terms of tasks:

1. Tasks consists of operations defined in terms of the goal they seek,
2. The system can be defined by its operation, which can be broken down into sub-operations defined by their contribution to the core goal
3. The relationship between operations and sub-operations is hierarchical.

The application of Hierarchical Task Analysis to describe a system operation in terms of its goals has been broken down as a guideline by Stanton (2006) as follows:

- *“Define the purpose of the analysis*

- *Define the boundaries of system description*
- *Analyse sources of information for the system*
- *Describe the system's goals and sub-goals, in a manageable way*
- *Link goals and sub-goals, including the rules determining their sequence*
- *Sub-goals should be described applying a sensible stopping-rule*
- *Verify with subject-matter expert*
- *Iterate analysis"*

System analysis should focus on the context of operation, who is it aimed to, what it does in terms of the actions that are performed and how each are related to each other. Additionally, each task should be described in terms of simpler units up to the point where it fits the analysed application. Stanton provides a procedure to describe the sub-goal hierarchy as shown in Figure 3.4.

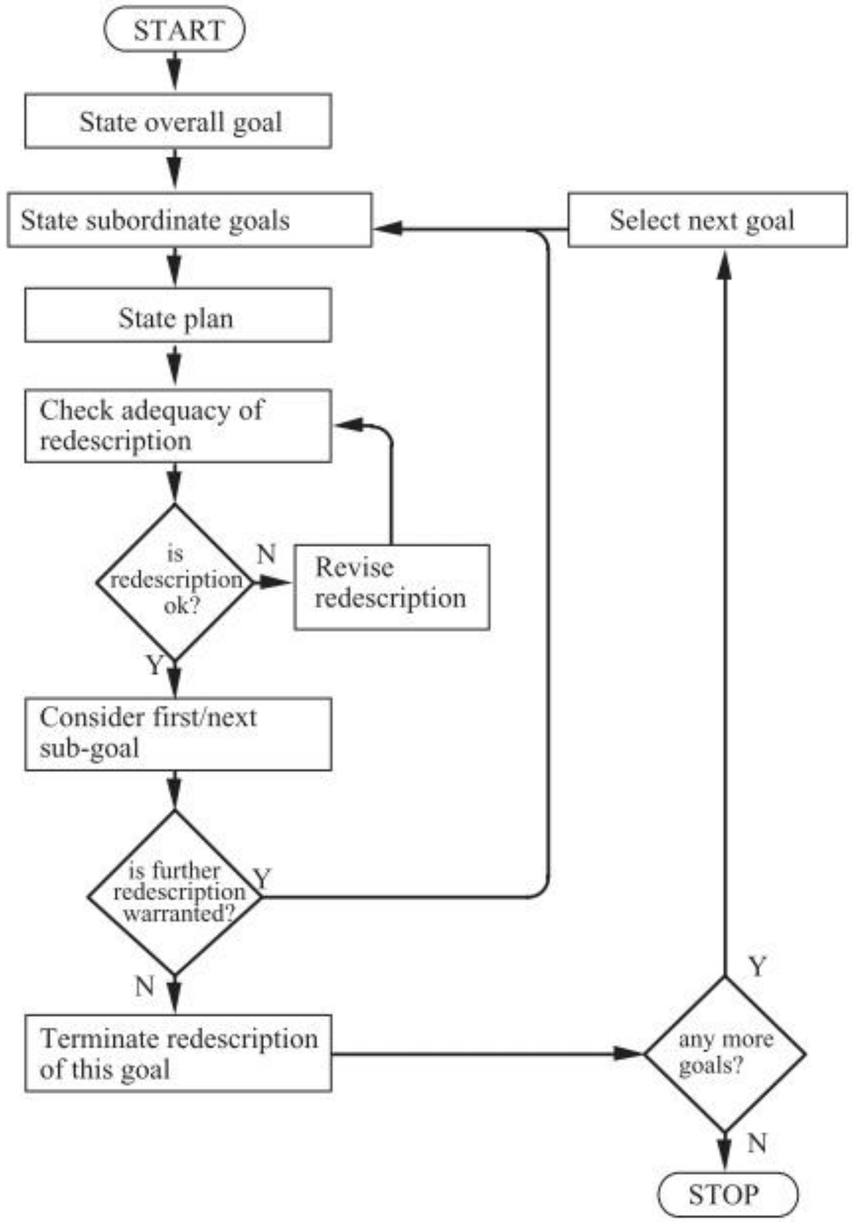

Figure 3.4 A procedure to break down hierarchy in sub-goals (Stanton, 2006).

3.5 Analysing human error for goal deviation identification

As noted, one of the main concerns of Human-IoT interaction is the misalignment between user's goals, and the machine's. This section provides a review of techniques based on usability and human based errors, with the expectation not only to highlight mistakes, but to determine how deviations in usability can be used to state system requirements in a collaborative environment.

Human error has been analysed mostly in the context of safety critical systems such as power plants or aircraft (Norman, 1983; Cooper et al., 1996), with the aim to "assist in analysing the dependability and reliability of systems with a human component" (Fields et al., 1997).

Norman (1983) proposes that the psychological mechanisms in human error can be applied to examine the human-machine interface, highlighting error description as follows:

- ***Mode errors***, in which users perform actions to operate the machine under the assumption of a particular mode of operation, when in fact they are in another.
- ***Description errors***, in which errors occur when actions are not clear, leading to ambiguity.
- ***Lack of consistency errors***, leading to perform actions with the previous knowledge of successful actions, but that don't apply to other use cases.
- ***Activation error***, related to *"inappropriate actions get performed and appropriate actions fail to get done"* due to forgetfulness.

To address this, Norman proposes that analysing errors should inform system design to identify possible interaction problems, and proposes that human-machine interaction should focus on providing feedback, adequate response sequences, and is consistent in structure and design to prevent memory and representation problems from the user.

3.5.1 Technique for Human Error Assessment

In regards to exploring error for the definition of requirements, Fields et al. (1997) define a iterative process involving a proposed user interface. In a Technique for Human Error Assessment (THEA) the system's purpose and performance models are analysed under different scenarios, in which agents perform tasks towards a goal. Error identification requires asking question about causal factors to identify them and how they impact the system. The output of the system is given in terms of suggestions for system requirements, and the iteration of the process once these are applied (*Figure 3.5*).

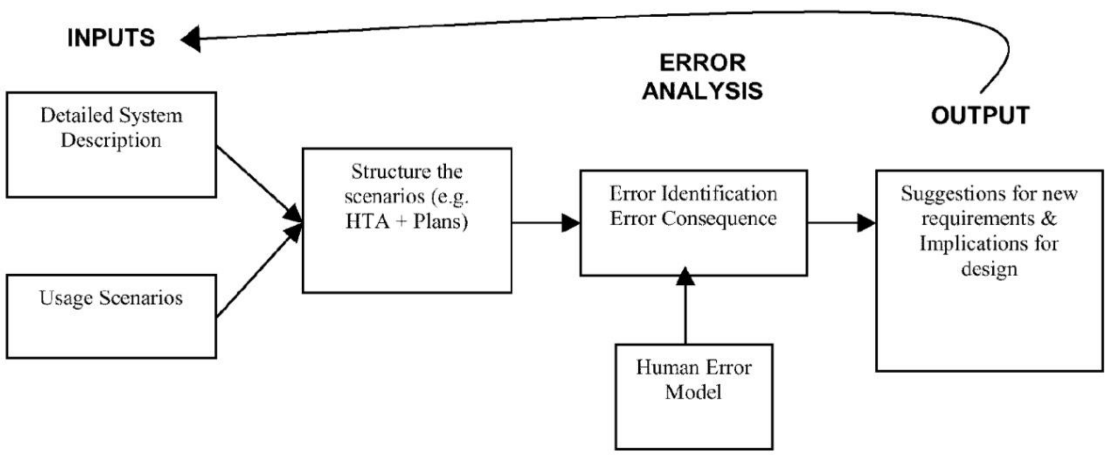

Figure 3.5 The THEA process (Pocock et al., 2001).

As discussed earlier in this chapter, this thesis frames the IoT is as a collaboration of actors, each with their own role and purpose. Thus, the breakdown of usage scenarios requires the analysis of actors involved in tasks and plans to achieve the system's goals.

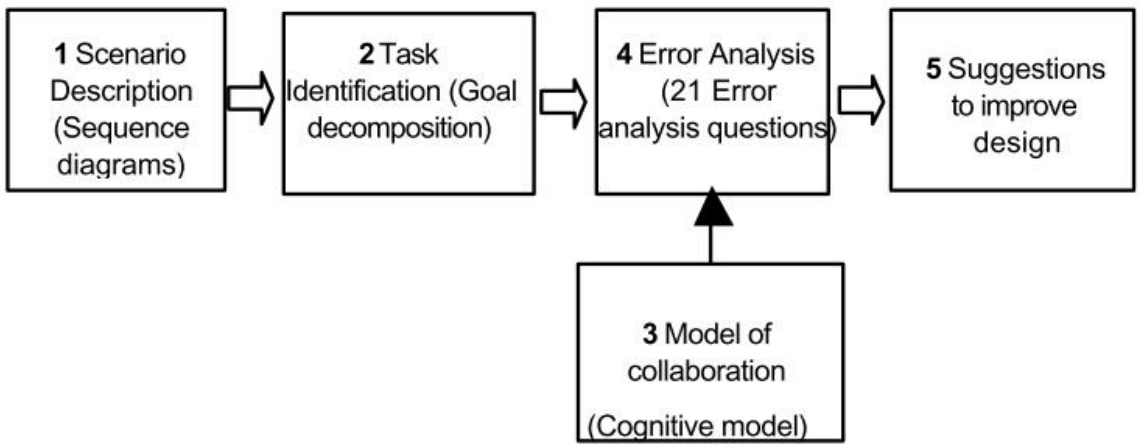

Figure 3.6 The CHLOE process (Miguel and Wright, 2014).

3.5.2 Human error analysis for collaborative work

The CHLOE framework focuses on identifying errors in collaborative work (Miguel and Wright, 2014) within a process similar to THEA in regards to scenario description, decomposition of goals in tasks and producing suggestions to improve the system, it introduces a model of collaboration in the process loop, as shown in Figure 3.6.

CHLOE focuses on socially enabled collaborations in human-human, and human-technology-human environments, in which the latter are mediated through technology. Notwithstanding, this framework considers agency on behalf of those involved, and models their collaboration in the context of a shared understanding the system's purpose. Figure 3.7 shows a simplification of the collaboration process in which participants form their own mental models of the system, understand the system goal and form a plan based on goals to achieve it. A shared understanding allows users to collaborate on shared goals, whilst interfacing with agents under certain constraints, such as their user interfaces. Notably, a collaborative approach is the basis of the conversational IoT defined in chapter 4.

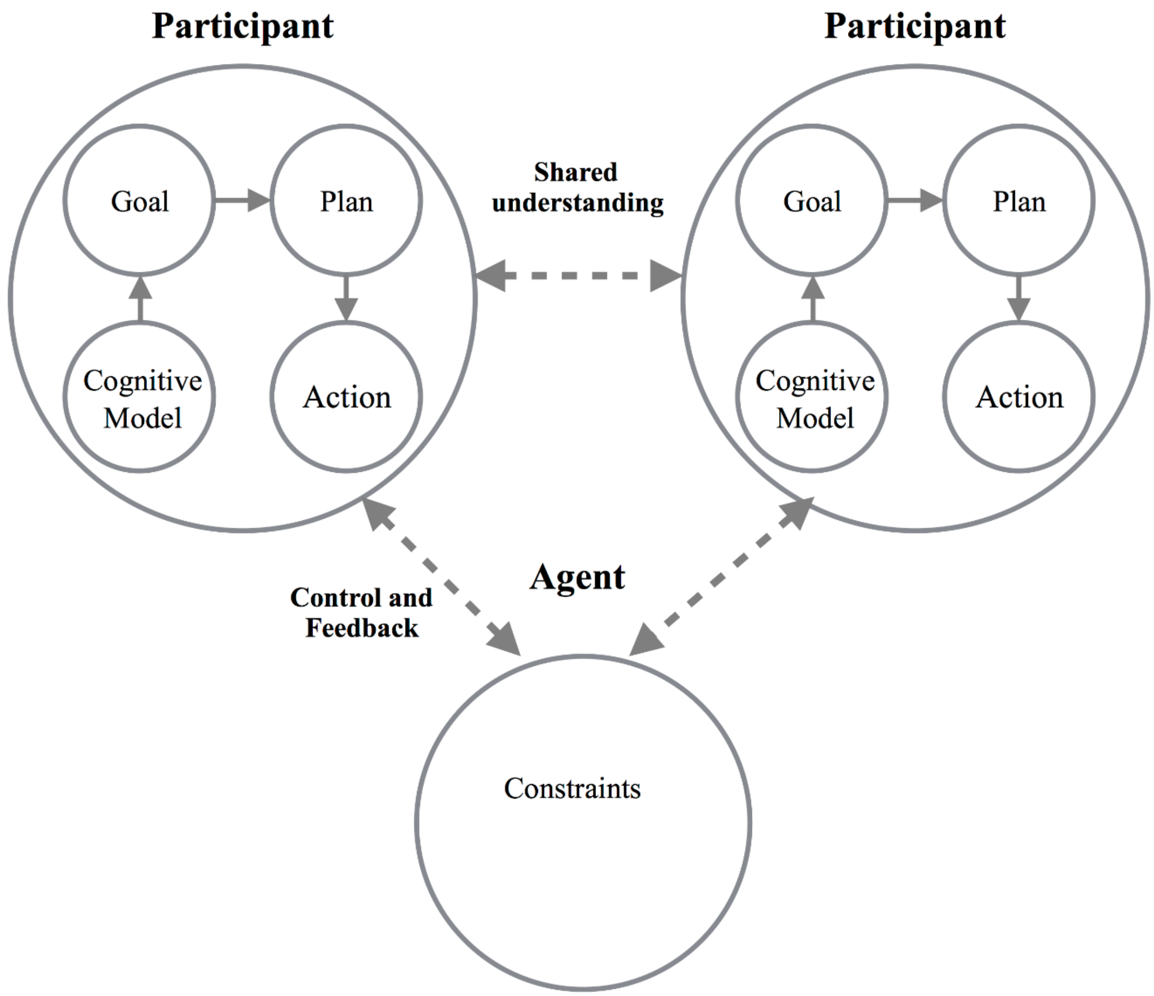

Figure 3.7 CHLOE collaboration process, adapted from (Miguel and Wright, 2014) .

3.5.3 Task Analysis for Error Identification

Task Analysis for Error Identification (TAFEI) presents a method that describes "*a form of dialogue between users and products with a view to predicting likely types of human error arising from dialogues described in terms of state-space diagrams*" (Baber and Stanton, 2002).

TAFEI (Baber and Stanton, 2002) characterises a dialogue occurring between users and objects pursuing a goal cooperatively, sharing information and assisting each other. This method analyses how participants in these conversations select the appropriate actions given the goal that they want to achieve and is supported by the product. As such, Baber and Stanton define a goal-directed methodology, in which human-object interaction is characterised through a series of ‘legal’ states. In the context of TAFEI a ‘legal’ state is such that is supported by the system, and its leads to the completion of the specific goal. In this regards, products can support different goals, but some state-transitions could be consider irrelevant (‘illegal’) to the task at hand, whilst being ‘legal’ for others. Moreover, TAFEI is a state based method, suited for IoT devices that are inherently based on states as introduced in chapter 2.

TAFEI provides a methodology to model user interactions, highlighting system’s goals. In the context of the IoT, TAFEI provides a perspective in which HII interactions are analysed from the perspective of system’s valid (or invalid, which in this tool’s case are errors) goals and sub goals.

Its primary focus is on the turn-based interaction between human and product, working as a system to pursue a goal. TAFEI has been used to analyse products in task-based scenarios, and successfully applied to products such as ATM and vending machines (Baber and Stanton, 1997), and critical-use and safety scenarios as surgery (Kuang et al., 2009) , industrial meat grinders (Mohammadian et al., 2012) and electrical substations (Stanton and Baber, 1996).

Using TAFEI as a modelling methodology, common activities would be identified to belong to the same overarching *theme* of the network, and thus would enable a conversational IoT system with common grounding, across different *topics*.

One of the drawbacks found in CHLOE (Miguel and Wright, 2014) is the difficulty in identifying the roles of the participants in the collaboration, often disregarding the agent’s involvement, as reported by analyst led trials. Conversely, TAFEI is very clear in providing analysis for both the machine's and humans' roles, tasks and state transitions, bringing them together in a unified model. Hence the following chapters provides a worked example of TAFEI, building upon the concept of instrumented objects in everyday situations. In them, users interact with the objects, performing activities to achieve a goal. In this context, the overarching theme of the conversations becomes the system's main goals, as described by TAFEI analysis. Moreover, by identifying system's plans, tasks and states, an informed decision on sensor placement will be demonstrated as an extension of TAFEI for the IoT.

3.6 Conclusion

In this chapter we have explored the notion of an Internet of Things that shifts from a technology based paradigm to one in in which human users are introduced, and have to 'make sense' of the *things* and of how these objects present their data and physical features. As presented in chapter 2, for some of these 'smart' devices, the notion of agency is introduced. As such, devices act on their own accord to accomplish their purpose, which in this chapter has been characterised in terms of the tasks they complete to attain goals.

Moreover, in terms of smart systems Kuniavsky, (2010) argues device's and user's roles must be treated similarly in "a network of relationships" with a common goal, and that by understanding both their requirements and how they associate to each other, products design can be informed in the expectation of a successful product. Thus, roles for each actor should be designed and not just occur by accident. Consequently, this chapter aims to provide an exploration of agency is balanced between humans and *things* in order to reach the common system goal.

The IoT can be conceptualised as a human-machine system, in which each of the participants take upon roles, interacting with each other, with their own specific goals. In the following chapter, the notion of the relationships and the networks that characterise it will be explored in the context of socially linked nodes, in which common interests are shared, leading to a discussion in subsequent chapters of how the roles are affected in terms of tasks and goals (chapter 4) and how these roles inform system design and development (chapter 5).

4 A Social Internet of Things

This chapter is partly based on the paper "*Towards Theme Discovery Paradigm in the Internet of Things*" by, Cervantes-Solis, J. W., & Baber, C. (2016), presented in the Contemporary Ergonomics and Human Factors 2016 conference. The author of this thesis developed the concepts presented in the work, conducted the research and wrote the paper with the support of Prof Baber.

4.1 Introduction

In the past two chapters two visions of the IoT have been presented: one in which the IoT is fundamentally based on a technology and data approach, and another where human users are introduced, noting that the former minimises its influence on areas that improve aspects of human activity (Stankovic, 2014), whereas the latter relies in technology to promote system usability. As such, there is a potential paradigm shift to a *social* organisation of objects and humans where smart, physical-computing objects interact with other *things*, and with their human users. The expectation would be to analyse how these relationships can be characterised so they support human activities. Moreover, this chapter focuses on identifying how these activities are defined in the context of the IoT.

As the IoT gets adopted into everyday human activities, these smart *things* will fulfil support roles in different environments, and interact with their users and other objects. However, these interactions are not always clear and apparent to those involved, so a more meaningful communication strategy ought to be implemented between the two if a vision of a society of smart objects is to be achieved. A collaborative environment in which humans and *things* establish connections to form networks leads to analyse the nature of these exchanges and how they are represented amongst those involved.

In much the same manner that conversations hold meaning to those involved only when there is mutual interest and shared information, this chapter introduces the concept of a social-like Internet of Things in which actors engage in conversations framed by a common theme.

The notion of themes in a Social Internet of Things (IoT) is introduced as a means of describing the *conversations* that occur in these networks. As will be explored in more detail in Chapter 5, in the context of this thesis, in IoT conversations *theme* refers to the aggregation of *topics* that contribute to a conversation in a particular *context*, providing a high level definition of the network's purpose. The *context* relates to a clearly defined environment, characterized over time by the recurrence of these interactions. When a collection of *things* collaborate in the pursuit of a common theme, a *conversation* can be characterised in terms of *topics*. As such, this chapter provides a description of a categorisation of these concepts and their role in a Social IoT.

4.2 The Social IoT

When smart devices are adopted into everyday usage scenarios, understanding their activity both in term of their connections and their particular datasets could become increasingly problematic for their users given the limited capabilities of the user interfaces as mentioned in 3.3. One approach to addressing such problems is to shift analysis from the networks or the data-centric *things,* and to consider instead the ways in which they are used in social-like scenarios, defined by specific contexts and environments. This concept has been defined as the Social IoT (Atzori et al., 2014b; Guo et al., 2012a) in which the *things*, the networks and users could be defined in terms their relationships and the functions they perform as members of a society. This raises the possibility that things in these networks can have socially defined roles, in addition to their technically enabled functions. As described by Atzori et al. (2011) in their Social IoT Architecture (SIoT) *things* are described by their:

- relationships
- services
- and trustworthiness

That is, things in the IoT can be characterised by the level of trust they have amongst network's participants, the nature of the relationships, and the purpose of these relationships. Given these characteristics, the framework allows for service composition and discoverability of *things* allowing them to make themselves, and their functionality, available to their relevant peers as defined by these social-like networks. Moreover, *things*' roles might vary across different networks, such that the objects could be called upon to perform the same functions in different networks, albeit in different environments, provided that the relationships social attributes are relevant and shared. For example, a temperature sensing object could be used in the context of an industrial application to provide temperature readings in a furnace or in an office as a part of the ambient heating. The interpretation given to the information they provide would have different value and meaning to the different stakeholders, depending on how they approach the device, as will be discussed in section 4.3.

By considering these social attributes, information exchange becomes related to the object's role in an activity to achieve a goal (or the tasks it contributes to the goal), and less so on their specific data sets or function. Thus, in contrast to industrial or consumer IoT systems, the expectation would be that these exchanges become more meaningful between the actors of this Social IoT. As such, as will be discussed in section 4.2, in social-like environment, the involved parties usually engage in conversations when there is a requirement for information exchange (Khan et al., 2016).

Thus, the information that the *things* convey to user's needs to be presented in such a way that conversation-like exchanges are represented between the actors in this Social IoT, where the theme of the conversation is made clear to all. To support knowledge-based interactions, the concept of *theme* has been identified to characterise the overarching purpose of the network (Cervantes-Solis et al., 2015a).

4.3 The Human-Things system

Ross (1973) argues that agency is a social interaction between two or more parties, in which:

"…the agent, acts for, on behalf of, or as representative for the other, designated the principal, in a particular domain of decision problems".

In the smart IoT paradigm, these definitions suggest devices or a collection of devices that possess attributes allowing them to take the appropriate actions on behalf of users, given decision making informed by a set of inferences on the environment.

Stankovic (2014) argues that involving the humans in their design and operational models, would enable improvement in areas that directly impact users, such as safety and usability, and points three main challenges for the development of Human in the Loop (HiTL) applications: first, to characterise the full range of applications that fall within the HiTL domain; second, improve on the techniques to derive models of human physiological and psychological behaviour; and third, to identify the position of the human in feedback control models. The first two requirements warrant their own research, but in the context of this work, the latter challenge provides a framework to understand the role of the human in an IoT. From control theory, Stankovic (2014) identifies the possible placement of a human user, in one of the following categories:

1. Outside of the loop,
2. As part of the controller,
3. As a member of the system model,
4. As a sensor,
5. As an actuator.

This categorisation places the human as a part of the system, fulfilling different roles as required. In an automatic temperature control system, the human user must define a set point (a desired temperature) that the system will aim to attain: the human becomes a controller. Conversely, in the same example, the user also acts as a sensor, by ‘feeling’ cold or warm, influencing temperature settings. Automatic controllers are more suited to machine-based decision making processes, particularly those involving tedious and monotonous tasks (Norman, 1993a). Thus, one must consider when is the role of a controller most suited for a human to take. Figure 4.1 shows the duality on the human’s role both as a controller and as an observer recipient of the system’s services. As described by the figure, the user’s interaction with the system is by issuing commands and receiving feedback from the system through a central node that in turn relays commands (set points) to devices and collects data from devices. As such, humans become participants in the interactions with the things, placed as part their control loop.

Schirner et al. (2013) argue that for tasks involving “*perception, intuitive control and high level decision making*” humans perform better than autonomous machines. These notions suggest that when humans become involved in Human in the Loop systems, an approach would be to consider solutions that delegate tasks between the two parties. In this situation, where the desired set points established by the human might not be in alignment with the system's, there might be a requirement for negotiation and agreement.

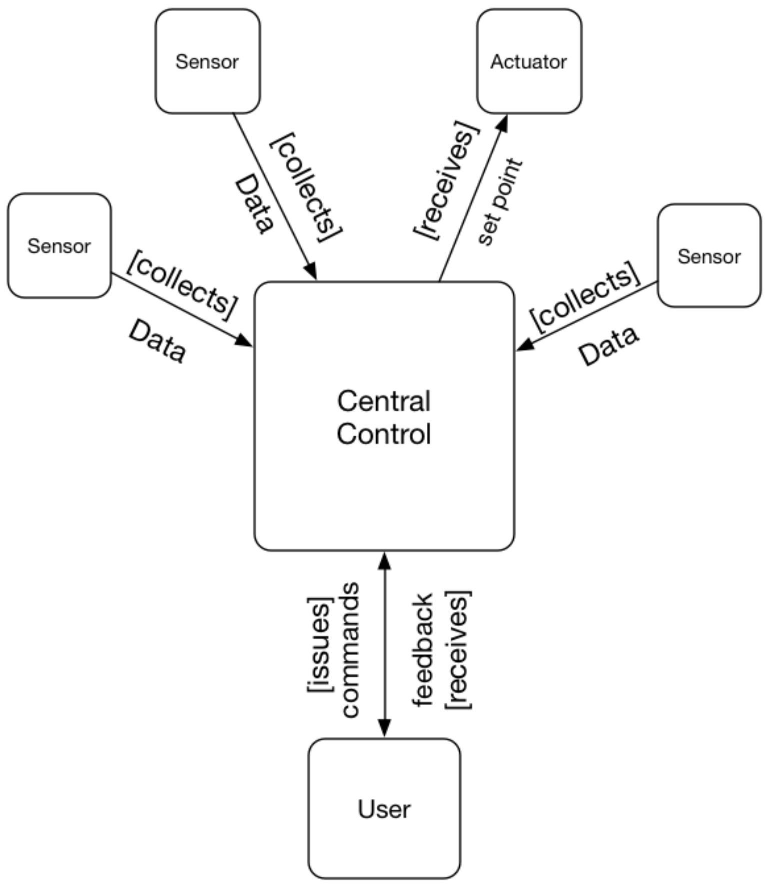

Figure 4.1 IoT-Human in the loop system.

In agents that engage in collaborations with other agents, this negotiation is expected to occur in an organised manner, providing the adequate framework of information and intention exchange, as will be discussed in Chapter 4 in the context of a social IoT.

If we consider the notion of a human being part of the system loop, we should also posit the scenario in which the human is outside of the loop, at best characterised as an observer of exchanges and services provided by the system, and at worst by being left out of the interaction processes. By reconsidering the characteristics from a smart system as defined in the previous chapter (transparency, reliability, helpful and context-aware), we could frame human's role not only as how they relate to the control loop as described by Stankovic, but also as one in which there's an expectation of these objects such as they support human activity, particular in order to complete specific goals. This places an expectation of agency on the objects from the point of view of the user. When considering the tasks and goals that the IoT system supports, we should posit how roles are balanced in terms of agency, and whether there could be a conflict in what the system's purpose is assumed to be, as will be discussed in following chapters.

Jennings and Moreau (2014) argue for the inclusion of humans as part of the IoT, considering them part of a collective, stating that the IoT has enabled a *"ubiquitous information substrate"* of which people become dependent of them for everyday activities. The concept of human-agent collectives (HAC's) is introduced to demonstrate the social-like collaboration between humans and ubiquitous computing.

Thus, by considering the cooperative aspect of the relationship between humans and cognified objects described in this section, this thesis proposes to understand the Internet of Things as a Human-*Things* system in which both parties collaborate to achieve a common goal.

In the following sections the nature of these goals will be described to characterise its commonalities.

4.4 Machine-centred goals

Sterling (2014) argues that the IoT is no more than a reaction to current market forces, looking to monetise data produced by connected devices. Sterling posits that most of the solutions found in the IoT do not really follow the user’s best interests, but the manufacturer’s or technology ‘giant’ harvesting the information.

Morozov (2014) has applied the concept of ‘*technological solutionism’* as a way of describing what he believes to be the state of recent technological developments. He argues that solutionism occurs when someone invents a problem, creates a narrative to frame it and in the process misrepresents the problem as something genuine and urgent, and then advocates for technology to provide a solution to the problem.

These notions suggest a scenario in which the IoT does not fully considers its human stakeholders. The existence of devices such as a smart toaster, a smart kettle or a smart saltshaker would seem to confirm Sterling’s and Morozov’s visions, and certainly would elicit an argument as to the purpose of these devices (Figure 4.2).

Figure 4.2 'Smart' devices. From left to right: a smart toaster, a smart kettle, and a smart salt shaker. (Source: griffin.com, appkettle.com, mysmalt.com).

Controlled trough a mobile app, the smart toaster and kettle offer the capability of programming and fine tuning their actions according to the user’s needs. In the case of the smart saltshaker, a mobile app is used to set the amount of salt desired, and automatically dispense it. In addition, it is also able to play songs and change its LED colours, which makes one wonder what would be the purpose of those features, as they do not directly relate to the salt shaker's main goal.

Norman argues that a product's design should support the user's activities (Norman, 2002). Analogously, a common criterion to support a product's business plans is its ability to reduce friction or 'solve a pain'(Osterwalder and Pigneur, 2010). As such, the 'not-cognified' counterparts of the products found in Figure 4.2 would support the corresponding activities as well, arguably with fewer actions and at a lower cost.

Thus, the necessity for such devices comes into question, first in their capacity of solving real problems, and secondly as to how effective they are in supporting the user's actions and goals.

A data centric approach implies that some processes often occur in the background without providing users with any information of how they operate. Indeed, most of the times users should not be required to know how the system came upon given responses or actions, as long as it produced them in line with its established purpose. However, this could have a negative effect. Kuniavsky (2010) proposes that objects become 'service avatars' providing a representation of their functionality, the drawback being that their physical attributes are hidden from the user. Moreover, systems that are appear to 'smarter' and more abstract than expected by the users, would look to complete goals that could diverge from the user's in pursuit of other optimisation parameters, deriving in user misunderstanding (Yang and Newman, 2013). Accordingly, it would be of benefit for the system's designers to have a way of analysing the system's requirements from a user perspective. In addition to smart objects' and systems' being augmented by SPC traits to act autonomously, their behaviour should not be to exclusively operate autonomously and achieve its own goals. It should be complemented to promote a cooperative behaviour with its stakeholders, allowing the opportunity to convey useful information to its users, as will be explored in Chapter 4.

4.5 User centred goals

Norman (1993) argues that technology design often follows the path of having people behave in machine-centred ways, not always suited for a human. In this regard, Norman observes, technology tends to fail because of this misrepresentation of what needs to be supported: the human or the machine? Arguably, this would depend on the application, for example, those requiring a more precise, repetitive and monotonous tasks would be suited to a machine, whereas those involving cognitive or creative processes would suit a human best. The question would be how to appropriately set these goals when considering hybrid systems, in which the machine performs tasks alongside a human user and vice versa. Thus, Norman introduces the concept of 'technological affordances', an extension of the notion of affordance that expresses the idea that "*technologies make some activities possible or easy, other activities impossible or difficult*".

Maes (2017) argues that smart devices and their software have not been designed with the user's goals in mind. For example, recent mobile phone applications 'fight' over each other to gain the user's attention, effectively creating confusion on the part of the human due the volume and frequency of interactions. Maes proposes an integrated experience, putting the user in the centre by providing systems that are not only context aware, but also user aware, and that provide a proactive and personalised experience, supporting the goals of the user, *in a "symbiotic relationship of human and machine that can help with* [the user's] *self-actualization by changing* *the way they make decisions, learn, remember and regulate mood".* As a consequence, Maes posits that technology *"assists us, powers us, and augments us".*

A characterisation of systems that follow human-centred goals could be derived from both Norman's and Maes' concepts as follows: human-centred systems should support activities related to decision making, learning and memory, and mood regulation , not hindering, but augmenting user's activities and well-being.

4.6 Conflicting goals

For the IoT, where devices are augmented with SPC capabilities, HCI's models and theories are observed from a new perspective, as traditional methods have to be re-framed to accommodate not only for physical interactions but also for data enabled interactions.

The effect of having a partial view of the system's operation has been explored from the perspective of thermostat control. Kempton (1986) analysed the mental model that a temperature control system creates on its user and how it might differ from the system designer's model of operation. Kempton found that some users followed their 'feeling' of how the system operated, while others approached it in a more analytical fashion. That is, the first group followed their own instincts and physical sensations to make assumptions about the systems operation: if they temperature control setting was increased, it should naturally lead to an immediate increase in temperature. As such, Kemp argues, this group operated the system as a 'valve' from which 'heat' flows according to the valve being shut or open. In contrast, participants from the second group tended to have a wider understanding of the technical operation of the heating system, and were aware of the existence of a furnace that needed to heat water, that was pumped into pipes in order to reach the radiators as controlled by a thermostat. Kemp defined this approach as 'feedback' control, and lead to users being more aware of a system that needed to adjust itself to reach the user's comfort settings.

In both cases, based on their own assumptions about the system, each group attempted to create mental models of how temperature could be controlled to achieve a comfortable environment. That is, users would be optimising for their own parameter (comfort). Both groups failed to fully consider the relation between furnace operation and energy consumption. Although the 'analytical' group was closer to the designed operation, both groups reported insecurity on the success of their interaction with the system, leaving them to wonder if it was indeed working correctly. These observations, lead the author to conclude that *"a theory that is useful for designing thermostats is not guaranteed to be a good theory to for using them"*.

Though Kempton's research was conducted over a fully analogue system, with a controller similar to that shown in Figure 4.3 (left) and obviously lacking a computing element, the effect of system's goals and user's expectations is explored. Thus, for Human Computer Interaction, Kempton's research provides an appropriate observation that could be applied to systems whose aim is to automate tasks, such as the IoT as per the definition explored in previous chapters. Moreover, a corollary of this study is the observation that actors in the system (the user and the heating system) present conflicting goals. The furnace's (machine) goal would be to attain a temperature level (and to some degree energy consumption), while the user's would be to attain a comfort level.

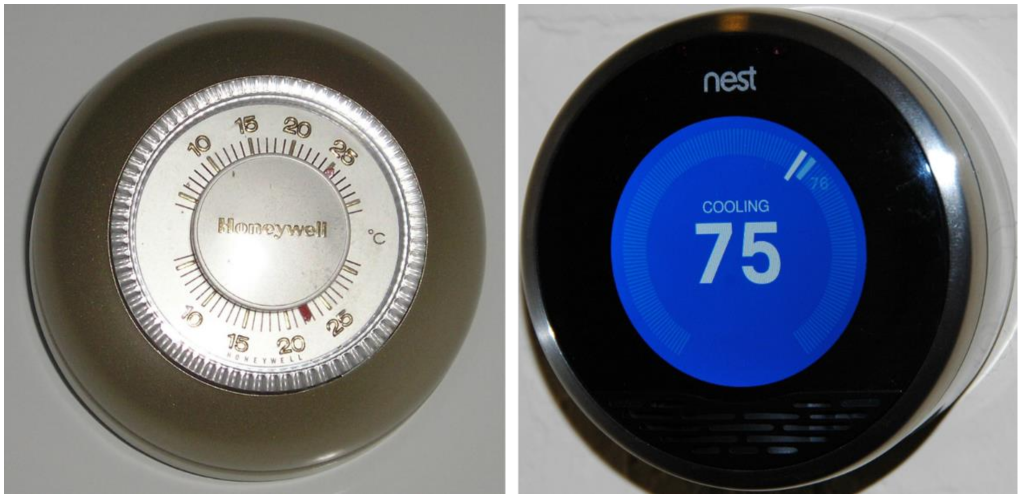

Figure 4.3 An analogue thermostat controller (left) and a digital Nest 'smart' thermostat controller (right) (Image sources: Wikimedia Commons)

Interestingly, research on the effect of usability on modern IoT enabled thermostats has also been made. The Nest (Figure 4.3 right) is an IoT device developed to control centralised air conditioning systems. As previously described, this device not only fulfils the goal of a common thermostat, but it learns the user's comfort settings, while optimising for energy consumption. Yang and Newman (2013) posit similar implications to those found by Kempton, by analysing a digital, smart device. By looking to optimise its settings through its algorithms, Yang and Newman found that the system failed to convey its secondary goals to its users, creating frustration and disengagement. This lack of communication and misunderstanding of goals is not dissimilar to that found by Kempton, suggesting a requirement to extend HCI methods to incorporate aspects of the IoT, such as its capability of making intelligent decisions on behalf of the user.

Human-IoT Interaction (HII) aims to create synergetic partnership amongst its participants looking to attain common goals in social-like structures (Nunes et al., 2015). 'Smart objects' and humans collaborate towards common aims, emphasising goal achievement, over system's rules, highlighting the overarching purpose of the system (Cervantes-Solis et al., 2015b). In this environment, it is often the case that both devices and human users have to negotiate to some extent their role within this association, based on trust and common interests, much like the social-like interactions that will be discussed in chapter section 4.7.1.

Complementing the vision presented in section 4.3, an intelligent IoT would be a system comprised of both *things* and their human users, harmoniously supporting of goal achievement as a collaborative endeavour.

4.7 Conversational IoT

From a technical perspective, protocols that support a breakdown of message components (such as MQQT defined in Chapter 2) do not fully address the requirements that a human-based approach to interaction requires, acknowledging common representations of knowledge and its associated mental modes. As such, for the IoT, the concept of a 'Conversational IoT' has been discussed in the context of natural language and text-based conversations, through the implementation of virtual assistants (McTear et al., 2016). This approach aims to semantically extract descriptions of the services that the IoT provides, enabling speech-based interfaces to communicate with users, providing textual descriptions of the system's actions and its programmability (Braines et al., 2017).

In contrast to speech based communication between the IoT and humans, Gajendar (2016) proposes to embrace HCI aspects that emphasise on the system's physicality, the actions *things* support and how they affect users' relationship with them. This section analyses the 'conversational IoT' from the point of view of things' affordances, the tasks and goals they support and how they enable human interaction in a turn-based exchange framed under a common theme.

4.7.1 Friendship relationships in the IoT

In social networks, friendship describes common interests and trust between parties (Nitti et al., 2014). C*onversations* commonly occur between people that share a relationship, or are 'friendly' to each other, and they have contextual relevancy to the specific information exchange (Gibbins et al., 2004; Clark et al., 1991). As discussed in 4.2, this thesis explores the notion as Social IoT, where social traits such as trust, nature of the relationships and purpose of the relationships can be attributed to the system's nodes. In this context, Atzori et al. (2014) suggest that *things* can build their own social network and generate new services from the collaboration with other friends in the network. As such, the Social IoT could take advantage of traits of friendship relations such as how friends might have mutual prior knowledge and shared experiences; friends might trust each other with personal or private information; friends might recommend other friends or might seek to protect their own friends. In much the same manner that social network support conversations, things in the IoT can engage in conversations amongst themselves, and as discussed in 4.3 we could posit that *things* and humans can also engage in conversational exchanges, beyond the commonly used data-based approach to interaction described in Chapter 2. This notion will be discussed in the following chapters by exploring how these conversation can take place.

4.7.2 Social objects and their conversations

Norman (2007) analyses 'future things' as machines that have sufficient intelligence to communicate their intentions and outcomes to their users. Norman argues that despite these capabilities communication exchange with the machine as it is often a one-way conversation. The machine will perform its function, without much human intervention, in fact he compares the exchange as "*two monologues*" as opposed to a conversation between two parties. As a solution, Norman proposes that a collaboration between human and machine in which activities are synchronised, by providing a reason and an explanation of how this synchronisation is achieved. In addition, he suggests this collaboration should be based on trust, through a negotiation of shared experiences, knowledge and understanding of what they are pursuing. This agreement imbues actors in these collaborations with social-like attributes, which as noted in section 4.7.1, form friendship relationships.

Bleecker (2005) introduced the concept of 'blogjects' for objects and things that exist within *"the sphere of [the] networked social discourse variously called the blogosphere, or social web"*. This notion was introduced as a predecessor to Sterling's conception of 'spimes' that are searchable, trackable and share their trajectories across time and space, in contrast 'blogjects' were intended to not only make information available, but also to provides a mean of circulating the information enabling a conversation. Bleecker posits that this enables an Internet of Things in which "socially meaningful exchanges" occur, modifying cultural experiences through media sharing in a collaboration between human and sensor data.

Moreover, 'blogjects' engage in conversations with other devices *"by starting, maintaining and being critical attractors in conversations around topics that have relevance and meaning to others who have a stake in that discussion"*. In this regard the social interactions of these objects and their users, gain visibility as they are reinforced over time, or conversely, 'die out' if they lack relevance.

By conferring the ability to establish a two-way interaction, both parties are assumed to be able to interact with a degree of autonomy. In this context, Bleecker (2005) argues that agency in fact must be reframed in terms of not only of their capacity to act automously, but also in how they are able to effect change providing a framework for meaningful conversations.

For computational devices the Turing test has been used as a tool to measure the degree of intelligence by establishing a conversation with the machine, and evaluate whether it could pass for a human to another human (Turing, 1950). In the context of this thesis, the notion of a conversation provides an interesting approach to how these conversations are supported in devices such as those found in the IoT with constrained capabilities in terms of interfaces or computational processing power.

For the IoT, Rubens (2014) analyses how the Turing Test could be applied under these constrains. Notably, as originally conceived, the test involves a 'single' computing system, that is, it does not necessarily makes the assumption that intelligence could be distributed over a range of devices, in an scheme like the one found in the IoT.

Rubens posits what would be the nature of such a conversation with objects such as a kettle when it clearly does not provide an interface that allows it to 'talk', but performs its expected goals. Thus, Rubens argues that intelligence in the IoT is not a measure of the object being capable of sustaining a speech or text based conversation, but of its capacity to support an 'operational dialogue': the machine's ability to take action conducting to the expected goal, as intended and expected by the users. Furthermore, Rubens points that this 'intelligence' should be able to support predictive behaviour from the machine, such as coffee machine inferring when will it be used and thus turn itself on, and a degree of transparency on its processes such that they become opaque actions to its users. Notably, this approach to an 'intelligent conversation' in the IoT requires the analysis of goals and tasks in an organised manner within a common thread, and not entirely on the notion of speech or text based communications.

4.7.3 Conversational Common ground

Within the context of human-human communication, (Clark, 1996) defines ‘grounding’ as a *“collective process in which the participants try to reach a mutual belief”*. This proposes that conversation is a social activity, in which the content of the exchange must be negotiated by a clearly defined process. Moreover, the established ‘common ground’ must be updated through the pursuit of positive evidence of understanding. Such evidence can come from common forms of reinforcement, such as: acknowledgement, turn taking, and continued attention. Hence a conversation is an active process in which participants recognize that they understand what is being said, agree that the conversation is divided into stages or sections of communication that do not overstep on each other, and that conversation requires participants to constantly attend to what their partners are doing at any given time. As such, this model of conversation frames positive, meaningful exchanges between parties. These guidelines define a state-based communication that defines the turns (or sequences) in which objects interact collaboratively towards the same outcome, following a common topic.

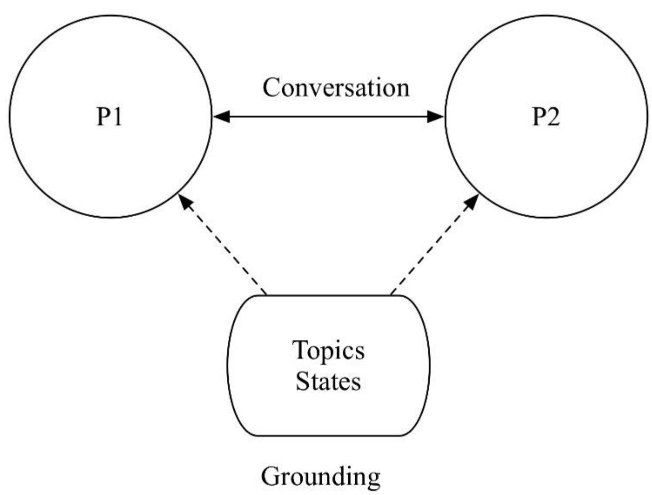

Figure 4.4 A model for conversation based on common grounding.

Within this notion of conversation, information exchange is not a matter of presenting well-defined 'units of meaning' but rather a continuous movement towards understanding, with each partner adding and modifying the topic through provision of information that indicates their comprehension. As with any form of interaction between people and computers, it is a moot point as to far this common understanding can be achieved, but within the IoT we would argue that the situation is exacerbated. Not only is it unlikely that all parties have access to the same information, knowledge and, possibly, goals but also the 'conversation' involves multiple agents who might be pursuing different topics. From this, one can readily understand why there might be confusion in the human-IoT interaction.

4.8 Meaning

The definition of 'meaning' can be derived from different fields such as philosophy, psychology and linguistics. Although this thesis is by no means a philosophical exploration of the concept of meaning, it is worthwhile noting that its different schools of thought relate the idea to that of purpose, or a an individual's basis of existence (Blackburn, 2005). The concept of 'purpose' is akin to that is used throughout this thesis as a system's core goals.

From a psychology perspective, 'meaning' has connotations related to behaviour and cognitivism and in order for a concept to possess 'meaning' from the perspective of an individual, it must have some value attributed to its use or experience (Meretz, 1999). The psychological process of 'meaning-making' describes how persons make sense of life events, their relationships and their own selves.

On the other hand, the IoT's potential to influence the economic value chain of different industries, has framed the notion of 'value' in a very direct relation to economic wealth (LaValle et al., 2013). However, in the context of this research, 'value' is considered a broader term that relates to that found in psychology, of 'making sense' and appropriation. As such, in the context of HCI methodologies, it is expected to promote a system's understanding from its user's point of view, focusing on creating engaging and valuable experiences and outcomes.

As described in (Chandler, 1994) the field of linguistics provides its own interpretation of meaning through semantics. It studies the relationships between language's most basic units (signs and symbols), and their 'signifiers', or the concept they convey. Their interpretation is defined through their 'connotation', that is to say their particular circumstances and context.

Semantics provides formalisms in which symbols provide representations, references and a literal meaning (their 'denotation'). As defined by Montague's grammar (Montague, 1970) *"meaning of a sentence can be deconstructed to the meaning of its parts"*, hence, 'meaning' can be described as a result of the aggregation of different units of language.

Moreover, the concept of connotation provides the notion that meanings are not complete without their context.

In the context of this research, the concepts found in semantics provide an analogue to the notion of units of information, which within the same context, provide value to their user. In a 'society of *things'* IoT model, nodes are described as the basic unit of the networks, working collaboratively towards the same goal. Hence, in much the same way that semantics approaches the problem of meaning, the interactions in a collective of smart objects, within the same context, can be understood as defining 'meaning' for the network. In other words, the functionality of the system as described by its goals.

4.8.1 Semantics in Computer Science

In computer science, semantics has been approached as a solution to the problem of providing a structure for the information found in computing systems (García-Sánchez et al., 2009), used to model data-enabled systems, aiming to establish less rigid approaches to the information that it can convey.

In particular, for the internet and its web-based applications, Berners-Lee et al. (2001) propose the concept of a 'Semantic Web' in which software agents take the task of providing meaning to the data stream users create when browsing the web. These agents would produce structure to the information, such that they would be able to perform tasks on the user's behalf, according to the context. In contrast to the 'traditional' approach to the web in which the information is expressed in terms of the raw data itself (i.e., the contents of a document), the semantic web establishes common semantical descriptions and rules to describe resources and relationship to other resources. This common ontology allows for the creation of structured links that provide an explanation or meaning to the resources.

While the communications infrastructure and protocols (Thoma et al., 2014; Russell and Paradiso, 2014) are a significant aspect of the development of the IoT in terms of device relationships, the fundamental physical attributes of *things* should also be taken into consideration (Guo et al., 2012b) in relation to the object's affordances, or its attributes as tangible interfaces (Ishii and Ullmer, 1997). As discussed in Chapter 3 these physical characteristics provide links between functionality and the tasks they support, providing meaning to the interaction, supporting a paradigm shift from a 'data-based' vision, to a 'knowledge-based' view (Berners-Lee et al., 2001). The approach taken by research in semantic web could be applied to identify semantic relationships in IoT networks (Kirstein and Varakliotis, 2014; Russell and Paradiso, 2014; Wang et al., 2012; Wu et al., 2014). Borrowing from World Wide Web protocols, these approaches are focused on supporting shared vocabularies through the use of Uniform Resource Identifiers (URI) and hyperlinks, establishing mechanisms for clients to address resources and other nodes in a subscribe to push/pull data architecture, analogous to Hypertext Transfer Protocol (HTTP). Linking resources allows for descriptions of the applications they enable based on their relationships, location, ownership and functionality, as shown in Figure 4.5.

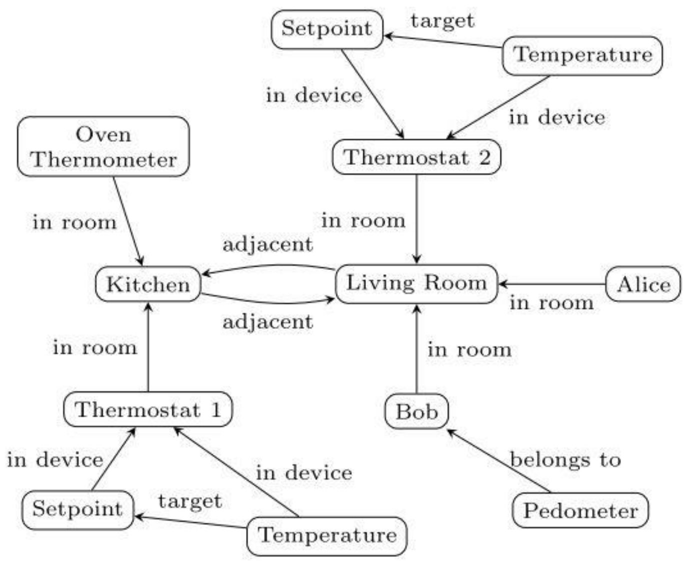

Figure 4.5 Linking resources through their functionality, location and ownership (image adapted from Russell and Paradiso, 2014)

4.8.2 Knowledge

A major challenge for the IoT is to turn a vast amount of data from various devices into an output that facilitates insights (knowledge) for the end user, enabling the creation of meaning. *Computing for Human Experience*, as described by (Sheth, 2010), aims to *"enable a system that makes conclusions and decisions with human like intuition"*. The semantic web approach has been discussed as a solution for IoT standardisation. Figure 4.6 shows an architecture for semantic computing, as proposed by (Sheth, 2010). This approach relies on the extraction of metadata from patterns found in the different sources of information, based on semantical observations on data. This method relies on the annotation of metadata provided by the data sources, and on known conceptual models that characterise the nature of IoT nodes, and what is expected from them.

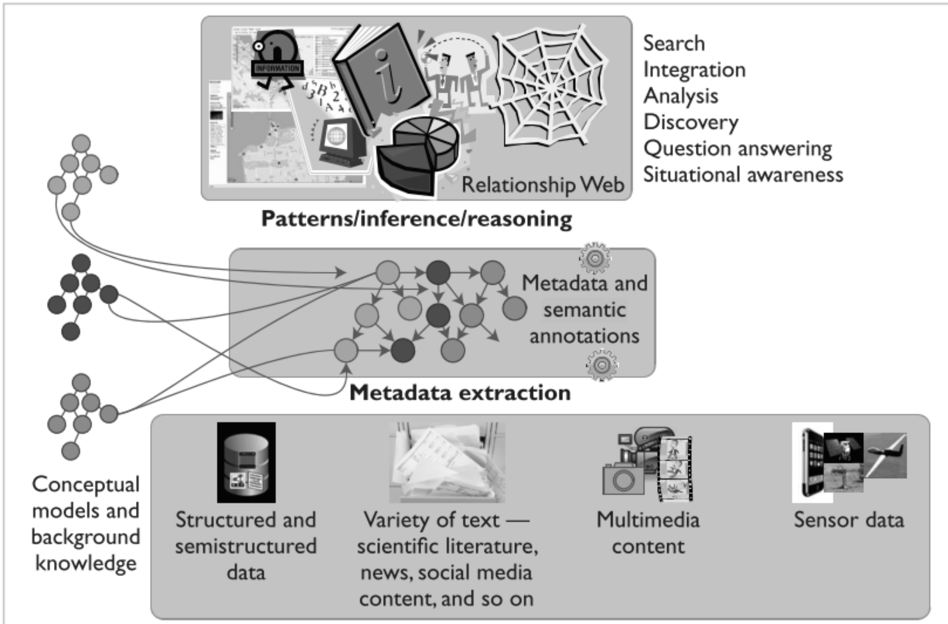

Figure 4.6 A Semantic Computing Architecture, from Sheth (2010).

For the IoT, (Zhao et al., 2015) present a method for searching knowledge in the IoT using semantic mining based on topic discovery. This method provides *"topic-relevant information according to user's demand"*, and the *"interactivity between users and the surrounding environment"*. Zhao et al., provide in this way an extension for semantical extraction relying on the relationships found between systems, users and environment, matching IoT resources by their relatedness to others, proposing *"knowledge networks"* organised by shared topics. In other words, the purpose of the network is defined in terms of the contextual organisation of common semantical units. In the context of this research this proposition is aligned to the notion of providing a common ground that provides context to the interactions found amongst devices, breaking them down into simpler units. In the conversational IoT this is supported by an overarching theme comprised of topics as will be discussed in section 5.2.

4.8.3 Collaborative sensemaking

When considering a collaborative system in the context of meaning as described earlier, we should ask how the participants in the collective agree on the tasks and goal. In the IoT, sensemaking not only relates to the steps taken by the devices or humans to gain an understanding of their purpose, but also to how this supports engagement to proactively reinforce its social aspects.

Pirolli and Card (2005) argue that ‘sensemaking is *“information gathering, re-representation of the information in a schema that aids analysis, the development of insight through the manipulation of this representation, and the creation of some knowledge product or direct action based on the insight”.* This cycle will be explored later in terms of distributed environments, such as those mentioned in chapter 2, devices on the edge follow their own conversation with their users (in contrast to a centralised paradigm), but should be able to follow their own turn-taking, attention and sensemaking. In this context, Preece et al. (2015) argue that as a result of automation found in these devices *“the user becomes a more active participant in the process, able to ask the system for information as well as receive it*”. Hence, users become a crucial part of the loop for meaningful interactions.

As described in section 3.2 sense-making and mental models play an important role in how human users take action on IoT systems. Moreover the IoT has been described as a distributed system comprised of different entities looking to attain common goals (as discussed in chapter 2). As such, sense-making process should address systems where resources are distributed across their components, and, as introduced in section 2.5, in which every component might be also looking to reach their goals. (Roschellel and Teasley, 1995) describe collaboration as "*mutual engagement of the participants in a co-ordinated effort to solve the problem together*".

Moreover, Umapathy (2010) describe the process of collaborative sensemaking as the process in which different entities understand a situation by collective consensus and take action. In the context of the IoT this notion of collaborative sensemaking implies that each of the nodes that comprise a system has a role in how it provides meaning. As will be described in Chapter 5, this extension of sensemaking as a collaborative process provides a framework for the development of a design methodology for an IoT that supports human activities through defined tasks and goals, and by acknowledging the technological capabilities and physical attributes of *things* and how they are understood and in by users.

4.9 Conclusion

Parts of the conclusion section were taken from (Cervantes-Solis and Baber, 2016).

This chapters focuses on inspecting the interactions of a society of smart objects, were human users and instrumented devices network to achieve a particular outcome as collaborative system, and providing the background relating to the nature of Human-IoT conversations. It presents a framework to characterise the purpose of social-like interactions in the IoT, based on its tasks and goals.

Knowledge representation in computing shifts from data centric domain to a meaning based domain. On the one hand, there is a requirement for the development of technical aspects the IoT, such as specific protocols for device communication in the IoT (Fan and Chen, 2010) or the taxonomy and syntax of the data interchange (Zhu et al., 2005). Nevertheless, there is also the aspect of investigating the tools and techniques with which meaning could be communicated by a network and understood by other networks and their users. The conversational approach presented in this chapter lays the foundation for an structure to describe interactions between human and users, as will be discussed in the following chapter.

The social framework will serve as the basis for the development of a methodology to analyse user interaction in IoT systems The methodology that will be described in chapter 5 aims to support IoT system development to not only consider sensor data, but also human users though system usability framed in a conversational approach grounded under a common theme. In this regard, further exploration of the concepts of Themes and Topics as related to the human and machine tasks and goals is required. This notion will be explored in more detail providing a knowledge structure to describe these interactions.

5 *Designing for a Human-Centred IoT*

As discussed in the previous chapters, the IoT has been primarily focused on its technological development, with applications based on providing solutions highlighting data-centred approaches, relying on machine learning techniques to provide insights to their users. Thus, the question of whether an approach based on human user requirements was explored in chapter 3, finding that a purely technical view of the IoT leaves users in a secondary plane, effectively hindering engagement with *things*. Further, the problem of how to provide meaning to users was introduced, in terms of the goals expected by the users. A framework for characterising the IoT a conversation a conversational IoT was explored, along with some techniques to identify tasks and goals in system usability. Things' and humans' goals misalignment was identified as a reason hindering IoT system usability. As such, techniques to analyse goal deviation were introduced. Thus, the problem would be to provide a methodology addressing how to effectively analyse an IoT system such that both devices' and humans' actions support each of their goals, and to provide a framework to model and develop a human-centred IoT.

This chapter proposes such methodology based on Task Analysis for Error Identification (TAFEI), paving the ground for IoT system modelling and design.

5.1 The design of smart objects

As discussed in Chapter 2, design and modelling efforts in the IoT have been primarily through data centric frameworks, focusing on the expected outcome of the system, as opposed to the tasks and interactions required to achieve it with a human user at the centre of the analysis. As discussed in chapter 3, methodologies for goal and task-based modelling can be applied to the IoT, focusing on the concept of a collaborative and 'conversational' IoT.

As discussed, *cognification* is an attribute applied to devices when they are imbued with sensing, processing and communication capabilities (SPC), and as an extension, behave with agency, enabling *things* and humans to organise in social-like structures. Recalling the notion discussed in Chapter 2 that 'smart' systems are sometimes enabled by smartphone applications, we often find that interactions in these structures occur between a digital representation of the object and the user, and not the physical object itself. In this context, users are provided with extensions of the *thing's* behaviour either through their data or representation of their data. Moreover, improvements on SPC characteristics enable technological properties that lead to more complex and richer data that allow for machine learning and AI solutions that arguably embed higher degrees of automation and decision making that are considered intelligent. Although these increments in 'smartness' could provide additional functionality in IoT systems, from the point of view of a user the effect could be the opposite, as smart devices also gain an additional layer of complexity. Therefore, their usability is impacted, as the additional functionality occurs in a layer hidden to the user. As previously discussed, the effect of smart thermostats highlights the possibility of IoT systems becoming opaque to users by not providing a full explanation of what they are doing, or cues related on which goal they are pursuing.

For HCI, the challenge then is to create sufficient transparency for people to understand how things are functioning in an IoT, without burdening humans with undue and unnecessary control decisions. Given that the IoT functions as a network in which information is exchanged between its nodes, one could consider this exchange in terms of a conversation as discussed in chapter 4. Consequently, ideas are exchanged between participants and these ideas gain meaning through their context and the nature of the relationship between participants. The suggestion is that the key focus of analysis is not simply information exchange but rather than translation of information into an ‘idea’. In other words, conversation is about managing *topics* which occur in a specific *context*, giving purpose to the interactions, in the form of an overarching *theme*. It is also worth, at this point, consider how the ‘conversation’ metaphor might collapse in the face of IoT. We have noted that there is a need for continuous movement towards understanding in a conversation. At one level this could imply a desire to have people continually interacting with things in an IoT, which would go against the desire to off-load activities and could create all manner of problems relating to distraction and disruption to human activity. When using the word ‘conversation’ the aim is to highlight the need to establish a shared topic amongst conversation partners, and to assume that, given agreement of topic, it is possible for the partners to pursue entirely independent activities. Thus, by considering the system’s goals as the centre of IoT interaction design, this research posits that in the social-like IoT, conversations could be developed following the concept of ‘grounding’, aiming to provide mutual agreement on the expected outcome, in a turn-based fashion.

As described in Chapter 3, smart object design should consider a hybrid approach in which device behaviour is related to its tangible interface and data-based enabled interactions, and the user’s mental models that support their activities and expectations.

5.2 Meaning: Themes and Topics

Some parts of this section are taken from the paper “*Towards Theme Discovery Paradigm in the Internet of Things*” by, Cervantes-Solis, J. W., & Baber, C. (2016), published in the proceedings of the Contemporary Ergonomics and Human Factors 2016 conference. The author of this thesis developed the concepts presented in the work, conducted the research and wrote the paper with the support of Prof. Baber.

As discussed in chapter 4, one of the problems faced in usability for the IoT is a lack of understanding of what the system is expected to achieve. The concept of social conversations, involves the notions of *context*, *topics* and *theme* providing a framework to agree on the purpose of the IoT system. In this research the ***context*** of the network is considered to be the clearly defined and mutual environment in which human and *things* cooperate for mutually agreed goals. For example, sensors collecting temperature readings in a single room are located in the same physical location. Moreover, when a particular collection of objects perform defined actions to reach their goal, we acknowledge that ***topics*** in the conversation are established. Extending the previous temperature control scenario, temperature sensors would communicate temperature readings to a control hub, whilst humidity sensors would exchange moisture levels. The control hub would then issue commands to adjust settings to a furnace or boiler. Two topics would be identified in this system: a 'temperature control topic' and a 'humidity control topic'. Thus, the concept of ***theme*** in the IoT refers to the collection of *topics* that contribute to interactions in a particular *context*, providing a high level definition of what the network does. Accordingly, the theme of our example network would be climate control in a certain environment. As such, instead of looking purely at data or sensor types, as found in current IoT systems, this thesis proposes to characterise the themes of these networks in terms of their goals and tasks.

The term 'topic' is used in a number of IoT architectures to describe communication, i.e., how nodes adhere to assigned data buses. For example, as described in Chapter 2, in MQTT, devices subscribe to a 'topic' if they are to communicate with the messaging broker, which in turns manages communications. Similarly, in the Node-RED data-flow programming tool presented in Chapter 2, messages are delivered to nodes as payloads to previously defined participants of a 'topic'. These definitions of 'topic' feel too constrained as they hardcode the level and nature of interactivity between nodes, focusing on exchanging data. In contrast, this thesis pursues the concept of *topic* in a framework of loosely connected devices, and propose that by their interaction with each other, meaningful and contextual-based connections emerge. In this context, the question would be how to implement this concepts in smart systems design, as will be discussed later in this chapter.

5.3 A knowledge structure for a *theme*-based conversational IoT

As discussed in Chapter 4, ontologies in the IoT are required to provide commonly agreed descriptions of the relationships and structure of the network's elements.

(Gruber, 1995) identifies ontologies to represent domain knowledge as "*declarative formalism, and a set of objects that describe relationships amongst them*". As such, an ontology requires a rigorous and formal methodology for its definition. In the context of this thesis, in lieu of the rigorous methodology to define a formal ontology, a knowledge structure is proposed to provide a structural description of the elements and relationships of the elements in the proposed conversational IoT.

In this section, a basic ontology-like knowledge structure for a Theme based conversation IoT is presented, specifying a framework to define the types, properties and relationships of the actors involved in these exchanges.

As defined in chapter 2, a *thing* is a physical object with sensing, processing and communication capabilities, which can be described by the service it provides, in relation to its data. The data stream coming from sensor nodes in an IoT system, can be classified by the *actions* the *thing* produces or requires. At a higher level, those functions determine the intended outcomes, or *goals***,** in the network. Each *thing* is constrained in its scope by the interactions it can have with other *things*, either because of their functions, physical location and proximity with other *things* or by the communication protocols they use or networks to which they are able to connect. These are considered the *system boundaries*, and in the case of Social IoT they become analogous to the context of the relationships to other *things* in the network. The previous description provides the basis for the structure that defines the elements and their interactions in a conversational IoT. Moreover, by reframing this structure as a social system as described in chapter 4, it could be argued that devices who are not socially linked to others, are considered to be outside from their context and, thought they could communicate to each other, they wouldn’t necessarily collaborate towards the same goal.

In this framework, goals are reached through actions aggregated from sensor node data (Figure 5.1). In the Social IoT structure proposed in this work, this is akin to conversation topics, occurring within an overarching, common theme.

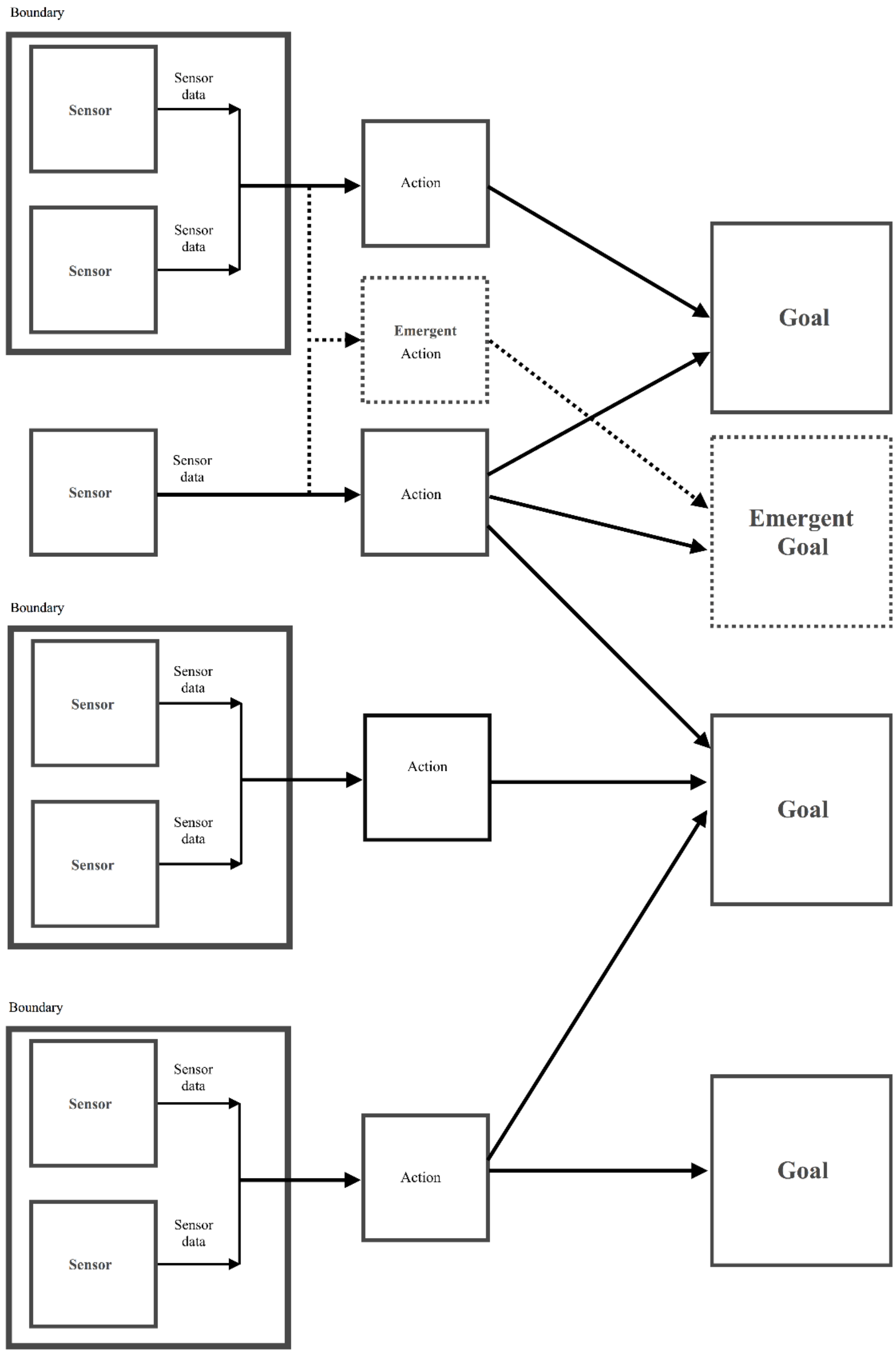

Figure 5.1 From sensor data to goals.

As an example, **sensor data** describes the data type that a transducer can measure (acceleration, humidity, magnetic field, light, etc.). By grouping these data, **actions** that describe a unified goal can be considered. In terms of a conversation, these actions are the topics that provide meaning. Thus, a *thing* could be cognified with an accelerometer, magnetometer, gyroscope and GPS whose data could be aggregated into an IMU (Inertial Measurement Unit) action, a Pedometer action, and a positioning action, with the goals of providing measure of walking distance, step counter, bearing (orientation), and geographical location framed within a 'Support a fitness regime' theme. Similarly, another thing could be imbued with a temperature sensor, grouped with a barometer and UV sensors to collect data supporting actions such as ambient temperature, atmospheric pressure and UV Level, with an Environmental weather goal, supporting for a 'Weather forecast' theme or a separate 'What-to-wear' theme. Table 5.1 shows a summary of the previously described *things*.

Table 5.1 Things *characterised in terms of the sensor data, actions, goals and themes.*

	Sensor data	Actions	Goals	Theme
Thing 1	Accelerometer, magnetometer, gyroscope, GPS	• Inertial Measurement Unit (IMU) • Pedometer • Positioning	• Walking distance • Step counter • Bearing • Geographical location	'Support fitness regime'
Thing 2	Temperature, barometer, UV detector	• Ambient temperature • Atmospheric pressure • UV Levels	• Environmental weather	• 'Weather forecast' • 'What-to-wear'

In this frame of reference, there is a possibility of new topics emerging, with the combination of seemingly unrelated functions. For instance, a pedometer and a barometer could be used to count the number of floors in a building, or a switch in a fridge and another in a coffee machine could be used to determine that a coffee with milk has been made.

Thus different networks need not share data, but a *topic* of conversation (as sensor node actions), which in the context in which the system operates, defines the *Theme* of the network.

By re-examining Figure 5.1, this work posits that goals are comparable to themes, whereas sensor node actions are analogous to topics. Moreover, in terms of the technical implementation, a potential benefit of this approach could mean that data is handled as locally as possible, akin to what has been proposed by edge or fog computing, while enabling a higher level meaning exchange amongst *things*.

Moreover, a *context* is required for the system to operate in, such that the topics are meaningful to the particular conversation. Without a common context of understanding between each other, different topics would behave as noise in the environment. As described in the previous chapter through the concept of common ground in conversations.

As illustrated in Figure 5.2, a **theme** is defined as the collection of **topics** occurring in the same **context**, such that this theme represents the overarching focus of a conversation, as identified by the user's goal. Moreover, according to the conversational interface framework proposed by McTear et al. (2016), utterances are the minimal unit of information found in conversational systems, and are related to the actions a machine performs *"in the pursuit of a goal"*. As such, in the proposed knowledge structure, utterances would be comparable to sensor node actions.

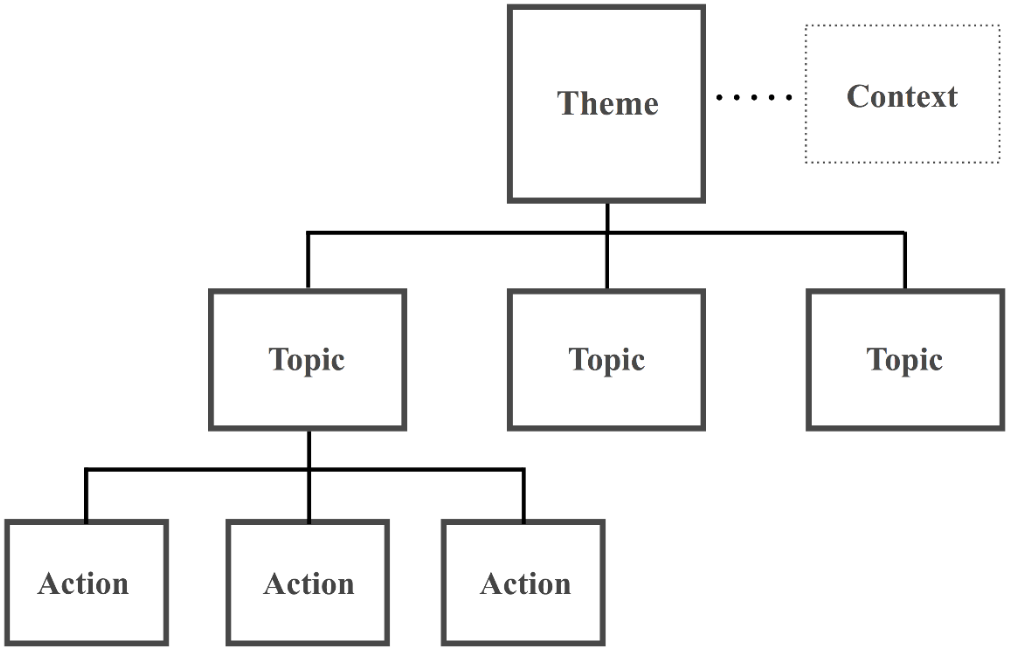

Figure 5.2 A knowledge structure to support a Conversational IoT.

In terms of the IoT system comprised of both humans and *things* this thesis posits, this framework needs an analysis of what is required to produce topics in terms of their corresponding sensor node actions and who will be supported by the goals. This involves understanding not only the machine's perspective as described previously, but also the user's. Thus, identifying user actions that need to occur in order for the relevant sensor node actions to be triggered is required. For example *Thing 1,* shown in Table 5.1, needs a person moving (walking or running) for the sensors to operate, enabling machine actions. The user would then interact with the device through the available interfaces, such as reading a display, and by doing so complementing their own goals such as an awareness of the distance walked and calories burn in the context of a 'support fitness regime' goal. Shifting from a data-centric approach, to the described meaning based paradigm, allows to characterise system interactions in terms of users' requirements, as opposed to the devices'.

The following sections focuses on complementing the methodology with a human-based task and goal analysis approach, providing insights on user actions and goals.

5.4 What and how to augment?

As discussed in the previous chapters, the Internet of Things is comprised of objects augmented by sensing, processing and communication capabilities. When considering humans as beneficiaries of the products and services enabled by these technologies, a consideration should be made on what and how to augment in devices to create cognified counterparts, whilst addressing the need to support user goals, which as discussed in Chapter 2 characterises the purpose of the system.

As discussed in terms of conversational grounding, the initial focus should be placed on the context of operation. Based on the 'planes of experience' framework presented in Chapter 3, a second step would be to focus on the purpose of the system, and thirdly on the physical aspects that support the *thing's* goals. Identifying these goals, and how they support or hinder the user's goals becomes a focal point of smart object design. Additionally, goals and actions should support a conversational exchange, in the terms presented in Chapter 4.

5.5 Task and goal analysis for system requirement definition

As noted previously, there is a notion of agents collaborating with each other in pursuit of a common, core goal. As such, the steps taken by each of these agents is an important consideration in order to be able to describe what the system is doing and how it will do it.

The system can be characterised by its goals, by a clear criteria (such as a utility function in agents, as discussed in chapter 2). Analogously, sub-goals are can also be defined in terms of a particular performance criteria, and the series of rules that organise the sequence in which these are accomplished. Hence, the system can be described in terms of basic units, much like the argument made in Chapter 3 regarding conversations. Communication exchanges can be broken down into hierarchically organised simpler units: actions form topics, and topics can be aggregated into a common conversational thread or theme, as shown in Figure 5.2. Moreover, common grounding provides contextual significance, turn-taking and order for the conversation.

5.5.1 Hierarchical Task Analysis: a human based goal description.

Described in Chapter 3, Hierarchical Task Analysis (HTA) has been identified as a tool to describe a system's functionality through its tasks, and how those tasks actions relate to the system's core goal. Moreover, the system's operation can be broken down as sub-operations (sub-goals) and their relation to the core goal. In this hierarchical description, sub units can be used to break down the actions into minimal descriptions, according to the application's requirements.

According to the guidelines presented in Chapter 3 to provide a system description in terms of its goals, it could be argued that these guidelines can be applied to the knowledge structure presented earlier in this chapter. Table 5.2 summarises these guidelines in the context of the conversational IoT.

Table 5.2 HTA and Conversational IoT Knowledge structure equivalence.

HTA	**A knowledge structure for a conversational IoT**
Purpose of activity	Theme
Boundaries and sources of information	Context
Goals	Topics
Sub goals	Actions
Links in goals and sub goals	Actions aggregating into topics
Plans	Rules for controlling topics

As an iterative process, goals can be described in terms of sub-goals (topics in the knowledge structure), that can be broken down further into simpler units describing specific sensor data. This property posits an important opportunity to identify where to augment a *thing* as will be discussed later in this chapter. Moreover, the relationships in the HTA methodology and the knowledge structure allow analysis of how topics hierarchically relate to each other to describe goals. However, an interesting feature of HTA is that it provides a human-based analysis of goals, as the plans the human takes to complete the goals are described as a series of tasks. That is, it allows an understanding of what the user aims to achieve in terms of tasks supported by the system's parts.

The steps required to analyse a system in the HTA framework is presented in chapter 3. They can be summarised as:

1. Identify the purpose of the activity
2. Identify the objects and the tasks you could do with these which are relevant to the goal.
3. Break down tasks into simpler tasks, and iterate according to the application and the context (stopping rule).
4. Identify the plans humans need to take to complete goals, characterised as sequences of tasks.

The following section provides a worked example of HTA for the recurring example of a heating system.

5.5.1.1 Applying HTA for the Conversational IoT, a worked example

5.5.1.1.1 Determining a goal

The user's expectations with the system should be identified, in terms of what the system is capable of doing. In this example, a basic central heating system has the purpose of providing an automatic control of the temperature in a room or building. Thus, as their main goal, users would expect to be able to 'use thermostat' to adjust ambient temperature to their desired comfort level.

5.5.1.1.2 Determining tasks

Tasks in the system can be identified in terms of how the human user interacts with the machine. In a simple central heating system, users interact with a form of interface providing the current ambient temperature reading, and a control unit to adjust the temperature setting. Often they are found in the same device, as shown in Figure 5.3, but they require two different actions (reading a display and adjusting a dial) to support two different tasks: 'Read temperature' and 'Use control'. Moreover, some task can be decomposed into simpler tasks, allowing a finer description of what needs to be done by a user completing a goal. For this example, the task of reading a display can't be described further in terms of simpler tasks, in this case it is assumed that a 'stopping rule' applies (as will be described below, this is denoted by underling the task in the HTA diagram). The task related to the control unit can be described in terms of the tasks of 'increasing temperature' and 'decreasing temperature'.

5.5.1.1.3 Defining plans

The sequence in which users will complete tasks in order to complete the expected goal is defined as a plan. As each task can be divided into simpler tasks, plans for those tasks need to be provided as well.

For the example, Table 5.3 shows the system's supported actions, while Table 5.4 shows the plans that support user's tasks, and will be discussed further in the context of the HTA diagram presented in the following section.

Figure 5.3 A central heating control unit integrating two functionalities: displaying current temperature and controlling temperature setting (Image source: Wikimedia commons).

Table 5.3 Actions supported in a central heating system.

Object	**Expected user action**
Temperature gauge	Check temperature (visual)
Control dial	Adjust temperature

Table 5.4 Plans for the 'use thermostat' goal, as related to the HTA of a Central Heating system

Plan	Plan breakdown
P0. Use thermostat	P0: 1→ if(temperature not at an acceptable level)→2→else→1→exit
P2. Use control dial	P2:if(cold)→2.2→else→2.1→else→exit

5.5.1.1.4 The HTA diagram

The Hierarchical Task Analysis is presented through a diagram summarising the previous descriptions. Shows the HTA for the 'Use thermostat' goal in a central heating system. Plans are labelled P0, P1 and P2 and are described in Table 5.4.

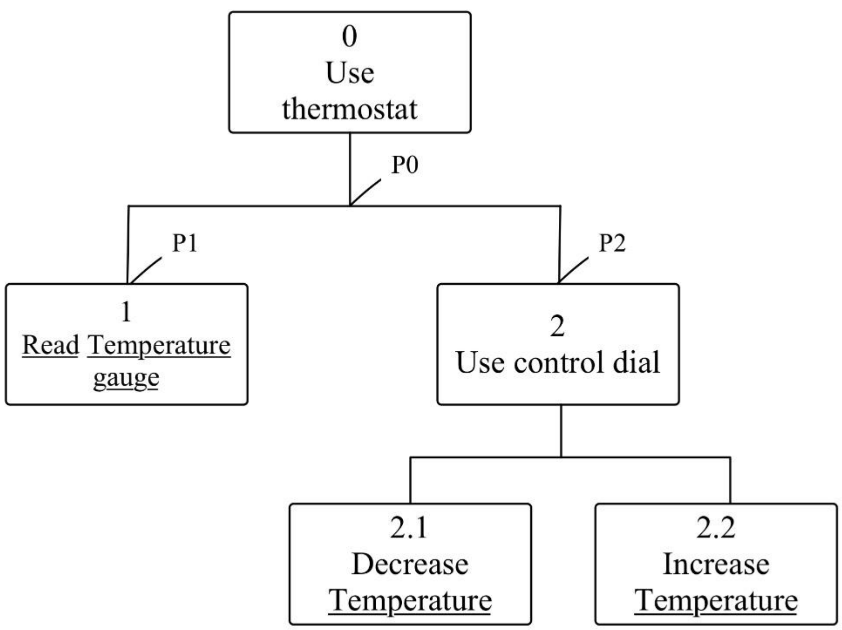

Figure 5.4 HTA for the 'Use thermostat' goal in a central heating system. Plans are described in Table 5.4.

5.5.2 State diagrams: a machine-based goal description.

The concept of state based machines was introduced in Chapter 2 in the context of event-driven systems. These systems can be described using behavioural state diagrams (SD) providing a characterisation of a system's components and their relationships. States and their transitions represent the status of the system's components and their tasks.

Where HTA can provide a human based approach of tasks and goals, State Diagrams provide a view of the machine's. For the running central heating example, Figure 5.5 shows a SD describing the machine's components and interactions.

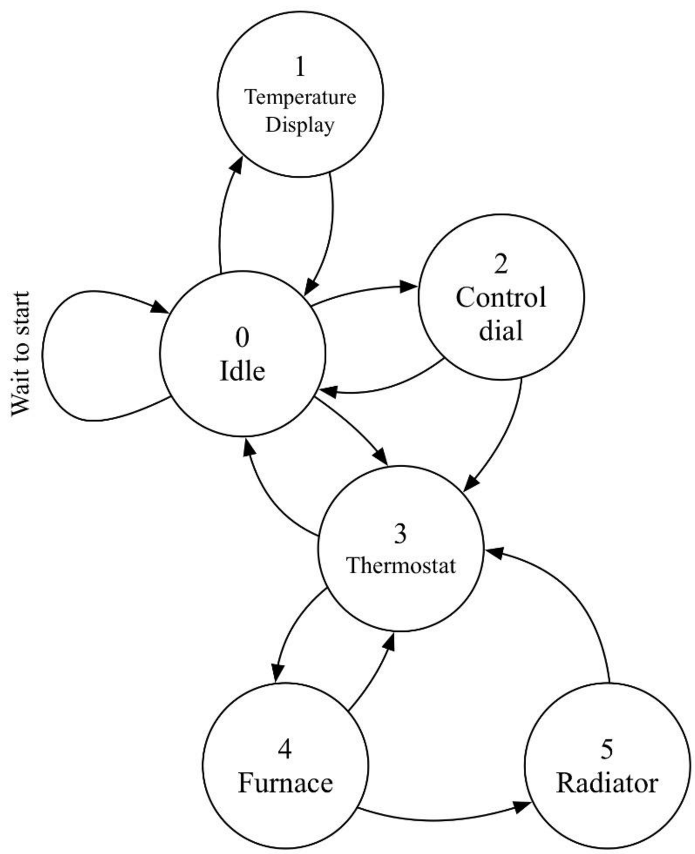

Figure 5.5 State diagram for a machine-based description of the Central Heating System.

5.6 TAFEI and the Conversational IoT

HTA and State Space Diagrams each provide the tools to model tasks, goals and their interactions. However, each focuses on a particular role in the system. The former providing a view on human-centred tasks and the latter on machine-centred transitions. Thus, the question would be how to bring them together such that the goals for both points of view consider the other.

As has been discussed, on the main drawbacks on the IoT as applied to its human users is the understanding of goals such that they are complemented and aligned to each other. Chapter 3 presents an overview of some methodologies for goal deviation analysis, such as CHLOE, THEA and TAFEI. Although each present particular benefits over the others, it was found that the latter presents the additional benefit of bringing together goal descriptions for both the human user's and the machine's in terms of actions performed by them through a unified, state-based diagram.

By modelling human-object interaction as a form of state-space diagram, TAFEI illustrates two aspects of the notion of conversation that is relevant to our conception. First and foremost it indicates the turn-taking between human and objects to show when the human is expected to intervene and also when transitions in the state of the object exclude human intervention. From this two requirements for user interface content could be proposed: (i) cues to tell the user when (and how) to act, and (ii) indication of the objects current state and intended actions. Second, each TAFEI is developed to indicate a particular goal. It would be expected to create multiple such diagrams in order to explore when states might occur in more than one goal. TAFEI allows us to provide a framework in which both users and machine know when it's their turn to act, or whether they need to wait. If a topic is not clear to the user, some machine transitions might appear invisible, effectively 'locking' the user out of the conversation. TAFEI provides the turn taking approach required in a conversation, however, evidently users are not necessarily aware of the full set of states, transitions and tasks that TAFEI provides, it would only be required to be aware of the common ground that the conversation is based on, and this is provided by the expected goal at any particular time. This suggests that some design consideration should be addressed to support the transparency required to identify the topic the system is engaged at any given time. Some systems might inform users through traditional user interfaces such as displays or meters, but in other cases, affordances could be used to support them, or as suggested by Baber, to construct affording situations.

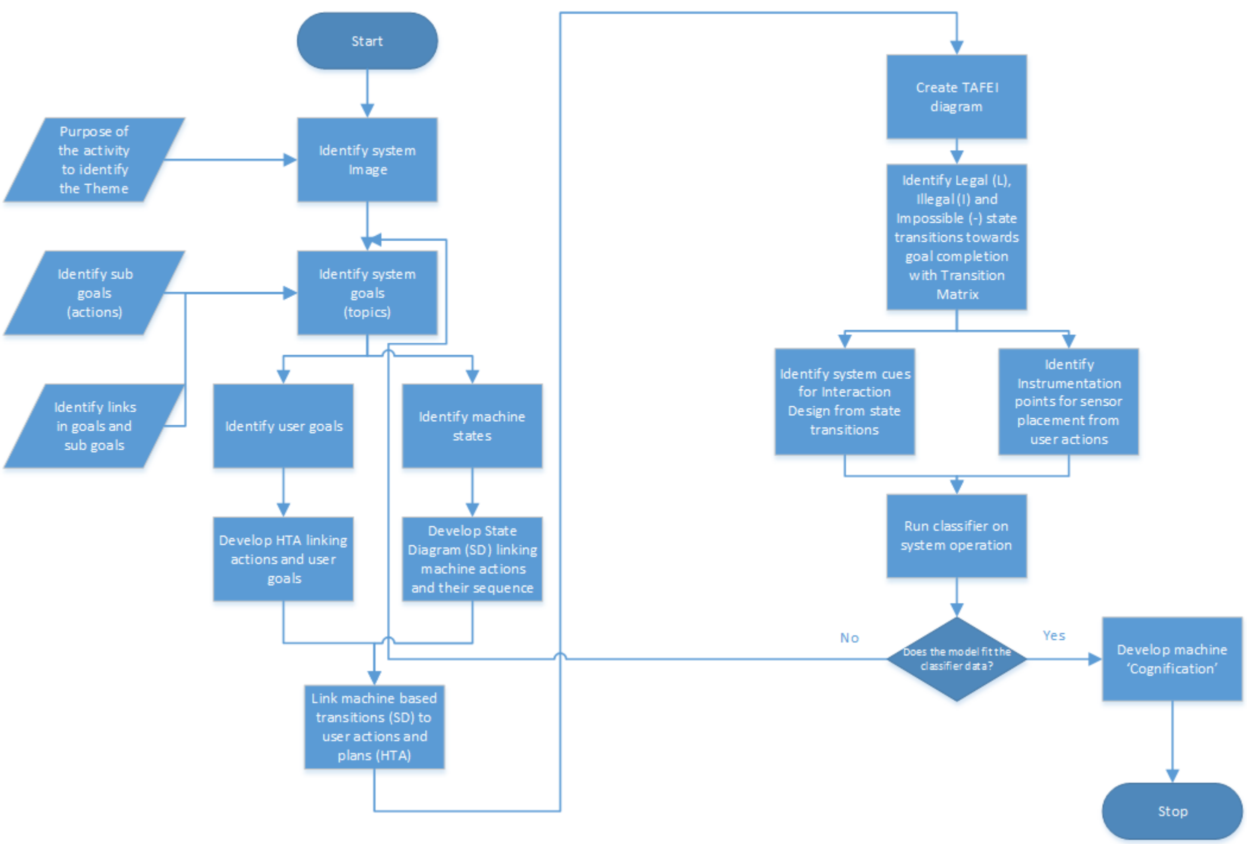

Figure 5.6 Summary of required steps to apply TAFEI for the Conversational IoT

5.6.1 Applying TAFEI for the conversational IoT

The flowchart presented in Figure 5.6 shows a summary of the steps required to apply TAFEI for the Conversational IoT, considering human and machine's actions to support a defined goal, as described in the previous sections.

This section applies the methodology for the previously discussed Central Heating example.

Goals and tasks will be characterised in terms of the system's HTA and State Diagrams. By analysing the two diagrams, a vision of their relationship is obtained and summarised with a state-based diagram, linking the states in the SD (Figure 5.5) and the plans in the HTA (Figure 5.4 and Table 5.4). A TAFEI diagram for the central heating example system is shown in Figure 5.7. As observed, state 0 is defined as 'idle' in 'standby for user action'. A user following P1 would trigger a transition to state 1, in which the system would be waiting for 'reading temperature display' from the 'temperature gauge'. Following plan P2 would make a transition to state 2, in which the user would be required to interact with the 'control dial' to adjust the temperature setting.

Notably, some state transitions do not directly relate to the user, but to the machine. These transitions are those previously described as 'opaque' to the user, as they occur in a different layer. Identifying these states allows for a description of where the interaction design could be supported by the appropriate communication cues, as will be discussed in chapter 7 with the design and development of a demonstrator system.

The final step in TAFEI involves the creation of a State Transition Matrix (STM) to identify which state transitions are legal in the context of goal completion. These transitions are marked as 'L' in the matrix, and require to focus on the particular goal at hand, to analyse whether the transition contributes towards achieving the expected goal. A transition could be possible, but if it does not fits the goal, it is considered ‘invalid’, and noted as ‘I’. Finally, if a transition is not possible, it is considered ‘impossible’ and marked as ‘-‘ in the matrix. Figure 5.8 shows the STM for the central heating example, where legal transitions (L) occur from state 0 to state 1; from state 1 to state 2; from state 2 to state 3, and so on for a complete cycle of operation of the central heating system. Conversely, a transition from state 0 to state 3 is possible, for example when the system is regulating temperature on its own, but in terms of TAFEI it is considered illegal since it does not supports a user goal, in this case ‘set temperature’.

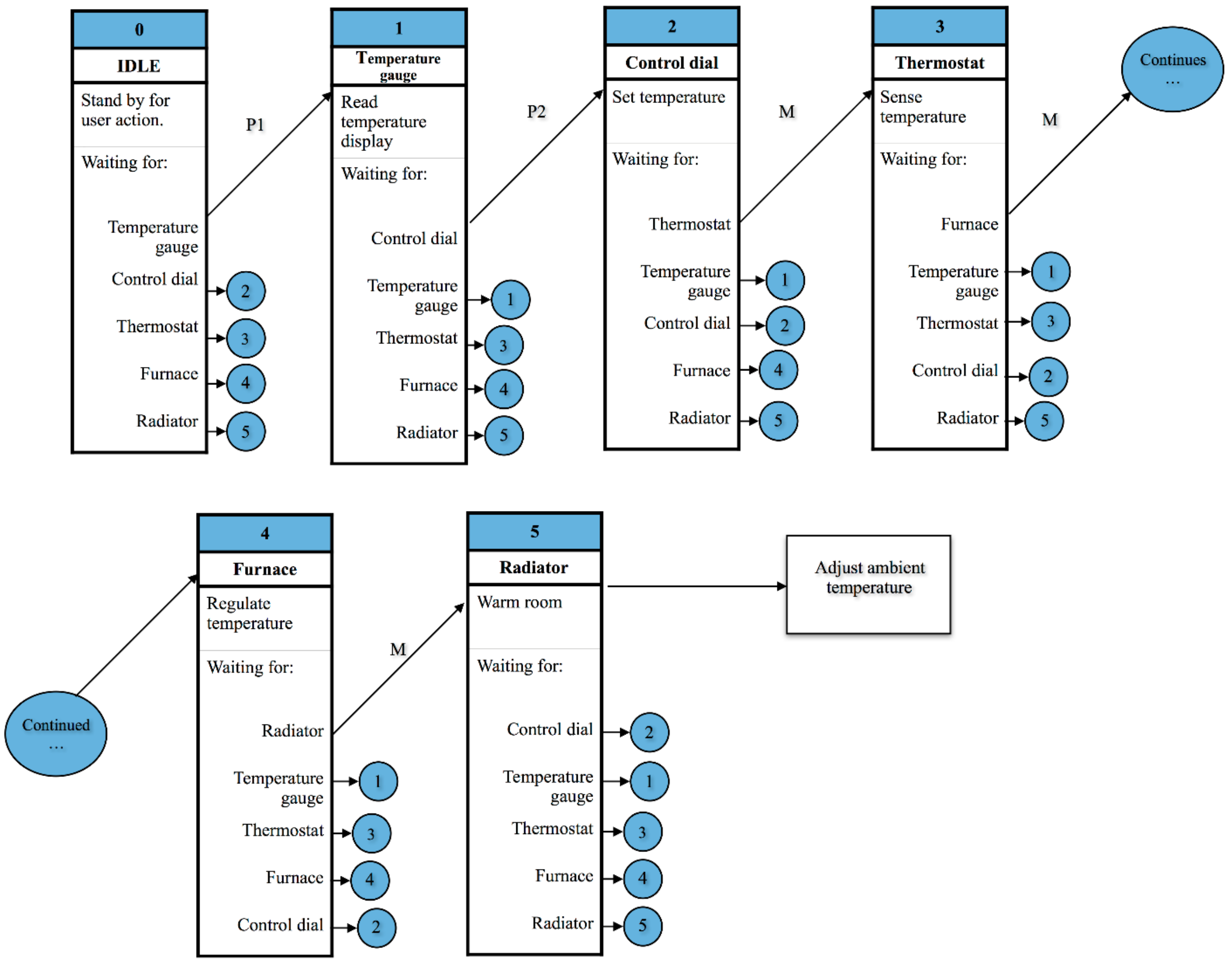

Figure 5.7 TAFEI diagram for a 'set temperature' goal in Central Heating System.

From State \ To State	0	1	2	3	4	5
0	I	L	L	I	I	I
1	I	L	L	I	I	I
2	I	I	-	L	-	-
3	I	I	L	-	L	I
4	I	I	I	I	-	L
5	I	I	I	I	I	-

Figure 5.8 State Transition Matrix (STM) for 'set temperature' goal in Central Heating System.

5.7 Conclusions

Interaction designer Donald Norman (2007) points *"The machine is not intelligent: the intelligence is in the mind of the designer",* highlighting the need for design methods suited to smart systems.

In this chapter, using the concepts that define the topics and theme in a social IoT are used to develop a conversational knowledge structure centred on topics to support theme communication within a Social IoT. It proposes that the relations between these topics and themes are characterised through the association of sensor functions and their specific outcomes contributing to an overarching theme agreed by a conversational common ground. By providing a clear and common framework an IoT that supports conversations and theme sharing with other networks, *things* and users would benefit from a common understanding of each other purposes and intentions, supporting a more transparent Human-IoT Interaction.

As discussed in this chapter, feedback is essential to a successful and meaningful human-IoT interaction. Users need to know the status of the machine, its actions and what is preparing to do. Even in optimal operation, users need to have the confidence that indeed, the system is operating as expected. This feedback is not only provided through a purpose-built interface, but as discussed in chapter 3, it can be achieved by cues provided by their affordances, for example humming sounds from a motor working or LEDs blinking.

In this thesis, the interactions between humans and things in IoT are characterised through the mapping of context to goals. This is presented in terms of the notion of IoT conversations (in which humans and objects cooperate to pursue specific topics in terms of themes). In this regard, TAFEI provides an adequate design methodology not only to analyse deviations in system usability, but also to provide a system-level description of user and machine based tasks to support device instrumentation.

TAFEI provides a human centred approach to system modelling and requirements definition. It considers a system comprised of both human users and ‘things’ in a systematic analysis of actions required to achieve goals within a system. By using this information to instrument the object, we could support system autonomy design by establishing rules that monitor when actions occur. For example, by placing a sensor on a coffee machine, the system could keep track of the amount of coffee consumed and in turn, proactively inform the user to purchase more consumables, or by linking to e-commerce platforms, make machine-based decisions such as order the supplies on its own.

Based on the application of Task Analysis for Error Identification, the following chapter describes how demonstrators are built to support interaction with a simple IoT system. Furthermore, data collected from interactions with these systems over a period of several weeks are analysed and discussed in chapter 7.

6 *Understanding Topics and Themes in the IoT*

6.1 Introduction

This chapter is based on the paper "*Rule and Theme Discovery in Human Interactions with an 'Internet of Things.'*" by Cervantes-Solis, J. W., Baber, C., Khattab, A., & Mitch, R. (2015), published in the Proceedings of the British HCI 2015 Conference.

J. Waldo Cervantes-Solis and Prof. Chris Baber developed the study and methodology, whilst Ahmad Khattab and Roman Mitch developed the hardware. The author of this thesis completed the results, analysis conceptual background and paper.

This chapter focuses on how users understand 'smart' objects and 'smart' environments in the context of HCI. This chapter presents a study where humans arrange tangible interfaces on an instrumented grid in order to determine their goals. The participants' role was twofold: to move the tangible interfaces and to ensure that all their goals were met. The task was presented either as a rule discovery task (i.e., to deduce the goal of each object) or as a theme (pattern) discovery task (i.e., to deduce an appropriate arrangement of boxes to satisfy the goals). Differences between these conditions were identified and discussed as the framework for a definition of a goal centred approach to Human-IoT Interaction.

6.2 Background

Portions of this section were taken from (Cervantes-Solis et al., 2015a).

The objective in developing this study was to create a collection of smart objects with which people could interact as a 'society of mind' (Minsky, 1988). Inspired by the work of Walter (1950) and Brooks (1991) the study explores how a collection of objects could appear 'intelligent', or at best, could solve a simple problem, a 'society of smart objects'. While the robots of Grey Walter were capable of moving themselves as stimuli from its simple sensor changed, in this study the objects were moved by the human. Given the physical nature of smart objects, humans were provided with a specific, physical role in this society of objects. By requiring humans to move the objects, it would be possible to consider how (or if) control is exercised by the users. For example, the person could move the objects on the basis of their own intentions and plans, or could wait for the objects to respond at each step in the interaction and prompt the user to act.

6.3 Methodology

This section was taken from (Cervantes-Solis et al., 2015a), including the description of architecture, smart objects' description and implementation, the description of the study, data analysis and results.

The testbed was originally conceptualised as an exploration of how smart objects would communicate their goals to users and understating users understanding of instrumented devices, and influenced by Norman's (1993) concept of 'experiential' and 'reflective' cognitive artefacts, in which he differentiates between those objects that *"provide ways to experience and act upon the world"* and those that *"modify and act upon representations of the world"*. Moreover, these objects directly influence reflective and experiential cognitive processes. Under this framework, this study was interested in questioning how does the IoT influences its user's understanding of what it does, and which goals does it supports.

Of interest was also the notion of whether users thought of the system as a collection of devices or as individuals and their own role in making sense of the purpose of the system. Moreover, the study whether this purpose could be used as an extension of the knowledge created by the system, and who would be responsible to provide this information. As such, the testbed was developed as a simple game in which users had to ‘guess’ the placement of objects within a grid. The testbed platform comprised tangible interfaces, with a simple LED-based user interface and hard-coded with a specific rules determining their goal. The grid was developed from a table with sensors that could detect whether an object was placed on top of one of the sixteen pads identifying a coordinate on the grid. Participants were tasked to arrange each of the tangible interfaces on the grid such that each object’s goals were satisfied.

The experiment was run under the University of Birmingham’s ethics guidelines. Participants were informed of the nature of the study, and were given the option to opt out. All gave their consent for the data to be used in the analysis, and for their anonymised results to be published in a conference paper.

6.3.1 Architecture

Centrally controlled IoT systems often follow architectures such as the one shown in chapter 2. These topologies involve a central node with the role of collecting data, issuing commands, policy enforcing (rules) and interfacing with users to receive input and provide feedback if required.

In order to investigate the roles of objects and users within a ‘smart’ system, the design principle for the testbed was to provide an environment in which no single component had a full view of the purpose of the network or the other objects. Each of the actors in the study was tasked to fulfil a particular role in the system. Thus, the architecture was develop to be a collection of loosely connected devices, recreating relatively decentralised network topology. Figure 6.1 shows the block diagram architecture for the testbed, highlighting information and action flow, based on the decentralised architecture shown in chapter 2.

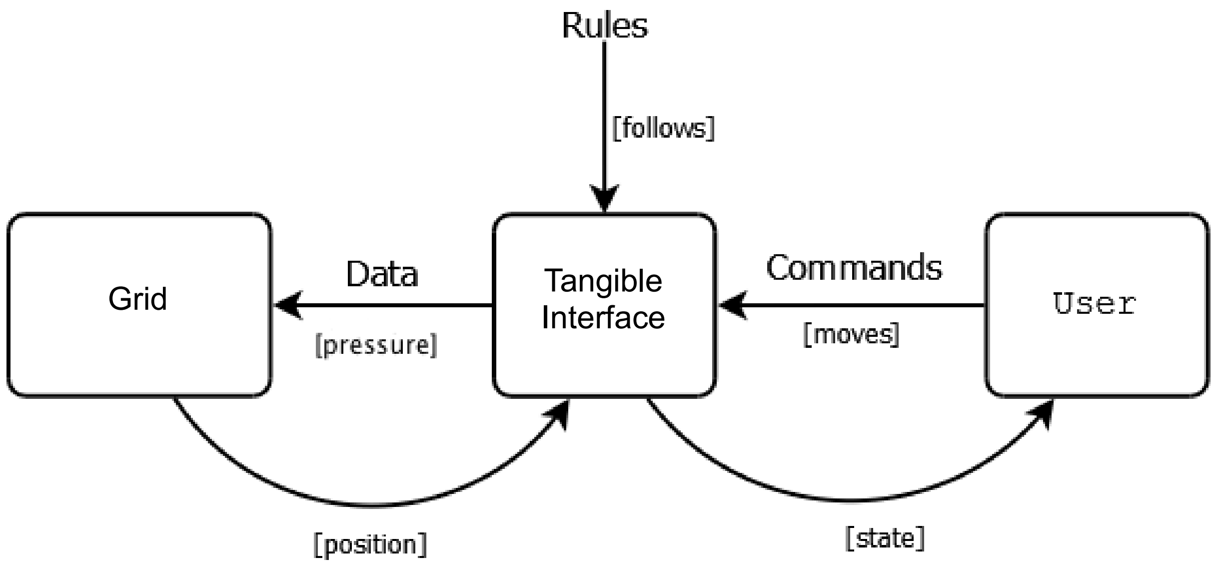

Figure 6.1 Testbed system architecture

As observed, in the proposed 'decentralised' architecture, flow of information would occur within the appropriate entities, without the others participating in the exchange. The user would interact with the tangible interface through a command, in this case the physical action of *moving it*, whilst the object would interact with the grid trough a pressure sensor (switch), and consequently message back its relative position to the tangible interface. Rules would be predefined for the tangible interfaces to evaluate whether their goal had been fulfilled, and if so, they would show their state to the user through a set of LEDs.

In terms of the technical implementation, Figure 6.2 shows the state diagram of machine-based interactions in the system, as discussed in Chapter 5.

As will be described below, objects were required to connect to a wireless network to communicate between each other. Moreover, to be able to collect data about the experiment, it was decided that hub node would be implemented, acting as a router and a data collecting device. Given that the communication would be handled by this node, it was also decided that it would present an opportunity to disassociate another layer of information from each object by delegating some functionality to this node as described in the following section.

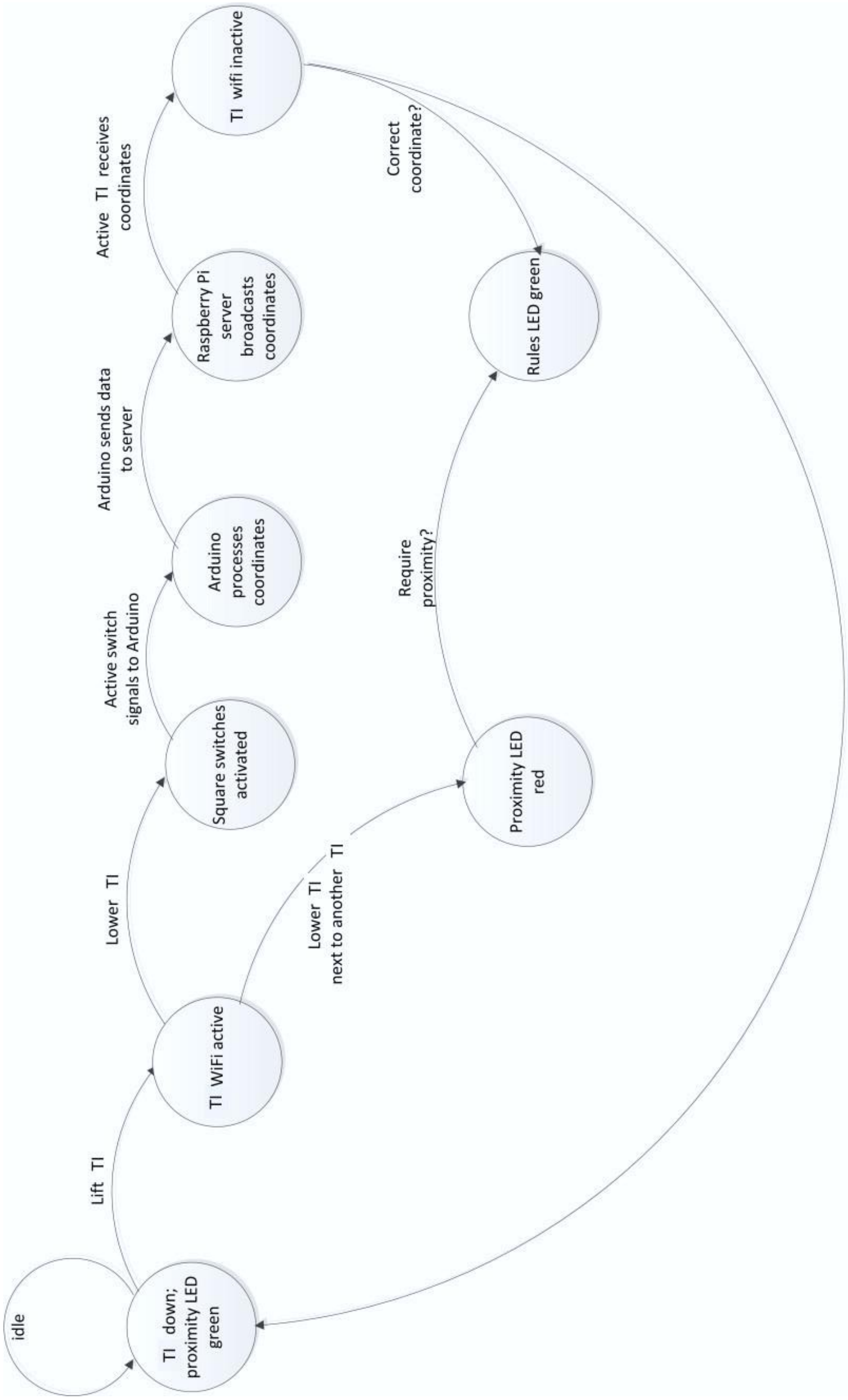

Figure 6.2 Experiment State diagram, showing interactions required on the Tangible Interfaces (TI) and the grid.

6.3.2 The testbed architecture

The tangible interfaces that were developed and used in the experiment were based on wooden boxes fitted with sensors (tangible interfaces), a microcontroller and wireless connectivity, and a table with sensors (grid), managed by a connecting hub/server, and manipulated by a human user as shown in Figure 6.3.

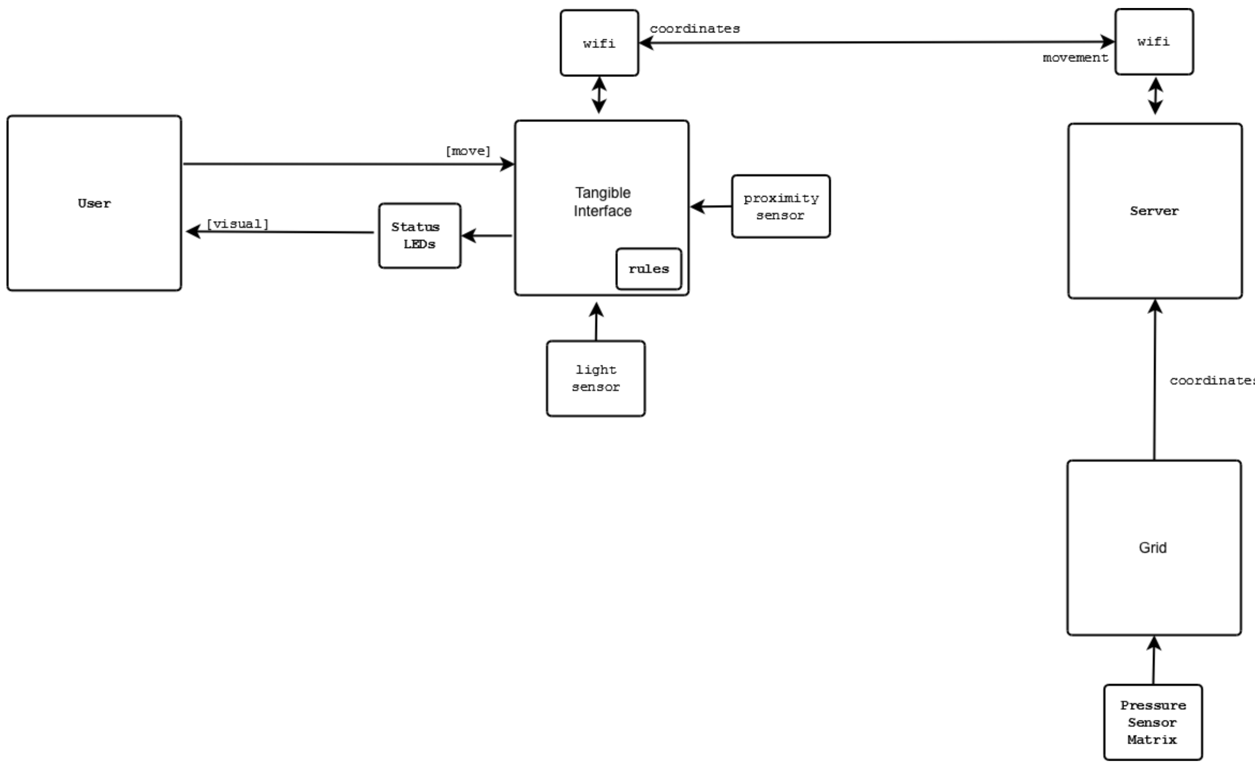

Figure 6.3 Puzzle architecture diagram. The communication links show the type of interaction expected from each node.

6.3.2.1 Grid

The table-based grid was instrumented with switches that that detected when an object was placed on them. The switches were managed by an Arduino-based Lilypad microcontroller, which could determine the location of the activated pad within an *x, y* coordinate in a grid. This coordinate was conveyed to a hub/server, and relayed to the boxes if required. Figure 6.4 shows the experimental setup, including grid and the tangible interfaces used.

Figure 6.4 Experimental testbed, including instrumented grid and tangible interfaces.

6.3.2.2 Tangible interfaces

Four tangible interfaces (TI) were implemented using the same technological architecture. Each device consisted of a Wi-Fi transceiver and an infrared (IR) proximity sensor, controlled by a Raspberry Pi single-board computer. By establishing communication with a hub (described below), each TI would be informed of its location on the grid by messaging the hub, which would relay information from the grid. When a TI was placed on top of a pad, the grid would communicate its location to the hub. In addition, a light sensor was used as a cue for the TI to initialise communication, and wait for its coordinate to be transmitted from the hub.

Through the IR sensor, the TI could detect proximity to another TI in its vicinity.

For user interface, the experiment design required the simplest way to convey its state to participants. As such, each TI had three Light Emitting Diodes (LED) representing its state. If the

TI's goal had been satisfied, a 'goal' LED turns from red to green. In addition to the 'goal' LED, the TI had two extra LEDs to indicate its 'communication' and 'proximity' status. Figure 6.5 shows one of the TIs used in the study, whilst Figure 6.6 shows a view of the user interface as implemented with LEDs. The interface labels are defined as: 'P' stands for proximity, 'R' for rules, and the middle LED indicates communication status. (N.B., although the TIs show geometrical figures on one of its sides, they serve no purpose in the study. They were a consequence of the wooden box used as enclosure for the on-board electronics).

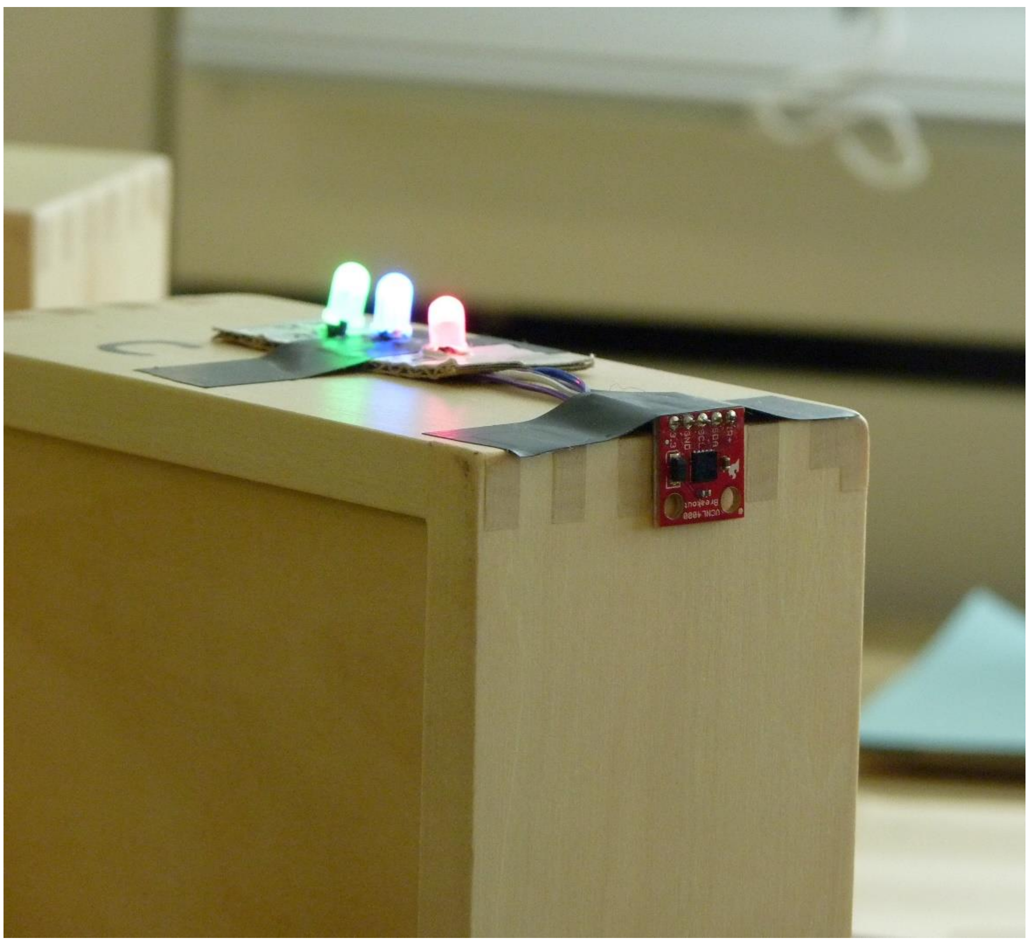

Figure 6.5 Tangible Interface used in experiment. User Interface LEDs (top) and proximity sensor are shown.

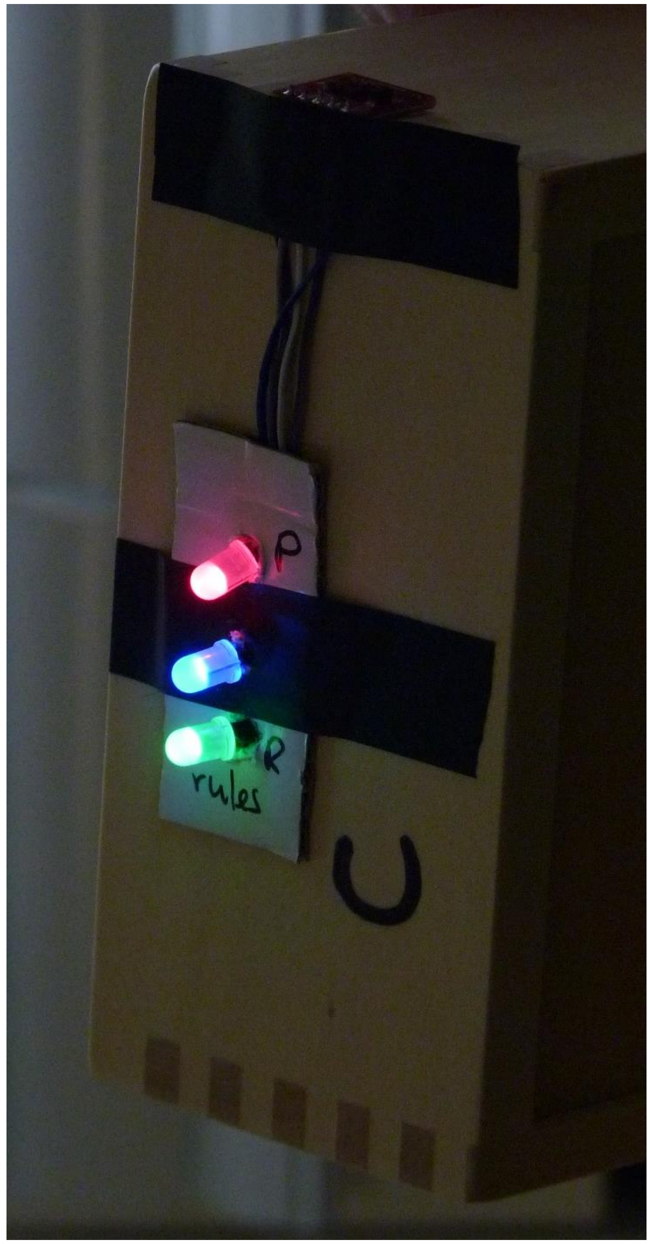

Figure 6.6 Tangible Interface user interface implemented with LEDs.

6.3.2.3 Hub

As mentioned above, the testbed was designed to be a collection of loosely connected devices. They would still need to be able to connect to a physical medium for data exchange, and also to be able to collect data about them to fulfil the study. As such, a Raspberry Pi computer was used as a Wi-Fi router and as message relay hub. In addition, this hub also served as a logger of user activity, recording the sequence and box movements across the grid.

Whenever a TI is lifted, its 'communication' LED would turn blue (middle LED), indicating that a connection with the grid is being established. On successful connection to the hub, the TI announces its identification code. This triggers the server to log the TI ID. When the TI is placed on a grid square, the grid sends back the corresponding coordinate, which gets registered by the server. This architecture implies that on their own, each object would not know their location or status, requiring of the hub to keep track of it, and to relay it to the other. Thus, once the grid obtains the coordinate, it is communicated to the TI, and their momentary connection ceases (as enabled by the hub). Technical limitations on this configuration established the condition on the puzzle that only one TI could be moved at any given time. In this manner, each TI becomes 'aware' of its coordinate and uses this information to check its rules (Table 6.1). If the TI is placed on an acceptable location and conditions as established by its hardcoded rules, then the 'Rules' LED could turn green.

6.3.2.4 User

In addition to the smart objects, the study involved a human user to consider their role as another actor in the system. As such, the user's primary role was to provide the physical action of moving the TIs, with a secondary role to determine whether the goals of all TIs had been satisfied.

6.3.3 Objective of study

The study was conceptualised as a puzzle game in which the participant would need to correctly position four TIs on a grid, following a 'hidden' (to the user) parameter in each TI. The goal of each TI was defined by a set of rules only known to the TI itself as part of its programming. Rules were defined by the coordinate on which the TI was placed on the grid, and / or the proximity to another TI. Each of the TIes was individually labelled for identification purposes with letters A to D, as shown in Table 6.1.

Table 6.1 Rules programmed in 'puzzle' Tangible Interfaces (TI). Dashes indicate that condition did not applied to the TI.

TI	**X Coordinate**	**Y Coordinate**	**Proximity**
A	***ODD***	**-**	**-**
B	***EVEN***	**-**	**-**
C	**-**	**-**	***ACTIVE***
D	***EVEN***	***EVEN***	***ACTIVE***

The rules for three of the Tangible Interfaces were defined to provide simple constrains regarding their own position or in relation to other TIs, whilst for last TI, a stricter set of rules was applied. As per Table 6.1Table 6.1, TI A, required to be placed in any odd numbered X coordinate, that is, 1 or 3, regardless of the Y coordinate and TI B would need to placed on an even numbered coordinate. TI C would just require to be in proximity to another TI, regardless of the X, Y coordinates. Finally, TI D imposed more restrictions a as it would need to be placed in even X and Y coordinates and next to another TI.

Thus, participants would move the TIs into their appropriate positions, trying to determine the TIs goals.

In summary every component in the network only had a partial view of the system's purpose, such that:

- The grid detects a TI placed on its grid, and logs its position
- The TI only knows its position by communicating with the grid
- Only the TIs know the rules of the game they adhere to

- The user moves the TIs, getting their status feedback through their LEDs

6.3.4 Study

The study was divided in two conditions. In each, participants were asked to solve the puzzle by following three different sets of instructions:

- *Condition 1, Patterns*: Users were informed that the fulfilment of goal state involved the TIs forming a pattern (or shape) in the grid.
- *Condition 2, Rules*: Users were informed that the fulfilment of the goal state involved the location (coordinate) of the TIs on the grid and their proximity to another TI.

Condition 1, would be addressing the possibility of identifying the purpose of the system in terms of its status, that is, a data-based paradigm as discussed in Chapter 2. Condition 2 would relate to the semantics of the network, possibly a human-centred description of the goal, as proposed in Chapter 3.

It was expected that participants would take different approaches to problem solving, to find what each object can do and what it needs (Figure 6.7). Referring back to the knowledge structure developed in Chapter 5, we can describe the TIs as *things* capable of performing ‘actions’ (what they can do) in pursuit of a ‘goal’ (what they need). Notably, as discussed in Chapter 2, this view aligns with the notion of objects possessing agency and pursuing goals. In terms of the social IoT introduce in previous chapters, this shows that a balance of agency must be addressed in the IoT, as both humans and things are capable of having goals.

Figure 6.7 Participant of study interacting with the puzzle.

The ‘actions’ would be defined in terms of rules, which are specific to the object and which could involve the person generating an internal representation for each object (as a result of developing a mental model of what the rules the TI will follow). Consequently, this would involve a bottom-up approach to problem solving. In contrast, a ‘goal’ would be defined by the arrangement of objects on the grid, as required by each object and their collaboration. This would provide an external representation, enabling a top-down approach to problem solving.

Participants had a time limit restriction for each trial of 6 minutes. Time was not considered a dependant variable on the study, however, this this allowed to limit the attempts towards finding a solution.

After their first trial was completed, participants for each condition were asked by the investigator what the pattern or rule set they used to solve the puzzle, and for their second attempt (trial 2) they were asked to repeat the experiment with the knowledge about the system they gained during the first trial.

As mentioned, the location and sequence of TI movement was recorded by the hub node. Thus, analysis for this study was based on these data, the participants' comments, and a record of the final position of the TIs as observed by the investigator.

Finally, a control condition in which participants knew what rules to apply for each TI and hence, knew exactly the complete and correct functionality of the experiment, was run to provide ground truth data.

6.3.5 Data analysis and results

For this study, results were analysed in terms of overall performance and in terms of the number of moves for each TI.

As previously mentioned, participants were asked to move the TIs around the grid to try to discover where they should be placed in order to fulfil their goals. This process initiated as a trial and error process for participants, relying on the TIs' LEDs to guide them. Also, given the range of rules found amongst TIs, there is not a definite solution to the 'puzzle'. Figure 6.8 shows a solution based on participants finding the TIs' rules, whilst Figure 6.9 shows a pattern based solution. In both cases all the devices' goals were fulfilled, indicating to participants that they had accomplished the task through their LED interface (middle LED in this case).

Figure 6.8 A puzzle solution based on users following individual rules.

Figure 6.9 A puzzle solution based on users following patterns (s-shape).

6.3.5.1 Performance

Performance in this study is defined as the number of correct and incorrect moves participants took to find a solution. An independent t-test was conducted to compare this attribute across the *Patterns* and *Rules* conditions on two trials, and was found there is no difference between conditions on trial 1 [$t(18) = 0.524$, $p = 0.6$], nor on trial 2 [$t(18) = 1.028$, $p = 0.32$]. Hence, it was found that in both trials, participants made a similar number of moves to reach a solution. However, by comparing performance across the trials (first trial with no knowledge of the system and second trial with knowledge of the system), while there was no difference in performance for participants using *patterns* [$t(18) = 1.228$, $p = 0.235$] there was a significant reduction in performance for people using *rules* [$t(18) = 2.667$, $p = 0.016$]. These results suggests that participants following patterns appear to maintain a level of performance, whilst those using rules performed poorly in the second trial. One explanation for this could be that people in the rules condition had not formulated complete and correct sets of rules, which affected their performance, whist participants using patterns sought to apply their understanding of arranging TIs. When looking at the type of patterns used, participants in trial 2 of the rules condition were far more likely to place the TIs away from each other, i.e., no pattern, in both trials (P1 = 0; R1 = 3 and P2 = 2 and R2 = 5).

This analysis allowed to explore the research question set in chapter about the nature of Human-IoT Interactions. The results from the analyses are summarised in Figure 6.10 and its corresponding data shown in Table 6.2. Baseline data is presented to allow for contrasting the conditions with the minimal number of moves required to complete the test in either of the conditions. As such, these results also suggest that patterns conditions allow for participants to get closer to the ideal number of movements. Moreover, the rules condition also suggest that although participants were able to recognise the ‘shapes’ formed by the arrangement of the tangible interfaces, this hindered their ability to recognise additional rules could prevent the system to reach a state in which all conditions were met. In particular for some of the TIs with more constrains (as shown in Table 6.1), whose effect is discussed in the following section.

Table 6.2 Number of Correct Moves per trial in performance test.

		Patterns Condition	e	Rules Condition	e	Baseline Condition	e
Number of Correct Moves	Trial 1	7.500	4.905	9.000	4.967	5.500	1.732
	Trial 2	7.300	4.029	8.300	5.618	5.000	0.816

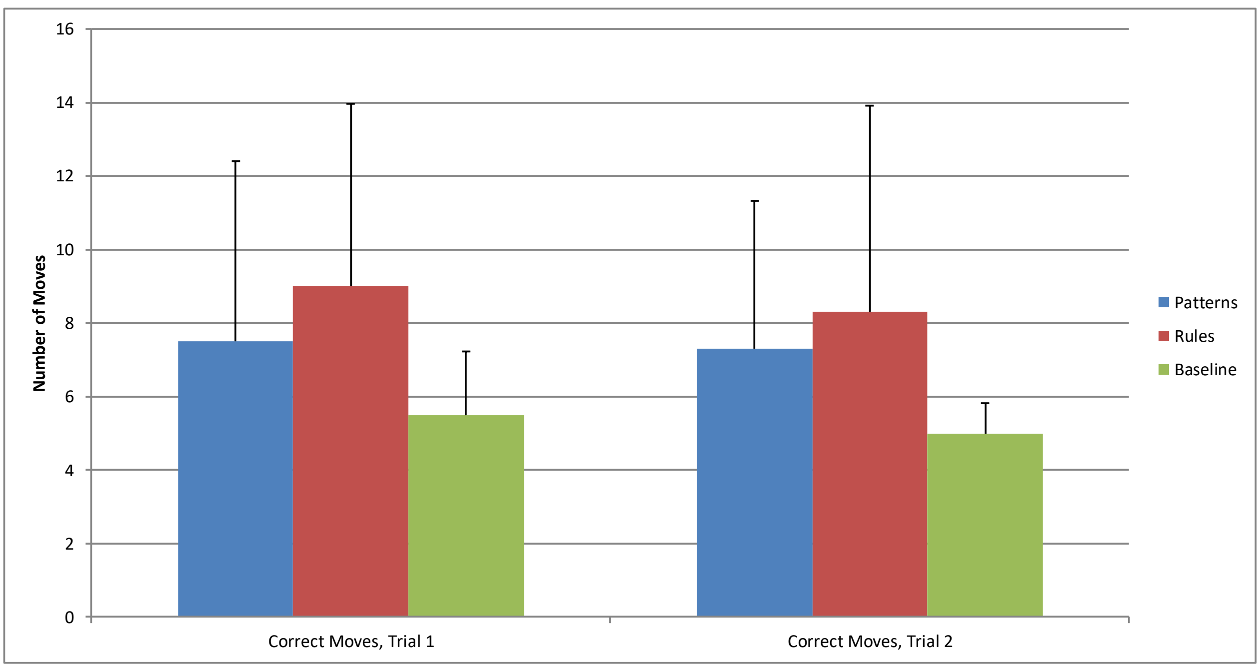

Figure 6.10 Average performance for users across trials and conditions.

6.3.5.2 Number of moves

In terms of how people moved the TIs, the results from a variance analysis suggest a significant main effect of TI [$F(3,54) = 21.9$, $p = 0.0001$], and a significant interaction between TI and trial [$F(3, 54) = 2.8$, $p = 0.05$]. No other within subjects effect reached significance, nor was there a between subjects effect [$F(1,18) = 0.737$, $p = 0.4$]. This suggests that there was little effect of condition on the movement of the TIs. Participants tended to move TIs A and B to a square in which the 'rules' LED turned green, and then left these in place while they moved TIs C and D. These results are illustrated by Figure 6.11 and its accompanying data shown in Table 6.3, and allow for the exploration of the research question of the thesis related to how humans make sense of interactions in the IoT. As observed for Tis C and D (those with more constrains are shown in Table 6.1), it took a higher number of moves for user to find the correct placement on the grid, hindering on the participants ability to find the governing rules of the Tangible Interfaces. However, when contrasting the results from the rules and patterns conditions, these ‘difficult’ TIs presented better results when they were arranged next to others forming shapes. The results from the analyses from these two sections suggest that providing a pattern that conveys meaning to the participant’s interactions allows for a better understanding of the system’s purpose.

Table 6.3 Average Number of moves per Tangible Interface (TI) across two trials.

	Patterns	e	Rules	e	Baseline	e
TI A, Trial 1	2.20	1.87	2.60	1.58	1.25	0.50
TI B, Trial 1	2.50	1.65	2.20	0.92	1.75	0.96
TI C, Trial 1	7.10	9.12	11.40	8.62	1.75	0.96
TI D, Trial 1	12.20	10.26	14.20	9.70	2.25	0.96
TI A, Trial 2	2.10	1.60	2.90	3.03	1.00	0.00
TI B, Trial 2	2.80	1.87	3.60	4.27	1.75	0.96
TI C, Trial 2	4.00	3.13	4.50	5.23	1.50	0.58
TI D, Trial 2	8.40	11.55	7.60	8.60	1.50	0.58

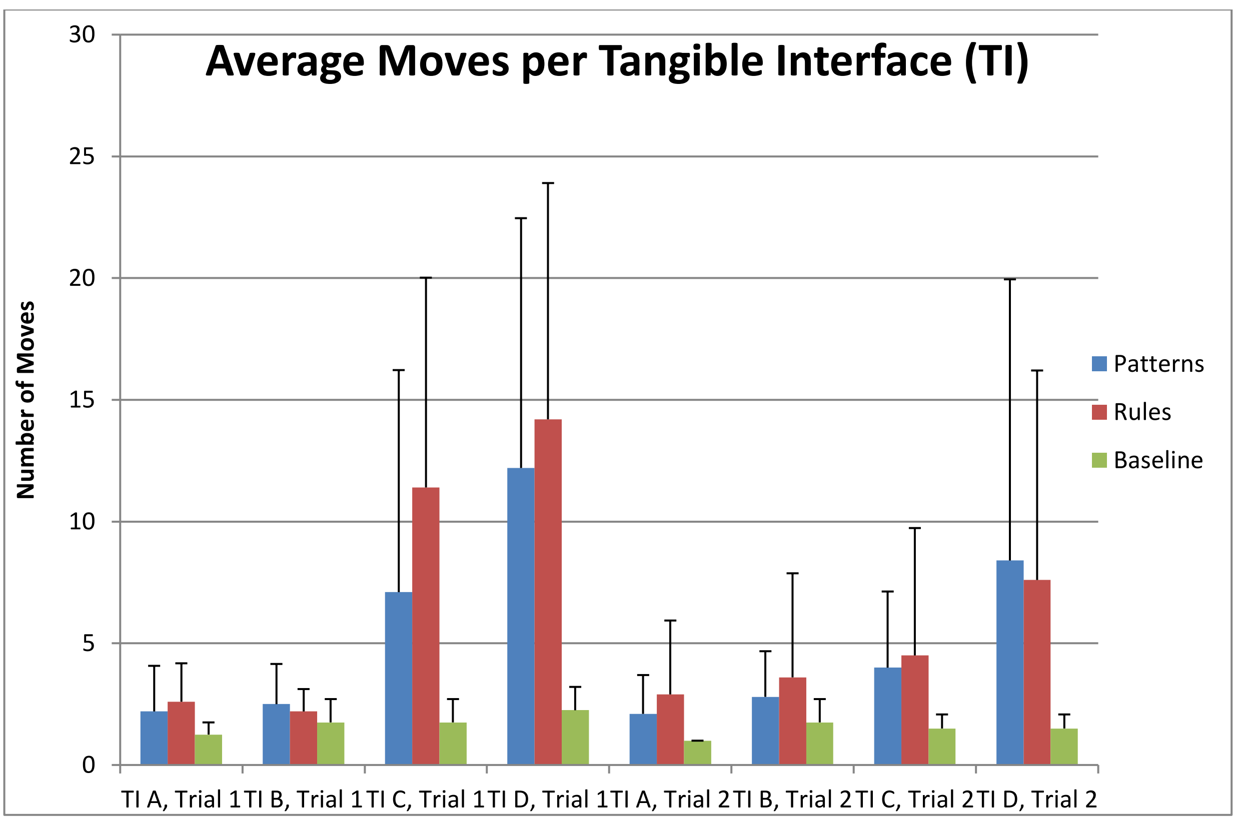

Figure 6.11 Average number of moves per Tangible Interface across trials and conditions

6.4 Conclusions

Portions of this section were taken from (Cervantes-Solis et al., 2015a).

This chapter analyses how humans react to a ‘smart environment’ and understand its purpose, noting the approach taken by both users and machine in the pursuit of their goal.

The study allowed to characterize goals in terms of both data and human centred paradigms, by allowing users to discover the functionality of the network, or its ‘theme’ as defined in the knowledge structure presented in chapter 5.

In the context of the central heating example used across this thesis, it has been discussed that they present some challenges to user because they do not provide users with a full description of what is happening in the background, as suggested by the results on the ‘rules’ condition trials. Conversely, the results found in this study suggest that mental models play a fundamental role in characterizing an IoT system. Users benefit from having a meaning-based approach to interacting with the machine, as suggested by the ‘pattern’s condition.

As defined in chapter 2 of this thesis, in the context of Human-IoT interaction it is expected that actors, both machine and human perform specific roles in a collaborative fashion with the system’s goal as the guideline for the cooperation. Through the guise of a puzzle game, the study presented in this chapter aimed to analyse how such a collaboration is enabled in a simple ‘smart’ environment. By concealing the machine’s (the Tangible Interfaces) goal’s, users were expected to try to engage with the objects to put them in their desired stated. In fact, an interesting response was shown by some participants by labelling the end status of the TIs as ‘happy’. In addition to giving human-like attributes to the machine, it imbued a sense of collaboration towards a state that implied well-being, as a subjective measure of accomplishment.

An architecture in which all of the nodes had a partial view of the system, enabled a system in which knowledge was pushed to the edges of the network, as opposed to having one device in charge of managing all interactions and the corresponding interpretation (as found in centralised architectures). Thus, this allowed for an analysis of the role of human users in the system, as monitors, controllers or nodes.

The results from the study suggest two principal conclusions. First, when the smart object relies on a simple rule that relates movement to spatial coordinates (such as for TIs A and B), participants were able to easily recognise this rule. However, this proved to constrain subsequent activity. As participants placed TIs A and B in a correct position (as informed by the corresponding LED), they did not seek to move these TIs further, affecting their strategy for the remaining TIs. This was true in both in the 'rules' and the 'pattern' conditions, across both trials (see Figure 6.10). In TIs with proximity rules (TI C), participants were likely not to realise this and concentrated on finding a coordinate. Thus, TI C is moved more frequently than the coordinate rule TIs (A and B). Interestingly, participants in the 'patterns' condition moved TI C less than those in the 'rules' condition. For 'patterns', a location for TI C could be defined by its relation to TIs A or B, i.e., participants would place TI C near one of the TIs already in place. In the 'rules' condition the relationship between TIs was less discernible. Finally, TI D was moved a great deal in both conditions. It is believed that the combination of rules for TI D led to confusion for the participants in both conditions. Even though the rules were not complex, the combination of more than one rule led to TI combinations that participants struggled to resolve. Second, when participants focus on rules, they showed deterioration in performance from first to second trial. This could be due to them applying incomplete or erroneous rule sets. Also, this deterioration suggests that the 'pattern' group might have been less restricted by the need to determine what each individual TI required and focused more on the combination of boxes forming shapes on the grid.

These results highlight the question of what needs to be ‘discovered’ by users in an internet of *thing,* and how sense making occurs in this environments. The results point to an interesting question for the design of networks of smart objects. On the one hand, there is a requirement to identify and define an object’s function and goals. In the study, this corresponded to the identification of individual rules. This could be considered as analogous to ‘service discovery’ in computer networks, where resources broadcast what can they do to other nodes. On the other hand, there is the need to discover an overarching ‘pattern’ in the solution. Although not in the rigorous context of the field, this could be comparable to the ‘semantics’ of the network activity, describing in its meaning and purpose as presented in chapter 3.

Results from this study suggest that human interaction with smart objects should focus more on the higher-level outcome of system wide activities, and less on individual object’s rules or functions. In the study, the patterns condition enabled a clearer understanding of the object’s requirements or goals. As such, a central, common thread shared amongst system’s actors would provide a guideline for interactions. Thus, the concept of ‘discovering’ the ‘theme’ of the network is introduced, analogous to the notion of service discovery in networks. Themes are also considered the common threads in a conversation, as defined in chapter 3.

The IoT vision implies that physical objects are imbued with SPC capabilities, making them prone to various degrees of autonomy and smartness. Thus, it is expected that many devices would communicate with each other to complete tasks and goals. This leads to the question of how the user could either eavesdrop on this exchange of messages (and so, determine the goals being pursued) or how the user could participate in the exchange. The study presented in this chapter also lead to suggestion that users look to find ‘correct’ solutions, in the sense that theirs is an understanding that a goal should be accomplished, and their role towards completion of the system goal.

Having analysed how roles are enacted in terms of themes and topics, the following chapter will delve into the requirements for modelling IoT systems that put human goals at the centre.

7 *Modelling an experimental Testbed*

Based on the design framework presented in Chapter 5, this chapter describes the development of an experimental testbed. Focusing on the outcomes of the methodology, a set of requirements is defined to enable system instrumentation. The demonstrator systems allowed for data collection which subsequently were used to demonstrate the system's operation in alignment with the model, as related to the system's goals and tasks. This chapter shows how a human centred system analysis through the proposed methodology allows for the understanding of emergent autonomous and intelligent opportunities to support the system's primary goal, with a focus on its usability.

This chapters describes how TAFEI can be used to model an IoT systems through its tasks, the objects involved in a goal, and their state transitions, on a two part study on two models. The first part of each study applies the TAFEI methodology to provide a description of goal completion in a collaborative system comprised of a human user and instrumented objects. The second part of each study involved the instrumentation objects informed by the human centred description of the system to systematically collect and analyse sensor data to validate the approach.

The platforms presented in this chapter were developed with the aim to extend the TAFEI methodology presented in chapter 5, first on a single device with a specific them, and then extending it on a network of devices used to achieve goals within the same theme. Given a research lab setting, it was observed that common activities in people in the environment related to drinks consumption. Hence, the platforms were developed with the expectation that the related themes could be decomposed into a collection of topics, which relate to coffee making in the first testbed, and different types of drink for the second. In this respect, a topic could be analogous to a goal, i.e., the topic of making a cup of tea involves the goal of making a cup of tea, together with actions and events that relate to this, such as use of consumables such as water, electricity, teabags, milk etc. This means that, in order to achieve the goal, it is also necessary to ensure that the consumables are available. For this reason, one could say that a ‘goal’ is the desired outcome of a system, and the ‘topic’ is the necessary condition required for this goal to be met. In this case, the topic of the conversation (within the system) would involve confirming that the conditions have been met and checking that pursuit of the goal is proceeding without problem.

This chapter presents the development of two platforms: one based solely in the instrumentation of a coffee machine, analysing its interaction requirements for its most common goals. Moving forward, a second testbed was developed in which the coffee machine becomes a part of a broader system, aiming to support any kind of drinks making activities, in contrast to only coffee. In this regard, these two approaches would aim to focus on the differences of designing interactions for two different ‘scales of experience’ as noted in Chapter 5.

7.1 Applying TAFEI in a simple object

7.1.1 A coffee making device

Coffee makers are almost ubiquitous in office environments. Given its context of operation, it is expected that human users would use these objects as part of their everyday activities. As such, these object was selected to develop a testbed for the application of TAFEI as an interaction design methodology for smart objects.

The selected device was a Nespresso coffee machine. This appliance operates by using capsules for a single serving of coffee, and thus, this approach provided s trackable mode of operation, suited for a task based interaction and requirements analysis.

7.1.1.1 System image and points of interaction

As described in the previous chapter, the first step to apply TAFEI is to provide a system image, identifying the system's components, as shown in Figure 7.1. The system image highlights the main points of interaction from a user perspective, enabling a user-centric perspective of task and goal analysis.

Figure 7.1 A breakdown of the components of a capsule-based coffee machine. (Image adapted from Nespresso-Krups Inissia user's manual.

Based on the system image shown in Figure 7.1, Table 7.1 shows the points of physical interaction that users can find on the coffee machine and the expected action from the user. This is required by TAFEI to provide a description of the tasks required to complete a goal within the system. Moreover, as will be discussed later, this will inform the sensor placement for instrumentation.

Table 7.1 Interaction points found in the analysed coffee machine. A brief description of the expected user action that can be performed on the device is presented.

Object	**Expected user action**
Button	Press
Lever	Move up/down
Capsule	Place capsule
Used capsule container	• Remove/Replace • Empty used capsules
Water tank	• Remove/Replace • Fill with water

7.1.1.2 System states and goals

Based on the system image and identified points of interaction in the previous section, it is assumed that the object's operation in order to complete a goal can be described in terms of a transitional states system defined by the user supported actions. From a system perspective, State Space Diagrams show the transitions required to achieve the desired topic but require an understanding of actions available to the user, described through Hierarchical Task Analysis (HTA) as defined in chapter 5. This provides a breakdown of the plans involved to achieve system's goals, in this case to make a cup of coffee.

The goals that users can perform with the coffee machine are shown in Table 7.2.

Table 7.2 Goals supported by the coffee machine.

Goals
Make a cup of coffee
Empty used capsules container
Fill water tank

Figure 7.2 shows the HTA diagram for the coffee-making themed system, with its corresponding plans described in Table 7.3.

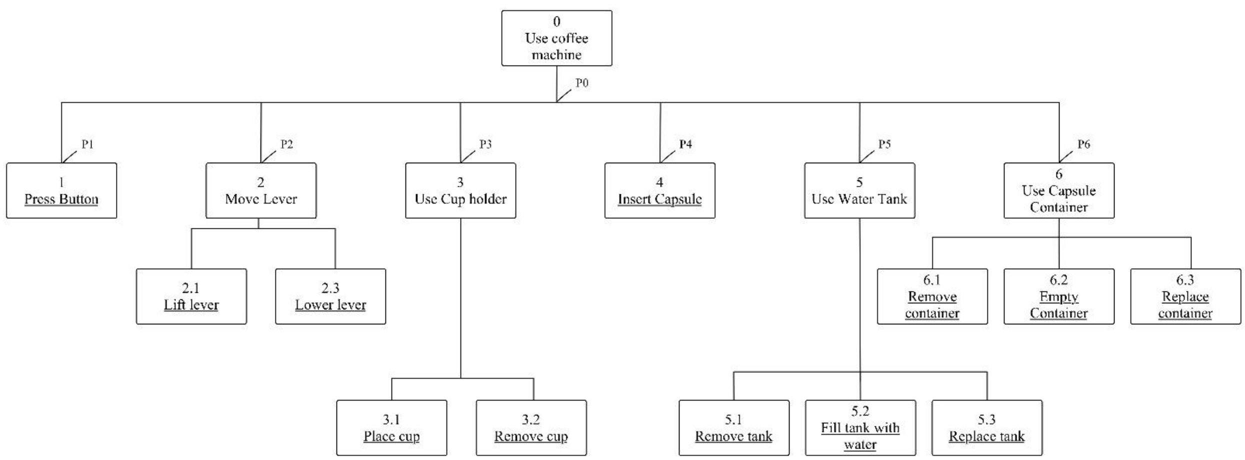

Figure 7.2 Hierarchical Task Analysis diagram for coffee-making themed system, plans are shown in Table 7.3.

Table 7.3 User plans for the coffee machine HTA shown in Figure 7.2.

Plan	Plan breakdown
P0. Make a cup of coffee	$P0_i$: 3→1→2→4→2→1→exit $P0_{ii}$: 3→if(water not available)→5→2→4→2→1→exit $P0_{iii}$: 3→1→2→4→2→if(capsule stuck) →6→2→1→exit
P1. Press button	P1:1.1→if(more coffee wanted)→1.1→else→exit
P2. Use lever	P2: 2.1→if(capsule not correct)→2.1→else→2.2→exit

Plan	Plan breakdown
P3: Place cup	P3: 3.1→if(coffee not ready)→3.1→else→3.2→exit
P4: Insert capsule	P4: 4.1→exit
P5:Refill water tank	P5: if(tank empty)→5.1→5.2→if(not full)→5.2→else→5.3→exit
P6: Empty used capsules container	P6: if(container full) →6.1→6.2→if(not full)→6.2→else→6.3→exit

Plans identify the ways in which users would complete tasks with the device in the pursuit of a goal, in this case making a cup of coffee with this particular coffee maker. As shown, a user wanting to make a cup of coffee would need to follow 'P0' as the higher level sequence of operation, requiring the user to place their cup on the tray, press the brew button to turn the machine one, lift the lever, place a capsule, lower the lever, and press the button again to brew coffee, ending the sequence by removing the cup from the tray. Alternatively, plans '$P0_{ii}$" and '$P0_{iii}$" take into consideration the possibilities of an empty water tank or a full used-capsules container (when full, the latter, prevents operation of the lever).

P2 implies that a user would have placed their cup on the tray, lift the lever, insert a capsule, make sure that the capsule is placed properly and lower the lever to carry on into P3. P3 requires to press the brew button, and also addresses the possibility of the user wanting extra coffee from the same capsule (something commonly done for a larger beverage).

A plan-oriented view of the system alongside the system image, allows to identify not only the tasks and its sequences, but also provides insight on sensor placement for object instrumentation, as will be described in section 7.1.1.4. While an HTA diagram provides a user perspective on the tasks, a State Diagram (SD) provides a machine level characterization of actions available to the object. Figure 7.3, shows the State Diagram showing the states and transitions for the coffee machine.

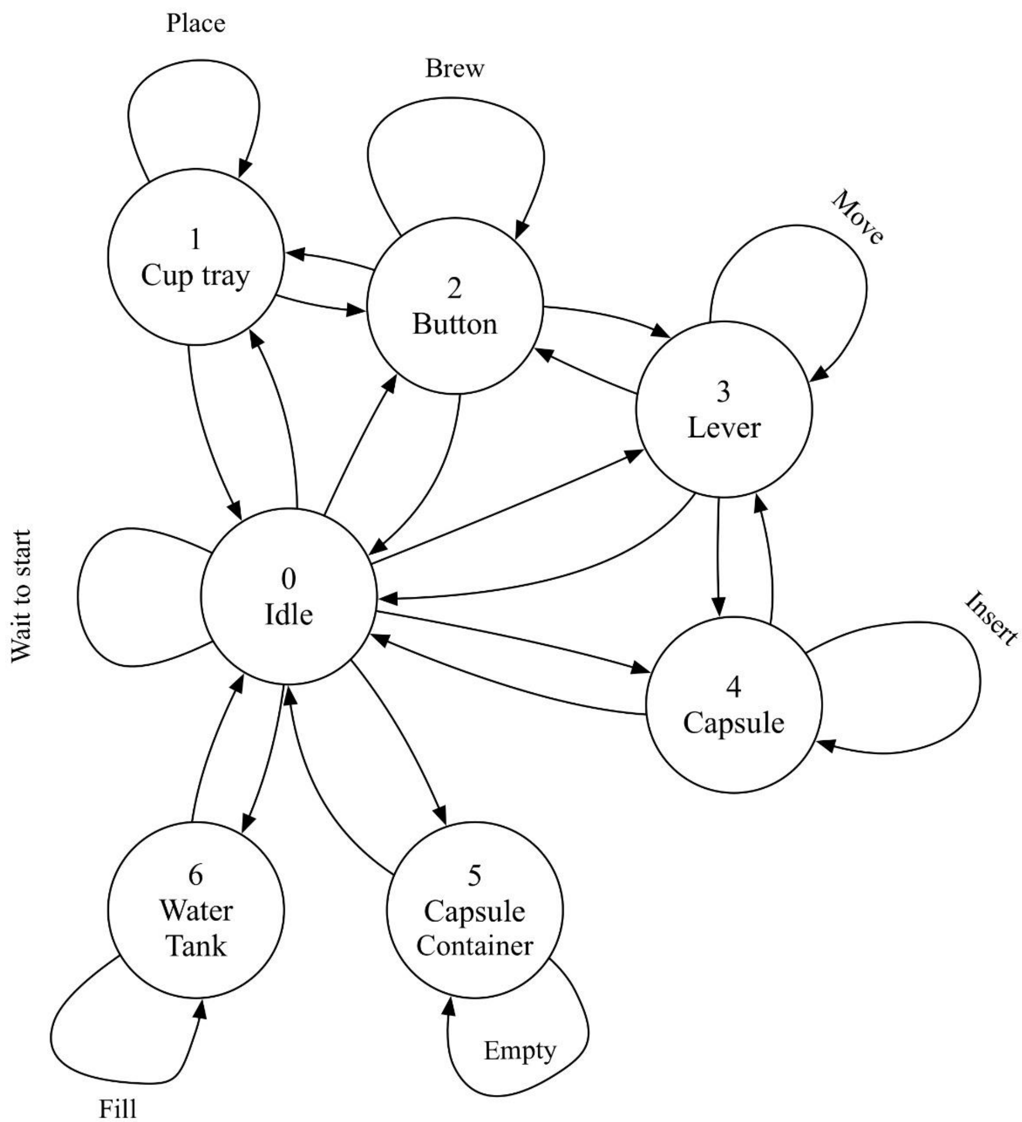

Figure 7.3 State Diagram for Coffee Machine

The state transitions in the SD show what the machine is doing or expecting from itself, or in some cases from the user, as an organised sequence in terms of the points of interaction.

7.1.1.3 TAFEI for a coffee making theme

With user actions specified by an HTA and machine actions through a SD, a TAFEI diagram is developed as a combination of the two, providing a description of the human-machine system actions involved in goal fulfilment. Moreover, TAFEI determines machine state transitions as characterized by the user plans.

Figure 7.4 shows the TAFEI diagram for the ‘make a cup of coffee’ goal.

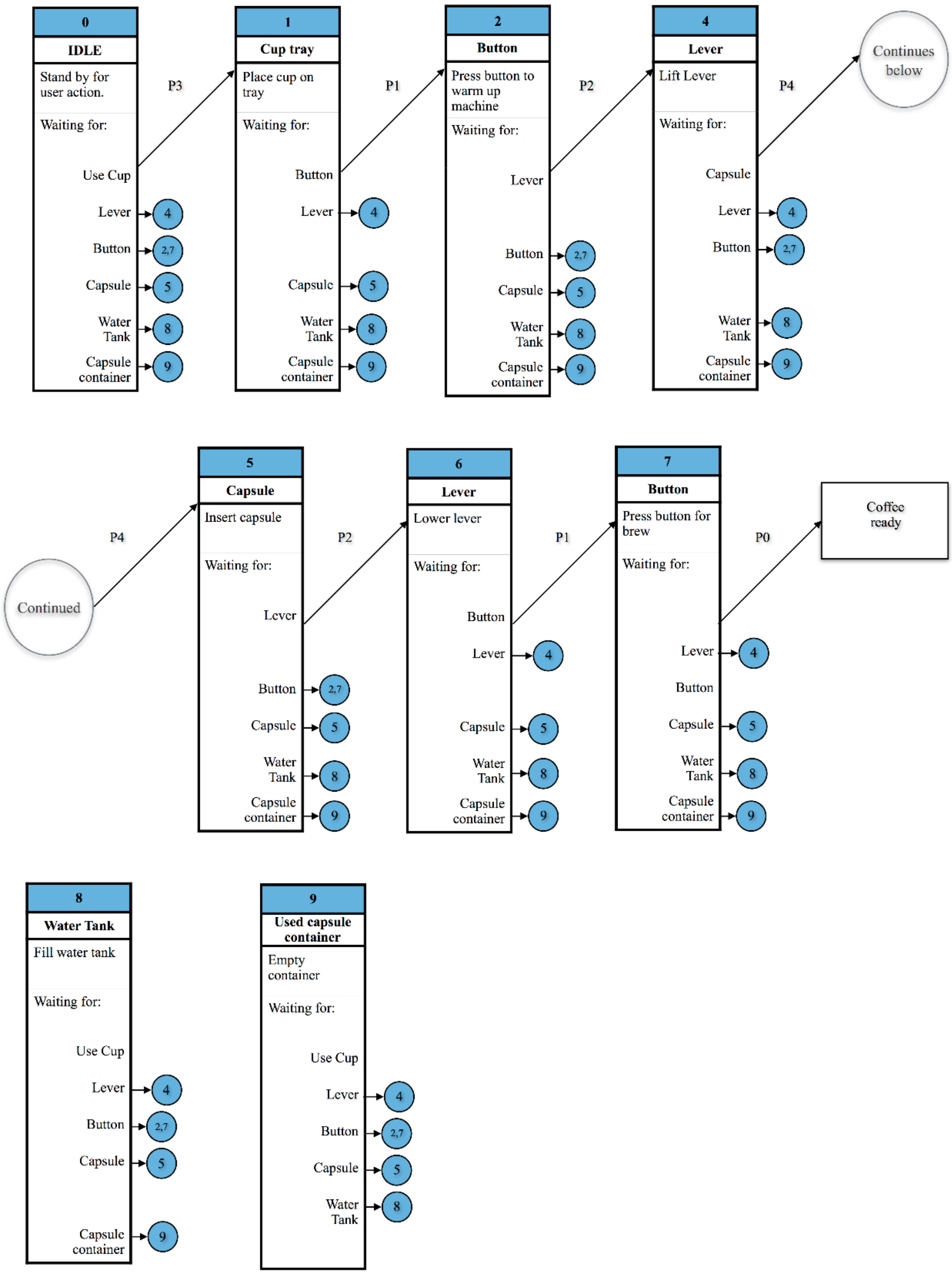

Figure 7.4 TAFEI diagram for a coffee machine.

From state 0, the TAFEI diagram shows which plan is followed by the user and the machine's state transitions, as the user interacts with the coffee machine.

Summarising the state and HTA diagram analysis, Figure 7.5 shows the system's TAFEI transition matrix, in which legal transitions for the 'Make a cup of coffee' theme are marked as 'L'. As discussed, TAFEI is generally used to identify errors in product usability design. In the context of devices that can potentially be imbued with a notion of intelligence, the description of interactions that are not part of the main theme becomes a tool to establish different goals that are either actions that performed by the system or that through interactions with other parts of the system would enable secondary goals or themes. Notably, the former might not require user intervention as it might be implied by the system's or the device's embedded intelligence, and could enable additional knowledge to the user. By observing the illegal and impossible transitions (marked as 'I' and '-', respectively) in the main goal's state diagram, states 5 and 6, relate to filling up the coffee machine's water tank and emptying the used capsule container, hence a secondary theme emerges in the form of 'Coffee machine servicing'.

From State \ To State	0	1	2	3	4	5	6
0	I	L	I	I	I	I	I
1	I	I	L	I	I	I	I
2	I	I	I	L	I	I	I
3	I	-	-	I	L	I	I
4	I	-	-	-	I	-	-
5	I	-	-	-	-	I	-
6	I	-	-	-	-	-	I

Figure 7.5 State Transition Matrix for Coffee Machine

7.1.1.4 Instrumenting a coffee machine

The detailed breakdown of all the required plans and actions in the system, allows for its interpretation as a network where state transitions occur towards the achievement of a particular goal. As such, one of the aims of this study was to produce a framework in which an IoT system could be modelled and implemented in in a real-life environment. Using the Node-RED programming language as a development environment proved to be a suitable alternative for implementation, as it follows a flow programming paradigm, in which nodes become part of a network, following a set of rules provided by the governing logic (Figure 7.6). By using the information described in by the TAFEI diagram and Transition matrix, it is possible to provide a model of the system in terms of programmable function nodes within Node-Red. As discussed in Chapter 2, flow-base programming supports system description in terms of states, even driven transitions, inputs and outputs. Thus, a flow can be defined to model the behaviour of the system, with nodes representing objects and their rules, sequentially linked to each other. As such, Node-Red was used to as a tool to translate SDs into code. Moreover, subsequent logic can be implemented with ease, allowing for the experimentation with decision-making nodes, and output nodes to connect the *things* with external services, users or other *things*.

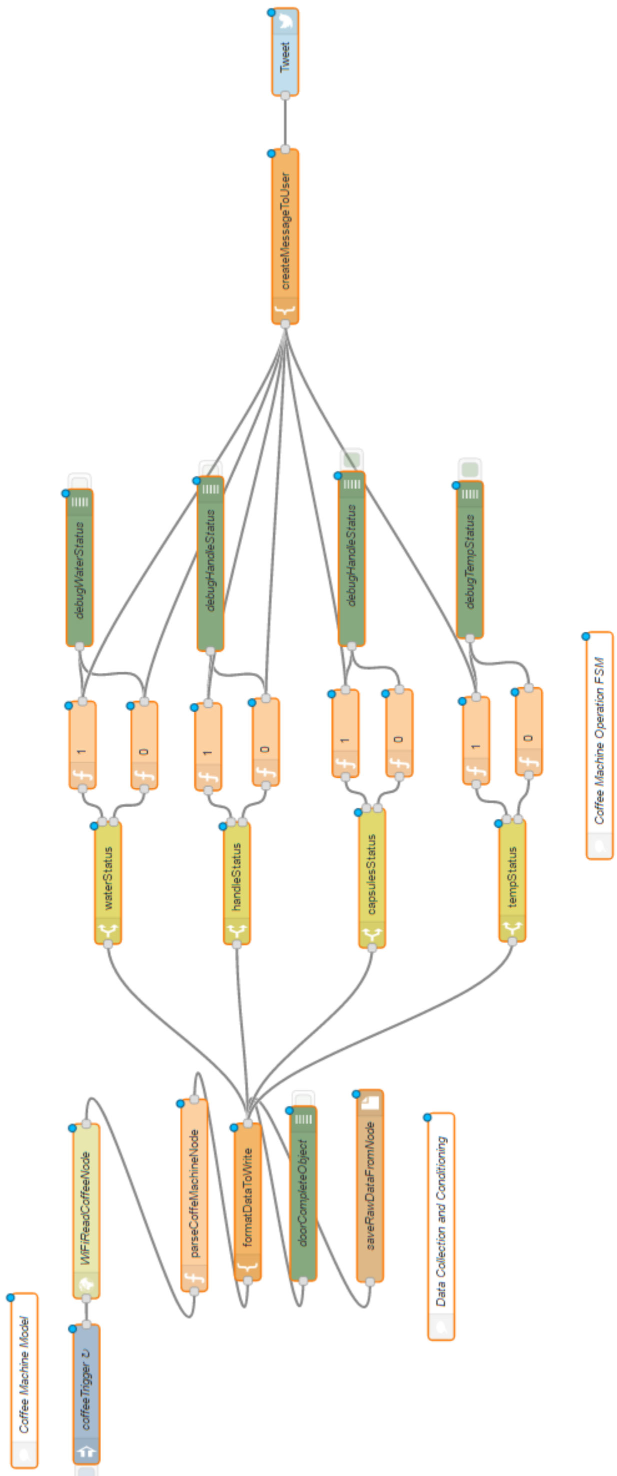

Figure 7.6 Node-RED flow for coffee machine automation.

Plans defined in the HTA diagram (Figure 7.2), where user action is expected, are used to label transitions in the TAFEI diagram and could be used to provide system cues to improve user interaction. Similarly, states that provide more than one transition (such as the one in found state 5 to state 4 or 6, given the possibility that the user might want more coffee from the same capsule) could be identified as 'problematic' and trigger user cues in the communication exchange.

For example, as presented in Figure 7.6, by the system could detect when some of the described conditions are met, and then communicate with the user through a tweet using the Twitter API (or any other available mechanism enabled by the IoT middleware).

Figure 7.7 shows the instrumented coffee machine as a result of the TAFEI analysis. The following section will provide a TAFEI analysis of a system comprised of different devices, and using the more complex system as an example, provide a more detailed description of how device instrumentation was developed.

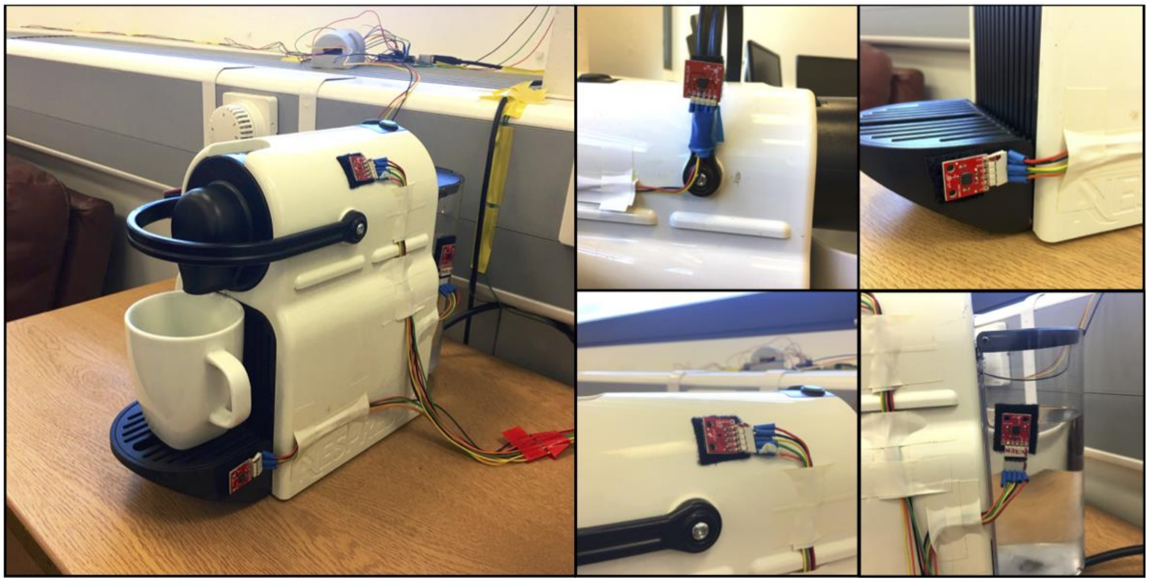

Figure 7.7 An instrumented coffee machine and the implemented sensors. Clockwise from top: lever, cup tray/used capsule container, water tank.

7.2 Applying TAFEI in a multi-object system

7.2.1 A drinks-making themed system in an office environment

TAFEI was originally conceived as a tool to analyse usability in objects, rather than systems comprised of different artefacts (Baber and Stanton, 2002). Following the model description and instrumentation of a single-device system as shown in section 7.1, a system comprised of more than one object was devised to identify the differences in analysing the model using TAFEI, for a more complex system capable of supporting different goals framed within a common theme.

7.2.1.1 System Image and Components

As noted in the previous section, the first step in constructing a TAFEI description is to identify the system components. In this case, the system comprises of the people and the things which can be used to support the goal of 'making a drink', e.g., cups, containers for the various consumables related to drink making (tea bags, coffee granules, sugar, milk etc.), devices used in making drinks (such as kettles, coffee makers, refrigerators etc.), water, etc., within the office environment (which could include chairs, desks, other furniture, doors etc.). In order to define a minimal set of objects for this environment, we assume that (a) users have their own cups (and so identifying a cup would also identify a user), and that (b) identifying a user identifies the desk and chair of that user. This means that, rather than including person, chair, and desk as discrete objects in this domain, we would simply identify the cup. If the theme was, say, 'desk occupancy', then we would need to identify other objects. Alternatively, if the theme was 'drink making at home' then we might include different objects.

Table 7.4 shows the objects identified as part of drinks making activities in the office environment, and the minimal physical action required to interact with these objects. In the same way described in section 7.1.1, this not only provides TAFEI's human centred description of the goals, but also informs the implementation of the object´s instrumentation.

Table 7.4 Objects found in the 'having a drink' theme within an office environment. A brief description of the expected user action that can be performed on the device is presented.

Object	**Expected user action**
Cup	Lift/Replace
Coffee machine	• Lever lift/down • Press brew button
Water cooler	Button press/release
Fridge	• Open/Close • Take/Replace milk

7.2.1.2 System states and goals

From the described minimal sets of objects and actions (Table 7.4), we assume that each object possesses a set of discrete states, and that transition between states arises from an action (either performed by a human or by the object). In order to keep the description tractable, the actions and transitions are considered in terms of a specific topic, e.g., ‘making coffee with milk’, or ‘making tea without milk’. The resulting state-space diagrams will show all possible transitions across the available objects within this topic. TAFEI assumes that, unless otherwise constrained, each object will be ‘waiting for’ a transition from the current state to one of the possible states that the object could occupy. So, a cup on the desk could be ‘waiting for lifted’ (following the action of pick up cup), or a kettle that is empty could be ‘waiting for filled’ or ‘waiting for switch on’. The latter state, of course, is undesirable and should not be performed until the kettle is filled. This indicates the way that TAFEI seeks to highlight potential for errors, i.e., undesirable transitions between states.

Figure 7.8 shows the HTA diagram for the ‘have a drink theme’, with its corresponding plans shown in Table 7.6.

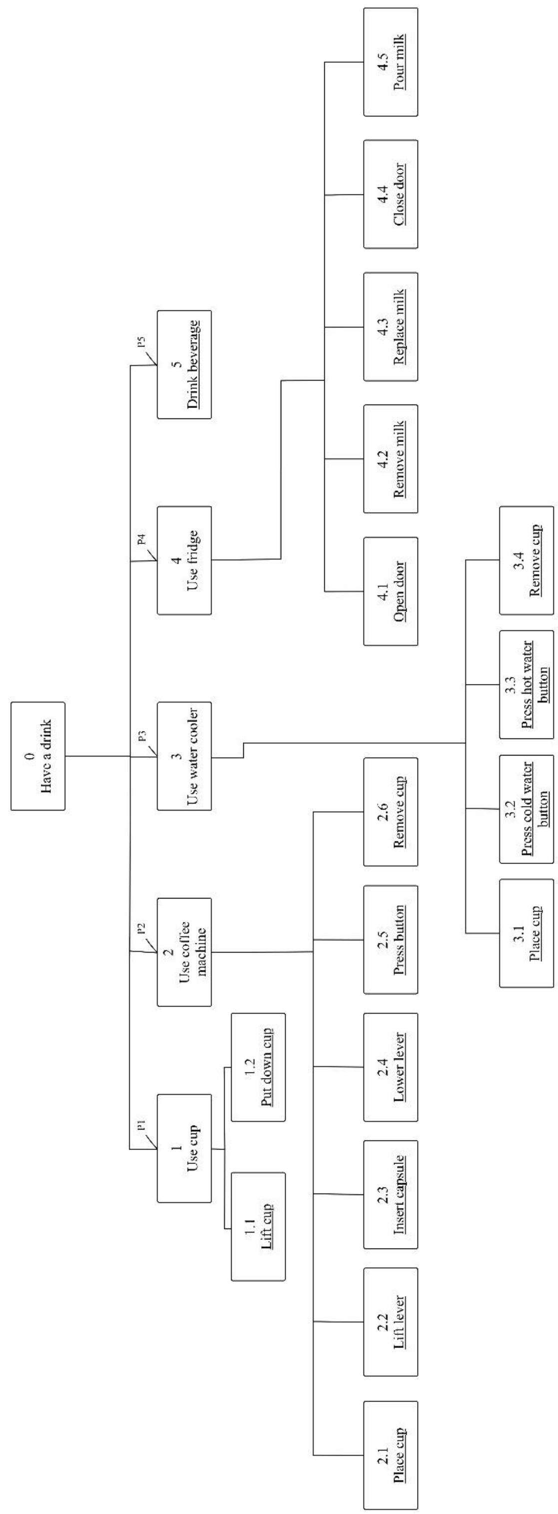

Figure 7.8 Hierarchical Task Analysis diagram for 'Having a drink' theme. Plans are shown in Table 7.6.

In Table 7.5 the activities supported by the 'having a drink' themes are shown. Thus, from the Hierarchical Task Analysis diagram for this theme (Figure 7.8) we can describe the plans a user could follow to complete specific topics or goals, as shown in Table 7.6.

Table 7.5 Goals supported by the 'having a drink' theme.

Goals
Water
Coffee
Coffee & hot water
Coffee & milk
Coffee & milk & hot water
Tea
Tea & milk

Table 7.6 User plans on the 'Have a drink' theme for HTA in Figure 7.8.

Plan	Plan breakdown
P0. Have a drink	$P0_i$: If(drink available)→1→5→6→exit $P0_{ii}$: If(drink available)→1→5→if(drink more) →5→else→6→exit $P0_{iii}$: If(drink not available)→1→if(coffee)→2→elseif(water) →3→elseif(tea) →3→elseif(milk)→4→6→exit
P1. Use cup	P1:1→exit
P2. Use coffee machine	P2: 2.1→2.2→2.3→if(capsule not correct) →2.3→else→2.4→2.5→if(not enough coffee) →2.5→else→2.6→exit
P3: Use water cooler	P3: 3.1→if(cold) →3.2→elseif(hot) →3.3→if(not enough water) →3.1→else→3.4→exit
P4: Use fridge	P4: 4.1→if(milky)→4.2→4.5→if(not enough milk) →4.5→else→4.3→4.4→exit

The plans shown in Table 7.6, describe how a user would perform tasks on the system with the involved objects (Figure 7.9). For example, ‘P0’ describes the higher-level sequence of tasks, which is precisely ‘have a drink’. It follows that if a drink is available on the user’s cup, they would first pick up the cup, then drink, then put the cup down back again. $P0_{ii}$ and $P0_{iii}$ describe the possibilities of a user drinking again, or in the event of no drink available, make one from a choice of coffee, tea, water or milk.

Figure 7.9 Objects part of the ‘having a drink’ theme. Clockwise from top right: Cup and coaster, water cooler, fridge door, coffee machine.

Plans P1 to P5 provide a detailed description for each of the tasks. Hence, as per the system image for the coffee machine shown in Figure 7.1, P2 follows its own plan as described in section 7.1.1.2 “System states and goals” which analyses the coffee machine on its own. Since it is the same coffee machine, the described plan still applies and can be reused. Each plan involves tasks, their sequence and crucially, decision points that provide an insight on object instrumentation. As observed, some plans imply that some pre-conditions are met, for example, that there is a cup already in the possession of the user, or that consumables are available (coffee capsules and milk). As mentioned in the previous section when applying each of the steps required by the TAFEI methodology, a State Diagram (SD) is required to characterise the actions available to the objects, providing a machine-based perspective to contrast the HTA’s user-centred perspective. Figure 7.10 shows the SD for objects in the ‘having a drink’ theme.

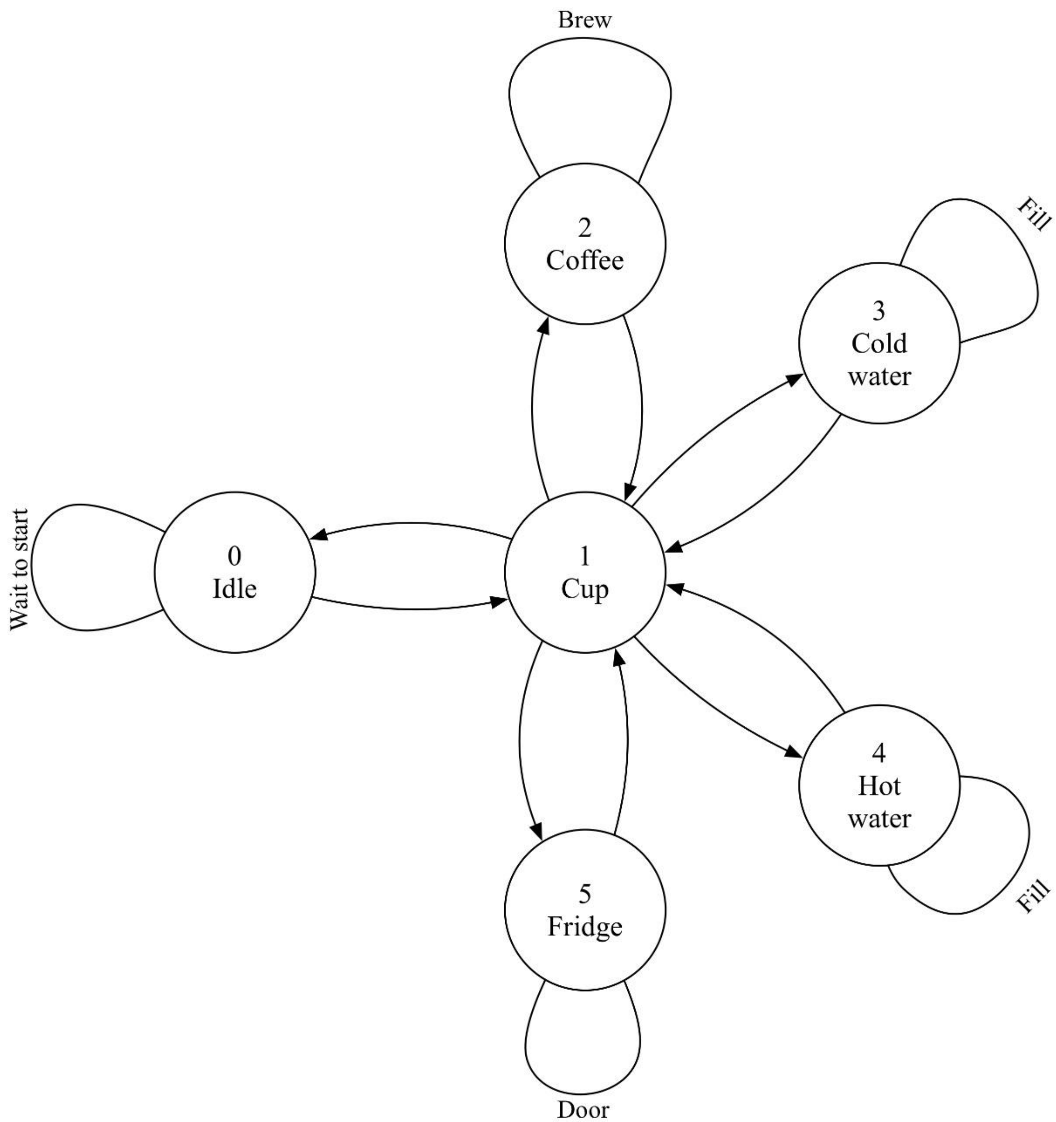

Figure 7.10 State Space Diagram for 'Having a drink' theme.

7.2.1.3 TAFEI for a drinks-making themed system instrumentation

As mentioned in section 7.1.1.3, TAFEI characterises state transitions in terms of user plans. Thus, a different TAFEI diagram is required for each topic in the analysed theme of 'drinks making'.

For brevity this section describes two topics: having a cup of cold water and having a cup of coffee with hot water (an Americano type coffee).

Figure 7.11 and Figure 7.12 show the TAFEI diagram for the analysed goals, including the definition of plans towards the fulfilment of the tasks described in the HTA (as specified in Table 7.5).

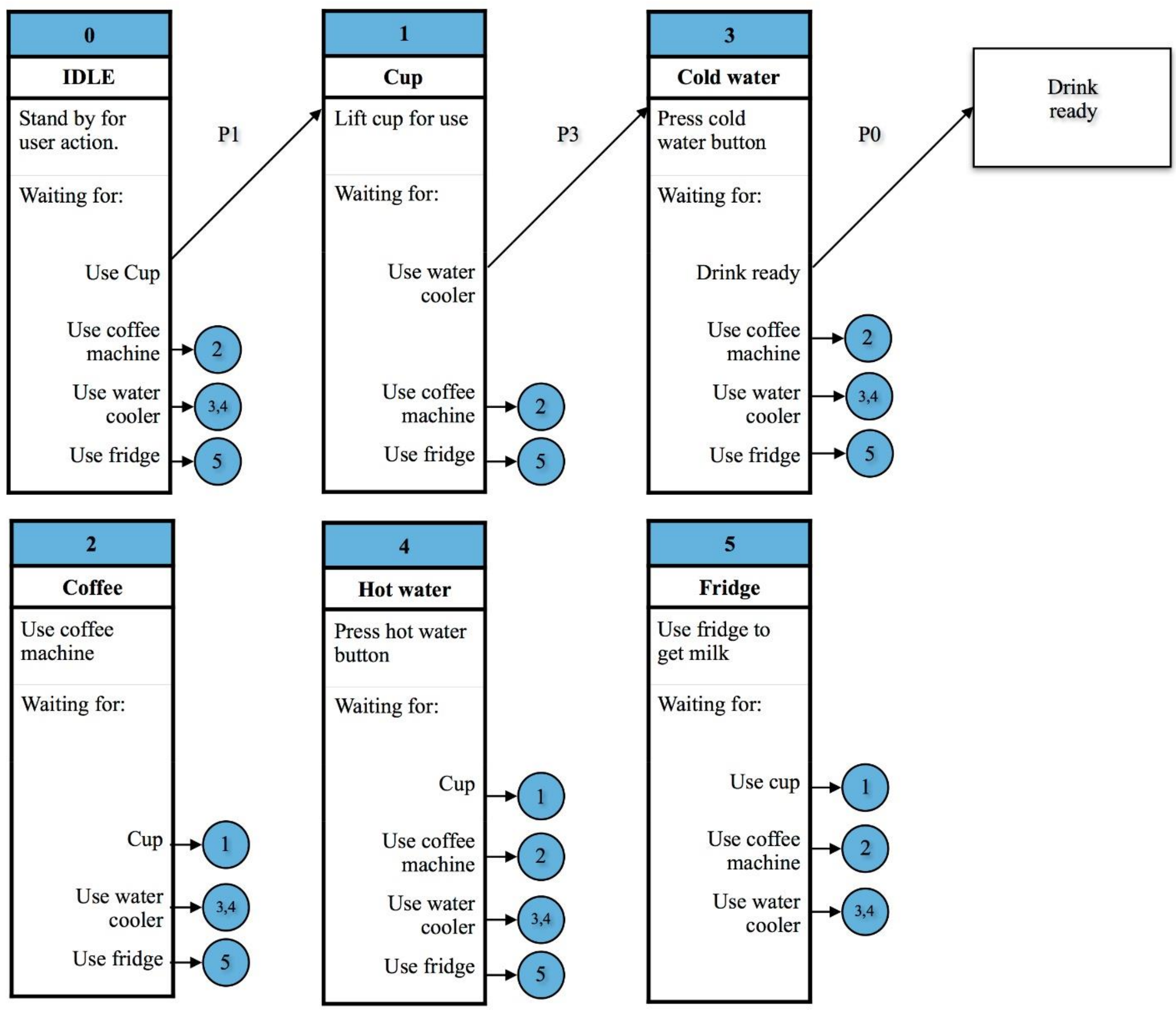

Figure 7.11 TAFEI diagram for 'Having a cup of cold water' goal.

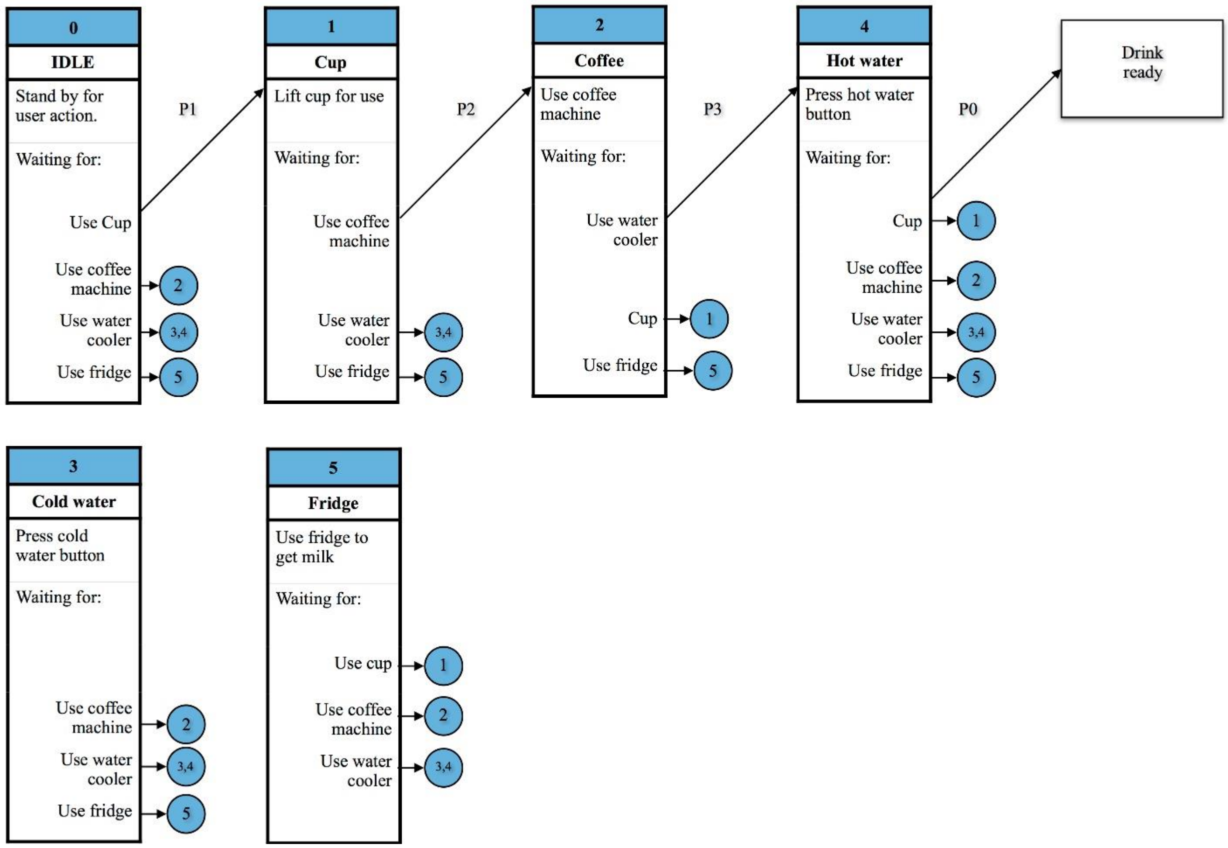

Figure 7.12 TAFEI diagram for 'Having a cup of coffee with hot water' goal.

For the 'Cold water' goal, the TAFEI diagram starts in the 'IDLE' state (state 0). In that state, the system is waiting for any of the objects to be used (cup, coffee machine, water cooler and fridge). Only using the cup would lead to a valid transition (to state 1) to complete the goal by having the user follow plan 1 (P1). Other objects would lead to states that although possible within the system, do not contribute to the goal. Thus, from state 1 using the 'water cooler' following plan 3 (P3), would lead to a valid transition to state 3, completing the goal with plan 0 (P0). States 2, 4 and 5 are shown in the diagram for to provide a complete view of the system, but they are not part of the transitions for this goal. Valid and invalid transitions toward goal completion are presented in TAFEI as a 'State Transition Matrix' (STM). Highlighting the required transitions for the goal, it shows a summarized representation of both the state and hierarchal task analyses.

Figure 7.13 and Figure 7.14 show STMs for ‘Cold water’ and ‘Coffee and hot water’ goals. Legal transitions for the goal are marked as ‘L’. Illegal and impossible transitions are marked as ‘I’ and ‘-‘, respectively. In this context, an illegal transition is that which involves action that doesn’t support completing the expected goal; moreover, those transitions that can’t occur are considered impossible.

		To State					
		0	1	2	3	4	5
From State	0	I	L	I	I	I	I
	1	I	I	I	L	I	I
	2	I	I	I	I	I	I
	3	L	I	I	I	I	I
	4	I	I	I	I	I	I
	5	I	I	I	I	I	I

Figure 7.13 State Transition Matrix for ‘Having a cup of cold water’ goal.

		To State					
		0	1	2	3	4	5
From State	0	I	L	I	I	I	I
	1	I	I	L	I	I	I
	2	I	I	I	I	L	I
	3	I	I	I	I	I	I
	4	L	I	I	I	I	I
	5	I	I	I	I	I	I

Figure 7.14 State Transition Matrix for 'Having a cup of coffee with hot water' goal.

The states in the matrices correspond to those shown in the TAFEI diagrams (Figure 7.11 and Figure 7.12), and include all possible states within the system, even if they are not part of the analysed goal.

As shown in Figure 7.13, the State Transition Matrix for the 'cold water' goal presents three 'legal' transitions to complete the goal: from state 0 to state 1; from state 1 to state 3; and from state 3 to state 0 to complete a legal sequence.

By analysing the sequences, actions and conditions for a goal within the system, we can identify which objects relate to a specific topic. Specifically by reviewing the HTA, conditions found in the tasks provide a definition of suitable points for instrumentation, enabling 'smart' behaviour from a system perspective. In this context, it is considered that decision points on plans support an understanding of a task being performed, or more accurately the involved object. TAFEI makes a distinction between *Consumables* and *Things* (objects). When designing instrumentation, the former would imply a higher number of sensors. This could provide a higher granularity input to automatic activity recognition algorithms, enabling more detailed descriptors of system actions. However, it creates more complex systems that present the drawbacks on usability described in chapter 3. By using TAFEI we would not only provide a user centred approach to instrumentation, but also a minimal set of sensors that fit the system's purpose. Thus, as a design constraint, it was decided that no sensors would be placed on consumables. Moreover, we hypothesized that if required, how these consumables would be inferred from the basic system functionality. For example, coffee capsules are linked to lifting the coffee machine lever, water to the button presses on the water cooler, and milk to fridge door opening and closing[2].Furthermore, another design constraint was to minimize disruption on the office environment and its users.

As such, sensor placement was implemented in such a way that the objects wouldn't need to be disassembled or that they interfered with their normal use. This led to the decision of not instrumenting cups directly, but to build coasters that provided the same effect of detection lift and replace actions. Interestingly, this posits the situation of users without a coaster and how would they be involved in the study? As these users would be those that didn´t had a desk in the study's office, a solution was conceived by instrumenting the office door as described with more detail in section 8.1. Finally, the coffee machine presented the most instrumentation restrictions. As mentioned, object functionality was not to be disrupted. Thus, we considered how to properly identify the required action under the given limitations. It was decided that sensors would the attached to the coffee machine's lever, provided that when making a coffee it is always required move it in order to place a capsule in the machine. Intrinsically, this action consistently implies

[2] For the duration of the study reported in this chapter, the office's fridge was only used to store milk for drinks making. Thus it could be safely assumed that when opened it was to get milk.

that a coffee is being made. Consequently, this action is also linked to the coffee capsule consumable usage.

Based on the previous considerations, but more importantly, on the requirements specified by the tasks and goals identified by TAFEI, Table 7.7 presents the system's instrumented objects and its sensor placement.

Table 7.7 Objects found in the 'having a drink' theme within an office environment, and the sensors used to instrument them.

Object	**Sensor placement**	**Sensor**
Cup	Coaster	Force sensitive resistor
Coffee machine	Lever	Accelerometer
Water cooler	Hot water and cold water buttons	Push button
Fridge	Door	Magnetic switch
Office door	Door	Magnetic switch

The objects shown in Figure 7.15 were instrumented as informed by Table 7.7, and correspond to tasks found in the 'Having a drink' theme, and support the plans defined by the HTA. The coaster allows detection of cup actions; switches on the water dispenser buttons allow for detection of serving water actions; an accelerometer on the coffee machine lever provides a mean for detecting coffee-making actions, and finally a magnetic switch in the fridge door, enables detection of fridge usage. Details of instrumentation will be provided in the following chapter.

Figure 7.15 Instrumented objects. Clockwise from top right: Cup and instrumented coaster; water cooler buttons; fridge door; coffee machine lever.

7.3 Conclusion

As the IoT permeates into more human-in-the-loop applications, and objects rely not only on their physical attributes, but also on their digital representations, the relationships they hold with users are affected, sometimes in unexpected ways. When objects are 'cognified', an additional layer of information is available to users. As such, affordances as traditionally interpreted, are not the only method for an object to convey information on how to interact with it and what they are for (their goal, or when the object gets socially linked to other objects or users, their theme).

By repurposing TAFEI's original aim of modelling systems focusing on errors as users attempt to carry out their main goal, we show how for instrumented objects it is possible to extend its functionality, providing a framework in which intelligence can be embedded into the system. When devices that traditionally were not considered 'smart', such as a coffee machine, become IoT enabled, they have extended capabilities and present opportunities for proactive and intelligent behaviour. These scenarios would allow a system to predict a user's intent and to provide them with additional information.

In the 'coffee machine' testbed, the main goal is characterised by a 'coffee making' *theme* with clearly identified states, plans and transitions. With additional sensors, such as the one found in the coffee machine's water tank and discarded coffee capsules container, it is possible to describe the states required to identify their capacity level (empty or full water tank; capsules overfilling the canister), defining additional *topics* and interactions available to the system, enabling a new 'servicing' *theme*, facilitating the knowledge of whether the water tank needs to be filled or the capsule container replaced.

The study aimed for the minimal number of objects (and sensors) required to accomplish goals within the system's theme. This paradigm supported system instrumentation granularity at an object level. That is, although TAFEI provided a way to inform instrumentation points, it was done to identify single objects as related to state transitions. Notwithstanding, this study suggests that increasing granularity at a device level could enable further opportunities for autonomous and intelligent behaviour. For example, instrumentation on the coffee machine's water tank could provide a more accurate metric on the amount of water used to prepare coffee, and correlate that information to when the machine needs refilling and overtime, when it needs cleaning or descaling. As such, these additional layers on instrumentation show that emerging themes could be involved in the system, for example a ‘maintenance’ mode.

It is expected that the application of TAFEI analysis would allow the consideration of human factors in the design of IoT systems and smart objects, alongside decision based. By allowing users to become more aware of the system’s themes, meaningful interactions and user engagement would be promoted, enhancing IoT adoption.

Consequently, to demonstrate how users interact with a system developed using TAFEI, the following chapter describes how such a system was deployed in a real-world scenario, allowing for data collection and its subsequent analysis to find correlations between the conversation-based model and user generated data.

8 Developing an experimental Testbed

8.1 Testbed

Based on the outcome from the TAFEI model, a testbed was developed. System instrumentation was informed by TAFEI's outcomes. In terms of technical implementation sensor nodes comprised of sensors and wireless connectivity were developed. Moreover, middleware for sensor node integration and data connection was implemented using the Node-RED framework.

8.1.1 Sensors

Sensor placement was defined by how the device was expected be used according to the TAFEI model. As such, each of the devices would require sensors that supported the users' actions in the least disruptive way. That is, the instrumented devices were to be instrumented with minimal modification on their functionality and their appearance.

Due to TAFEI's state transition based modelling approach, the sensors would be required to support a binary description of the system states. Thus, devices would be considered to be in use or not, with no middle ground to describe their behaviour. For example, the fridge would be required to inform when it was opened to get something out of it, but not exactly what was being taken out (as mentioned, for the duration of the study only milk was stored in the fridge). As will be detailed later in this section, this was accomplished by positioning a sensor on its door.

Thus, some sensors required calibration and conditioning, and thus required additional hardware for this purpose. Due to its flexibility, Arduino Uno boards were used to provide the required support.

As described in Table 7.4 for the 'drinks making' testbed, sensors were required for the devices involved in the study, and were instrumented as follows.

8.1.1.1 Cups and coasters

As described in Table 7.4 the supported action for the cup is lift and replace from a desk or table for the user to drink from it or to prepare any drink.

Given that the cup is a device that would be continually used, and moreover, would require washing up on a regular basis, directly instrumenting the device would represent an engineering challenge out of the scope of this work. Moreover, it was also expected that user might want to use different cups for the duration of the study according to their personal preferences. Thus, a solution was found by instrumenting coasters, instead of placing sensors directly on the cups. For this purpose, the device would require to detect whether a cup would be placed or removed from it.

The technical solution for this task involved the placement of a Force Sensitive Resistor (FSR) (Figure 8.1). The electrical characteristics of the device change according to the force applied on its surface, making it suitable for object detection. By placing this sensor below the coaster, making contact with a flat surface (i.e. a table or desk) it was possible to detect when a mug was placed on top. The instrumented object is shown in Figure 7.15.

Figure 8.1 Force Sensitive Resistor (FSR).

The output from the sensor is an analogue voltage reading that correlates to the weight of the object placed upon its surface. Thus, to comply with the model's requirement, the sensor output required a signal calibration and conditioning stage. This required the conversion of analogue to digital, and setting the correct thresholds to distinguish between an empty coaster and when a cup was placed in binary form. Although this output was designed to comply with the model's specific requirements, an interesting caveat is that if by implementing the sensor with its full analogue measurement range, an empty or full cup could be detected, enabling different behaviour and outcomes from the system, as discussed in the final section of this chapter. The conditioning module was implemented in an Arduino Uno board

A total of 5 coasters were implemented for the participants that had a desk in the office. Wireless connectivity was implemented using a ESP8266 Wi-Fi enabled board as described in section 8.1.2.

8.1.1.2 Fridge

As described in Table 7.4, the supported action for the fridge is to close and open its door. Notably, for the duration of the study only milk was kept in the fridge, thus, any action performed using this appliance necessarily related to removing and replacing a bottle of milk.

A magnetic switch (Figure 7.15) was used to detect the supported action. This device is made of two separate magnetic plaques that close an electric circuit when in close proximity. One terminal of the sensor was placed on the door of the fridge, whilst the other remained fixed to its side as observed. The output produced by the sensor was a binary signal and thus suitable to be used directly as required by the state based model. As such, this signal didn't require any conditioning.

8.1.1.3 Coffee machine lever

As noted in the previous chapter, the developed TAFEI model required detection of when the coffee machine was used. Given that the coffee machine usage could be implied by the placement of capsules by movement of its lever (system image view as shown in Figure 7.1). For this purpose an accelerometer was placed on the side of the lever to detect its change from a horizontal position to vertical and vice versa.

The accelerometer used for this application (Figure 8.2) produced an analogue voltage proportional to the acceleration on the measured axis. To accommodate for the TAFEI state based model described in chapter 5, a binary output was required from the sensor. As with the coaster sensor, the analogue signal required calibration and conditioning, accomplished with an Arduino Uno board.

Figure 8.2 Sparkfun's ADXL335 accelerometer sensor (Image: sparkfun.com).

8.1.1.4 Water cooler buttons

The particular water cooler appliance used in the study had the capabilities of dispensing both cold and hot water, by using two different buttons as shown in Figure 7.15 (water dispenser buttons). Thus each of the buttons was instrumented to detect interaction with the device. This device was identified to be of concern, as it would be the one most used by all participants. Thus sensor placement had to support for continuous and heavy use, and different approaches for instrumentation were tested.

Each of the buttons produced a binary output, and thus did not require additional conditioning to support the model's requirements.

8.1.2 Connectivity

Each sensor required wireless connectivity into a network. Given its flexibility and ease of integration Wi-Fi was selected as the main communications protocol, supported by a communication hub as described below. As such, each sensor component was supported by a Wi-Fi module to provide connectivity. The module used was a Sparkfun Thing8266 (Figure 8.3).

Figure 8.3 Sparkfun's ESP8266 Wi-Fi enabled module (Image: sparkfun.com).

This Arduino based board is capable of receiving up to 6 digital input signals and one analogue signal. Additionally, the on board computer runs a basic HTTP stack to implement an on-board webserver. Hence, the status of the board's inputs is updated through simple HTTP POST commands that can be read by other devices in the network using HTTP requests.

Each of the available sensors was supported by its own Wi-Fi module, and addressed in the network by its own IP address.

8.1.3 Gateway

As part of the IoT platform a communication hub is required to provide a centralised connection point for devices in the network. Often, this is achieve through a gateway that provides the required network services, such as NAT and DHCP. This testbed was supported by an Intel Edison board acting as an Access Point (AP) and router to provide connectivity to sensor nodes. This single board computer is capable of providing network services for connecting devices, whilst providing a full-fledged Linux server for IoT middleware as described in chapter 1.

Figure 8.4 Intel Edison single board computer (Image: intel.com).

8.1.4 Middleware

In addition to serve as a device gateway, the Edison board acted as a Linux server running the Node-RED platform. Its flow based programming paradigm was found to have a direct representation of state based system descriptions, and thus was identified as a well suited platform for the development of the testbed. As described in Chapter 2, Node-RED provides a framework that allows for the characterisation of system states, its transitions and the rules governing their behaviour. Moreover, the data-flow approach allows the modelling of system objects as function nodes, providing a direct representation of the physical system in the program flow. By using this state and even-driven approach, it is possible to relate to a human-based model such as TAFEI. Shows the Node-RED flow for the office's instrumented objects.

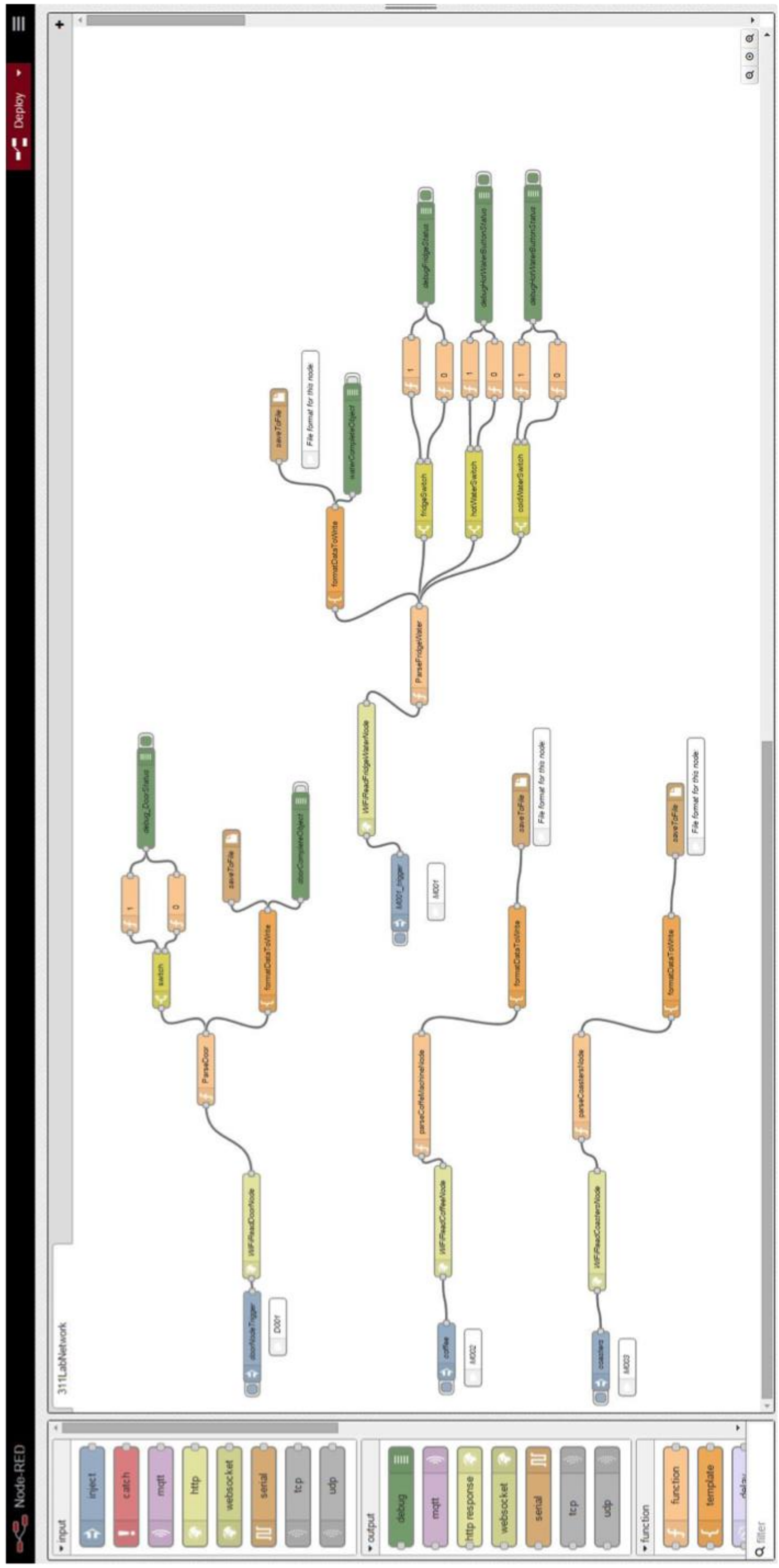

Figure 8.5 Node-RED flow for smart office environment supporting the 'drinks making' theme.

8.1.5 Data Collection

On start-up, the server initialises Node-RED as a node.js application, and runs its programmed flows on the background. As such, data from all sensor nodes would be captured by Node-RED by issuing HTTP GET requests to the particular webservers in their Wi-Fi boards. All data were collected at 500 ms intervals in a polling approach (as opposed to collecting data in an interrupt driven scheme, were sensor signals would only be stored when an event occurred). Then, data would be parsed by a purpose built node within Node-RED, scraping the sensor status and converting it into a binary data type. Data coming off this stage would be appended with a unique ID and a timestamp, and finally stored in a .csv file for offline processing as described in the next section.

Thus, four different .csv files were produced in any given day, and they were manually backed up at regular intervals (one day in average to avoid the Edison board's memory from overflowing).

As previously discussed, each node produced its own data file and as such, it was required to combine them all in one single file. Thus, a python script was written such as each day's worth of data from each node was assembled for the entire period in which the experiment ran, and to aggregate all sensor data in one single file, specifying each of the observation's timestamp.

The created raw data file, was formatted such that each observation included the status of each of the sensor (features) at a given timestamp.

8.1.6 Data conditioning

Because the activations could occur at any time, asynchronously of each other, in the raw data file no single observation contains more than one active sensor at a time. This made it necessary to reprocess the data to obtain meaningful representations of activities being performed in the room as will be discussed in the following section.

A pre-processing algorithm developed on python was used to filter the data set before analysis (Figure 8.6). As each sensor node produced its own data in a *.csv* file, the first step of data pre-processing required appending all data sources into a single file. This allowed arranging them in sequences according to their timestamp, enabling the time-window analysis described in chapter 7. Next, data was cleaned to remove unnecessary empty rows produced the sensor nodes, and rows containing inactive sensors within the office's out-of-hours periods. Finally, data were organized in feature vectors, including each of the sensors as described in Figure 8.7

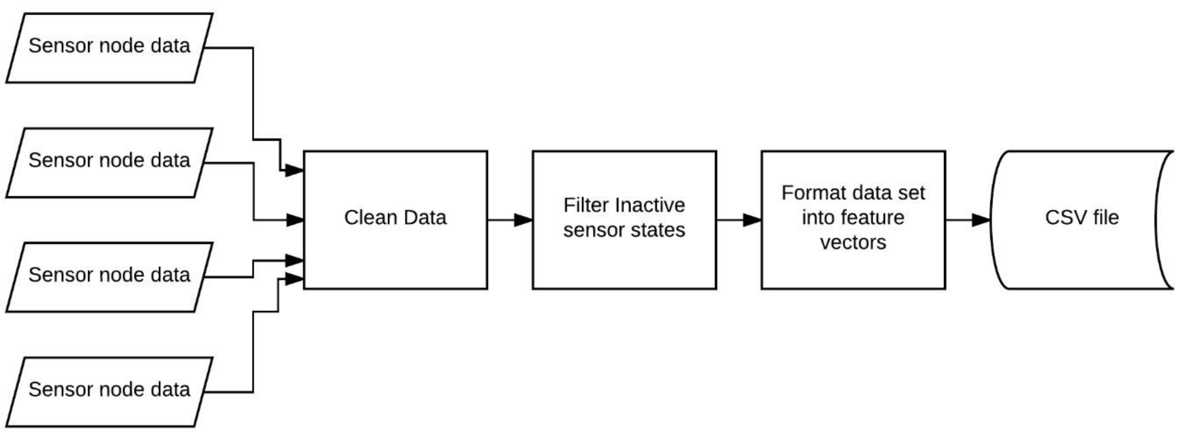

Figure 8.6 Data-preprocessing algorithm.

Thus, each data row defined a feature vector describing the state of the system at any given time, as the examples shown in Figure 8.7, saving the output as a single *.csv* file.

Timestamp	Coaster1	Coaster2	Coaster3	Coaster4	Coaster 5	Coffee	Door	Fridge	hotWater	coldWater
09/11 08:28:09	1	0	0	0	0	0	0	0	0	0
09/11 08:28:09	0	0	0	1	0	0	0	0	0	0
09/11 08:28:10	1	0	0	0	0	0	0	0	0	0
09/11 08:28:10	0	0	0	0	0	1	0	0	0	0
09/11 08:28:11	1	0	0	0	0	0	0	0	0	0

Figure 8.7 Feature vector examples from data pre-processing algorithm.

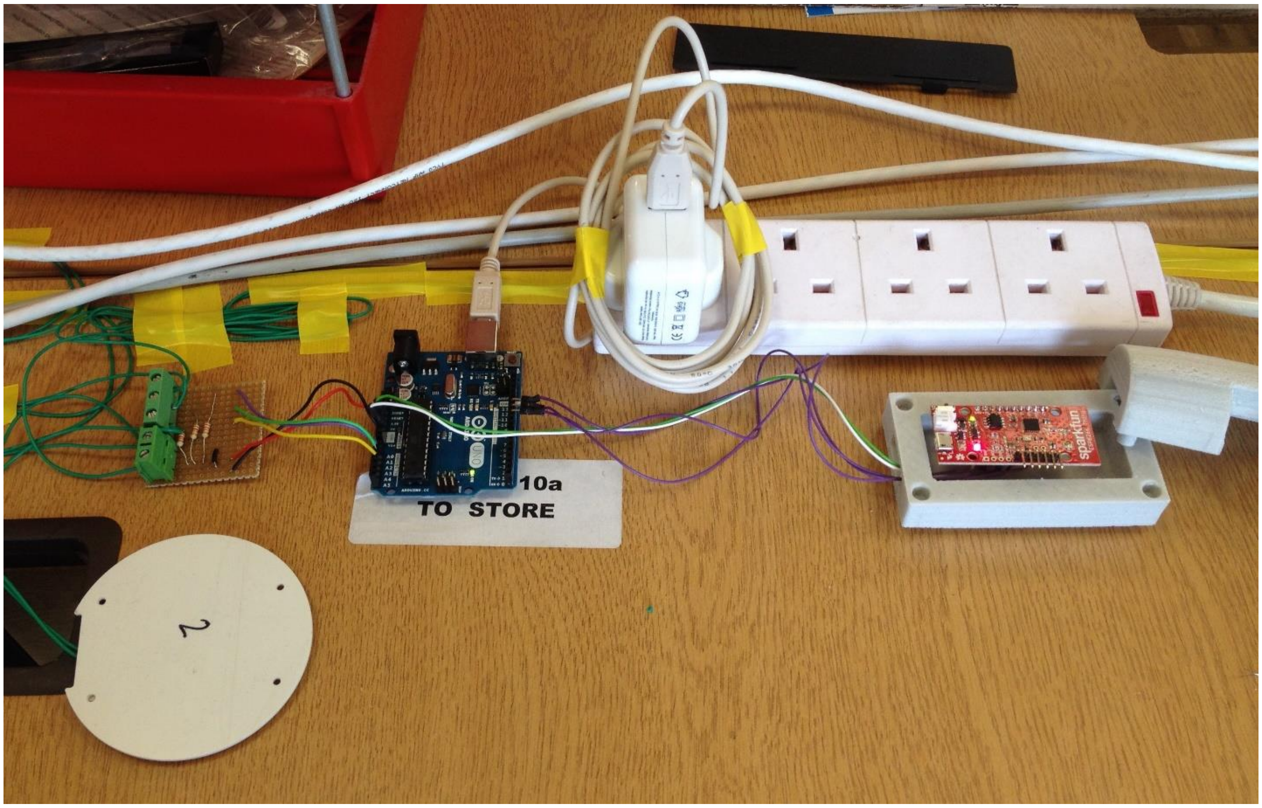

Figure 8.8 Sensor node connected to a coaster.

8.2 Conclusion

In this study a system with a clear and simple goal was used as a way demonstrate TAFEI's suitability as a modelling tool for an IoT system's goals. With additional sensors, such as the one found in the coffee machine's water tank and discarded coffee capsules container, it is possible to describe the states required to identify their capacity level (empty or full water tank; capsules overfilling the canister), defining additional *topics* and interactions available to the system, enabling a new 'servicing' *theme*, facilitating the knowledge of whether the water tank needs to be filled or the capsule container replaced.

The study presented in Chapter 7 aimed for the minimal number of objects (and sensors) required to accomplish goals within the system's theme. This paradigm supported system instrumentation granularity at an object level. That is, although TAFEI provided a way to inform instrumentation points, it was done to identify single objects as related to state transitions. Notwithstanding, this study suggests that increasing granularity at a device level could enable further opportunities for autonomous and intelligent behaviour. For example, instrumentation on the coffee machine's water tank could provide a more accurate metric on the amount of water used to prepare coffee, and correlate that information to when the machine needs refilling and overtime, when it needs cleaning or descaling as shown in the coffee machine's analysis in Chapter 7. As such, these additional layers on instrumentation show that emerging themes could be involved in the system, for example a 'maintenance' mode.

9 *People using the testbed*

9.1 Introduction

The previous chapter describes an application of the framework proposed in this thesis (chapter 5). In the described scenario a test bed based on drinks-making and consumption in a multi occupancy office was developed and deployed in a real-world environment.

Given that the developed framework required the identification of specific themes and goals (topics in the conversational IoT discussed in Chapter 4) characterised by their tasks (or actions as per the Knowledge structure presented in Chapter 5), specific goals for the test bed where defined within a specific theme. Thus the considered theme was that related to ‘drinks making and consumption’ whilst the goals where identified by the possible actions supported by the system image such as: ´making a cup of tea´, ´making a cup of coffee´, ´getting a cup of cold water´, etc.

The testbed allowed for data collection and a study to analyse it was developed with the aim of answering the hypothesis of whether the user-data could be used to characterise and validate the framework proposed in chapter 5.

This chapter describes the study and the results from the analysed data.

9.2 Participants

The test bed described in the previous chapter was installed in a multi-occupancy office and people working in the office were asked to use the sensorised objects to make drinks. The study was designed and conducted in accordance with the University of Birmingham ethics guidelines. This was explained to participants, who were also informed they could opt out and withdraw their data. Their data and resulting analyses were anonymized.

11 participant's data were collected, during a 3-month period. In order to provide ground truth, participants were asked to record their actions on a flipchart. Additionally, 5 of those participants had coasters in their desks. Over this time period, a total of 309 drink making actions were recorded by participants. Although participants used different wording and terminology to describe the actions they logged during the study, ultimately all related to the devices and the drinks that were most commonly made. Hence, the text descriptions were classified into the previously defined TAFEI goals, as shown in Table 7.5.

Participants in the study were asked to act as naturally as possible when having a drink, and to write a record of the time and date and what kind of drink they had. As discussed in the previous chapter, instrumenting a coaster for the cups was required to provide more flexibility to participants (they would be able to change cups or wash them without interfering with the sensors). However, some participants in the experiment did not have any coasters as they worked in different offices. This presented an opportunity to allow for investigating differences in activity recognition amongst those participants who could be identified with those who could not, without interfering with the defined HTAs. As such, each participant's recorded activities involved a direct interaction with instrumented appliances, characterizing a user, an activity or both.

9.3 Data collection

Data were sampled at 500 ms intervals, determined by the maximum refresh rate of the Wi-Fi modules. This produced an initial set of over 11 million observations. Although the system ran for 24 hours a day, 7 days a week collecting sensor information, the analysis was constrained to "regular" office hours, that is, from 7 am to 7 pm, and only on weekdays. Therefore, much of the data related to out of hours or when no recorded actions were made.

Consequently, this set was reduced to only reflect times of day when people were in the office. System activities were sampled at fixed intervals, as opposed to interrupt-driven, to mimic a system that could externally observe the sensor activations, without the need of modifying the behaviour and functionality of the sensor nodes.

As defined in the TAFEI analysis stage, participants preparing a ‘cup of coffee with milk’ would trigger their cup/coaster sensor (if they had one), the coffee machine sensor, and the fridge door sensor to get the milk. By analysing device activation sequence, and characterizing the related actions, the type of beverage that was prepared could be inferred, and over time, assigning those patterns to individuals.

For instance, as described by the TAFEI, a sequence could begin when the coaster sensor detects removal of cup, and ends when the coaster sensor is activated again, provided that other sensors were also active during the sequence. Hence, once the beginning and the end of that sequence are identified, everything that belongs within this time frame, could potentially be identified as that person making a particular type of coffee. As discussed in Chapter 4, a conversation is considered to be taking place within the IoT system, establishing a sequence of system states in which users and objects negotiate turns to complete a goal. Thus, this study allowed an exploration on how these sequences of activations relate to the *topics* in the network, as described by TAFEI.

9.4 Data preparation

The first stage of the analysis involved unsupervised classification to all collected data, that is, not cross-referencing any of the user logged activities, analysing the full data stream. Data were collected from the system, and analysed offline, looking at the aggregated sensor data from all sensor nodes, following the algorithm described in Figure 8.6. Sensors that initiated and finished an activity were unknown. Thus, a sliding time window was used to examine the data set. This procedure required obtaining feature vectors from sensor data using overlapping time intervals to avoid data loss from potentially cutting off activities at their start or end.

To define the sliding window length, users were observed as they performed any of the involved activities, and the time from start to finish was manually recorded. With the aid of the user-logged activities as labels for the feature vectors, a second analysis was performed. For the duration of the study, participants were asked to write down their actions on a log, including the time and date. However, it wasn't always reported in the same order in the process, i.e., before or after the actual time when they prepared their drink. Hence, a fixed-time window was used to algorithmically search for active sensors in the data, given the recorded activity by the participants. The window size was 10 minutes, considering plus and minus five minutes from the user-recorded activity time, allowing for an adequate time frame for both the start and end of the sequence. Thus, raw data files were processed to extract the active sensors within the proposed time window, resulting in a data set with clearly identified feature vectors, which included the status of the sensors, a timestamp and more importantly, labels for each of them indicating the corresponding user and activity. These data were used as ground truth and validation of the analysis.

9.5 Statistical data analysis

An exploratory analysis of the data was performed using different unsupervised learning tools, such as K-means, hierarchical clustering and binary logistics regression using IBM SPSS[3]

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[3]https://www.ibm.com/analytics/us/en/technology/sps/

data analysis software tools. Table 9.1 shows the descriptive statistics of the analysed data. Table 9.2 and Table 9.3 show the summary of statistics for the participants and the user-recorded activities.

Table 9.1 Descriptive statistics for the analysed data.

		User	Activity	Coaster1	Coaster2	Coaster3	Coaster4	Coffee	Door	Fridge	Hot water button	Cold water button
N	Valid	309	309	309	309	309	309	309	309	309	309	309
	Missing	0	0	0	0	0	0	0	0	0	0	0
Mean				.1359	.2557	.4725	.1553	.3883	.5955	.1521	.3495	.3657
Median				0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
Mode				0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	0.00
Std. Deviation				.34326	.43694	.50005	.36282	.48817	.49160	.35970	.47759	.48241
Variance				.118	.191	.250	.132	.238	.242	.129	.228	.233
Skewness				2.135	1.126	.111	1.912	.460	-.391	1.947	.634	.560
Std. Error of				.139	.139	.139	.139	.139	.139	.139	.139	.139
Kurtosis				2.575	-.738	-2.001	1.668	-1.800	-1.859	1.802	-1.608	-1.697
Std. Error of Kurtosis				.276	.276	.276	.276	.276	.276	.276	.276	.276
Sum				42.00	79.00	146.00	48.00	120.00	184.00	47.00	108.00	113.00
Percentiles	25			0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	50			0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000
	75			0.0000	1.0000	1.0000	0.0000	1.0000	1.0000	0.0000	1.0000	1.0000

Table 9.2 Descriptive statistics for study's participants.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	User 1	47	15.2	15.2	15.2
	User 2	9	2.9	2.9	18.1
	User 3	81	26.2	26.2	44.3
	User 4	16	5.2	5.2	49.5
	User 5	4	1.3	1.3	50.8
	User 6	28	9.1	9.1	59.9
	User 7	1	.3	.3	60.2
	User 8	1	.3	.3	60.5
	User 9	14	4.5	4.5	65.0
	User 10	41	13.3	13.3	78.3
	User 11	67	21.7	21.7	100.0
	Total	309	100.0	100.0	

Table 9.3 Descriptive statistics for user-recorded activities.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	coffee + hot water	55	17.8	17.8	17.8
	coffee + milk	9	2.9	2.9	20.7
	coffee+milk+hot water	6	1.9	1.9	22.7
	cold water	137	44.3	44.3	67.0
	hot water	57	18.4	18.4	85.4
	tea + milk	29	9.4	9.4	94.8
	water (hot + cold)	16	5.2	5.2	100.0
	Total	309	100.0	100.0	

Principal Components Analysis (PCA), a multivariate analysis technique which aims to transform the data into a lower dimensional representation to simplify its description, provides a means of classifying observations into categories, and a metric for the underlying connections amongst the analysed data (Abdi and Williams, 2010; Distefano et al., 2009; Augello and Gaglio, 2014). An aspect of the present research was to establish a method to identify *topics* and *themes* within an assumed 'conversation' amongst IoT network actors. The PCA approach presented an opportunity to interpret the resulting classification as an indicator and measure of *topic* and *theme* membership of each of the sensors in the dataset, and their corresponding identified activities. Hence, component loadings are considered analogous to the degree of contribution each sensor has in a particular conversation.

As such PCA was run on the data set using SPSS, through its Factor Analysis module, using varimax rotation, with the default 25 maximum iterations for convergence. The exploratory factor extraction method used was based on eigenvalues, and its corresponding scree plot, to explore the adequate number or factors. Each factor contributes to explaining the variance of the data set.

The method iterates until an adequate percentage of variance is explained cumulatively by each component, until a threshold is reached. Similar analyses have been performed with a 70% of explained cumulative variance, and is considered a suitable limit (Beaumont, 2012).

9.6 Results from study's data analysis

A first analysis identified cross loadings on one of the variables, generating noise in the data set. This led to inspect data sources, finding that one of the participants had not used their instrumented coaster (described in Chapter 8) in the correct way, and all data belonging to that user was removed from the study.

As shown in Figure 9.1 a scree plot was produced by PCA with the collected data for the 'Drinks making' office testbed. This graphical method allows to identify the point where the eigenvalues allow to identify the required number of components that explain most of the variance in data. SPSS is capable of performing an automatic selection of components, but as an exploratory analysis, the number of components were manually changed. Moreover, SPSS's output produces a table identifying the variance and components, allowing to determine that for this data set, the optimal number of components to use were 5. A larger number of components led to each of them correlate to individual variables, neglecting the inherent underlying latent correlations amongst them. T. Thus, using 5 components the total explained variance was of 72.60%, which according to the previous section, would be sufficient to determine the relationship between sensors (variables).

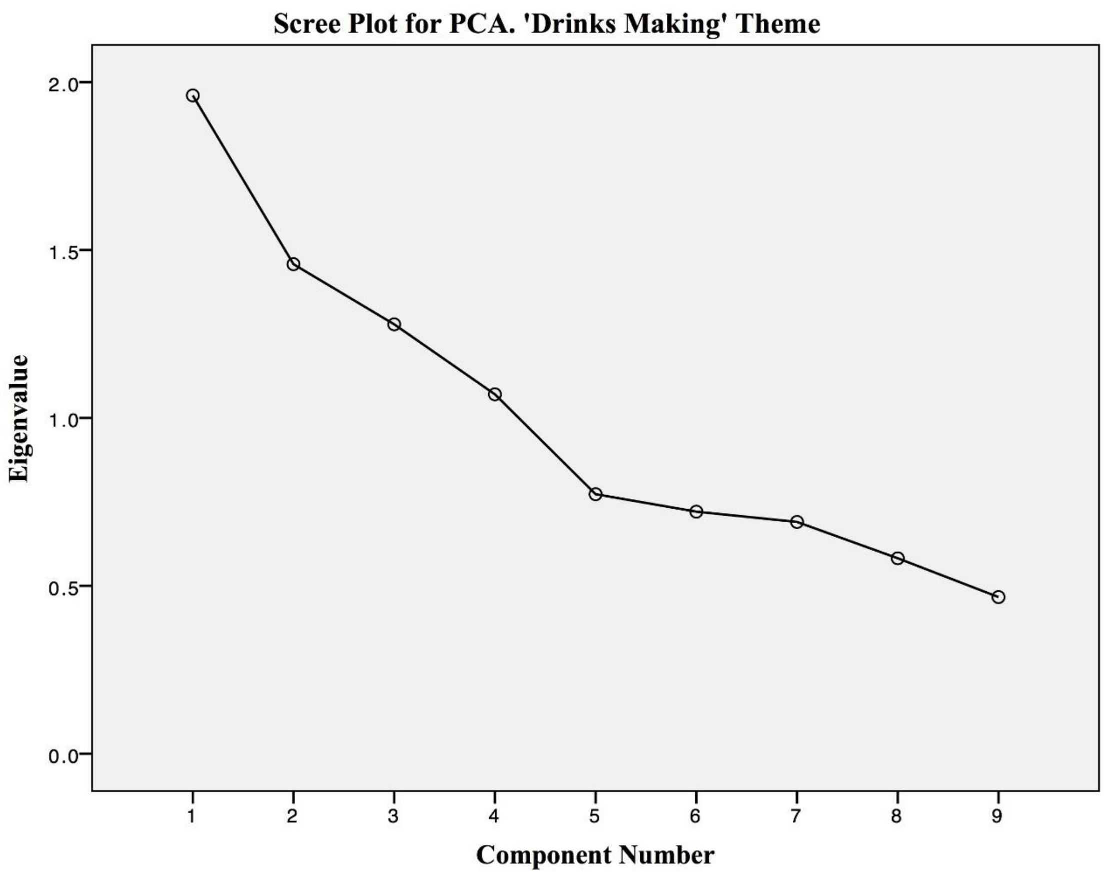

Figure 9.1 Scree plot for PCA analysis of 'Drinks Making' study.

Moreover, Table 9.4 and Table 9.5 present a summary of the statistics from the PCA factor analysis method, showing the correlation matrix as a means of an initial identification of cross-loading components and the variance analysis to determine the number or components to consider in the test. By observing the correlation matrix it is possible to identify clustering between groups of variable that will be extracted as components (Beaumont, 2012).

Table 9.4 PCA Correlation Matrix for 'Drinks Making' Study.

		Coaster1	Coaster2	Coaster3	Coaster4	Coffee	Door	Fridge	hot	cold
Correlation	Coaster1	1.000	.071	-.035	.273	-.006	.115	.148	.006	.091
	Coaster2	.071	1.000	-.035	-.128	.066	.166	.454	.099	-.060
	Coaster3	-.035	-.035	1.000	.077	-.102	.067	-.022	.272	-.207
	Coaster4	.273	-.128	.077	1.000	-.140	.008	-.082	-.127	.194
	Coffee	-.006	.066	-.102	-.140	1.000	.210	.125	.001	-.122
	Door	.115	.166	.067	.008	.210	1.000	.165	.258	-.155
	Fridge	.148	.454	-.022	-.082	.125	.165	1.000	.238	.015
	Hot Water Button	.006	.099	.272	-.127	.001	.258	.238	1.000	-.289
	Cold Water Button	.091	-.060	-.207	.194	-.122	-.155	.015	-.289	1.000
Sig. (1-tailed)	Coaster1		.108	.271	.000	.458	.021	.005	.456	.055
	Coaster2	.108		.272	.012	.125	.002	.000	.041	.147
	Coaster3	.271	.272		.088	.036	.121	.351	.000	.000
	Coaster4	.000	.012	.088		.007	.447	.075	.013	.000
	Coffee	.458	.125	.036	.007		.000	.014	.494	.016
	Door	.021	.002	.121	.447	.000		.002	.000	.003
	Fridge	.005	.000	.351	.075	.014	.002		.000	.395
	hot	.456	.041	.000	.013	.494	.000	.000		.000
	cold	.055	.147	.000	.000	.016	.003	.395	.000	

Table 9.5 PCA variance analysis for 'Drinks Making' study

Component	Initial Eigenvalues			Loadings			Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1.928	21.417	21.417	1.928	21.417	21.417	1.566	17.399	17.399
2	1.465	16.281	37.698	1.465	16.281	37.698	1.391	15.456	32.855
3	1.327	14.749	52.447	1.327	14.749	52.447	1.224	13.602	46.456
4	1.070	11.887	64.334	1.070	11.887	64.334	1.217	13.524	59.980
5	.744	8.271	72.605	.744	8.271	72.605	1.136	12.624	72.605
6	.733	8.145	80.749						
7	.691	7.678	88.427						
8	.586	6.516	94.943						
9	.455	5.057	100.000						

The previous scree plot (Figure 9.1) and PCA statistical summaries (Table 9.4 and Table 9.5) show that for this study five components would provide the required number of components to consider as signifiers for the data set. Thus, five factors were used as observed in Table 9.6, showing the interpretation given to each of the extracted components. The components where selected by applying the commonly used criteria of stablishing a threshold of 0.4 (Beaumont, 2012). Thus, Table 9.6 only shows the loadings above said criteria.

Table 9.6 PCA rotated component matrix for sliding windows data set, sensor loadings and descriptors for extracted components. Descriptors relate to the TAFEI goals.

Sensor	Components for sliding windows data set				
	1	**2**	**3**	**4**	**5**
Coaster1	.846				
Coaster2		.779			
Coaster3			.807		
Coaster4	.801				
Coffee					
ColdWater					.944
Door				.902	
Fridge		.700			
HotWater			.439	.436	
Higher Loading Sensors in component	Coaster 1 Coaster 4	Coaster 2 Fridge	Coaster 3 HotWater	Door HotWater	ColdWater
Descriptor	N/A	"drink with milk"	"Hot water related drink"	"Coffee related drink"	"plain water drink"

As discussed in the previous section, a second data set was used as ground truth for validation of the method. This '*recorded-activities data set*', provided labels for users and activities, and a structured approach to the classification technique. Using the same PCA extraction method and settings in SPSS as on the sliding windows data set Table 9.7 shows, albeit slight changes in the order of the components, the sensors found in the components and their descriptors closely matching the ones produced in the unsupervised classification approach. This similarity suggests that the latent relationships within both data sets are comparable, allowing to use the extracted components as the *topics* in the conversation established by nodes engaging with each other in the network. Furthermore, as shown by TAFEI, the sensors identified as part of each component, directly relate to the tasks identified, and thus the component loadings describe the plans to achieve specific goals.

Table 9.7 PCA rotated component matrix 'recorded-activities data set' (labelled), sensor loadings and descriptor for extracted components. Descriptors relate to the TAFEI goals.

Sensor	**Components for labeled data set**				
	1	**2**	**3**	**4**	**5**
Coaster1				.915	
Coaster2	.819				
Coaster3		.799			
Coaster4				.598	.505
Coffee			.768		
ColdWater					.856
Door			.763		
Fridge	.834				
HotWater		.656			
Higher Loading Sensors in component	Fridge Coaster 2	Coaster 3 HotWater	Coffee HotWater	Coaster 1 Coaster 4	ColdWater Coaster 4
Descriptor	"drink with milk"	"Hot water related drink"	"Coffee related drink"	N/A	"plain water drink"

PCA regression scores from the r*ecorded-activities data set'* were used to define weighting of the extracted components. The user labelled data set and extracted PCA components clearly related to the activities from the study and the TAFEI model. Participants could be recognized through the extracted features, and in alignment with the modelled TAFEI goals, a subset of the results from user and activity identification analysis are presented below.

Averages for the PCA scores weightings on the labelled featured vectors were obtained and plotted to visualize the degree of membership of the scores in the activities and the users performing the activity. In the case of activities Figure 9.2 shows an instance in which the PCA extracted components and scores for the activity '*coffee + hot water*' are examined. It can be observed that for this activity, there is a higher loading on component 3 (PC3) and less so towards component 2 (PC2), which as per Table 9.7, suggests that participants interacted with the sensors related to '*coffee'* and '*door'*, and less so with '*hot water'* '*coaster 3'*. This shows a similarity to the objects involved in the TAFEI modelled goal, supported by empirical observations during the study, and the participant's logged activities.

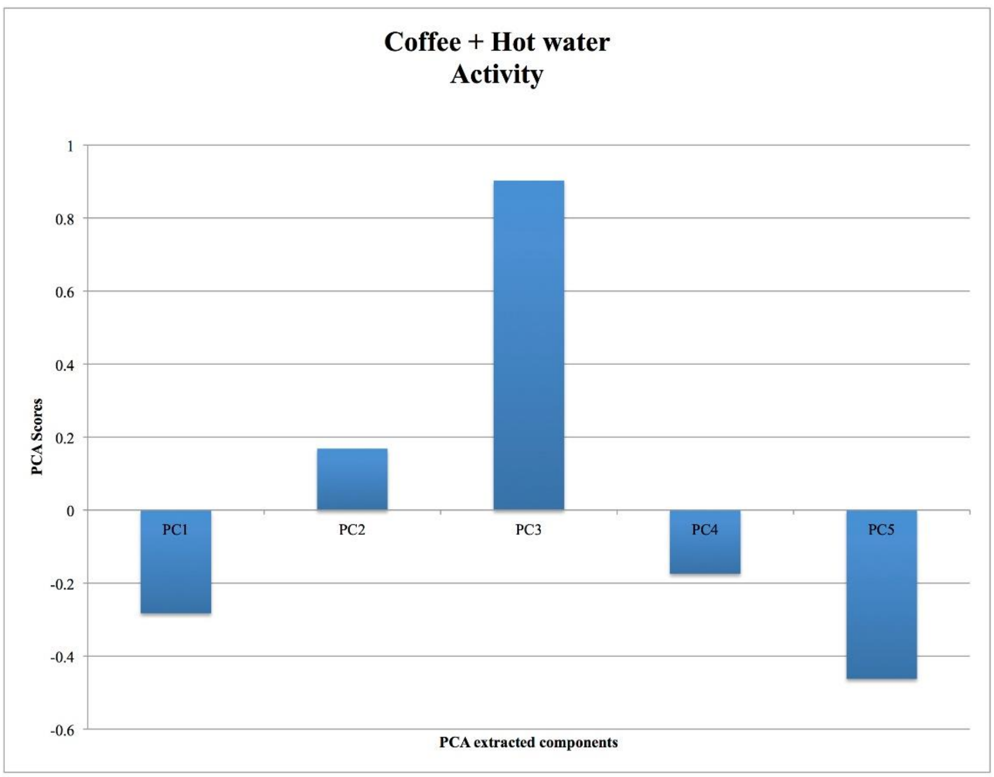

Figure 9.2 'Coffee + hot water' activity PCA Components and average PCA scores.

Furthermore, by using PCA scores to classify users, Figure 9.3 shows a case where groupings were made amongst the two users who reported that they had undertaken the '*Coffee + hot water'* activity. It can be observed that for *User 1*, there was a clear loading towards component 3 (PC3), interacting with the '*coffee'* and '*door'* sensors, as per table 6. In this case, it was observed that for the duration of the study this participant had a clear pattern of behaviour when preparing this drink. This user didn't have a coaster associated, nor was based in the office. Thus, to use the coffee machine, the user had to access the office through the main door. Conversely, *User 11* had a coaster associated, and thus, a heavier loading towards component 2 was found, with a slightly lower loading to component 3, confirming their observed behaviours. Correspondingly, by examining results from user classification for goals, the relationship between sensors found in each component and plans defined in the HTA can be observed. As described, the components found for User 1 in the 'coffee and hot water' activity (Figure 9.3), show that the interactions occur with the coffee machine and the door, as described in the TAFEI diagram through plans P2 and P3 (Table 3), whereas for User 11, the objects are their coaster, the hot water button and the coffee machine, as established by plans P1, P2 and P3, validating the modelled behaviour in TAFEI.

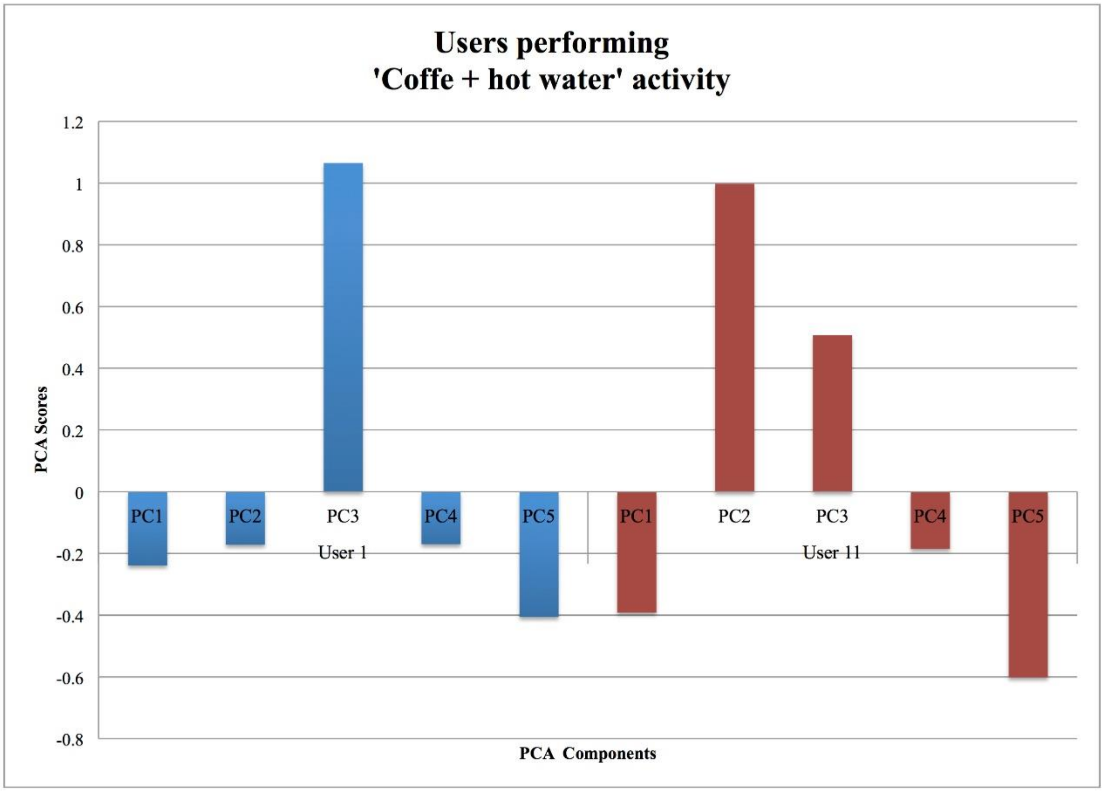

Figure 9.3 Average PCA scores comparison for two different users performing the 'Coffee + hot water' *activity.*

9.7 Conclusions

TAFEI provides a human centred approach to system modelling and requirements definition. It considers a system comprised of both human users and 'things' in a systematic analysis of actions required to achieve goals within a system. By using this information to instrument the object, we could support system autonomy design by establishing rules that monitor when actions occur. For example, by having a sensor on the coffee machine lever, the system could keep track of the number of capsules used, and in turn, proactively inform the user to purchase more consumables, or by linking to e-commerce platforms, make machine-based decisions such as order the supplies on its own.

The study aimed for the minimal number of objects (and sensors) required to accomplish goals within the system's theme. This paradigm supported system instrumentation granularity at an object level. That is, although TAFEI provided a way to inform instrumentation points, it was done to identify single objects as related to state transitions. Notwithstanding, this study suggests that increasing granularity at a device level could enable further opportunities for autonomous and intelligent behaviour. For example, instrumentation on the coffee machine's water tank could provide a more accurate metric on the amount of water used to prepare coffee, and correlate that information to when the machine needs refilling and overtime, when it needs cleaning or descaling. As such, these additional layers on instrumentation show that emerging themes could be involved in the system, for example a 'maintenance' mode.

This work posits that a conversation occurs in the human-machine system through an exchange of actions, following a sequence of states within a theme. Topics in a conversation become its guideline in an organized, turn based information exchange. Analogously, we argue that goals in the system provide a common ground for the human-machine interaction, and we can make a distinction between human based transition and machine based transitions in a collaborative exchange within the topic. For example, in the case of a coffee machine, the act of coffee being brewed becomes quite evident, providing a clear cue on system status. Common ground is established by both parties agreeing on what the conversation is about, thus, if users can't directly perceive with the outcome of the goal, they won't be part of the conversation negatively affecting their engagement, as suggested by the intelligent thermostat studies discussed in the introduction. If the user sets the temperature, say at the highest level, and nothing happens the user is left to wonder if the system is functioning properly. It might be maximizing energy savings, but the user might not be locked into that conversation, thus missing information. Conversely, for a system designer, this becomes a tool to scrutinize all interactions, plans, states and actions that form conversations to inform development of new topics, or to enhance user interfaces or system notifications. By the same token it also provides the basis for analysing user intent. In conjunction, user intent and system notification could also be used as to support the development of autonomous and ‘intelligent’ system behaviour as expected from the IoT.

TAFEI analysis is by definition subjective, as it relies on the analyst’s point of view. Consequently, it could be argued that instrumenting the chosen objects would perhaps not be sufficient to provide an explanation of the task and goals being performed. As such, to test the hypothesis that was set earlier in the chapter, PCA was used to define meaning of the interactions amongst sensors and to provide a measure of correspondence with the modelled behaviour, linking plans as defined by TAFEI with PCA’s extracted components. By using the components and their scores from explicit connections, we found the implicit interactions between devices when they were used to fulfil a goal within a theme, such as ‘having a drink’, validating our human centred framework for system design.

Thus, this thesis proposes that users and devices establish a partnership amongst them, cooperating with each other towards a simple goal. In doing so a ‘conversation’ is enacted, allowing the objects to convey meaningful information (knowledge) given their common ground. The extracted components from the data-mining tool involve co-activation of sensors, and as such, we suggest that these represent the collaborating *topics* in a discussion. When these *topics* occur within a particular *context* -for instance an office drinks making environment- a *theme* emerges, giving meaning and purpose to the communication exchange between network nodes. Thus, through device instrumentation and data collection and PCA analysis we suggest how the components found can be employed to describe their inherent connections, in the same manner that we propose *topics* can be used to aggregate into themes, or subsets of the supported theme as topics or goals.

This study aims to fill the gap in requirement definition towards the implementation of devices that effectively contribute to parsimonious collaboration between users and the IoT. Although TAFEI was originally conceived to analyses errors in usability, we show how it can be repurposed to identify user interactions that deviate from the originally conceived goals and could potentially lead to opportunities to develop intelligent behaviour. As such, TAFEI is used to make predictions of possible interactions in the system, both from a user and machine perspective. For example, the coffee machine has at least five points of user interaction that warrant their own analysis through TAFEI and PCA. This finer approach can lead to the discovery of additional topics and themes in both the system and the object, by showcasing actions taken by the user, and actions made 'in the background' by the system. In such a system, the definition of background activities would allow the modelling of 'intelligent' activities. For example, in the case of the finely instrumented coffee machine, a machine-based goal would allow the system to keep track of its frequency of use, and thus proactively identify service related activities, such as descaling or prediction of coffee capsule usage.

It has been argued that the user values a system or object through its perceived value, or its capacity to provide meaning. Thus, TAFEI's analysis of diverging goals can be used to observe opportunities to increase user engagement with the system, promoting usability and adoption.

Through analysis of device collaboration both at an interaction and data level to fulfil a particular task, we show how they cooperate towards achieving a goal that provides meaning to the user. By modelling a system with a methodology such as TAFEI we show how to identify actions on its nodes as defined by its goals, and the steps that a user takes to successfully accomplish the task.

10 Discussion

Although the Internet of Things concept initially suffered from being treated as concept pushed by economic and marketing forces, and considered no more than 'hype' or a 'buzz word', research and application development have advanced the area, providing significant results warranting continuous research efforts. Nevertheless, the necessity for an IoT could be questioned. As such, the first research question this thesis asked was whether a human-centred vision of the IoT could be favoured over the purportedly prevailing technology-based IoT. By reviewing the fundamental features of a techno-centric IoT, such as its devices, its networks, and its management infrastructure, we provide a framework to analyse how these traits define and influence how human users react and interact with the IoT. Features such as constrained user interfaces have the potential to limit the information conveyed to users, or data processes occurring over wireless network connections can hide *things'* activities from users leading to interaction problems, as discussed in Chapter 3.

Consequently, from a human user point of view, we could ask what is the purpose of an Internet of Things application and what kind of services would they be addressing. Even though smart devices might not completely solve complex problems on behalf of humans, they could be aimed to at the least reduce friction on daily activities. Arguably, some product designers aim to solve these problems in such a way that users just don't consider them problems anymore as friction is reduced over time. As such, an interesting position for designers is to address what to cognify such that this friction is reduced in a meaningful way. How do designers identify opportunities for smart behaviour and in the same regard, how do users become engaged with the provided solutions?

In a more proactive scenario, given recent advancements in machine learning and artificial intelligence perhaps the machines themselves could be capable to provide answers to those questions by way of learning our habits. Nevertheless, a paradigm in which all is left to the machine might lead to Norman's (2007) assertion that machines are not intelligent, but intelligence is in the mind of the designer. Hence, ideally objects should be able to learn and infer from their human users, but before that stage is reached, we should focus on the design of smart systems that are meaningful to their users and promote engagement.

This thesis posits that the IoT not only should aim to reduce friction in everyday activities or create valuable and rich experience to their users, but also to proactively engage in collaborative endeavours in a virtuous circle of operation: friction is reduced when systems are actually used for their intended purpose.

As discussed in chapter 2, a smart kettle or a smart toaster might be considered 'useless' devices, laden with technologically solutionism (Morozov, 2014). In the case of the smart toaster, the notion of smartness is provided due to the fact that it allows user to set the toast level, the type of bread, it notifies of the remaining time for toast to ready to your liking. But why? Is it something that we really need? Does it actually supports and extends any user action? A meaningful action? Is it removing friction on the user's everyday activities? At best most of these devices end up used in much the same way as their dumb' counterparts, or shelved because their special features actually become cumbersome to the user. Notably, the first 'electrified' versions of these appliances were developed out of a desire of users to reduce time and effort in chores as simple as boiling water and toasting bread. A tin opener is also a tool born out of desire for efficiency, however, does it warrants cognification?

Thus, the question of how to characterise the IoT to support user activities, can be answered in terms of cognification (Kelly, 2017) of *things* such that they not only reduce friction, effort, time or cost, but also support user goals, as described in Chapter 4.

Interestingly, there could be an argument in favour of devices such as the smart kitchen appliances as those mentioned, perhaps would become more evident if we consider that they are two of the most used home appliances in the UK (Appliances Direct, 2016), making a case for the developers to place a connected device in every household to collect data related to energy consumption or household occupancy patterns for example. Arguably, not all applications would necessarily benefit all stakeholders in the product's value chain, but given their potential ubiquitousness, what if they could provide information to the energy grid about the household's energy consumption aggregating information for different users, providing the data analytics to proactively adjust the grid's energy management. In the case of the saltshaker presented in the same chapter of this thesis, it would be debatable whether the device is useful or not. However, on their website, the creators of the device imply that the device is in fact a centrepiece for the digital home, in the guise of an object common to dining tables. This shows a clear disconnection of what the designers intend, how the product is marketed and most importantly whether it solves a problem (friction) for the users.

The previous examples provide scenarios in which there is a disassociation of a 'smart' devices goals and the users. Moreover, what is the impact of the machine making decisions without the user's being fully informed? This has been analysed in the thesis, observing that these situations often result in frustration from the user.

Consequently, if a misalignment of goals exist between a smart machine and its users, the question could be how an agreement is negotiated in terms of completing goals? As actors in the network are considered agents, each carry out their own tasks and goals. Hence, this thesis posits that a social-like collaboration needs to occur between those involved in the network, with the purpose of achieving each other's goals. To characterise these collaborative endeavours, the notion of a conversational IoT is presented in chapter 4, not in the commonly used approach of speech based communications, aiming to provide natural language user interfaces like those used in *chatbots* or virtual assistants such as Amazon's Alexa (Amazon, 2018) or Google's Home (Google, 2018). Although these devices provide interfaces that perform activities on behalf of the users, such as controlling ambient temperature or lightning, they do not completely address the goal-based approach of the IoT as defined in Chapter 4. Firstly, interaction occurs in a centralised topology, focusing on providing a middleware based solution to interaction in the IoT, as presented in Chapter 2. In terms of their speech capabilities, they become interpreters of input and output commands that are previously hardcoded. As such, the conversational capabilities focus on providing an intermediate layer between users and *things*, in charge of 'translating' user goals to machine language. The conversational IoT paradigm presented in Chapter 4 posits that conversations are based on the exchange of actions to convey ideas. As obvious at it might be, it is important to state that objects are incapable of expressing their ideas, however they are capable of supporting exchanges with users through their physical attributes. In this context, conversations are enacted, based on the specification of turn-taking and feedback framed on the notion of a common interest and context. This implies a mutually beneficial collaboration in which participants seek not only to fulfil their tasks and goals, but also provide the means to not hinder the other party's own tasks and goals, and at best support them.

These collaboration have been analysed from different perspectives, from semantics and ontology to the services, leading to IoT system modelling. As discussed in Chapter 5, these models have often overlooked user experience and the fact that smart objects often rely on their digital representation, thus data exchanges often occur through communication channels undisclosed to the user. This leads to question how to best approach and implement Interaction Design strategies as applied to a human-centred IoT.

For HCI, the link of physical devices to a virtual equivalent through their instrumentation and cognification, presents interesting challenges in terms of the level of abstraction in which the 'cognified' object might not necessarily represent the same concept in both its physical and virtual representations. For example, the physical representation of a kettle is immediately conveyed through its affordances (a handle, a water container, a button to heat), but an instrumented kettle collects and produces data in a format not immediately obvious to its user. As such, the goal of this research has been to provide a framework in which the two spaces co-exist in coherent, meaningful way.

These motions not only address the aspect of HII, but could open new opportunities towards creating the vision of the IoT in which the devices are intelligent enough to provide answers to user's needs or even those use cases not necessarily considered initially, providing new services and insights. Commonly, devices are connected in centralised topologies, and thus their functionality, and the knowledge obtained from them, is rigid, considering that they would only establish communication with nodes within its own network, as defined by a hub. Nonetheless, this notion is at odds with the ubiquitousness of IoT devices. In a different scenario, 'things', regardless of their network membership, could be used in applications different to those originally intended for, by sharing their resources and information, addressing the issue of interoperability and device heterogeneity. However, a prerequisite before this can be achieved, is the need for a common communication schema, and thus, this research has proposed the notion of topics and themes as a way of understanding the interactions amongst devices, in a social-like paradigm.

10.1 Designing for usability

Chapter 5 of this thesis focuses on the use of Task Analysis for Error Identification (TAFEI) as a tool for IoT systems modelling, with the goal of analysing user intent and promoting meaningful interactions. In particular, Hierarchical Task Analysis (HTA) has been used to define system requirements through a representation of the system's sub-goals, and applying them to user interface design, workload design and error prediction.

Drawing upon strands of research in Task Analysis and Human-IoT Interaction (HII), this research focuses on the use of Task Analysis for Error Identification (TAFEI) as a tool for IoT systems modelling, with the goal of informing system instrumentation. The cognification imbued through the implementation of sensor and communication technology enables the prediction of user intent, which if done in a human-centric approach leads to the promotion of meaningful HII interactions.

Chapter 6 presents a study in which participants were expected to interact with cognified objects, attempting to discern their purpose. In this regard, it was observed that users tend to build mental models to make sense of *things*. Moreover, *things* provide a means of conveying their goals through their affordances. In this regard, it could be considered that the process becomes one of 'service discovery', or in terms of the collaborative environment presented in chapter 4, as a process of 'theme discovery'. The study's results suggest that users favour interactions were the theme of the system is presented, as opposed to those that are based on a data-driven approach. In the latter, users are presented with a status based view of the IoT, leading to an incomplete view of IoT interaction in which users feel as mere observers. In contrast, a theme based approach provides meaning, supporting mental representations of the system's purpose.

An interesting notion presented by this study is that of the nature of the *thing's* goals. It should be noted that a full analysis of a human-centred IoT should consider what the *things* are expecting to achieve.

As such, this thesis answered the question of how to enable interaction modelling strategies that favour service-based interactions, or in terms of the knowledge structure presented in chapter 4, theme and topic interactions, identified by goals and tasks.

In the context of the IoT, TAFEI provides a frame of reference in which interactions between the person and the object are analysed from the perspective of the system's goals and sub-goals. This enables a system to be designed and developed by providing useful meaning, not only to the owner of the business case the object supports, but also more importantly to the person using the system.

By repurposing TAFEI's original aim of modelling systems by focusing on errors as users attempt to carry out their main goal, it's possible to see how the system's functionality could be extended, and more importantly, how intelligence could be embedded in the system. When devices that traditionally were not considered 'smart', such as a coffee machine, become IoT-enabled, they can possess extended capabilities and present opportunities for proactive and intelligent behaviour. These scenarios could allow a system to predict a user's intent and to provide them with additional information.

The application of TAFEI would allow the consideration of human factors in the design of IoT systems and smart objects, alongside machine learning techniques. By allowing people to become more aware of the system's goals, meaningful interactions and engagement would be increased, enhancing successful adoption of objects in the Internet of Things.

A test bed was developed to investigate how loosely connected sensors, in a decentralised topology interact with each other towards the creation of a common interest, or overarching theme. 'Drinks making' was chosen as the theme of the network given that is well stablished routine, with minimal requirement for feedback, and it used existing objects. Moreover, it relied on previous knowledge and mental models involved in the operation of objects. As such, the system would be a non-intrusive in terms of modifying user behaviour.

Data collected from the test bed was analysed with Principal Components Analysis as a tool to extract the underlying meaning of interactions amongst objects. By using the extracted components and their scores from explicit connections, it was that found the implicit interactions between devices when they were used to fulfil a simple task, such as drinks making in an office environment. The extracted components from the data-mining tool involve co-activation of sensors, and as such, there's a suggestion that these represent the aggregation *topics* in a discussion. When these *topics* occur within a particular *context* -for instance an office drinks making environment- a *theme* emerges, giving meaning and purpose to the communication exchange between network nodes. As in social networks, objects are considered as part of the same cluster because of their social ties, a product of both their theme and context of conversation.

Analysing how devices collaborate to fulfil a particular task, provides a path into the conversation they sustain with each other to transfer knowledge within their network. This presents the opportunity for developing IoT systems that would be able to convey their purpose to other systems and potentially combine efforts to produce novel services different than the ones they were originally designed for. Moreover, as the networked systems grow in scale, smaller networks (clusters of sensors, actuators and users) act as local nodes that in turn could be considered localized ‘sensors’ in a wider scale, loosely connected Internet of Things.

For example, different ‘drinks making’ systems, located in different rooms across a building, could expand its functionality by communicating with the building’s energy management system, allowing it to receive knowledge from each of the rooms enabling it to administer its energy management policies more efficiently, from planning to scheduling and coordination of any available actuators and human user interfaces.

10.2 Restatement of Contributions

10.2.1 Research Questions revisited

As introduced in chapter 1, the main research questions postulated by this thesis where:

- Why is there a requirement for a human based view of the IoT over a ‘tech-centred’ paradigm?
- How can the IoT be characterised to support human activities?

The evolution of the Internet of Things from a technology perspective supported an analysis of how the IoT has, to some degree, deviated from addressing some usability challenges by focusing instead on the services that could be provided by their data and accompanying analytics. In chapter 2, this thesis focused on observing the technological requirements) for the IoT to identify their relation to human users and the affordances (chapter 3) they convey to support human-centred activities (Kawsar et al., 2010a; Kortuem et al., 2010; Baber, 2018; Giaccardi et al., 2014) and their related interactions (Jha and Lehnhoff, 2014; Jara et al., 2014; Nunes et al., 2015; Cervantes-Solis et al., 2015a; Golightly, 1996; Norman, 2007) and usability

(Stankovic et al., 2005; Kuniavsky, 2010; Pschetz et al., 2017). The research allowed to identify a requirement for an IoT paradigm that placed the human user at the centre, and this thesis addresses the first major research question by conceptualising the IoT as a system in which meaningful exchanges, framed as commonly grounded conversations, occurring amongst its nodes and in characterised as a Social IoT in chapter 4.

The second major research question of how the IoT can be characterised to support human activities is addressed in chapter 5 by proposing a human centred IoT development framework based on the observation of attributes required for smart object interaction (Chapter 5) to allow for the identification of system meaning from the human user (Cervantes-Solis and Baber, 2016), and how it is structured under the social IoT previously defined (chapter 5). Moreover a study was developed to analyse the nature of Human-IoT interaction (chapter 6) to support the development and application of a modelling framework (chapter 7 and 8), and validating the results obtained through data analysis techniques (chapter 9).

10.2.2 The Human-Centred IoT

This thesis explored how the IoT's technology centred development informed how users approached interaction with these systems. As a consequence, user's goals were not necessarily considered in the system's development. As such, this thesis reframes Human-IoT interaction as a social, collaborative system, described in terms of its capacity to support the activities of the involved social actors in pursuit of a common goal. In this regard, an IoT system should be characterised not only by the collection of technologies it incorporates, but also by the human user, reframing it as a goal based Human-Machine IoT System.

10.2.3 A Human-Centred Interaction Design Framework

This thesis presents a framework that allows for the design of Internet of Things systems with usability as it main focus, enabling the analysis of goals from both the human users and the machine (*things* in the IoT), by observing the actions and plans that users take to complete them, and linking them to the machine's states that are involved in those interactions. Moreover, the introduced paradigm shows how a Human Centric Internet of Things framework can be applied to design and implement the infrastructure required to deploy IoT systems.

The design framework presented in chapter 5 focused on analysing human behaviour to implement a model for an IoT system, identifying how to approach object instrumentation such that user's goals were supported. By framing the goals and actions under the notion of a conversational IoT in which organised turn taking takes place under a commonly agreed context, the notion of a theme and topics is proposed. This concept allows the interlinking of actions and state transitions to identify the intersection of themes and the instrumentation required to implement Internet of Things systems.

Furthermore, as part of the implementation, Node-Red, a data-flow programming tool, was used to complement the machine-based application acting as a middleware platform to connect the IoT network's nodes, data collection and application logic. The introduction of this programming paradigm allowed to focus on the state and turn taking nature of the IoT and the framework, allowing for the implementation of the state-based model provided by TAFEI, through a scalable and extensible technology platform that supports the use of APIs to interface with other systems and for data collection and analytics.

10.2.4 A redefinition of 'smart' systems

In the context of this research, focusing on human-machine interaction, with the aim of enhancing user engagement and value, the notion of 'smart' should be restated to consider the following principles:

- They are enhanced objects possessing attributes that allow them to share status of their location, surroundings, and usage as enabled by their SPC capabilities
- They should warrant user engagement and perceived value, otherwise objects become no more than glorified versions of themselves
- Should consider user's experience in their design to prevent misunderstanding on its purpose
- Should regard user's goals, and have the capability to negotiate and prioritise their own goals in this consideration.

10.3 Limitations of the research

The studies reported in this thesis are focused on experiments run under constrains such as a limited number of participants and the background of these participants. Both studies relied on academic staff, research students and undergraduate students with engineering or computer science backgrounds. As such, the results are potentially eschewed due to the inherent experience of these users with technology and knowledge and experience on smart systems. However, both experiments were designed to be as simple as possible (very simple and intuitive tangible interfaces for the first study) and as non-intrusive as possible (instrumenting devices such that their operation or usability was not interfered with in studies 2 and 3), to minimize for the mentioned cognitive biases.

Arguably, studies 2 and 3 could have been implemented by instrumenting more devices related to the office's environment and activities, allowing for additional data to be collected and that could be correlated to the study's data to obtain additional insights on themes, topics and user behaviour. However, the experimental design followed the methodology presented in chapter 5, aiming to identify the minimal number of sensors required to recognise activity patterns related to the specified goals and tasks.

Finally, both studies focused on small scale developments, showing how the framework can be applied to environments such as an office or stand-alone devices (such as a coffee machine in studies 2 and 3, or a puzzle in study 1). Although the middleware that was used to implement the testbed networks is enterprise ready, allowing for the scalability and replicability of the system, the studies did not allow for the testing of a large scale system, as will be expanded in the following section.

10.4 Future research

The thesis contributions relate to a framework that focuses on providing a human-centred approach to the IoT based on the analysis of goal and task based human behaviour to inform system implementation. In the context of the thesis, the system is characterised as the collaboration of its human users and its machine-based elements engaging in a collaborative endeavour to complete their expected goals, identifying human and machine based actions, enabling opportunities create affording situations (system cues for interaction) and system instrumentation to enable the machine's automated and intelligent behaviour. Moreover, the nature of the Human-IoT cooperation (conversations in the context of the thesis) has been characterised by its states and transitions, making it turn-based and contextual.

Hence, this framework not only focuses on Human-IoT interaction, but provides a methodological approach to model collaborative interactions between agents aiming to complete specific tasks.

As discussed in the literature review of the thesis, the autonomous view of the IoT requires the collaboration of intelligent agents that perform activities on behalf of their users. As such, an area where future research efforts is to extend the methodology to identify and refine agent interaction design. The framework allows for a top down approach to IoT system modelling, allowing to define requirements or goals (themes and topics in the context of the thesis), and align them with the required actions (tasks) required to reach them. As such, the method provides the specification of the intersection between goals and instrumentation, and it could be applied to identify the minimal number of sensors in IoT applications, simplifying the underlying electronics.

As mentioned in section 10.3, a limitation that was found in the reported studies is such that the framework was tested on the intended small scale systems. This research allowed us to observe the challenges of analysing interactions from loosely connected nodes in a controlled IoT network. An area of further development is to address the issues of how the concepts of Theme, Topic and Context are incorporated in IoT systems outside of the lab domain, and at a bigger scale and scope, in IoT systems applied to domains such as city infrastructure, industrial IoT or healthcare to name a few.

As the framework focuses on the interactions required from nodes to attain goals, it could be argued that at a different, larger, scale the interactions occur not at a device or user level local level, but at a service level.

Consumer based IoT networks are comprised of local networks of devices that collaborate with each other to provide localised services, for example ‘cognified’ appliances within the household, connected to each other to allow for the automation of home goals such as cleaning or cooking. Their application scale can be scaled up to allow for those local home-based IoT networks to communicate with each other to attain larger scale goals, for example, by connecting them to the electrical grid to automate the production and transmission of electrical power at a municipal level. As the level of scope becomes larger, the electrical grid can be modelled as a network where nodes are the aforementioned municipal grids collaborating to achieve the goal of balancing the national power grid.

As such, the framework in this thesis has the potential to be used to model and define these larger scale networks, by characterising the system’s nodes at different levels and scopes, but maintaining a focus on their intended tasks and goals (themes and topics).

Shifting the focus to a service level would also allow the framework to be applied to model and develop IoT enabled processes, focusing on their outcomes.

An area left unexplored by the work presented in this thesis is that of leveraging the machine learning algorithms (such as PCA) used to develop the framework, and integrating the models to develop automation and reasoning within the implemented systems. Future versions of the testbed system could be implemented by creating a controller with parameters defined by the methodology in a flow based programming platform supporting the system’s state-based description. As such, the use of machine learning algorithms could be the basis for additional avenues of research, investigating mechanisms for autonomous intent prediction based on tasks and goals. This could be extended to allow for automated processes that continuously verifies its themes and topics to identify those that are not recognised and that could be labelled as emergent behaviour, enabling the opportunity of developing further intelligent behaviour.

Finally, an area of research opportunity is that of extending the knowledge structure presented in chapter 5, to a formal ontology that could be used to extend the previously described research efforts. The establishment of a formal, rigorous ontology could enable the extensibility and replicability of the framework and promote its adoption into Internet of Things current areas of development.

11 References

Aazam, M., Khan, I., Alsaffar, A.A., et al. (2014) "Cloud of Things: Integrating Internet of Things and cloud computing and the issues involved." In *Proceedings of 2014 11th International Bhurban Conference on Applied Sciences & Technology (IBCAST) Islamabad, Pakistan, 14th - 18th January, 2014*. January 2014. IEEE. pp. 414–419.

Abdi, H. and Williams, L.J. (2010) Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2 (4): 433–459.

Amazon (2018) *Amazon Echo*.

Anantharam, P., Barnaghi, P. and Sheth, A. (2013) Data processing and semantics for advanced internet of things (IoT) applications: modeling, annotation, integration, and perception. *Proceedings of the 3rd International Conference on Web Intelligence, Mining and Semantics - WIMS '13*, p. 1.

Apple (2015) *HomeKit - Apple Developer*.

Ashton, K. (2009) That 'internet of things' thing. *RFiD Journal*, 22: 97–114.

Atzori, L., Carboni, D. and Iera, A. (2014a) Smart things in the social loop: Paradigms, technologies, and potentials. *Ad Hoc Networks*, 18: 121–132.

Atzori, L., Iera, A. and Morabito, G. (2010) The Internet of Things: A survey. *Computer Networks*, 54 (15): 2787–2805.

Atzori, L., Iera, A. and Morabito, G. (2011) SIoT: Giving a social structure to the internet of things. *IEEE Communications Letters*, 15 (11): 1193–1195.

Atzori, L., Iera, A. and Morabito, G. (2014b) From "smart objects" to "social objects": The next evolutionary step of the internet of things. *IEEE Communications Magazine*, 52

(January): 97–105.

Augello, A. and Gaglio, S. (2014) “Detection of User Activities in Intelligent Environments.” In *Advances onto the Internet of Things*. Springer. pp. 19–32.

Augusto, J.C. (2007) Ambient intelligence: The confluence of ubiquitous/pervasive computing and artificial intelligence. *Intelligent Computing Everywhere*, pp. 213–234.

Auto ID Labs (2014) *Auto ID Labs*.

Baber, C. (2014) Objects as agents: how ergotics and epistemic gestures could benefit gesture-based interaction. *CHI 2014 Workshop on Gesture-based Interaction Design: cognition and communication*.

Baber, C. (2018) *Designing Smart Objects to Support Affording Situations : Exploiting Affordance Through an Understanding of Forms of Engagement*., 9 (March): 1–8.

Baber, C. and Stanton, N. (1997) Rewritable routines in human interaction with public technology. *International Journal of Cognitive*, (January): 1–19.

Baber, C. and Stanton, N.A. (1994) Task analysis for error identification: a methodology for designing error-tolerant consumer products. *Ergonomics*, 37 (11): 1923–1941.

Baber, C. and Stanton, N.A. (2002) Task analysis for error identification: Theory, method and validation. *Theoretical Issues in Ergonomics Science*, 3 (2): 212–227.

Barthel, R., Hudson-smith, A., De Jode, M., et al. (2010) *Tales of Things The Internet of ‘Old’Things: Collecting Stories of Objects, Places and Spaces*.

Beaumont, R. (2012) An introduction to Principal Component Analysis & Factor Analysis Using SPSS 19 and R (psych package). *Journal of Geophysical Research*, (April): 24.

Bellotti, V., Back, M., Edwards, W.K., et al. (2002) Making sense of sensing systems: five questions for designers and researchers. *Proceedings of the SIGCHI conference on Human* *factors in computing systems Changing our world changing ourselves CHI 02*, 1 (1): 415–422.

Bellotti, V. and Edwards, K. (2001) Intelligibility and Accountability: Human Considerations in Context-Aware Systems. *Human-Computer Interaction*, 16 (2): 193–212.

Berners-Lee, T., Hendler, J. and Lassila, O. (2001) The semantic web. *Scientific american*, 284 (5): 28–37.

Bi, Z., Da Xu, L. and Wang, C. (2014) Internet of things for enterprise systems of modern manufacturing. *IEEE Transactions on industrial informatics*, 10 (2): 1537–1546.

Bijker, W.E. (2009) How is technology made?-That is the question! *Cambridge Journal of Economics*, 34 (1): 63–76.

Blackburn, S. (2005) *The Oxford dictionary of philosophy*. OUP Oxford.

Blackstock, M. and Lea, R. (2012) "WoTKit: a lightweight toolkit for the web of things." In *Proceedings of the Third International Workshop on the Web of Things*. 2012. p. 3.

Blackstock, M. and Lea, R. (2014) "Toward a distributed data flow platform for the web of things (distributed node-red)." In *Proceedings of the 5th International Workshop on Web of Things*. 2014. pp. 34–39.

Bleecker, J. (2005) A manifesto for networked objects–cohabiting with pigeons, arphids and aibos in the internet of things. *... : http://fr. scribd. com/doc/14748019/Why-Things-Matter*, pp. 1–17.

Bojanova, I., Hurlburt, G. and Voas, J. (2014) Imagineering an Internet of Anything. *Computer*, 47: 72–77.

Booth, P. (2014) *An Introduction to Human-Computer Interaction (Psychology Revivals)*. Psychology Press.

Bourgeois, J., Linden, J. Van Der, Kortuem, G., et al. (2014) Conversations with my washing machine: an in-the-wild study of demand-shifting with self-generated energy. *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing - UbiComp '14 Adjunct*, pp. 459–470.

Braines, D., O'Leary, N., Thomas, A., et al. (2017) Conversational Homes: A Uniform Natural Language Approach for Collaboration Among Humans and Devices. *International Journal on Advances in Intelligent Systems*, 10 (3): 223–237.

Brooks, R.A. (1991) Intelligence without representation. *Artificial intelligence*, 47 (1): 139–159.

Butler, B. (2016) *Most powerful Internet of Things companies | Network World*.

Carlson, D. and Pagel, M. (2014) Tap to Interact: Towards Dynamically Remixing the Internet of Things. *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*, pp. 1–3.

Cervantes-Solis, J.W. and Baber, C. (2016) "Towards Theme Discovery Paradigm in the Internet of Things." In Waterson, P., Sims, R. and Hubbard, E.-M. (eds.). *Contemporary Ergonomics and Human Factors 2016*. 2016. Chartered Institute of Ergonomics & Human Factors. pp. 335–340.

Cervantes-Solis, J.W., Baber, C., Khattab, A., et al. (2015a) "Rule and Theme Discovery in Human Interactions with an 'Internet of Things'." In *Proceedings of the British HCI 2015 Conference*. 2015. pp. 222–227.

Cervantes-Solis, J.W., Baber, C., Khattab, A., et al. (2015b) "Rule and theme discovery in human interactions with an "internet of things."" In *ACM International Conference Proceeding Series*. 2015.

Chandler, D. (1994) *Semiotics for Beginners*.

Chi, P., Chen, J., Liu, S., et al. (2007) Designing Smart Living Objects–Enhancing vs. Distracting Traditional Human–Object Interaction. *Human-Computer Interaction. Interaction …*.

Chilana, P.K., Ko, A.J. and Wobbrock, J. (2015) "From User-Centered to Adoption-Centered Design." In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*. New York, New York, USA, 2015. ACM Press. pp. 1749–1758.

Cila, N., Smit, I., Giaccardi, E., et al. (2017) "Products as Agents." In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*. New York, New York, USA, 2017. ACM Press. pp. 448–459.

Clark, H.H. (1996) *Using language*. Cambridge university press.

Clark, H.H., Brennan, S.E. and others (1991) Grounding in communication. *Perspectives on socially shared cognition.*, pp. 127–149.

Colistra, G., Pilloni, V. and Atzori, L. (2014) The problem of task allocation in the Internet of Things and the consensus-based approach. *Computer Networks*, 73: 98–111.

Connected Thinking (2017) *34% Have Problems With Smart Home Devices 05/18/2017*.

Cooper, S.E., Ramey-Smith, A.M., Wreathall, J., et al. (1996) *A technique for human error analysis (ATHEANA)*.

Coulouris, G.F., Dollimore, J. and Kindberg, T. (2005) *Distributed systems: concepts and design*. pearson education.

Coulton, P., Burnett, D., Gradinar, A., et al. (2014) Game design in an Internet of Things. *Transactions of the Digital Games Research Association*, 1 (3).

Derler, P., Lee, E. a. and Vincentelli, a. S. (2012) Modeling Cyber–Physical Systems. *Proceedings of the IEEE*, 100 (1): 13–28.

Ding, Y. and Jin, Y. (2013) *An Intelligent self-organization Scheme for the Internet of*

Things., (August): 41–53.

Distefano, C., Zhu, M. and Mîndrilă, D. (2009) *Understanding and Using Factor Scores: Considerations for the Applied Researcher.*, 14 (20).

Dix, A., Finlay, J., Abowd, G.D., et al. (2004) *Human-computer Interaction*. Third Edit. Pearson Education.

Dixon, C., Mahajan, R., Agarwal, S., et al. (2010) The home needs an operating system (and an app store). *Proceedings of the Ninth ACM SIGCOMM Workshop on Hot Topics in Networks - Hotnets '10*, pp. 1–6.

Fan, T. and Chen, Y. (2010) "A scheme of data management in the Internet of Things." In *2010 2nd IEEE InternationalConference on Network Infrastructure and Digital Content*. September 2010. Ieee. pp. 110–114.

Farooq, U. and Grudin, J. (2016) Human-Computer Integration. *Interactions*, November-D: 27–32.

Fayyad, U., Piatetsky-Shapiro, G., Smyth, P., et al. (2005) Knowledge discovery and data mining: Towards a unifying framework. *Knowledge Discovery and Data Mining*, (June): 82–88.

Feinberg, M. (2017) A Design Perspective on Data. *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems*, pp. 2952–2963.

Fersi, G. (2015) Middleware for internet of things: A study. *Proceedings - IEEE International Conference on Distributed Computing in Sensor Systems, DCOSS 2015*, pp. 230–235.

Fields, B., Harrison, M. and Wright, P. (1997) THEA: Human error analysis for requirements definition. *REPORT-UNIVERSITY OF YORK DEPARTMENT OF COMPUTER SCIENCE YCS*, ({YCS} 294).

Fishkin, K.P. (2004) A taxonomy for and analysis of tangible interfaces. *Personal and Ubiquitous Computing*, 8 (5): 347–358.

Fitbit (2015) *Fitbit*.

Fleisch, E. (2010) What is the internet of things? An economic perspective. *Economics, Management, and Financial Markets*, (2): 125–157.

Fortino, G. (2016) Agents Meet the IoT: Toward Ecosystems of Networked Smart Objects. *IEEE Systems, Man, and Cybernetics Magazine*, 2 (2): 43–47.

Gaglio, S. (2014) *Advances onto the Internet of Things*. Advances in Intelligent Systems and Computing. Gaglio, S. and Lo Re, G. (eds.). Cham: Springer International Publishing.

Gajendar, U. (2016) Empathizing with the smart and invisible. *Interactions*, 23 (4): 24–25.

Ganchev, I. and O'Droma, M. (2014) A Generic IoT Architecture for Smart Cities. *25th IET Irish Signals & Systems Conference 2014 and 2014 China-Ireland International Conference on Information and Communities Technologies (ISSC 2014/CIICT 2014)*, pp. 196–199.

García-Sánchez, F., Valencia-García, R., Martínez-Béjar, R., et al. (2009) An ontology, intelligent agent-based framework for the provision of semantic web services. *Expert Systems with Applications*, 36 (2 PART 2): 3167–3187.

Gartner Inc. (2014) *Gartner's 2014 Hype Cycle for Emerging Technologies Maps the Journey to Digital Business*.

Gartner Inc (2013) *Gartner Says the Internet of Things Installed Base Will Grow to 26 Billion Units By 2020*.

Giaccardi, E., Speed, C. and Rubens, N. (2014) Things Making Things: An Ethnography of the Impossible. *Proceedings of the 1st International Research Network for Design*

Anthropology (online proceedings), pp. 10–11.

Gibbins, N., Harris, S. and Shadbolt, N. (2004) Agent-based Semantic Web Services. *Web Semantics: Science, Services and Agents on the World Wide Web*, 1 (2): 141–154.

Golightly, D. (1996) Harnessing the interface for domain learning. *Conference on Human Factors in Computing Systems - Proceedings*, pp. 37–38.

Google (2018) *Google Home*.

Gračanin, D., McCrickard, D.S., Billingsley, A., et al. (2011) "Mobile interfaces for better living: supporting awareness in a smart home environment." In *International conference on universal access in human-computer interaction*. 2011. pp. 163–172.

Gruber, T. (1995) Toward principles for the design of ontologies used for knowledge sharing.pdf. *International journal of human computer studies*.

Gubbi, J., Buyya, R., Marusic, S., et al. (2013) Internet of Things (IoT): A vision, architectural elements, and future directions. *Future Generation Computer Systems*, 29 (7): 1645–1660.

Guo, B., Yu, Z., Zhou, X., et al. (2012a) "Opportunistic IoT: Exploring the social side of the internet of things." In *Proceedings of the 2012 IEEE 16th International Conference on Computer Supported Cooperative Work in Design, CSCWD 2012*. 2012. pp. 925–929.

Guo, B., Zhang, D., Yu, Z., et al. (2012b) From the internet of things to embedded intelligence. *World Wide Web*, 16 (4): 399–420.

Gyrard, A., Patel, P., Sheth, A., et al. (2016) Building the Web of Knowledge with Smart IoT Applications. *IEEE Intelligent Systems*, 31 (5): 83–88.

Hernandez, G., Arias, O., Buentello, D., et al. (2014) Smart Nest Thermostat : A Smart Spy in Your Home. *Blackhat USA*, pp. 1–8.

Houben, S., Golsteijn, C., Gallacher, S., et al. (2016) *Physikit : Data Engagement Through Physical Ambient Visualizations in the Home*.

iHealth (2015) *Wireless Smart Glucomonitoring system*.

Ikram, A., Anjum, A., Hill, R., et al. (2015) Approaching the Internet of things (IoT): a modelling, analysis and abstraction framework. *Concurrency and Computation: Practice and Experience*, 27 (8): 1966–1984.

Intel (2017) *Evolving the IoT*.

Ishii, H. and Ullmer, B. (1997) Tangible bits: towards seamless interfaces between people, bits, and atoms. *CHI '97 Proceedings of the ACM SIGCHI Conference on Human factors in computing systems*, (March): 3–3.

Islam, S.M.R., Kwak, D., Kabir, H., et al. (2015) The Internet of Things for Health Care : A Comprehensive Survey. *Access, IEEE*, 3: 678–708.

Jara, A.J., Olivieri, A.C., Bocchi, Y., et al. (2014) Semantic Web of Things: an analysis of the application semantics for the IoT moving towards the IoT convergence. *International Journal of Web and Grid Services*, 10 (2/3): 244.

Jara, A.J., Zamora, M.A. and Skarmeta, A.F.G. (2011) An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL). *Personal and Ubiquitous Computing*, 15 (4): 431–440.

Jennings, N. and Moreau, L. (2014) On human-agent collectives. *Communications of the ACM*, pp. 1–14.

Jha, S.S. and Lehnhoff, S. (2014) On Realizing an intelligent Internet of Things using Intelligent Agents. *MATES Doctoral Consortium 2014*, p. 23.

Jia, H., Wu, M., Jung, E., et al. (2012) Balancing human agency and object agency: an end-user interview study of the internet of things. *Proceedings of the 2012 ACM Conference on Ubiquitous Computing - UbiComp ’12*, pp. 1185–1188.

Jie, Y., Pei, J.Y., Jun, L., et al. (2013) Smart home system based on IOT technologies. *Proceedings - 2013 International Conference on Computational and Information Sciences, ICCIS 2013*, pp. 1789–1791.

Johnston, W.M., Hanna, J.R. and Millar, R.J. (2004) Advances in dataflow programming languages. *ACM computing surveys (CSUR)*, 36 (1): 1–34.

Kawsar, F., Kortuem, G. and Altakrouri, B. (2010a) Supporting interaction with the Internet of Things across objects, time and space. *2010 Internet of Things (IOT)*, pp. 1–8.

Kawsar, F., Nakajima, T., Park, J.H., et al. (2010b) Design and implementation of a framework for building distributed smart object systems. *Journal of Supercomputing*, 54 (1): 4–28.

Kelly, K. (2017) *The inevitable: understanding the 12 technological forces that will shape our future*. Penguin.

Kempton, W. (1986) Two theories of home heat control. *Cognitive Science*, 10 (1): 75–90.

Khalil, N., Abid, M.R., Benhaddou, D., et al. (2014) *Wireless Sensors Networks for Internet of Things*., (April): 21–24.

Khan, W.Z., Aalsalem, M.Y., Khan, M.K., et al. (2016) When social objects collaborate: Concepts, processing elements, attacks and challenges. *Computers and Electrical Engineering*, 58: 397–411.

Kirstein, P. and Varakliotis, S. (2014) Handling the Internet of Things with Care. *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*.

Kleiner Perkins Caufield & Byers (2015) *2015 Internet Trends*.

Kolios, P., Panayiotou, C., Ellinas, G., et al. (2016) Data-Driven Event Triggering for IoT Applications. *IEEE Internet of Things Journal*, 3 (6): 1146–1158.

Koreshoff, T.L., Leong, T.W. and Robertson, T. (2013) Approaching a human-centred internet of things. *Proceedings of the 25th Australian Computer-Human Interaction Conference on Augmentation, Application, Innovation, Collaboration - OzCHI '13*, pp. 363–366.

Kortuem, G., Kawsar, F., Fitton, D., et al. (2010) Smart objects as building blocks for the Internet of things. *IEEE Internet Computing*, 14 (1): 44–51.

Kuang, S.L., Hu, L., Zhang, S.T., et al. (2009) Applying TAFEI method to orthopaedic robot system's requirements analysis. *IE and EM 2009 - Proceedings 2009 IEEE 16th International Conference on Industrial Engineering and Engineering Management*, pp. 66–70.

Kuniavsky, M. (2010) *Smart things: ubiquitous computing user experience design*. Elsevier.

LaValle, S., Lesser, E., Shockley, R., et al. (2013) Big data, analytics and the path from insights to value. *MIT Sloan Management Review*, 21.

Lee, E. a. (2008) Cyber Physical Systems: Design Challenges. *2008 11th IEEE International Symposium on Object and Component-Oriented Real-Time Distributed Computing (ISORC)*, pp. 363–369.

Litman, T. (2014) Autonomous vehicle implementation predictions. *Victoria Transport Policy Institute*, 28.

Ma, H.-D. (2011) Internet of things: Objectives and scientific challenges. *Journal of Computer science and Technology*, 26 (6): 919–924.

Mainetti, L., Patrono, L. and Vilei, A. (2011) "Evolution of wireless sensor networks towards the Internet of Things: A survey." In *2011 19th International Conference on Software, Telecommunications and Computer Networks (SoftCOM)*. 2011. pp. 1–6.

Makinen, S.J. (2014) "Internet-of-things disrupting business ecosystems: A case in home automation." In *2014 IEEE International Conference on Industrial Engineering and Engineering Management*. 2014. pp. 1467–1470.

Malafouris, L. (2013) *How Things Shape the Mind*. MIT Press.

Manat, B. (2014) Towards a smarter Internet of Things : semantic visions. *2014 Eighth International Conference on Complex, Intelligent and Software Intensive Systems*, pp. 582–587.

Mano, M.M. (2012) *Digital design*. 12th ed. Pearson Education (ed.). EBSCO Publishing, Inc.

Manyika, J., Chui, M., Bisson, P., et al. (2015) The Internet of Things: Mapping the value beyond the hype. *McKinsey Global Institute*, (June): 144.

Mayer, S., Tschofen, A. and Zurich, E.T.H. (2014) User Interfaces for Smart Things – A Generative Approach with Semantic Interaction Descriptions. *ACM Transactions on Computer-Human Interaction (TOCHI)*, 21 (2): 1–25.

McKinsey & Company (2015) *The internet of Things. Opportunites and Challenges for Semiconductor Companies.*

McTear, M., Callejas, Z. and Griol, D. (2016) *The Conversational Interface: Talking to Smart Devices*. Switzerland: Springer. (thesis).

Mennicken, S., Vermeulen, J. and Huang, E.M. (2014) "From today's augmented houses to tomorrow's smart homes: new directions for home automation research." In *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. New York, New York, USA, 2014. ACM Press. pp. 105–115.

Meretz, S. (1999) Meaning Concepts used in Psychology and Computer Sciences. *Challenges to Theoretical Psychology*, 7: 120.

Michotte, A. (1963) *The perception of causality.*

Miguel, A. and Wright, P. (2014) "CHLOE: A technique for analysing collaborative systems." In *Analysis*. 2014.

Mineraud, J., Mazhelis, O., Su, X., et al. (2016) A gap analysis of Internet-of-Things platforms. *Computer Communications*, 89–90.

Minerva, R., Biru, A. and Rotondi, D. (2015) Towards a definition of the Internet of Things (IoT). *IEEE Internet Initiative*, (1): 1–86.

Minsky, M. (1988) *Society of mind*. Simon and Schuster.

Miorandi, D., Sicari, S., De Pellegrini, F., et al. (2012) Internet of things: Vision, applications and research challenges. *Ad Hoc Networks*, 10 (7): 1497–1516.

Mohammadian, M., Ar, C., Ar, M.N., et al. (2012) Human errors identification in operation of meat grinder using TAFEI technique. *Journal of Occupational Health and Epidemiology*, 1 (3): 171–181.

Montague, R. (1970) Universal grammar. *Theoria*, 36 (3): 373–398.

Morozov, E. (2014) *To save Everything, click here. The folly of Technological solutionism*.

MQTT.org (2017) *MQTT*.

Mr. Coffee (2017) *Mr. Coffee Smart Optimal Brew*.

Nazari Shirehjini, A.A. and Semsar, A. (2017) Human interaction with IoT-based smart environments. *Multimedia Tools and Applications*, 76 (11): 13343–13365.

Nest Labs (2014) *Nest*.

Nest Labs (2017) *Works with Nest*.

Newman, M. (2010) *Networks: an introduction*. Oxford university press.

Nitti, M., Atzori, L. and Cvijikj, I.P. (2014) Friendship selection in the Social Internet of Things: challenges and possible strategies. *IEEE Internet of Things Journal*, 4662 (c): 1–1.

Nitti, M., Pilloni, V., Colistra, G., et al. (2016) The Virtual Object as a Major Element of the Internet of Things: A Survey. *IEEE Communications Surveys and Tutorials*, 18 (2): 1228–1240.

Norman, D. (1983) Design rules based on analyses of human error. *Communications of the ACM*, 26 (4): 254–258.

Norman, D. (1993a) Things that make us smart. 1993. *Addison-Wesley*, pp. 43–76.

Norman, D. a (2007) The Design of Future Things. *Human Factors and Ergonomics in Manufacturing*, 18: 232.

Norman, D.A. (1993b) *Things That Make Us Smart. Defending Human Atributes in the Age of the Smart Machine*. Perseus Books.

Norman, D.A. (2002) *The design of everyday things*. Basic books.

Norman, D.A. (2014) "Some observations on mental models." In *Mental models*. Psychology Press. pp. 15–22.

Nunes, D., Zhang, P. and Silva, J. (2015) A survey on Human-in-the-Loop applications towards an Internet of All. *IEEE Communications Surveys & Tutorials*, 17 (X): 1–1.

O'Leary, N. and Conway-Jones, D. (2017) *Node red-a visual tool for wiring the internet of things*.

Olfati-Saber, R., Fax, J.A. and Murray, R.M. (2007) Consensus and Cooperation in Networked Multi-Agent Systems. *Proceedings of the IEEE*, 95 (1): 215–233.

OnyxBeacon (2015) *OnyxBeacon iBeacon™ hardware for micro location and context.*

iBeacon^{TM} CMS for retailers.

Ortiz, A., Ali, D., Park, S., et al. (2014) The Cluster Between Internet of Things and Social Networks: Review and Research Challenges. *ieeexplore.ieee.org*, 1 (3): 206–215.

Osterwalder, A. and Pigneur, Y. (2010) *Business model generation: a handbook for visionaries, game changers, and challengers*. John Wiley & Sons.

Parks Associates (n.d.) *Parks Associates: Purchase Intentions for Smart Home Devices Increased by 66% Year Over Year*.

Peña-López, I. (2005) ITU Internet Reports 2005: The internet of things. *Geneva: International Telecommunication Union (ITU)*.

Perera, C., Zaslavsky, A., Christen, P., et al. (2014) Context aware computing for the internet of things: A survey. *IEEE Communications Surveys and Tutorials*, 16 (1): 414–454.

Philips (2014) *Hue, Professional Wireless LED Lighting | Philips Lighting*.

Pirolli, P. and Card, S. (2005) "The sensemaking process and leverage points for analyst technology as identified through cognitive task analysis." In *Proceedings of international conference on intelligence analysis*. November 2005.

Pocock, S., Wright, P.C., Harrison, M.D., et al. (2001) "THEA: A Technique for Human Error Assessment Early in Design." In *Interact*. 2001. pp. 247–254.

Preece, A., Webberley, W. and Braines, D. (2015) "Conversational sensemaking." In Broome, B.D., Hanratty, T.P., Hall, D.L., et al. (eds.). *SPIE Sensing Technology+ Applications*. 15 May 2015. p. 94990I.

Pschetz, L., Tallyn, E., Gianni, R., et al. (2017) "Bitbarista." In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI '17*. New York, New York, USA, 2017. ACM Press. pp. 2964–2975.

Rajkumar, R., Lee, I., Sha, L., et al. (2010) “Cyber-physical systems: the next computing revolution.” In *Design Automation Conference (DAC), 2010 47th ACM/IEEE*. 2010. IEEE. pp. 731–736.

Razzaque, M.A., Milojevic-Jevric, M., Palade, A., et al. (2016) Middleware for internet of things: A survey. *IEEE Internet of Things Journal*, 3 (1): 70–95.

Regalado, A. (2014) How the Internet of Things Will Change Business | MIT Technology Review. *MIT Technology Review*.

Revell, K.M.A. and Stanton, N.A. (2017) Mental model interface design: putting users in control of home heating. *Building Research & Information*, 46 (3): 251–271.

Rode, J.A., Toye, E.F. and Blackwell, A.F. (2004) The fuzzy felt ethnography-understanding the programming patterns of domestic appliances. *Personal and Ubiquitous Computing*, 8 (3–4): 161–176.

Roschellel, J. and Teasley, S.D. (1995) The Construction of Shared Knowledge in Collaborative Problem Solving. *Computer supported collaborative learning*.

Rose, K., Eldridge, S. and Lyman, C. (2015) The internet of things: an overview. *Internet Society*, (October): 53.

Ross, S.A. (1973) *The Economic Theory of Agency: The Principal’s Problem*., 63 (2): 134–139.

Rubens, N. (2014) *Turing Test for the Internet of Things*., (figure 2): 1–4.

Russell, S. and Paradiso, J. (2014) Hypermedia APIs for Sensor Data: A pragmatic approach to the Web of Things. *Proceedings of the 11th International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services*.

Sabou, M., Wroe, C., Goble, C., et al. (2005) *Learning domain ontologies for semantic* *web service descriptions*., 3: 340–365.

Sarma, S., Brock, D. and Ashton, K. (2000) The Networked Physical World. *Auto-ID Center White Paper MIT- …*, pp. 1–16.

Satyanarayanan, M. (2001) Pervasive computing: Vision and challenges. *IEEE Personal Communications*, 8 (4): 10–17.

Satyanarayanan, M. (2014) "Cloudlets: Bringing the Cloud Down to the Internet of Things." In *CSSWearable/IoT Ecosystems Workshop. MobiQuitous 2014.* 2014.

Schilit, B., Adams, N. and Want, R. (1994) Context-aware computing applications. *1994 First Workshop on Mobile Computing Systems and Applications*, pp. 85–90.

Schirner, G., Erdgogmus, D., Chowdhury, K., et al. (2013) The Future of Human- in-the-Loop Cyber-Physical Systems. *ieeexplore.ieee.org*.

Schmitt, F., Cassens, J., Kindsmüller, M.C., et al. (2011) "Mental Models of Ambient Systems: A Modular Research Framework." In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. pp. 278–291.

Schroeder, G.N., Steinmetz, C., Pereira, C.E., et al. (2016) Digital Twin Data Modeling with AutomationML and a Communication Methodology for Data Exchange. *IFAC-PapersOnLine*, 49 (30): 12–17.

Scott, J. (2012) *Social network analysis*. Sage.

Scott, J., Bernheim Brush, A.J., Krumm, J., et al. (2011) PreHeat: controlling home heating using occupancy prediction. *Proceedings of the 13th International Conference on Ubiquitous Computing*, pp. 281–290.

Sezer, O.B., Dogdu, E. and Ozbayoglu, A.M. (2018) *Context-Aware Computing ,* *Learning , and Big Data in Internet of Things : A Survey*., 5 (1): 1–27.

Sheth, A. (2010) Computing for human experience: Semantics-empowered sensors, services, and social computing on the ubiquitous web. *Internet Computing, IEEE*, 410 (2): 273–8.

Sheth, A. (2016a) Internet of things to smart iot through semantic, cognitive, and perceptual computing. *IEEE Intelligent Systems*, 31 (2): 108–112.

Sheth, A. (2016b) Internet of Things to Smart IoT Through Semantic, Cognitive, and Perceptual Computing. *IEEE Intelligent Systems*, 31 (2): 108–112.

Shi, W., Cao, J., Zhang, Q., et al. (2016) Edge Computing: Vision and Challenges. *IEEE Internet of Things Journal*, 3 (5): 637–646.

Shin, D. (2014) A socio-technical framework for Internet-of-Things design: A human-centered design for the Internet of Things. *Telematics and Informatics*, 31 (4): 519–531.

Singh, D., Tripathi, G. and Jara, A.J. (2014) "A survey of Internet-of-Things: Future vision, architecture, challenges and services." In *2014 IEEE World Forum on Internet of Things, WF-IoT 2014*. March 2014. Ieee. pp. 287–292.

Smith, H. and Konsynski, B. (2003) Developments in practice x: Radio frequency identification (RFID) - an internet for physical objects. *Cais*, 12: 301–311.

Sparks, P. (2017) Arm Holdings Financial Results 2017. *ARM Holdings*.

Speed, C. (2011) An internet of things that do not exist. *interactions*, pp. 18–21.

Stankovic, J. (2014) Research Directions for the Internet of Things. *Internet of Things Journal, IEEE*, 1 (1): 3–9.

Stankovic, J.A., Lee, I. and Mok, A. (2005) Opportunities and Obligations for Physical Computing systems. *Computer*, (November): 23–31.

Stanton, N. and Baber, C. (1996) A systems approach to human error identification. *Safety*

Science, 22 (1–3): 215–228.

Stanton, N.A. (2006) Hierarchical task analysis: Developments, applications, and extensions. *Applied Ergonomics*, 37 (1): 55–79.

van Steen, M. and Tanenbaum, A.S. (2016) A brief introduction to distributed systems. *Computing*, 98 (10): 967–1009.

Sterling, B. (2005) *Shaping Things*. Cambridge, MA: MIT Press.

Sterling, B. (2014) *The Epic Struggle of the Internet of Things*. Strelka Press.

Swan, M. (2012) Sensor Mania! The Internet of Things, Wearable Computing, Objective Metrics, and the Quantified Self 2.0. *Journal of Sensor and Actuator Networks*, 1 (3): 217–253.

Takayama, L., Pantofaru, C., Robson, D., et al. (2012) Making Technology Homey : Finding Sources of Satisfaction and Meaning in Home Automation. *Ubicomp*, pp. 511–520.

Tanenbaum, A.S. (2002) *Computer Networks (4th Edition)*.

Thoma, M., Braun, T., Magerkurth, C., et al. (2014) "Managing things and services with semantics: A survey." In *IEEE/IFIP NOMS 2014 - IEEE/IFIP Network Operations and Management Symposium: Management in a Software Defined World*. May 2014. IEEE. pp. 1–5.

Tracey, D. and Sreenan, C. (2013) A holistic architecture for the Internet of Things, sensing services and big data. *Proceedings - 13th IEEE/ACM International Symposium on Cluster, Cloud, and Grid Computing, CCGrid 2013*, pp. 546–553.

Turing, A.M. (1950) *Computing Machinery and Intelligence*.

Umapathy, K. (2010) Requirements to support Collaborative Sensemaking Requirements to support Collaborative Sensemaking. *CSCW CIS Workshop (Vol. 10)*.

Ur, B., Jung, J. and Schechter, S. (2013) "The current state of access control for smart devices in homes." In *Workshop on Home Usable Privacy and Security (HUPS)*. 2013.

Wagner, F., Wagner, T., Wolstenholme, P., et al. (2006) *Modeling Software with Finite State Machines A Practical Approach*. CRC Press.

Walter, W. (1950) An Imitation of Life. *Scientific American*, 182: 42–45.

Wang, J. (2013) Zigbee light link and its applicationss. *IEEE Wireless Communications*, 20 (4): 6–7.

Wang, W., De, S., Toenjes, R., et al. (2012) "A Comprehensive Ontology for Knowledge Representation in the Internet of Things." In *2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications*. June 2012. IEEE. pp. 1793–1798.

Weiser, M. (1991) The Computer for the 21st Century. *Scientific American*. 265 (3) pp. 94–104.

Welbourne, E., Battle, L., Cole, G., et al. (2009) Building the Internet of Things Using RFID: The RFID Ecosystem Experience. *IEEE Internet Computing*, 13 (3): 48–55.

Wilson, C., Hargreaves, T. and Hauxwell-Baldwin, R. (2015) Smart homes and their users: a systematic analysis and key challenges. *Personal and Ubiquitous Computing*, 19 (2): 463–476.

Withings (2017) *Withings*.

Wolff, A. (2016) *Designing with Data: A Designerly Approach to Data and Data Analytics*., pp. 53–56.

Wooldridge, M. (2009) *An introduction to multiagent systems*. John Wiley & Sons.

Wu, Q., Ding, G., Xu, Y., et al. (2014) Cognitive Internet of Things: A New Paradigm beyond Connection. *IEEE Internet of Things Journal*, PP (99): 1–1.

Xu, M.X.M., Ma, L.M.L., Xia, F.X.F., et al. (2010) Design and Implementation of a Wireless Sensor Network for Smart Homes. *Ubiquitous Intelligence & Computing and*

7th International Conference on Autonomic & Trusted Computing (UIC/ATC), 2010 7th International Conference on, 2 (2): 1–5.

Yang, R. and Newman, M.W. (2013) Learning from a Learning Thermostat : Lessons for Intelligent Systems for the Home. *Proceedings of the 2013 ACM international joint conference on Pervasive and ubiquitous computing (UbiComp 2013)*, pp. 93–102.

Yarosh, L. and Zave, P. (2017) “Locked or Not?” In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems - CHI ’17*. New York, New York, USA, 2017. ACM Press. pp. 2993–2997.

Yue, H., Guo, L., Li, R., et al. (2012) *DataClouds: Enabling Community-based Data-Centric Services over Internet of Things*., 1 (5): 472–482.

Zanella, A., Bui, N., Castellani, A., et al. (2014) Internet of Things for Smart Cities. *IEEE Internet of Things Journal*, 1 (1): 22–32.

Zhao, F., Sun, Z. and Jin, H. (2015) Topic-centric and semantic-aware retrieval system for internet of things. *Information Fusion*, 23: 33–42.

Zhu, F., Mutka, M.W. and Ni, L.M. (2005) Service Discovery in Pervasive Computing Environments. *Pervasive Computing*, pp. 81–90.