IMAGE-BASED OCCUPANCY SENSING AND PRIVACY IMPLICATIONS

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ABSTRACT

IMAGE-BASED OCCUPANCY SENSING AND PRIVACY IMPLICATIONS

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As the use of data collection in the built environment increased, data pertaining to building occupancy has gained considerable importance in realms such as energy optimization and spatial usage analytics. However, many data collection approaches infringe on individuals' rights to privacy, and subsequently their comfort.

This thesis aims to address the tension between the proliferation of smart building technologies and individual privacy and autonomy, specifically focusing on image-based sensing. It explores the possibilities and consequences of data harvesting and occupancy sensing through image-based sensing, gathered by sources such as camera footage. It addresses the definitions and scope of 'smart' buildings, focuses on occupancy sensing in non-residential spaces, followed by research into image-based occupancy sensing and finally delving into privacy and its relevance in today's smart buildings.

The research is comprised of a field experiment gathering footage from two cameras, one with a privacy-preserving angle, along with a survey aimed towards individuals in the construction and adjacent fields, to find which camera angle they are more comfortable with in the non-residential areas they occupy.

Keywords: Smart Buildings, Sensors, Image-Based Sensing, Data Privacy

ÖZ

GÖRÜNTÜ TABANLI KULLANIM ALGILAMA VE GİZLİLİK UYGULAMALARI

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Yapılı çevrede kullanım verilerinin toplanması arttıkça, özellikle bina doluluğu ile ilgili analitikler büyük önem taşımaktadır. Bununla birlikte, birçok veri toplama yaklaşımı, bireylerin mahremiyet haklarını ve dolayısıyla rahatlıklarını ihlal etmektedir.

Bu tez, özellikle görüntü tabanlı algılamaya odaklanarak, akıllı bina teknolojilerinin yaygınlaşması ile bireysel mahremiyet ve özerklik arasındaki gerilimi ele almayı amaçlamaktadır. Kamera görüntüleri gibi kaynaklar tarafından toplanan görüntü tabanlı algılama yoluyla veri toplama ve doluluk algılama olasılıklarını ve sonuçlarını araştırır. 'Akıllı' binaların tanımlarını ve kapsamını ele alıyor, konut dışı alanlarda doluluk algılamaya odaklanıyor, ardından görüntü tabanlı doluluk algılama araştırmaları yapıyor ve son olarak mahremiyet ve günümüzün akıllı binalarındaki önemine değiniyor.

Araştırma, biri mahremiyeti koruyan açıya sahip iki kameradan alınan görüntülerin bir araya getirildiği bir saha deneyi ile inşaat ve bitişik alanlardaki bireylere, hangi kamera açısıyla daha rahat olduklarını bulmaya yönelik bir anketten oluşmaktadır.

Anahtar Kelimeler: Akıllı Binalar, Sensörler, Görüntü Tabanlı Algılama, Veri Gizliliği

To my family.

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Designing this research would not have been possible without the consistent help and encouragement of my wife, Shiza, who was always someone I could count on to help zone in on the specific issues I needed to tackle and was a crucial presence with a natural acumen and talent as a researcher in her own right.

I also owe the completion of this study to my family, especially my mother, whose love and support gave me the strength to continue despite moving towards an uncertain future while experiencing a pandemic in a foreign country.

Undertaking this research has been a wonderful experience due to the vision and guidance of my advisor, Assist. Prof. Dr. Mehmet Koray Pekeriçli. I have been lucky to have such a source of encouragement and inspiration, from the very beginning of my graduate program. I can only hope to receive this level of guidance in my future.

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CHAPTER 1

INTRODUCTION

This thesis investigates the use of image-based occupant sensing in smart buildings, delving into the underlying tension between the feasibility of occupant sensing technologies and the inherent privacy risks which may act as an obstacle to implementation. This introductory chapter details the background and motivations behind the study, lays out the aims and objectives of the research and culminates in an overview of the subsequent material.

1.1 Background

> "The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it."
>
> \- Mark Weiser (1991)

Mark Weiser began his *Scientific American* article in 1991, titled "The Computer for the 21st Century" with the above statement. He went on to describe computers that would be embedded inside everyday objects, imbuing them with an intelligence they do not currently possess. This would signify a shift from computers that must be interacted with, to computers that would almost be invisible, taking actions on people's behalf without the need for deliberate input, embedded in the devices we use and the spaces we inhabit. This concept, which has the goal of non-intrusive availability and utility of computers in the physical world, is referred to as 'ubiquitous computing', a term coined by Mark Weiser himself (1993).

We live in an era in which information holds tremendous value, surrounded by devices that communicate ceaselessly with each other. Our movements, activities, and preferences, be they physical or digital, are recorded and analyzed to better service our needs and harvest information about our patterns. This is also an essential component of smart buildings, which adapt themselves automatically to the needs of their inhabitants through the use of centralized systems that detect changes in the environment and accordingly control building systems (Sinopoli, 2009).

Smart buildings are made possible by technological augmentations to extract information from the built environment to minimize energy consumption and emissions as well as improve the productivity and wellbeing of occupants. These can use a technological framework called the Internet of Things (IoT), to communicate with one another (Moreno *et al*, 2014).

A report by the Oxford Future of Real Estate Initiative refers to this digital transformation of the property industry as PropTech, stating that this has been in progress since the 1980s, and of which we are now living in the third wave. The report claims that due to the unique issues of our time, "PropTech 3.0 will probably be driven by the global pressures of climate change and rapid urbanization and enabled through the maturing of exogenous technologies including the Internet of Things, Machine Learning and Artificial Intelligence and Blockchain." Since real estate and construction industries are to blame for around 40% of the greenhouse gas (GHG) emissions being released into the atmosphere, PropTech will be an important factor in the mitigation of this crisis (Baum, 2017).

However, any discussion regarding data collection must also consider inherent privacy risks. This is especially true when massive amounts of data are being collected from the spaces we inhabit and must also juxtaposed on the larger conversations taking place today regarding the increasing amount of data collection by corporations or governments, which can border on surveillance in extreme cases.

Image-based sensors identify objects and people by taking image data inputs and detecting whether people are present in the image or video. Data concerning biometric information of individuals is particularly sensitive, for example, names, fingerprint information, and most commonly, photos and videos capturing identifying visual features. In this regard, the issue of ethics is therefore paramount, especially on the topic of image-based sensors.

1.2 Research Objectives

This study aims to explore the potential of image-based occupancy sensing, with the possible privacy-related risks, user perceptions associated with the use of cameras inside buildings, and ways to overcome the obstacles that may appear for these reasons.

The literature review reveals the context behind smart buildings and occupant data collection, the benefits, and risks of various types of occupancy sensors, and ethical concerns associated with the use of occupancy sensing technologies such as image-based occupant counting in buildings.

1.3 Research Questions

The research questions of this study are as follows:

- To determine ways that image-based occupancy sensing techniques can protect privacy of recorded individuals by design.
- To investigate preferences regarding occupancy sensing with cameras.

1.4 Thesis Structure

This thesis is composed of six chapters.

The first chapter is comprised of the introduction, which summarizes the historical background and modern context, details the objectives, lists the research questions, and ends with a structure of the thesis.

The second chapter contains the literature review, which is composed of three major topics:

- Smart buildings and the relevant context, definitions, components, and stakeholder entities,
- Occupancy sensing systems used in smart buildings and a comparison of different types, including an in-depth analysis of image-based sensing, the topic of this thesis,
- Possible risks and regulations relating to data collection,
- Relevance of privacy in smart buildings

The third chapter describes the research material and methodology. This is split into two parts, with material and methodology presented separately for an image-based people counting technique comparison, and a questionnaire.

The fourth chapter contains the results of the research.

The fifth chapter contains discussion of the results.

Finally, the sixth chapter concludes the thesis, summarizing the research as well as recommending future pathways of research.

CHAPTER 2

LITERATURE REVIEW

In this chapter, a review of literature surveyed is presented, starting with a general overview of smart buildings, including their history and context amidst technological advances, and environmental benefits in the wake of Global Climate Change. Various infrastructural components of smart buildings are detailed and explained, as well as applications of smart building technologies.

Following smart buildings, a comparison of various occupancy sensing technologiesis provided. The focus is then narrowed to image-based occupancy sensing technologies, explaining their benefits and implicit risks. The most relevant of these risks is possible infringement of user privacy.

In line with this topic, the next section examines the contextual implications of data collection and surveillance by public or private entities on unaware or non-consenting users.

Finally, the last section delves into the importance of privacy frameworks in the context of the inherent needs as well as perceptions of users relating to privacy of their data and identification.

2.1 Smart Buildings

Today there is an increasing awareness of issues facing the planet, and its vulnerability to climate-related disasters. But it was only in the past century that the effects of building construction and operation on the planet have started being considered, with the theoretical framework for sustainable development first discussed in 1972, at the Club of Rome (Roaf *et al.*, 2009). According to Pérez-Lombard *et al.*, (2008) the rise in global energy use has heavy environmental impacts such as depleting ozone layer, global warming and climate change. The writers went on to claim that in the EU and USA, energy usage in buildings was greater than transport and industry sectors, with heating, ventilation and air-conditioning (HVAC) systems alone comprising almost half of total building energy consumption due to the increased need for thermal comfort. In the effort to mitigate climate change, modern tools and frameworks can be used to enhance the efficiency of buildings, and systems in the built environments, making buildings 'smarter' and reducing their impact on our planet.

Currently, advances in technology rapidly change the way human beings interact with their built environment and amongst themselves. In addition to various passive energy-saving strategies used by architects and engineers, it is now possible to use technological augmentations to extract information from the built environment. Such information can be used to minimize energy consumption and emissions as well as improve the productivity and wellbeing of occupants. Rashidi *et al.* (2011) described this as a smart environment, which was in their words, "an intelligent agent that perceives the state of the resident and the physical surroundings using sensors and acts on the environment using controllers in such a way that the specified performance measured is optimized."

Smart building technologies applied in homes, workplace, public institutions or other typologies are now steadily growing in popularity. It was estimated that smart home technologies have spread to 7.5% of households globally, with expected revenues of $44.2 billion in 2018 (Shin *et al.*, 2018).

This sub-chapter will hereafter examine the phenomena of smart buildings, and the context leading up to it.

2.1.1 The Need for Smarter Buildings

The motivations behind development and usage of smart buildings can be categorized as energy efficiency, associated financial benefits, and convenience.

The importance of energy efficiency is especially relevant when viewed in the context of the current developments in the Earth's climate. Due to the mass of climatic and statistical scientific data we currently have for perusal, it is impossible to refute the effect of human activity on Global Climate Change. Historical data indicates alarming trends in climatic statistics, and yet, for too long actions taken to combat climate change have remained insufficient compared to the scale of disaster predicted. Crowley (2000) stated that the rise in temperatures over the last century has been unprecedented in the past millennium, when considering natural patterns. In fact, only 25% of climate warming can be attributed to the natural variability of rising temperatures from 1000 to 1850 A.D. Much of the cause lies with the increases in greenhouse gases (GHG) in the past century, for instance, carbon dioxide (CO_2), methane, chlorofluorocarbons, and nitrous oxides. As more scientific predictions take shape, global warming proves to be a very real threat. According to Stern (2007), a rise in global temperatures by just 1^0 Celsius can cause sweeping damages to communities across the globe, while a 3^0 rise corresponds to critical dangers to wildlife, as well as drought and famine-sensitive countries. Further rises in temperature would prove calamitous, in terms of rising sea levels, disappearing glaciers, and particularly to developing countries in Africa and coastal countries susceptible to flooding. Table 2.1 illustrates these predictions in more detail.

The United Nation (UN) in 2015 marked climate action as number thirteen amongst its Sustainable Development Goals, marking it as an issue deserving of a global response. Accordingly, the UN formulated the following targets: the strengthening of the capacity for resilience to hazards caused by climate change, the imbibing of actionable measures in national policy, and increasing awareness by improving education on climate change, with regards to adaptation, early warning and prevention (United Nations, 2020).

Table 2.1: Climate change effects on development (Stern, 2007)

Temp rise (°C)	Water	Food	Health	Land	Environment
1°C	Small glaciers in the Andes disappear completely, threatening water supplies for 50 million people	Modest increases in cereal yields in temperate regions	At least 300,000 people each year die from climate-related diseases (predominantly diarrhoea, malaria, and malnutrition) Reduction in winter mortality in higher latitudes (Northern Europe, USA)	Permafrost thawing damages buildings and roads in parts of Canada and Russia	At least 10% of land species facing extinction (according to one estimate) 80% bleaching of coral reefs, including Great Barrier Reef
2°C	Potentially 20 - 30% decrease in water availability in some vulnerable regions, e.g. Southern Africa and Mediterranean	Sharp declines in crop yield in tropical regions (5 - 10% in Africa)	40 – 60 million more people exposed to malaria in Africa	Up to 10 million more people affected by coastal flooding each year	15 – 40% of species facing extinction (according to one estimate) High risk of extinction of Arctic species, including polar bear and caribou
3°C	In Southern Europe, serious droughts occur once every 10 years 1 - 4 billion more people suffer water shortages, while 1 – 5 billion gain water, which may increase flood risk	150 - 550 additional millions at risk of hunger (if carbon fertilisation weak) Agricultural yields in higher latitudes likely to peak	1 – 3 million more people die from malnutrition (if carbon fertilisation weak)	1 – 170 million more people affected by coastal flooding each year	20 – 50% of species facing extinction (according to one estimate), including 25 – 60% mammals, 30 – 40% birds and 15 – 70% butterflies in South Africa Collapse of Amazon rainforest (according to some models)
4°C	Potentially 30 – 50% decrease in water availability in Southern Africa and Mediterranean	Agricultural yields decline by 15 – 35% in Africa, and entire regions out of production (e.g. parts of Australia)	Up to 80 million more people exposed to malaria in Africa	7 – 300 million more people affected by coastal flooding each year	Loss of around half Arctic tundra Around half of all the world's nature reserves cannot fulfill objectives
5°C	Possible disappearance of large glaciers in Himalayas, affecting one-quarter of China's population and hundreds of millions in India	Continued increase in ocean acidity seriously disrupting marine ecosystems and possibly fish stocks		Sea level rise threatens small islands, low-lying coastal areas (Florida) and major world cities such as New York, London, and Tokyo	

According to Roaf *et al.*, (2009), while the possibility of climate change was first raised in the 1960s, the issue came to the public forum in Rome in 1972 at the first general meeting of the Club of Rome. By the mid-1980s, predictions made by scientists began to approximate recorded temperatures, confirming the advent of the crisis. At the time of writing, eleven of the past twelve years had been the hottest on record. Temperatures in the summers of 2003, when 35,000 deaths from heat stroke were counted in Europe alone and 2005 had proven higher than scientists' worst predictions.

The construction processes of buildings are a major cause of GHG emissions, due to the energy-intensive tasks that comprise the production, transport and subsequent installation of architectural and structural materials(Yan *et al.*, 2010). In the European Union alone, the construction, lifecycle and dismantling of buildings consumes around 50% of the total energy load, and the CO_2 emitted makes up almost 50% of the total emissions released into the environment. Energy consumptions in buildings in 2010 comprised "32% of total global final energy use (equal to 117 Exajoules), 19% of energy-related GHG emissions, and 33% of black carbon emissions" (Berardi, 2015). These figures are purported to increase rapidly in residential buildings especially as global population increases, in the countries with the largest populations, as shown by Figure 2.1.

This presents an urgent need to counteract the predicted trends of increase in energy use. In order to decrease emissions and optimize efficiency with regards to energy used, the construction and design sector can utilize the integration of technological augmentations into the built environment.

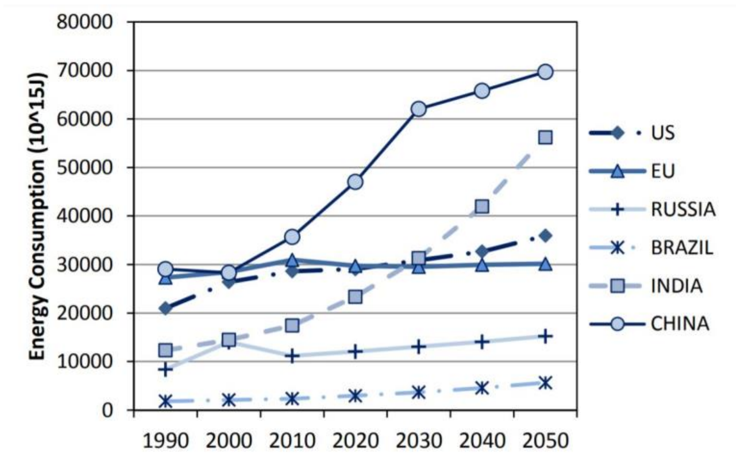


Figure 2.1: Projections of energy use in residential buildings (Berardi, 2015)

The effectiveness of integrating technology in order to optimize efficiency in building energy usage has been a growing source of interest in the construction industry. According to Moreno *et al.* (2014), buildings integrated with technology could prove to show quick returns, and pay for themselves. Out of the 40% of total energy consumption that buildings comprise in Europe, 8% could be reduced using technological augmentations, even if only thermal appliances were taken into consideration. In another study in South Australia, the use of infrared occupancy sensors resulted in 40% savings of electricity, with a mere 2 years of payback time (Garg & Bansal, 2000). Weng and Agarwal (2012) reported that the total cost of smart building technology installation in one building was estimated to be equal to the total yearly energy cost savings, at $0.13/kWh, displaying a payback time of one year.

The climate crisis was not the only driver for smart building development; Fletcher *et al.* (2018) reported that the associated cost reduction in energy and operation appeals to adopters of building automation technology, since cost reductions are demonstrated by straightforward calculations for return on investment in smart building technologies.

King and Perry (2017) described several individual smart technologies that can be leveraged for energy savings in the operations of HVAC systems, lighting, plug loads, and window shading systems, as shown in Table 2.2.

Table 2.2: Smart technology energy savings (King & Perry, 2017)

System	Technology	Energy savings
HVAC	Variable frequency drive	15–50% of pump or motor energy
HVAC	Smart thermostat	5–10% HVAC
Plug load	Smart plug	50–60%
Plug load	Advanced power strip	25–50%
Lighting	Advanced lighting controls	45%
Lighting	Web-based lighting mgmt system	20–30% above controls savings
Window shading	Automated shade system	21–38%
Window shading	Switchable film	32–43%
Window shading	Smart glass	20–30%

Additionally, improved user experience is becoming a key focus, with businesses recognizing links between human capital and workspace quality. Buildings that prioritize user experience provide occupants with greater control over their environment. Figure 2.2 displays some user-centric capabilities of smart buildings.

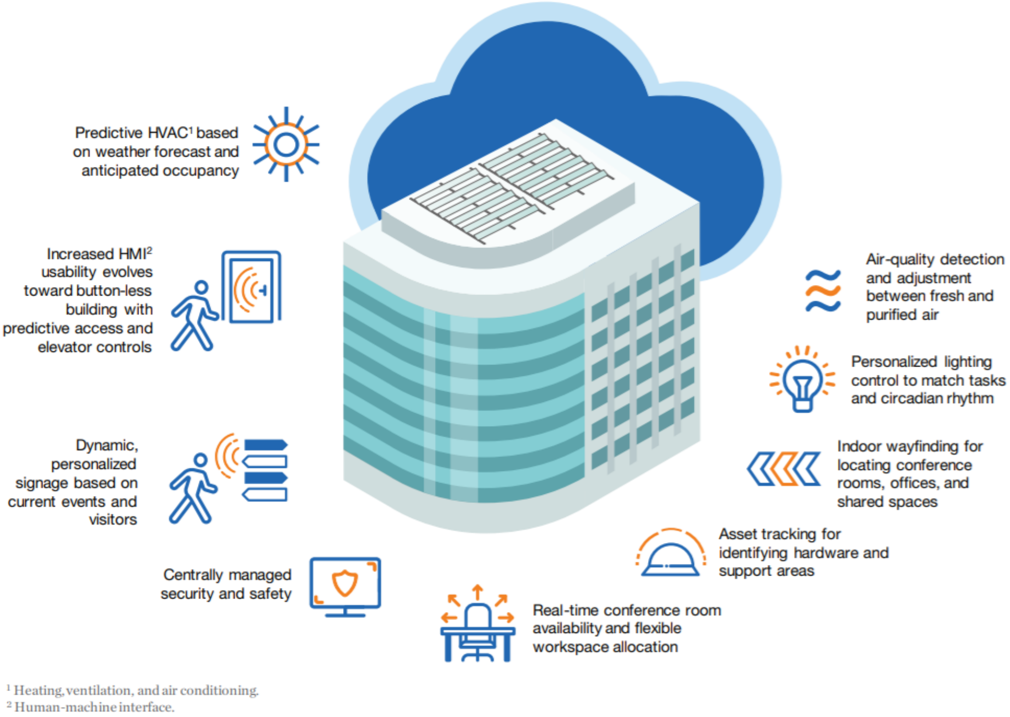


Figure 2.2: User-centric capabilities in smart buildings (Fletcher *et al.*, 2018)

2.1.2 Historical Development and Definitions of Smart Buildings

In 1984, an article in the New York Times described real estate developers as creating "a new generation of buildings that almost think for themselves called intelligent buildings". However, this referred more to automation, than to intelligence (Qolomany *et al.*, 2019). The concept of a smart building was first defined as the implementation of complex, centralized electronic systems for the control of building systems and communication frameworks for voice and data. Figure 2.3 illustrates the evolving features that followed subsequent iterations of the definition (Fântână & Oae, 2013).

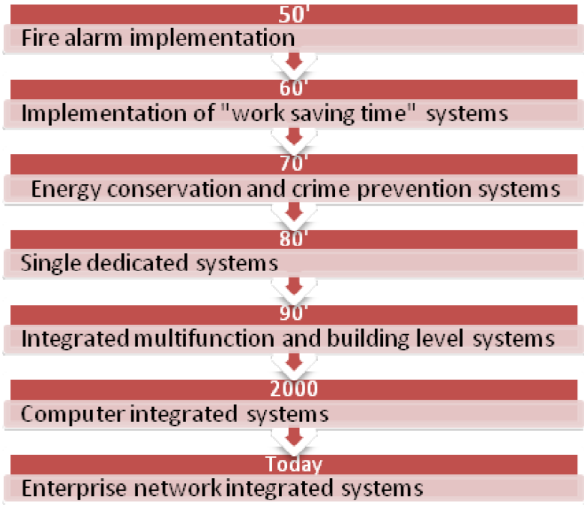


Figure 2.3: Evolving features of smart buildings (Fântână & Oae, 2013)

One concept that is constantly centered is that of the 'smart home'. This idea contained the central aspiration for the environment of buildings to adapt automatically to the needs and conditions to the people within them. However, according to Batov (2015), in current market conditions, the term "smart" is often misunderstood. He quotes the Oxford Dictionary definition as "A home equipped with lighting, heating, and electronic devices that can be controlled remotely by smartphone or computer" and points out a fundamental flaw; these buildings are not inherently smart but are in fact controlled by smart inhabitants. He claimed that in actuality, a better description would be by Mozer (2005), who stated "Instead of being programmed to perform certain actions, the house essentially programs itself by monitoring the environment and sensing actions performed by the inhabitants (*e.g.*, turning lights on and off, adjusting the thermostat), observing the occupancy and behavior patterns of the inhabitants, and learning to predict future states of the house," as opposed to a building that could merely be remotely controlled, or programmed to perform certain actions.

Rogers (2006) stated that the philosophy of ubiquitous computing first mentioned by Weiser (1991) was instrumental in inspiring scientists, governments, academic institutions and corporations to develop new ways that computers can enhance people's lives. Around thirty years after Weiser's article, we live in a world where we're surrounded by networks of interconnected devices communicating ceaselessly with each other. This is often referred to as Internet of Things (IoT). These smart devices imbue 'intelligence' into physical real-world objects, such as appliances, cars, buildings and even entire urban infrastructure systems. These devices are in constant communication with each other, hence the name: while humans communicate over the internet, 'things' communicate over the Internet of Things (Atzori *et al.*, 2010).

As IoT technology advances, it coincides with the development of "intelligent buildings", or "smart buildings" (the two terms used often interchangeably, but essentially refer to the same concept). The use of IoT sensors in the built environment has been especially lucrative, with the global Internet of Things market projected to grow from $381.30 billion in 2021 to $1,854.76 billion in 2028, according to a report by Fortune Business Insights (2021). It is important to note that one transformation that has developed parallel to the growth of the IoT industry, is the pivoting of businesses from product-oriented to data-driven services. In other words, the data collected from these sensors is of great value in every industry, and can be used for development, market research, or insights (Pflaum & Gölzer, 2018).

Sinopoli (2009) cites the driving force for continuing research into this topic as its benefits, such as:

- Financial benefits of integrated systems
- Increased energy efficiency and conservation
- Enhanced functionality of building systems
- Natural evolution of technology permeating our daily lives

The smart building market is accordingly predicted to increase in value from 7.42 billion dollars in 2017 to 31.74 billion dollars in 2022, according to Qolomany *et al.* (2019). In an optimistic forecast by Statista, as shown in Figure 2.4, the market size is predicted to grow to 53.45 billion dollars by 2022. This growth can be said to be the result of government initiatives and rising market trends of technology integrations, namely in the security, safety and building energy efficiency domain (Qolomany *et al.*, 2019).

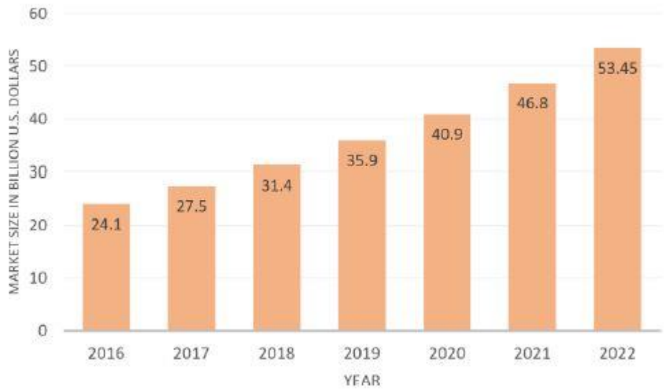


Figure 2.4: Predicted growth of smart buildings in the global market (Qolomany *et al.*, 2019)

2.1.3 Components of Smart Buildings

There have been various definitions of smart buildings over time, and accordingly the components which make up a smart building are not strictly defined. This often depends on the level of integration of various systems, and the services offered.

Batov (2015) categorized the components into hardware, software, and network infrastructure. The hardware level of a smart building essentially functions at both ends of the cycle of information between the physical environment and the SB system. It is composed of the inputs of the system, which can be the sensors, and control interfaces, as well as the outputs, which are the actuators of control devices. These change parameters within the building, such as the temperature, lighting and access (security), among others. The software level is referred to as the various procedures carried out digitally to analyze the data gathered, use it to 'learn' and predict future states of the environment. Batov (2015) emphasized the role of artificial intelligence in this level. The network level is the infrastructure that connects devices with each other and with the software, more akin to a 'nervous system'.

In his book *Smart Building Systems for Architects, Owners, and Builders*, Sinopoli (2009) described components of smart buildings not in terms of associated levels or categories, but in terms of individual systems, and the type of integration network used to connect them. Figure 2.5 shows the various systems listed as connected to a facility management system, interfaced with local or remote consoles.

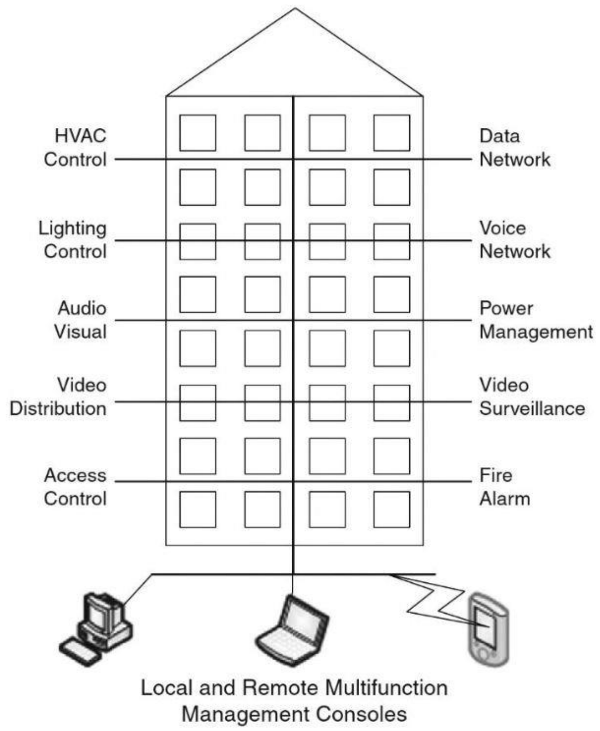


Figure 2.5: Integrated systems in a smart building (Sinopoli, 2009)

Sinopoli's (2009) definition of the 'smartness' of a building hinged on the interconnectivity between systems, which depended on the communication network model levels, as shown in Figure 2.6. This describes how data flows from the administrator or building manager at the top level (application layer), to the electrical cable network (physical layer).

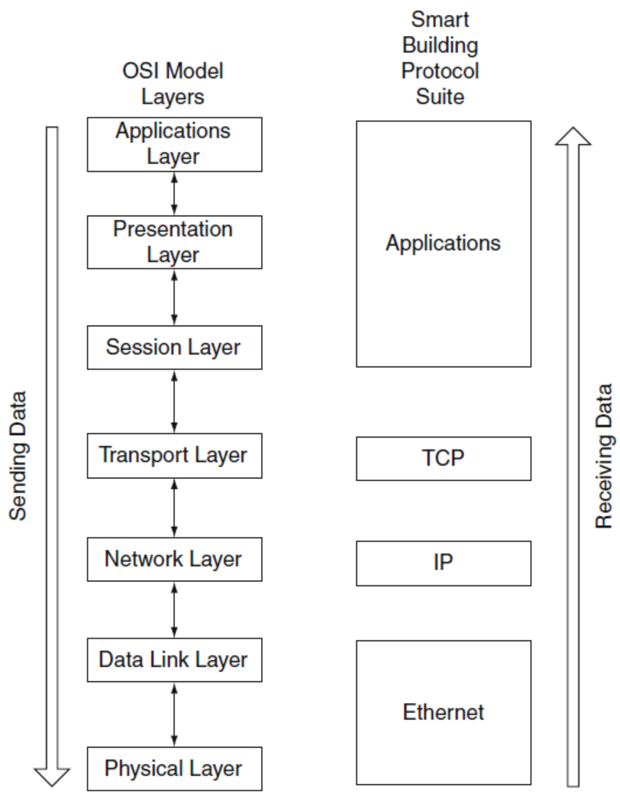


Figure 2.6: Network model layers (Sinopoli, 2009)

Qolomany *et al.* (2019) described smart buildings as compositions of heterogenous devices connected by the Internet of Things model. They proposed a representation showing the various layers of IoT architecture that form the basis for smart buildings. Figure 2.7 illustrates these layers, which are described as follows (from top level to bottom level):

- Application Layer: composed of a framework that has direct access to the functionalities of the smart building for various applications. Also composed of human-machine interfaces such as control panels.

- Processing and Reasoning Layer: processes the extracted data from the middleware before making decisions. Various techniques of data analysis are used to contextualize the data into useful knowledge.

- Context and Semantic Discovery Layer: responsible for managing context and semantic generation, configuration and storing. It is deemed necessary due to the heterogeneity of IoT devices, for which a repository must be consulted to understand the nature, context and quality of data.

- Middleware Layer: integrates heterogenous networks and devices that make up the sensing layer with the software that processes and acts on data collected. Essentially, it converts the different formats of data into a common representation.

- Network Layer: the infrastructure that enables data transmission and acts as a bridge between the sensing layer and the upper layers.

- Sensing Layer: physical sensors that monitor the environment, collect data on occupants, and detect any anomalies such as system damage or natural disasters. Also included are control actuators that adapt the workings of building systems to fulfil the objectives of the smart building, such as energy conservation, disaster management, delivering information to occupants (Qolomany *et al.*, 2019).

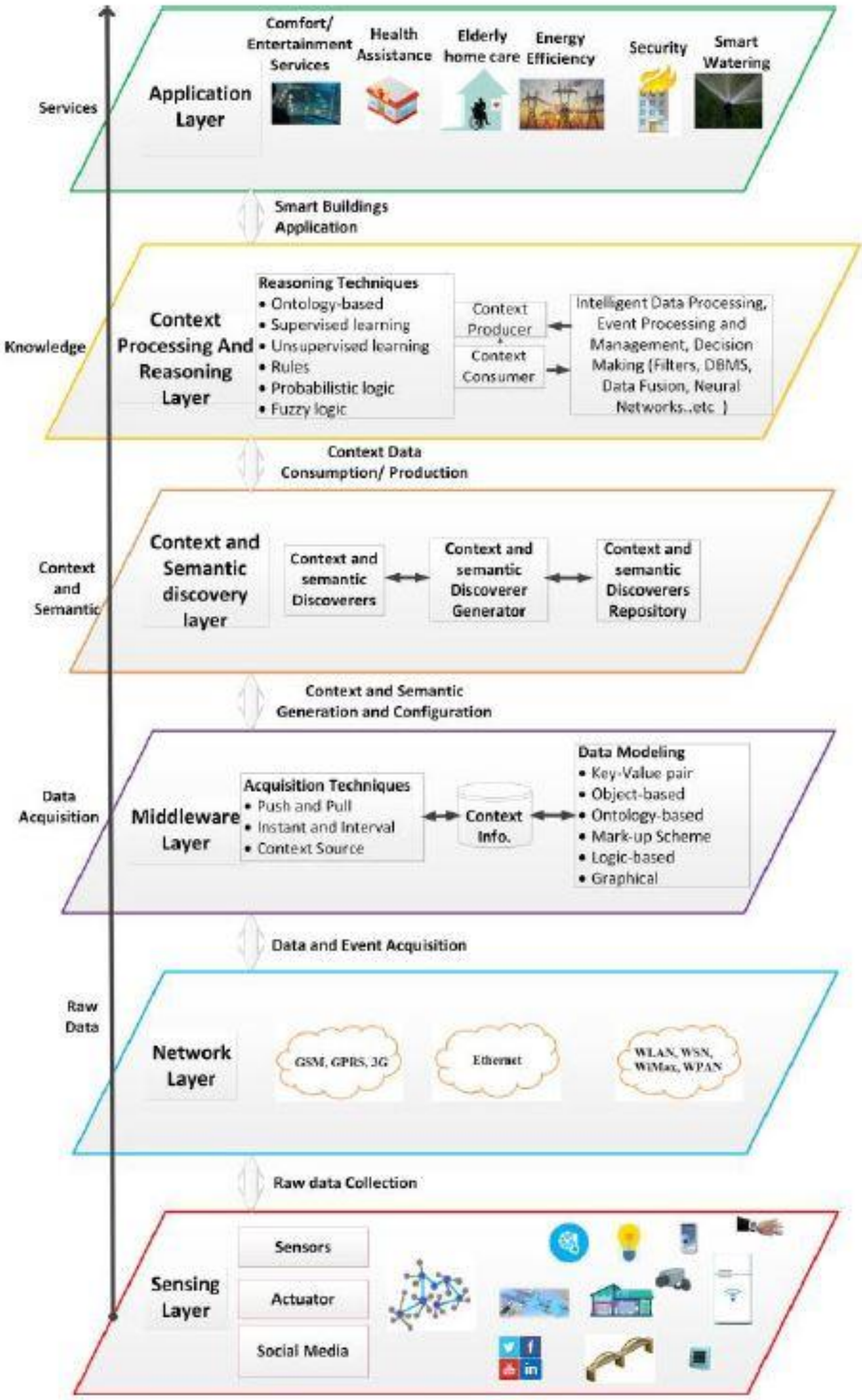


Figure 2.7: Layers of IoT architecture in smart buildings (Qolomany *et al.*, 2019)

As indicated by the varying descriptions presented, the components present in a smart building are not claimed to be standardized by any source. The 'smartness' of a building may not be binary; for instance, on the subject of smart homes, Marikyan *et al.* (2019) identified a spectrum between a 'traditional' home and a 'fully smart' one, stating that homes can be gradually made smarter as components are added.

Sovacool and Furszyfer Del Rio (2020) expanded on this idea, describing middle grounds between the two extremes with levels of smartness, namely basic, isolated, bundled, automated, intuitive, sentient, and finally aggregation, as shown in Figure 2.8.

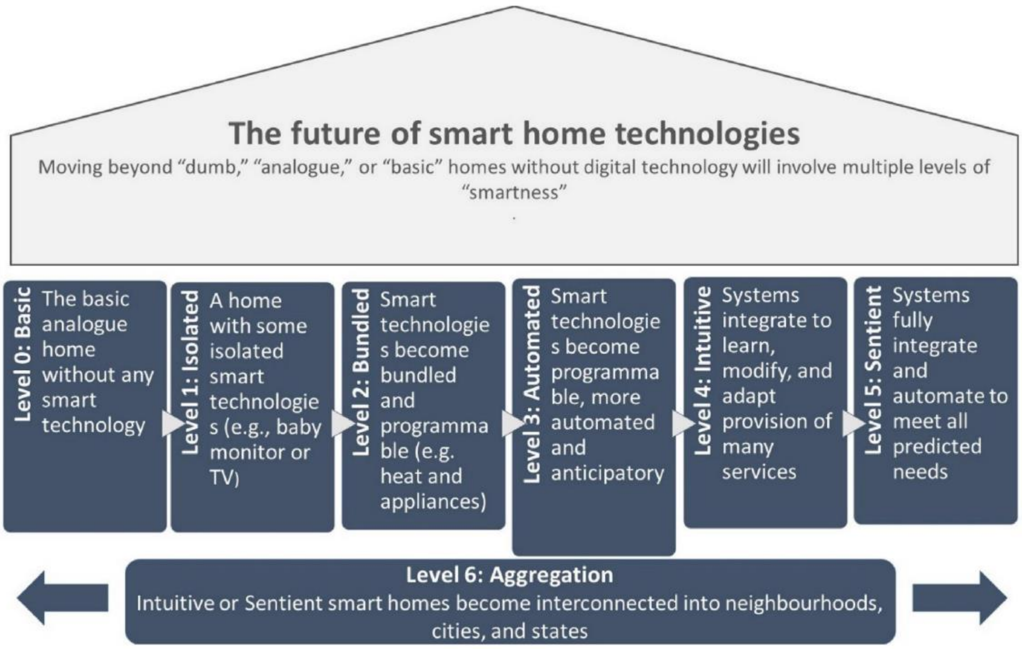


Figure 2.8: Spectrum of smart homes (Sovacool & Furszyfer Del Rio, 2020)

Buckman *et al.* (2014) also demonstrated the gradual shift of buildings from primitive structures to intelligent, interactive buildings, however, they contextualized this spectrum as the linear evolution of buildings with time. As shown in Figure 2.9, this results in several types of buildings that are smart to varying degree.

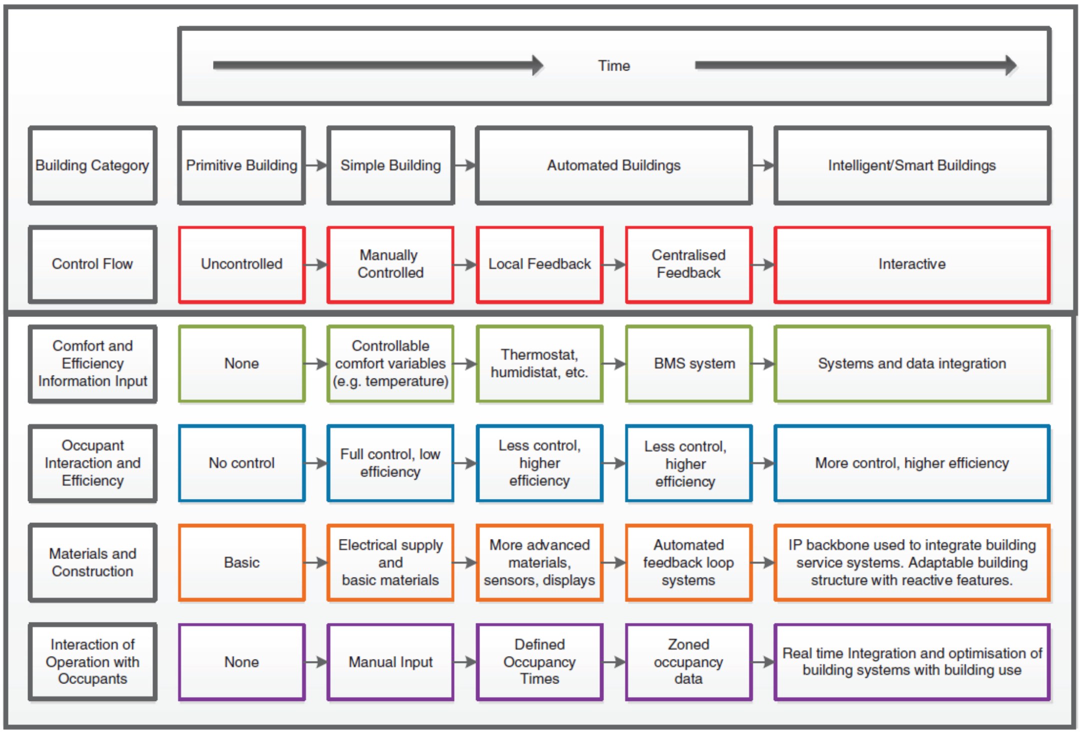


Figure 2.9: Progress of buildings from primitive to smart (Buckman *et al.*, 2014)

2.1.4 Smart Building Stakeholders

While the previous section covered the physical and virtual components of smart buildings, the following sub-topic will deal with the stakeholders in various scales of smart buildings, focusing primarily on identifying:

- the primary stakeholder entities in smart buildings,
- which entities have ownership and access privilege to the data collected,

- how the various entities benefit.

The answers to these differ depending on the various scales of applications, as well as the business models of the technology suppliers in question. For instance, what is typically referred to as a ‘smart home’ could be composed of interconnected smart IoT enabled devices (such as home assistants, appliances, light switches) purchased from single or multiple technology vendors (Mashhadi *et al.*, 2014). In this scenario, there is a relationship between the users and the manufacturers. The users, usually the residents, own the data. However, data collected by the devices may be used for further development, troubleshooting and feedback pertaining to the product; this is often subject to permissions given by the owner of the device. This depends on the perceptions of the users regarding their data privacy, weighed against the potential benefits. It is important to note that the design of the privacy controls also plays a major part, since technology-unaware users may not know how to adjust the privacy controls (Zheng *et al.*, 2018).

Atazadeh *et al.* (2019) investigated the issue of data ownership when it comes to the use of IoT devices in multi-owned buildings. They describe a specific scenario, where IoT devices could be used to monitor various parts of multi-owned buildings in order to help clarify the responsibility of apartment owners towards maintenance and upkeep dues. The research attempted to resolve the potential privacy breaches that could occur; for instance, if ‘Owner A’ installed a security camera facing their parking space, but inadvertently recorded the adjacent parking space belonging to ‘Owner B’. The proposed solution was a BIM-driven approach that would input IoT data streams, while containing information regarding IoT device coverage and subsequent data ownership. This scenario did not pertain to fully smart buildings with centralized control, so the issue of data ownership was clearer when it comes to apartment owners installing IoT devices overlooking their private spaces.

The prior examples of smart homes are therefore relatively straightforward with regards to the number of parties with data access. The owners of the devices, which is to say, the users who generate data have a certain degree of autonomy over its use.

However, the degree of privacy decreases as we shift the focus from homes to more public spaces, such as workplaces. In terms of definitions coined by Westin (1967), the privacy state of the individual changes from 'intimacy', meaning existing in a small, secluded family group, to 'anonymity', which is the state of being in public (an office setting) but maintaining the desire to be anonymous. Therefore, the scenario is more complex when it comes to the number of parties with access to data collected by smart devices, in environments where several distinct groups with varying levels of power are brought together.

Nappi and de Campos Ribeiro (2020) studied 41 publications pertaining to the use of IoT in office settings. When it came to IoT wearable devices, the researchers reported that in most cases, data ownership did not belong to the employees on whom data was collected, nor the employers; it belonged to the companies that produced the IoT devices, who in return usually only give limited access to this data. They described one example of employees being able to see the number of steps they'd taken while participating in a company health program, but not being able to download this data. The researchers concluded that of the 41 studies, not one raised any questions about data ownership, nor was there any mention about employee's understanding of the economic value their data held. Therefore, one of their recommendations was that there must be transparency regarding the parties with data ownership and access, as well as potential uses of the data, in order to increase acceptance by employees and assuage their privacy concerns.

At this point, only spaces containing interconnected smart devices with the use of IoT have been discussed, such as smart homes and smart offices. These differ from some definitions presented of a smart building, for instance, a building that integrates all components and subsystems such as HVAC, lighting, and electrical systems (Fântână & Oae, 2013).

Keeping with the prior definition of smart buildings, we can find an important example of an environment which fostered innovation in this field, in the city of Turin, Italy. Cascone *et al.* (2017) describe the stakeholders in the smart building project maintained by the “Politecnico di Torino Living Lab” office, made possible due to the Torino Living Lab initiative launched in 2016. The Living Lab approach, as an example of smart building experimentation, was appealing because it fostered innovation, tests brand-new solutions in real-life situations, and offered companies a chance to get direct feedback and suggestions from users (Westerlund & Leminen, 2011).

In the Living Lab context, stakeholders can take on the role of *users* who use the product being tested and whose feedback plays an important part in the design, *utilizers* whose expertise is used for improvement while not being part of the production entity, *enablers* who provide resources such as facilities and physical space, and *providers* who are the private entities who develop the products being tested (Leminen & Westerlund, 2012). Figure 2.10 shows these parties and associated benefits in the Living Lab model, which may exist within a regional or global network.

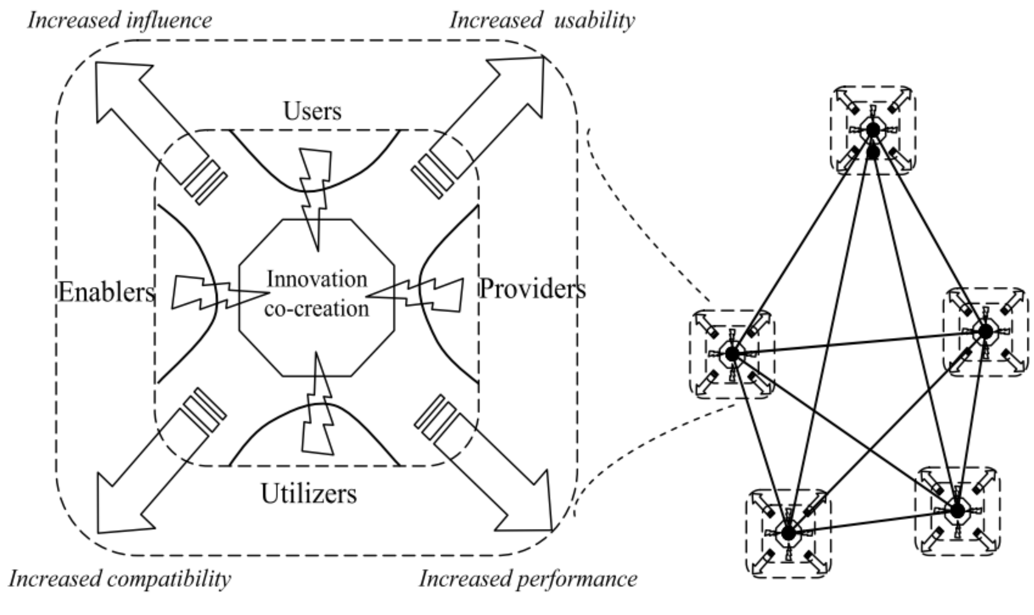


Figure 2.10: Living Lab benefits and participants (Leminen & Westerlund, 2012)

Cascone *et al.* (2017) described Torino Living Lab as being a result of the technology projects "Smart Energy Efficient Middleware for Public Spaces" (SEEMPubs) and "Wifi4Energy", which pertained to the use of wireless sensor networks in academic buildings for energy management. The technology suppliers occupied the *provider* role mentioned previously. These sensors monitored real-time energy consumption as well as environmental conditions in halls, lecture rooms, and offices. The diagram in Figure 2.11 demonstrates the entities involved in the projects, the subsequent categories of groups (explained below), and the direction of communication between different entities. However, the specific entities that had data access and ownership were not named in this research, as the writers themselves stated that this aspect of the project was unclear. A more detailed description of the categories of stakeholders in this project was provided by Cascone *et al.* (2017):

- Policymakers: These entities range from the most over-arching policymakers, which are the government, followed by the directors of the university, down to the Trade Unions which represent the users of the academic buildings in administrative dialogues. These groups share different responsibilities and jurisdictions.

- Users: This category represents the staff and other groups working within the academic buildings. These include the employees and the individuals managing them, while "Constructions and Logistics Area" works with Living Labs on where to place sensors, and "Goods and Services Provision Area" pays the electricity costs of the university.

- Technology Providers: This category represents the suppliers of various hardware and software components needed for the sensor network. These coordinate with the Living Lab, which analyzes the data gathered.

- Villains: External entities that represent threats to the system.

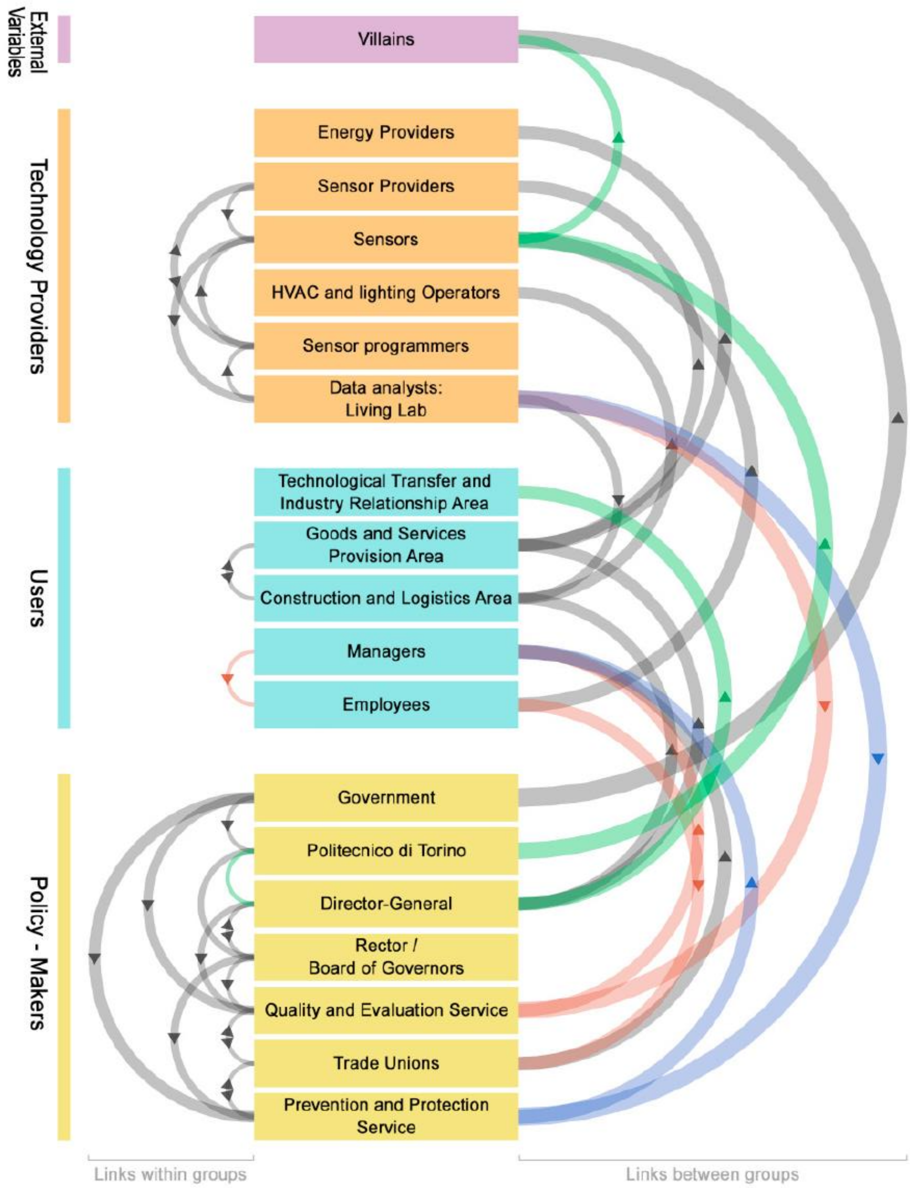


Figure 2.11: Stakeholder network in Politecnico di Torino Living Lab, with arrows showing direction of communication (Cascone *et al.*, 2017)

The motivations of various stakeholders can also be understood by investigating how these entities benefit, whether it is the top level of stakeholders who fund, supply, own and manage the smart building apparatus, or the bottom level composed of occupants whose data is collected and who use the smart building functionalities daily.

In smart home environments, residents reported a myriad of benefits to varying degree. Sovacool and Furszyfer Del Rio (2020) conducted 31 expert interviews, and reported the ranked benefits stated by each. Foremost among these were energy savings and convenience, with the complete responses shown in Table 2.3. They described a major reason for this as the energy inefficiency of buildings in Europe, and particularly, the United Kingdom.

On the other hand, the manufacturers of these smart home technologies can also reap certain benefits apart from the obvious financial profits gained from sales. According to an article published in the MIT Technology Review, manufacturers of smart home assistants such as Amazon's Echo devices (containing the virtual assistant Alexa) can use the data amassed from households to work on problems such as speech recognition, forming datasets with the verbal commands users give the device (Simonite, 2017). This caused unrest among users, as the 'always listening' microphones in these devices have security and privacy risks; especially since microphones are perceived as the most invasive sensors, after video cameras (J. Lau *et al.*, 2018).

On the subject of smart offices, Bariši *et al.* (2020) described the three principles of smart offices as efficient resource management, occupant comfort, and emergency resilience. Buckman *et al.* (2014) reported that in the workplace, control over the environment resulted in increased comfort, occupant satisfaction and lighting quality, while Papagiannidis *et al.* (2020) stated that since environmental comfort (in terms of lighting and thermal conditions) is a proven requirement for productivity, smart technology that manages and controls workspaces can bring about physical and psychological wellbeing of employees. This can be accomplished by using intelligent heating control systems and automated lighting systems.

Table 2.3: Smart home technology benefits reported by 31 expert interview respondents (Sovacool & Furszyfer Del Rio, 2020)

Rank	**Frequency (by interview)**		**Topic**
1	25	80.65%	Energy savings
1	25	80.65%	Convenience and controllability
2	15	48.39%	Financial benefits and saving money
2	15	48.39%	System benefits for grids, networks, operators
3	14	45.16%	Environmental benefits including carbon, pollution, waste
4	13	41.94%	Aesthetics including style, design, feel, and fashion
5	11	35.48%	Health benefits and assisted living
5	11	35.48%	Social benefits including inclusion, networking, status
6	9	29.03%	Educational benefits and learning
6	9	29.03%	Entertainment including music, movies, streaming
6	9	29.03%	Safety and security
7	8	25.81%	Other enhanced experiences (e.g., shopping)
8	4	12.90%	Free services or promotional gifts

According to Röcker (2009), while the employees benefit from the immediate application of these technologies, another group of beneficiaries is comprised of the 'indirect' users, those at the management level. These can use the captured information for analyses of user and business processes; however, this may lead to concerns if the employees are not aware or not accepting of this.

Nappi and de Campos Ribeiro (2020) stated that the use of IoT technology such as sensors can assist workplace managers to increase operational efficiency and improve occupants experience of the space, through the evaluation of occupancy patterns. Employers can also use this technology to identify job stress in their employees, with the use of wearable sensors. These supply physiological data which can reveal happiness levels and moods; but the researchers also state that the access to employee's personal data can cause privacy concerns.

In this context, one office type that stands out is the shared flexible co-working space, perhaps best commercialized by the American real estate company WeWork. According to an article in Architect Magazine in 2016, the company leased office space to 600,000 individuals on a membership basis; one of the standout aspects of the company was usage of data pertaining to occupancy, space quality, and layout. At the time, WeWork had unveiled a ‘beta floor’, a space fitted with sensors that tracked metrics such as temperature, air quality, and lighting, along with an overhead camera that used computer vision to count the people in the room. The data gathered from the camera allowed WeWork to generate heat maps of ‘hot desks’, showing where people liked to sit the most. As WeWork is a vertically integrated company, in the sense that they design, own and manage their co-working spaces, this allowed them to conduct post-occupancy evaluations to guide further evidence-based design and marketing (Lau, 2016).

In summary, this sub-chapter has explained the history, definitions, components and stakeholders involved in smart buildings. Development of smart buildings is driven by a need to conserve energy due to global climate change as well as lower energy and operation costs. Additional factors are improved occupant experience due to interactivity, increased functionality of building components, integration of building systems, and the availability of data that’s valuable to building stakeholders. Of course, the collection of the data is not possible without the integration of physical sensors in the built environment.

2.2 Sensing Layer and Data Collection in Smart Buildings

This sub-chapter will narrow the focus to the networks of sensors and other data collection apparatus in smart buildings.

The increasing importance of energy efficiency in the current market leads stakeholders in the industry to acknowledge research which shows that low-cost investments in optimization can lead to high economic returns over time. While the ability to make confident predictions of the exact amounts of energy that can be saved, was limited until recently, the number of buildings that maintain records of energy use has expanded the pool of building energy data that is available for analysis according to Mathew *et al.* (2015), who went on to state that the gathering of building data can be carried out to analyze energy use and extract patterns in order to predict energy demand in the future.

According to Lehrer and Vasudev (2010), an increasing number of companies are designing tools for the visualization of data, mainly to do with "energy and water use, and renewable power generation". These tools assist design teams in sharing goals and comparing actual performance to the simulated performance developed during the design process. One incentivizing factor is the LEED rating system (Azhar *et al.*, 2011), which provides extra points for innovation in sustainable buildings.

The types of data extracted from buildings can differ in importance, in the perspectives of various types of users. In a survey conducted by Lehrer and Vasudev (2010), users were asked to quantify their interest in types of energy. As shown by Figure 2.12, 91% of these prioritized lighting load data, while occupancy data was of most interest to 63%. However, all types of data were deemed valuable to some extent by the respondents.

In order to reliably analyze a building's performance, the data must comprise sufficient information on energy use (Wei *et al.*, 2018). A complete understanding requires the identification and classification of resources, and end-uses of energy in a building. The classification of building energy is dictated according to ISO Standard 12655:2013, as can be seen in Figure 2.13.

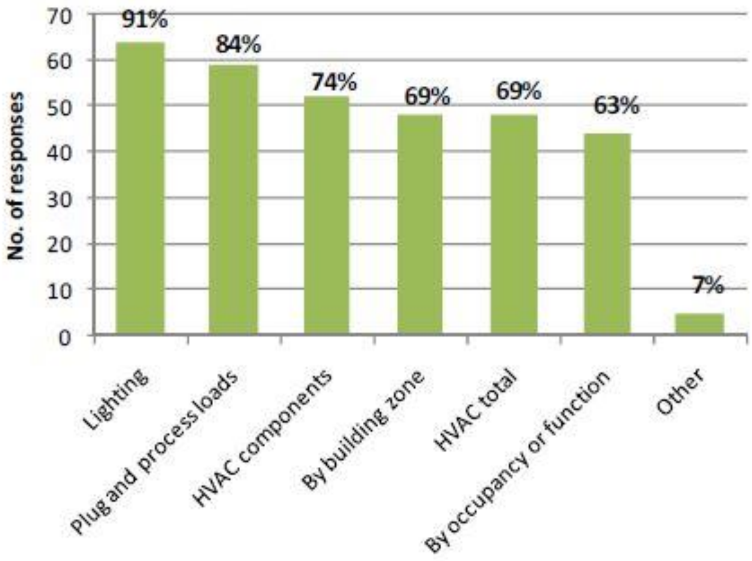


Figure 2.12: Usefulness of various classes of data (Lehrer & Vasudev, 2010)

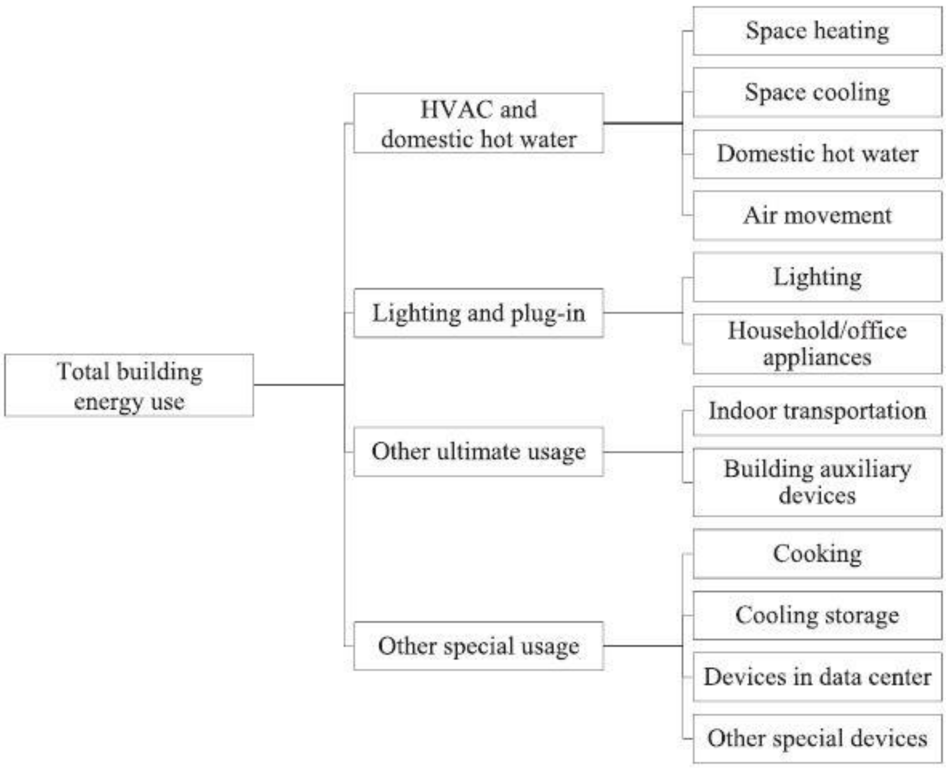


Figure 2.13: Classification of energy use in the building sector (Wei *et al.*, 2018)

According to Wei *et al.* (2018), since there are a wide variety of factors that influence building performance, such as external conditions like the weather, as well as user behavior, and thermal properties of the building's skin, several approaches have been developed in order to assess a building's performance.

Wei *et al.* (2018) defined each approach as follows:

1. White-box approaches, which require in-depth information, making them technical-intensive and subsequently expensive.

2. Grey-box based approaches, which modify white-box based approaches by approximating building energy using statistical techniques which combine physical data with historical data. One disadvantage of this is that their inputs are uncertain, and intersections between elements and user behavior are complex, resulting in uneconomical computational processes. A reason for this is that user behavior has a randomly determined pattern which can be analyzed but not predicted, *i.e.*, stochastic.

3. Black-box based approaches, which are a counterpart to the issues faced above, and do not use physical data in real-time, instead relying on historical data; allowing them to perform calculations at high speeds with high accuracy. These are also called data-driven approaches due to the large amount of data in use.

Wei *et al.* (2018) claimed that to achieve high efficiency in building energy use, performance evaluation should also account for factors such as "indoor air quality, occupant thermal comfort, occupancy behavior interaction and equipment energy-performance coefficient", instead of simply analyzing the amount of energy consumed and the heating/cooling loads.

Smart buildings that are capable of yielding data pertaining to their environments deliver massive amounts of information, typically at hourly intervals. In the words of Raftery and Keane (2011), “this yields a minimum of 8,760 data-points per data-stream per annum. Patterns occur at multiple frequencies within these large datasets. Furthermore, there are interdependencies between multiple discrete (hour of day, day of week, etc.) and continuous (dry bulb temperature, dew-point temperature, etc.) variables”.

Duarte *et al.* (2013) claimed that models which estimate building energy performance require inputs in the form of physical parameters such as building form, construction materials, and HVAC system specifications, which can easily be found in the construction data of the building. However, other inputs vary with time, such as plug loads, heating/cooling loads, or ventilation rates. Some of these are dependent on external factors such as the weather, occupancy rates, or both. The amount of people present in a building plays a large part in energy consumed in the form of office equipment, lighting, and HVAC system utilization. Occupancy is therefore an important factor in building energy simulations.

One data source for occupancy is occupancy schedules, or occupancy profiles. Mitra *et al.* (2020) stated that publicly available occupancy schedules are used for most residential energy modeling studies, citing examples based on ASHRAE Standard 90.1. These schedules contain information about the maximum number of people which can occupy the building, a 24-hour schedule which ranges in value from 0 (zero occupancy) to 1 (maximum occupancy), and multipliers which could factor in special conditions such as weekends, holidays, after-work hours, etc.

However, Davis and Nutter (2010) claimed that occupancy was a neglected component of building energy models, and that the default diversity factors which are derived from ASHRAE 90.1 are of use mainly in the absence of actual schedules for the specific building.

Duarte *et al.*, (2013) demonstrate an example of recommended diversity factors for ‘office occupancy’ in Figure 2.14, from ASHRAE 90.1-2004. However, they warn that this does not differentiate between open plan offices or private offices; additionally, these schedules were last updated in ASHRAE 90.1-1989. Their research analyzes sensor data to obtain diversity factors for an office environment, which proved to differ from ASHRAE 90.1-2004 diversity factors by up to 46%, highlighting the potentially misleading simulation results which may arise from depending on generalized standards.

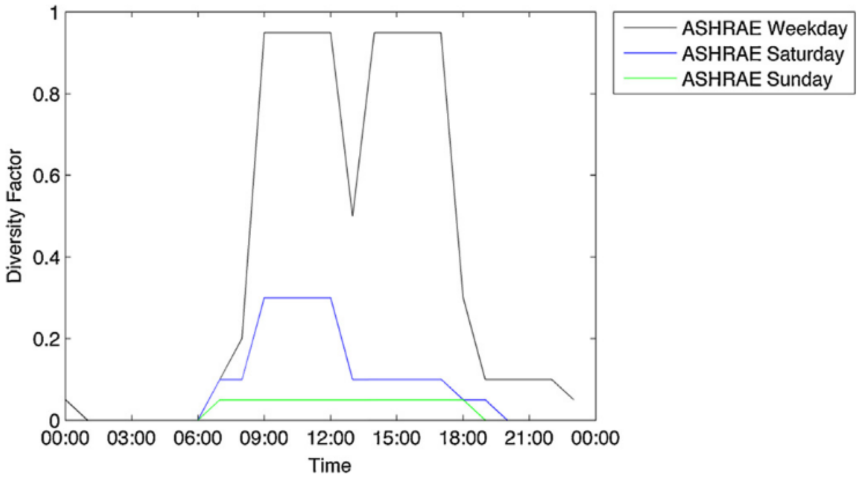


Figure 2.14: ASHRAE 90.1-2004 recommended diversity factor by day type, for 'office occupancy' (Duarte *et al.*, 2013)

2.2.1 Occupancy Sensors

According to a report by the Oxford Future of Real Estate Initiative (2020) occupancy sensing technologies have long been present in the commercial market and are widely in use. One notable example is in the EDGE Building in the city of Amsterdam. In this smart building, 30,000 sensors collect granular, area-specific data on occupancy, humidity, light levels, and temperature.

According to Ahmad *et al.* (2020), sensor granularity is a measure of the resolution of the data collected by a sensor, as illustrated in Figure 2.15. This can indicate the quality of data recorded by the sensor and may reveal more accurate results upon analysis.

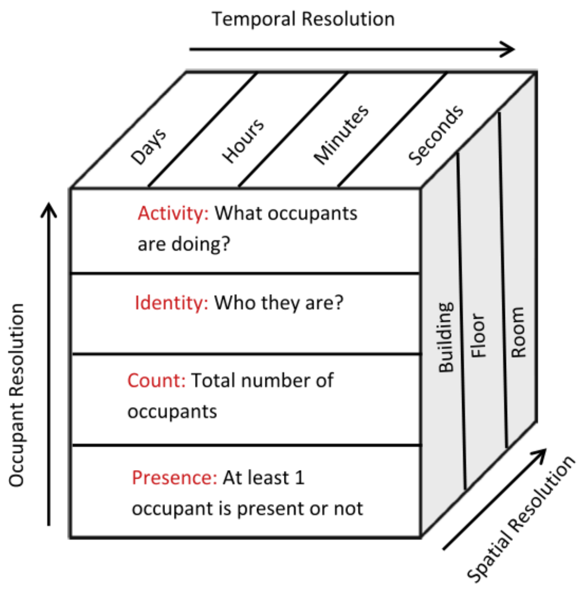


Figure 2.15: Occupancy, spatial and temporal resolution (Ahmad *et al.*, 2020)

According to Baum *et al.* (2020), electronic sensors can measure occupancy and conditions within the building in order to accomplish the following functions:

- Operation of systems based on necessity; for instance, turning off the lights when the room is empty,
- Operation based on prediction; using patterns to predict when certain areas will be used and condition the space ahead of time,
- Operation based on external/ambient factors, such as dimming lights when there is ample daylight,
- Finding areas where energy consumption can be reduced if the national power grid is compromised or overloaded,
- Predicting maintenance requirements; analyzing anomalies in unit power readings to predict when replacement/maintenance is required.

Kjærgaard and Sangogboye (2017), whose research was focused on categorizing occupancy sensing systems according to a wide array of features, referred to one feature as ‘sensor modality’, which meant the stimulus to which the sensor reacts in order to log occupancy data. According to their findings, this resulted in twelve different modalities, shown in Figure 2.16.

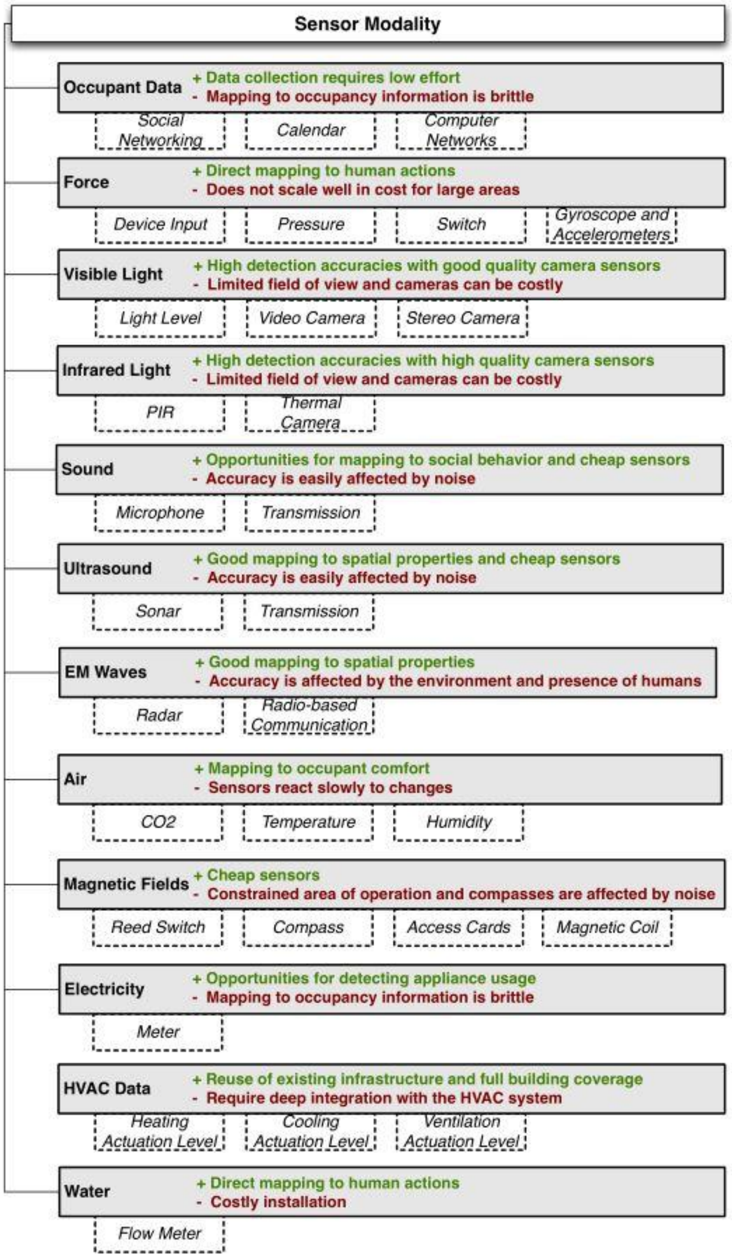


Figure 2.16: Distinct sensor modalities (Kjærgaard & Sangogboye, 2017)

2.2.1.1 Benefits of Occupancy Sensing

To properly appreciate the potential benefits of occupancy sensing for the purposes of automated building systems, it is necessary to understand the ways that irresponsible occupant behavior leads to energy waste. According to Labeodan *et al.* (2015), building users, if unaware or apathetic towards the need to conserve energy, can increase energy use "by up to one-third of its design performance". By contrast, users who consciously attempt to save energy can potentially cause energy savings of the same amount.

Masoso and Grobler (2010) further attempted to demonstrate the energy waste in indoor spaces, during non-working or unoccupied hours, due to the poor habits of occupants. They used sub-hourly energy profiles for six buildings (five in Botswana and one in South Africa), to display a comparison of energy used in working and non-working hours (*i.e.*, nighttime, and weekends). The graph in Figure 2.17 shows the energy consumption profiles for all six buildings, where it can be observed that the energy use on weekends and non-working hours is around 50-60% of the total energy consumption. Upon investigation, it was revealed that most of this was due to air-conditioning systems and energy-intensive laboratory equipment being left on after hours.

Of course, the sample was location-specific, and may not reflect the habits of occupants elsewhere. But as Labeodan *et al.* (2015) stated, occupants in non-residential buildings generally may exhibit less energy-conscious behavior since they do not have to be financially liable for extra energy costs. Labeodan *et al.* further emphasize the importance of automated actions to save energy by claiming "occupants cannot be completely trusted to exercise energy-conscious behavior, particularly in large commercial buildings where they are not directly responsible for the cost implication".

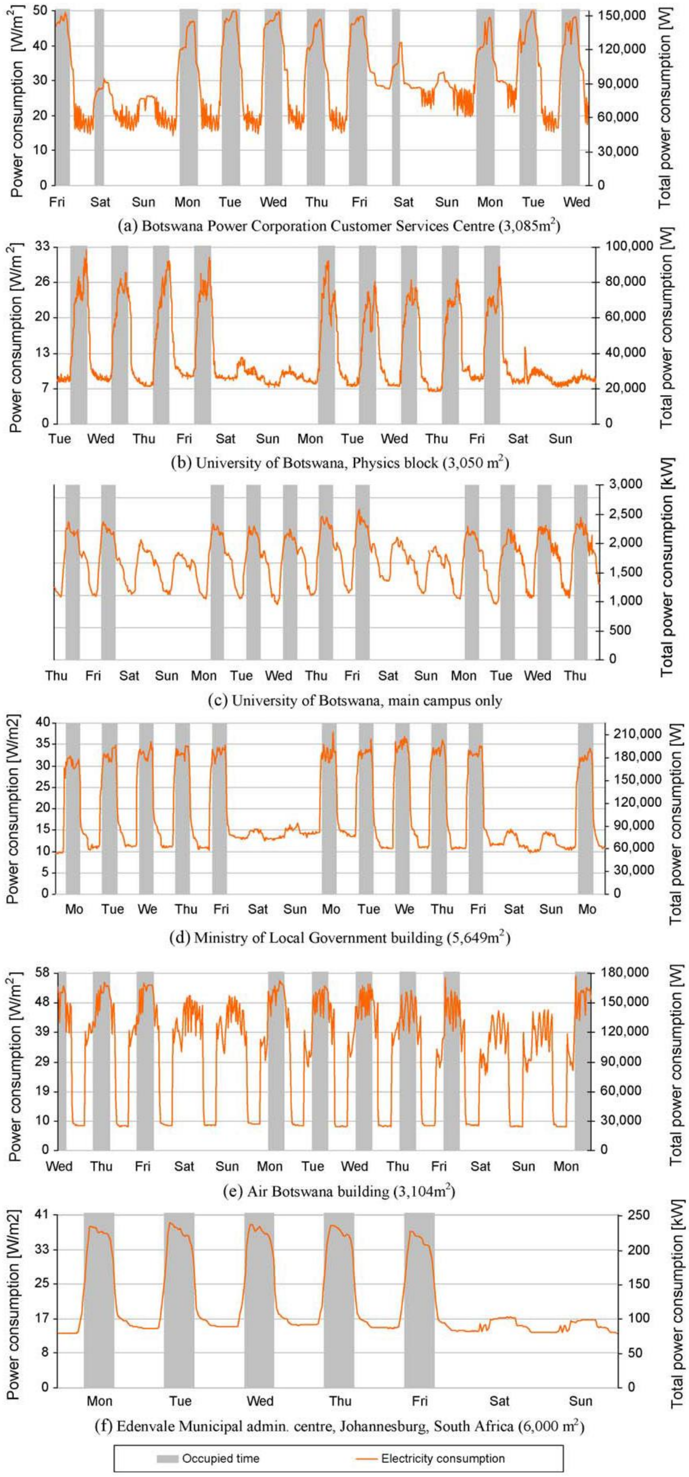


Figure 2.17: Sub-hourly energy consumption profiles of six office buildings (Masoso & Grobler, 2010)

In one study, Lindelöf and Morel (2006) studied the manual light switching behavior of occupants. This research pertained to working hours (distinguishing it from the example stated above), hence it demonstrated other factors besides mere negligence on the part of occupants. They concluded that unless users were particularly responsible, they would not switch off lights when not in use. For instance, light switches at the door (or in other words, not in arms reach from the door) were not adjusted even when natural lighting was sufficient, and intermediate light switching rarely occurred, for instance, when the occupant left the room for temporary periods in the middle of the workday.

In another survey with 208 respondents conducted by Gul and Patidar (2015) it was revealed that 92% of occupants in an academic building were visitors, with only 8% having an office in the building, as shown in Figure 2.18. This led to a high amount of electrical usage with low sense of responsibility, stressing the need for automated control (Gul & Patidar, 2015).

One major benefit of occupancy sensing is therefore removing dependency on building occupants to make energy-conscious decisions, and instead sense their presence and location in order to control building systems appropriately. Occupancy sensing can provide long-term information on how frequently spaces within buildings are used, so that facility managers and owners can make more efficient decisions on their use, for instance whether to scale down or seclude rarely used rooms, according to Bakker & Veuger (2021). They also state that the efficiency of managing those spaces is also increased as cleaning or maintenance can be less frequent and climate control and lighting can be adjusted appropriately. Provided that the resulting data is used well, this can save in upkeep, energy and real estate costs.

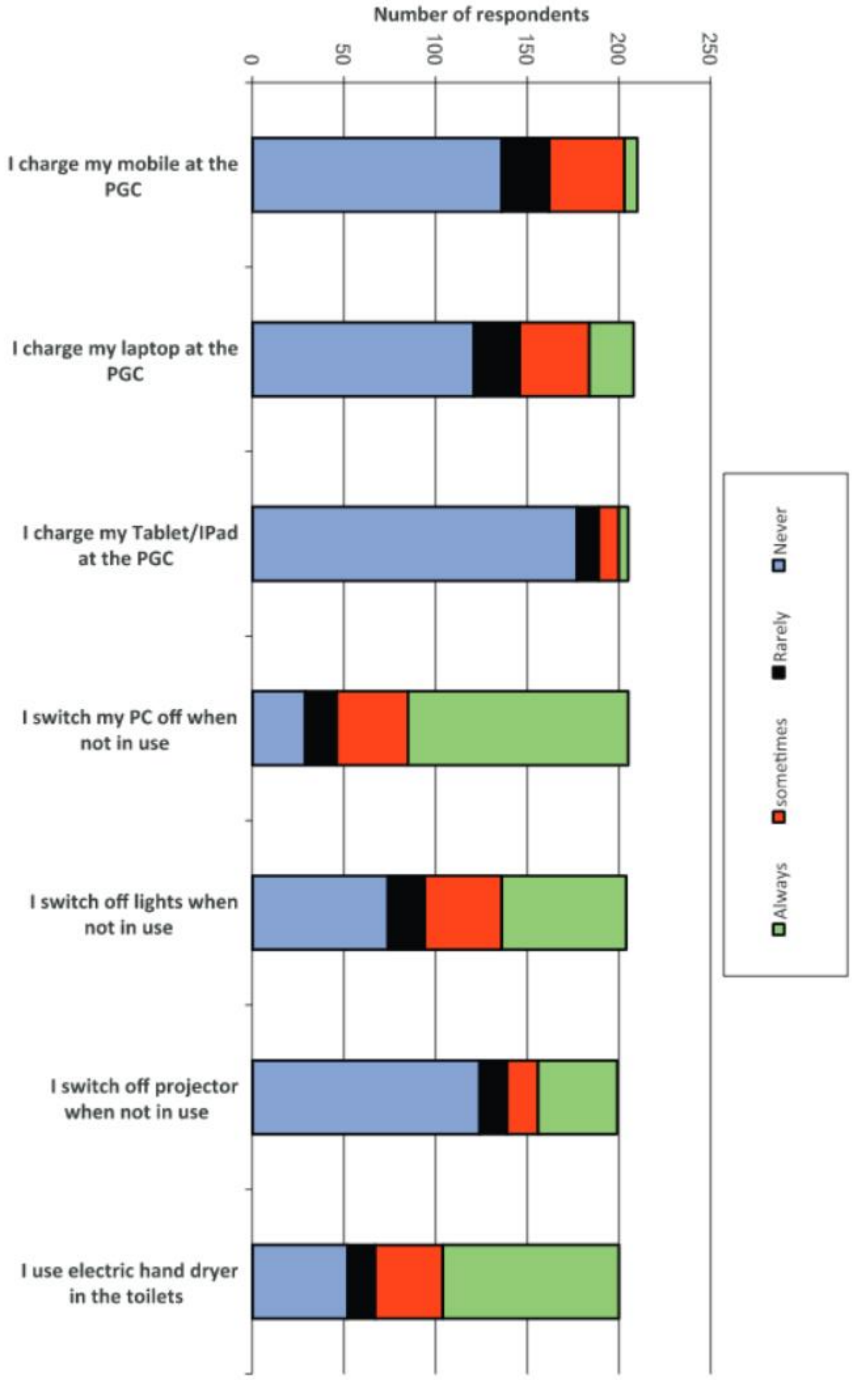


Figure 2.18: Results of occupant survey (Gul & Patidar, 2015)

Occupancy sensing can also facilitate the occupants of a building by providing real-time information on availability or crowdedness of a space. The American real estate company WeWork's used various techniques of occupancy sensing; one of these was the Product Research team's use of motion sensors in the headquarter building's nooks and phone booths to find occupancy rates in these single-person spaces, which were then displayed in a web app for employees to see which spaces are available (Bailey, 2016). A visualization of occupied phone booths is shown in Figure 2.19.

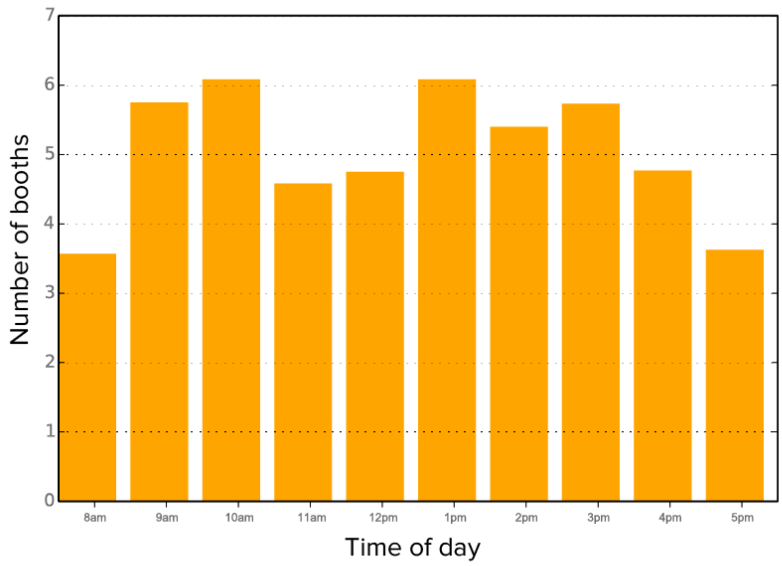


Figure 2.19: Phone booth occupancy (Bailey, 2016)

2.2.1.2 Comparison of Occupancy Sensing Technologies

The previous section is intended to emphasize the vastness of the diverse occupancy sensing market, with its wide array of products.

Since occupants often do not feel responsible for energy savings in buildings where they are not financially liable (Labeodan *et al.*, 2015), collection of occupant data may be beneficial in order to reap energy conservation benefits and cost savings.

Kjærgaard and Sangogboye (2017) further emphasize the numerous types of sensor modalities and distinct technologies. With the diversity of methods and types of results, building managers, real estate owners and construction professionals may find it difficult to pick a suitable system for use in offices.

In this section, occupancy sensing technologies will be categorized and compared, in order to identify characteristics most suitable to record and model occupant behavior in offices. A literature survey was carried out based on 28 academic papers that contained impartial evaluations of occupancy sensing systems, through either quantitative results stemming from comparative experiments, or qualitative observations in the discussion section. The research included, but was not limited to the following areas:

- design and comparison of occupancy models,
- building load prediction,
- testing of neural network models in occupancy predictions,
- development of novel occupancy sensing techniques,
- working patterns in offices.

The 5 main categories of sensor modalities were the following:

- Infrared-based (also referred to as PIR),
- Image-based (occupant tracking through camera or video),
- Force-based (activated by occupant exerting force *e.g.*, sitting on a chair),
- WIFI-based (tracking occupants from their connected phone devices),
- Environment-based (also referred to as CO_2 based, where CO_2 concentration reveals number of occupants).

Table 2.4 shows the academic papers surveyed, while describing the descriptive nature of each with regards to various perspectives, as well as offering a brief summary of the paper. Figure 2.20 shows the distribution of types of technologies mentioned.

Table 2.4: Results of academic paper survey

Paper no.	Author (Date)	Paper type					Types of technologies	Comments
1	(Kjærgaard & Sangogboye, 2017)	1	2	3			All	Categorization framework developed for occupancy sensors
2	(Labeodan et al., 2015)	1			4	5	CO2 and force-based sensors	Experiment comparing two technologies, recommending force-based.
3	(Davis & Nutter, 2010)	1			4		PIR and image-based sensors	Occupancy profiling of institute
4	(Shen et al., 2017)	1	2	3			All	Framework for using existing occupancy data
5	(Nguyen & Aiello, 2013)	1			4		PIR, RFID and image-based sensors	Review of case studies demonstrating potential of energy savings in HVAC, lighting, and plug loads
6	(Li et al., 2012)	1			4	5	Wifi-based sensing	Describing and recommending novel Wifi-sniffing technique
7	(Priyadarshini & Mehra, 2015)	1				5	All	Describing sensors in general, recommending PIR
8	(Kwon et al., 2014)			3			All	Compares cost of sensors
9	(Ahmad et al., 2018)	1		3		5	All	Compares all sensors and recommends image-based
10	(Yang et al., 2016)	1		3			All	Compares all sensors; fails to recommend single one
11	(Guo et al., 2010)	1		3			All	Compares all sensors in an office-use context
12	(Von Neida et al., 2001)				4		PIR	Analyzes PIR sensor data to get office occupancy pattern
13	(Duarte et al., 2013)				4		PIR	Analyzes PIR sensor data to get office occupancy pattern
14	(Zou et al., 2017)	1			4	5	Wifi-based sensing	Developing wifi-based and comparing with conventional systems. Recommended wifi.
15	(Breslav et al., 2013)				4		PIR	Simulating PIR sensors, in the context of sensor density
16	(Duarte et al., 2015)				4		PIR	Comparing ASHRAE diversity factors with measured occupancy schedules.
17	(Saha et al., 2019)						All	Comparing data analytics methods.
18	(Wang et al., 2018)				4	5	CO2 and Wifi-based sensing	Recommends fusion of Wifi-based and CO2 based sensing
19	(Zuraimi et al., 2017)					5	CO2 based sensing	Recommends CO2 based sensing
20	(Ekwevugbe et al., 2016)	1		3	4	5	All	Recommends fusion of multiple sensors.
21	(Ekwevugbe et al., 2013)	1			4	5	All	Uses a neural network prediction model and recommends CO2 and PIR
22	(Wang et al., 2005)				4			Develops occupancy profile based on PIR data.
23	(Yang et al., 2018)	1			4	5	CO2 and image-based sensors	Compares image-based with CO2 based, recommends image-based.
24	(Garg & Bansal, 2000)	1			4	5	PIR	Recommends smart PIR system that learns time delay.
25	(Dodier et al., 2006)	1				5	PIR and CO2 based sensors	Recommends PIR and CO2 based sensors
26	(Jin et al., 2018)		2		4	5	CO2 based sensing	Develops algorithm to improve CO2 based sensing and recommends this type.
27	(Goyal et al., 2013)				4		CO2 based sensing	Develops algorithm which uses CO2 and temperature sensors.
28	(Shen & Newsham, 2016)		2			5	Wifi/Bluetooth based sensing	Recommends wifi/bluetooth sensing but mentions drawbacks.

1	Describes a sensing system
2	Categorizes multiple systems
3	Compares two or more systems
4	Experimental Research
5	Recommends a system

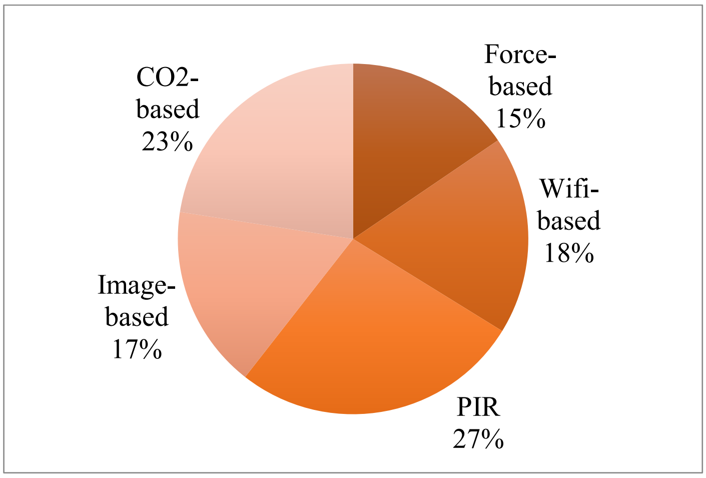


Figure 2.20: Distribution of mentioned technologies in 28 papers

To impartially judge the recommendations of the papers, the SWOT system (Strengths, Weakness, Opportunities, Threats) was used to record characteristics of each system in a single table (Table 2.5). The specific characteristics of each system are listed in order to identify optimal sensing systems for offices, so their qualities can be quantified. The reference numbers indicate the Paper Numbers according to Table 2.4.

The SWOT system is a popular system for comparative strategic planning. The categorization of internal and external issues is a convenient starting point, and can be created rapidly, benefiting from multiple viewpoints (Helms & Nixon, 2010). Each category is described as follows:

- Strengths refer to what the entity excels at, and what separates it from the competition,
- Weaknesses stop an entity from performing at its optimum level,
- Opportunities refer to favorable external factors that could give an entity an advantage over the competition,

- Threats refer to factors that can potentially be harmful (Helms & Nixon, 2010).

Table 2.5: Results of SWOT analysis

Sensor type	Strengths	Weaknesses	Opportunities	Threats
Infrared-based	Non-terminal (no device needed for occupant) [2, 10] No privacy concerns [9] Low cost [9, 10]	Can't provide count [2, 8] Binary output [9, 10] Low resolution [8, 10]	Can be used in conjunction with AI algorithms to adjust time delay according to occupant [24] Multiple sensors work better than single PIR sensor [20]	Prone to error [9]
Image-based	Non-terminal [2] Implicit, no hardware needed [2] High resolution, precise [8, 9]	Requires image detection software [9] High cost, if specialized cameras used [8]	Can provide count [2, 8] Can provide ID [8] Existing camera infrastructure can be used	Privacy concern [2, 10]
Force-based	Non-terminal [2] Low cost [9, 10]	Low resolution [8] Medium cost [8]		
Wifi-based	Implicit, no extra hardware needed [2, 9] Low power consumption [9]	Compatible device on occupant needed [2]	Can provide count [2, 8] Suitable for buildings with overlapping APs [10]	Privacy concern [2] Risk of inconsistent connection [9,10]
CO2-based	Non-terminal [2] Can be applied to demand control ventilations [10]	Slow response [10] High cost of CO2 detectors [20]	Can provide count [2, 8, 10]	Can be disrupted by environmental conditions [10]

Based on the analysis, image-based sensing appears to be most promising, as it can track location of occupant, while having the highest granularity and potential to use with existing CCTV hardware (Labeodan *et al.*, 2015). However, a major threat is that of privacy infringement (Yang *et al.*, 2016), which is also a primary focus of this thesis.

2.2.2 Image-Based Occupancy Sensing Techniques

The ability of computers and artificial systems to view, understand and recognize images is called computer vision, which has its roots in the 1960s. Since then, it has been used in a diverse array of applications which could not be reliably achieved by human labor; to state some examples, assembly and verification processes in the semiconductor industry, industrial inspection in the electronics and machinery industry, chromosome recognition in the biomedical sector, and character recognition in mail sorting systems, among others. In the context of this thesis, human, or pedestrian detection applications are important in fields such as self-driving cars, entertainment, robotics, surveillance and elderly care (Andreopoulos & Tsotsos, 2013; Dollár *et al.*, 2009; Dollár *et al.*, 2012).

2.2.2.1 Past Research in Image-Based Occupancy Sensing

The following section will demonstrate research methodologies which utilize image-based occupancy sensing.

According to Kjærgaard and Sangogboye's (2017) categorization framework, cameras can be classified as visible light modalities or infrared light modalities, based on the technology used in the camera. Labeodan *et al.* (2015) stated that image recording devices such as video cameras placed in buildings have shown to be capable of providing occupancy data such as location, count, identity, and activity. They cited Erickson *et al.* (2013) who developed a network of wireless imaging devices called OPTnet, using cameras as 'optical turnstiles' and reported energy savings of up to 26% upon using the data harvested, as well as an estimated ROI of eight to ten months. However, they described the process as difficult, claiming "one of the most time-consuming part was the processing of ground truth data.", due to the lengthy process of reading image data (Erickson *et al.*, 2013).

Davis and Nutter (2010) used security camera footage, among other sources such as scheduling data, doorway electronic counters, personal observations and surveys to create occupancy diversity factors for a university building. The researchers manually counted the people entering and exiting the building, without using object-detection algorithms. However, this stood the possibility of falling prey to human error, *i.e.,* miscounting.

Erickson *et al.* (2009)described the use of SCOPES, a wireless camera network for harvesting occupant movement patterns, which helped to create two prediction models for movement and occupancy count; In their words, 'the first model fitted a Multivariate Gaussian distribution to the sensed data and using it to predict mobility patterns for the environment in which the data was collected... while the second model is an Agent Based Model (ABM) that can be used for simulating mobility patterns for developing HVAC control strategies for buildings that lack an occupancy sensing infrastructure'. Erickson *et al.* also developed a method to check the ground truth, by installing webcams to record movement, and processed the data using a program Perlmagick which can annotate images with human beings in them. 'Transition areas' were set on which the SCOPES system acted, shown in Figure 2.21 in red and green lines.

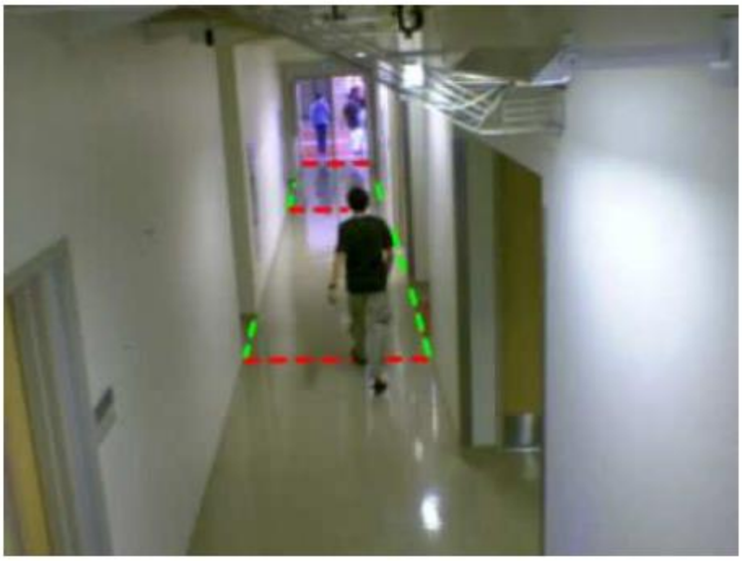


Figure 2.21: Webcam image showing transition areas (Erickson *et al.*, 2009)

Kjærgaard and Sangogboye (2017) compared the use of image-based occupancy sensing and wireless-based occupancy sensing, where the latter involved monitoring the locations of occupants' wireless devices. They stated that the image-based techniques were very accurate, however they were costly to scale, as this meant every space needed a camera; on the other hand, wireless-sensing was easier to scale but every occupant needed to be carrying a wireless device. As cameras get cheaper, the financial detriments of the first technique decrease.

Erickson *et al.* (2011) described the shortcomings of PIR sensors and CO_2 sensors to adjust HVAC usage, and state that PIR sensors cannot accurately predict how many people occupy a room, and CO_2 sensing has inherent delays due to which occupants are already uncomfortable by the time the HVAC system is adjusted. On the other hand, image-based sensors can provide accurate data on occupant count, able to sense rapid changes in real-time. An experiment is carried out using the SCOPES camera system, placed at nodes installed on transition boundaries, which activate when an occupant passes through, determining the direction of movement. Figure 2.22 shows a floor plan and location of nodes. Lightweight image processing is used, and object detection is carried out using background subtraction, and consecutive images are used to determine direction.

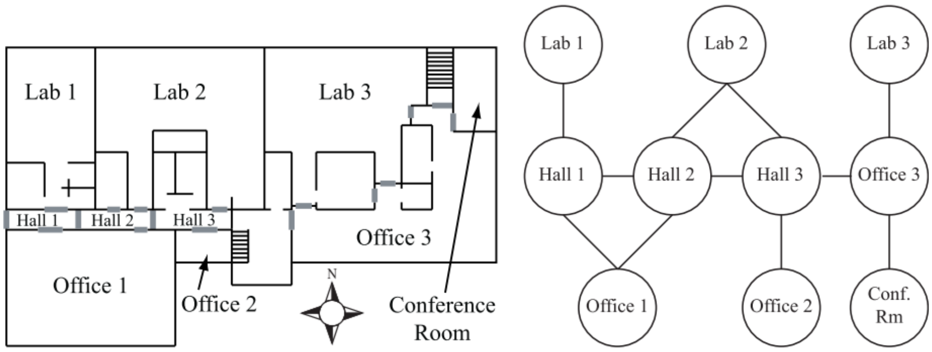


Figure 2.22: Floor plan with grey lines showing transition boundaries, and labelled nodes specifying areas (Erickson *et al.*, 2011)

According to Erickson *et al.* (2011) after data collection, a Markov Chain model is used, in which each state is represented by a vector. Each component of the vector represents occupancy in a particular room, as shown in Figure 2.23. For comparison, the researchers also used Blended Markov Chain (BMC) and Closest Distance Markov Chain (CDMC) for comparison with ground truth data and observe that BMC works better. This is used for defining a predictive control algorithm for temperature.

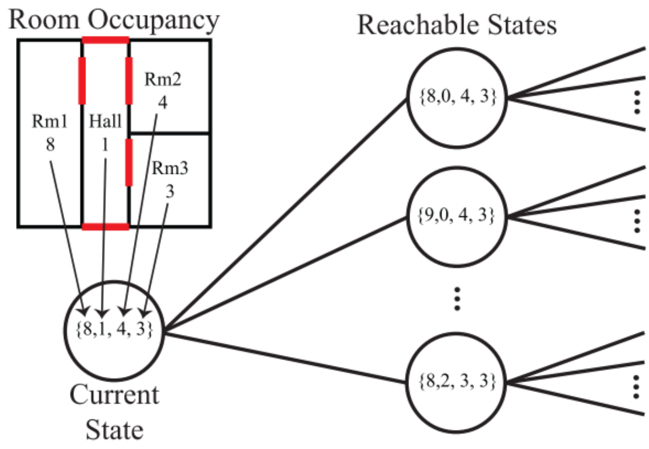


Figure 2.23: Occupancy Space Representation (Erickson *et al.*, 2011)

In another experiment, the occupancy counting of four methods were compared, for instance, face detection, overhead video based occupancy counting, physical model using CO_2 data, and statistical model using CO_2 data (Yang *et al.*, 2018). The testbed, a single-zone lecture room, is shown in Figure 2.24. According to the researchers, the video captured by the overhead camera was processed by a Pixel Box Background Subtraction algorithm and showed how many people enter and exit the area. The pan-tilt-zoom cameras (PTZ) use a support vector machine (SVM) model to detect human faces, capturing images every five minutes. The SVM model was trained from the Istituto Italiano di Tecnologia (IIT) dataset, and Coffeebreak head samples dataset (HOCoffee). The resulting image and dataset 5samples are displayed in Figure 2.25 and Figure 2.26. The lecture room was also divided into six zones as shown in Figure 2.27.

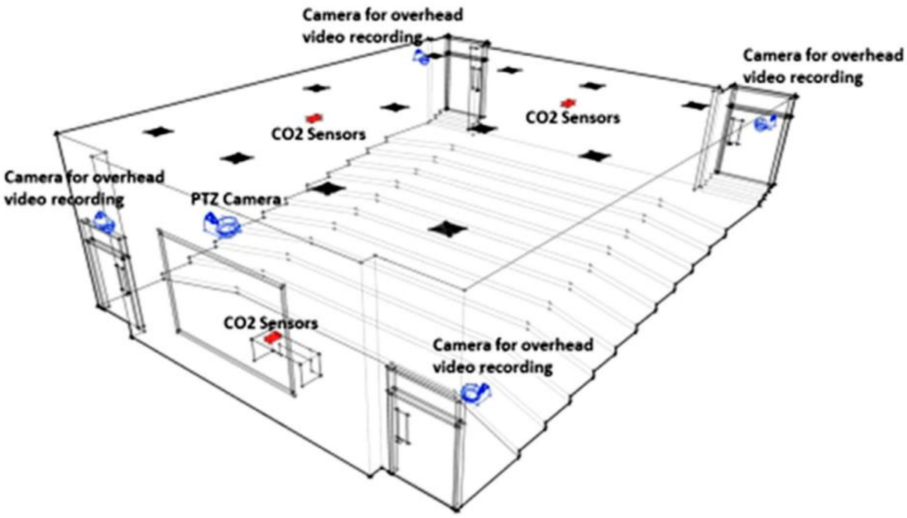


Figure 2.24: Testbed setup (Yang *et al.*, 2018)

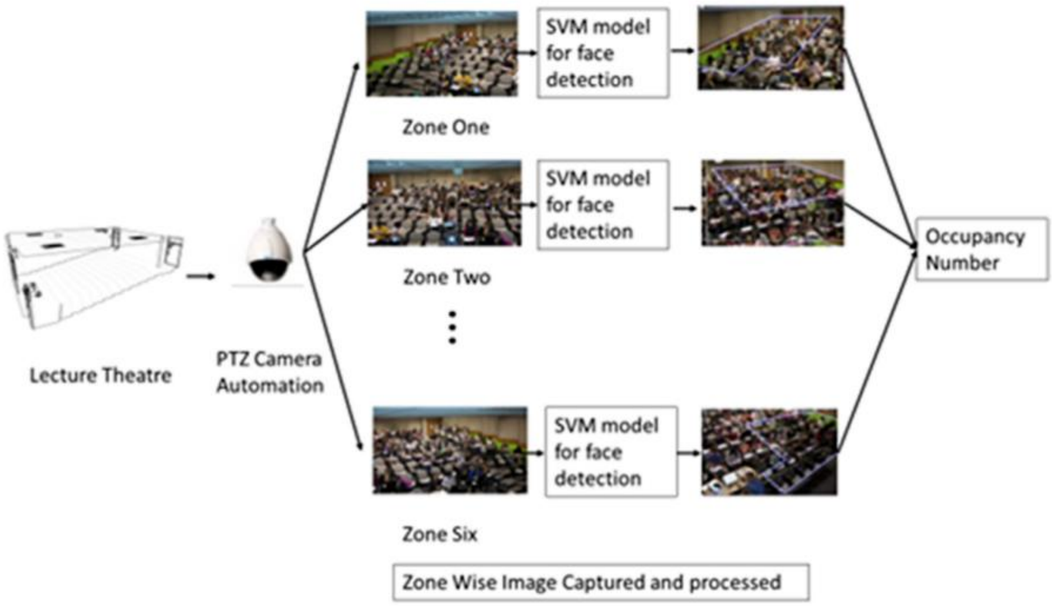


Figure 2.25: Occupancy counting system procedure (Yang *et al.*, 2018)

Figure 2.26: Dataset samples from IIT, HOCoffee and test images

Figure 2.27: Division of testbed into zones (Yang *et al.*, 2018)

2.2.2.2 Human-Detection Algorithms

According to Zhao *et al.* (2019) and Du (2018), the problem definition of object detection is to determine the location of objects in a given frame (localization), and identify what the object is, or what category it belongs to (classification). Andreopoulos and Tsotsos (2013) expanded the key tasks involved in object detection, as detection (determining whether an object is present), localization, recognition (essentially the same as classification), and understanding (recognition along with the role of the object in the context).

Zhao *et al.* (2019) defined three stages of traditional object detection as follows:

1. Informative Region Selection, which is essentially the scanning of the whole image to find possible positions of objects,

2. Feature extraction, by which visual features of objects are extracted to find meaningful characteristics for identification,

3. Classification, to identify the category or 'class' of the object, distinguishing it from others.

Similarly, the main challenges listed by Du (2018) are accuracy, speed, cost and complexity. Over the past 20 years, some pioneering traditional object detection techniques were Viola-Jones (Viola & Jones, 2001), Histogram Oriented Gradients or HOG (Dalal & Triggs, 2005), and Deformable Part-Based Models or DPM (Felzenszwalb *et al.*, 2008).

Du (2018) stated that as a key area in the field of image processing, development in object-detection algorithms has been progressing rapidly with the advent of Convolutional Neural Networks (CNN) and its variants since 2012.

According to its creators, Redmon *et al.* (2016), YOLO (short for You Only Look Once) is one such algorithm based on convolution neural networks, that stands out for its speed, learning very general representations of the objects it is meant to detect. The system first scales the image to 448 × 448 pixels, proceeds to run a single convolutional network on the pixels, and thresholds the results based on the model's confidence (Redmon *et al.*, 2016). This is demonstrated in Figure 2.28.

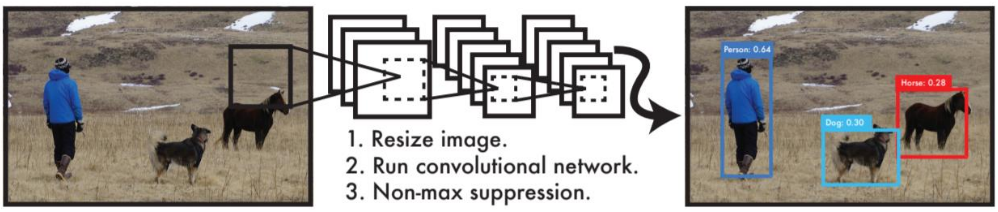


Figure 2.28: YOLO process summary, showing labelled objects (Redmon *et al.*, 2016)

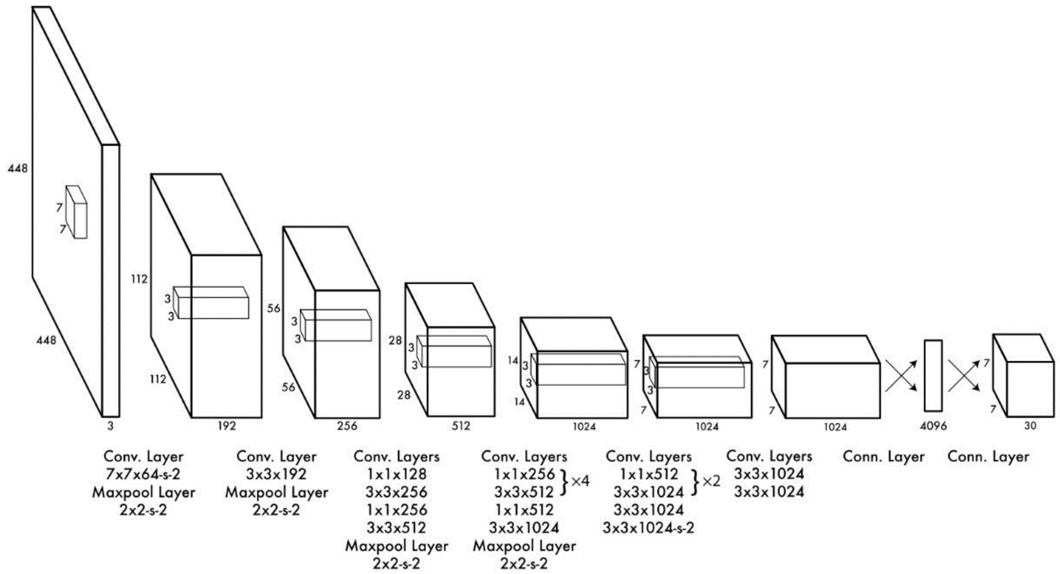


Figure 2.29: YOLO Deep Learning Architecture (Redmon *et al.*, 2016)

Multiple iterations of YOLO have been released. For instance, YOLOv2 performs at an optimal trade-off between speed in real-time and accuracy for object detection, when compared to other detection systems across multiple datasets (Du, 2018). Figure 2.30 shows YOLO labelling various objects in different datasets. In particular, it makes less than half the errors in background subtraction when compared to earlier models such as R-CNN (Region-Based Convolutional Neural Networks); while it does make more localization errors (Redmon *et al.*, 2016). This error comparison is shown in Figure 2.31.

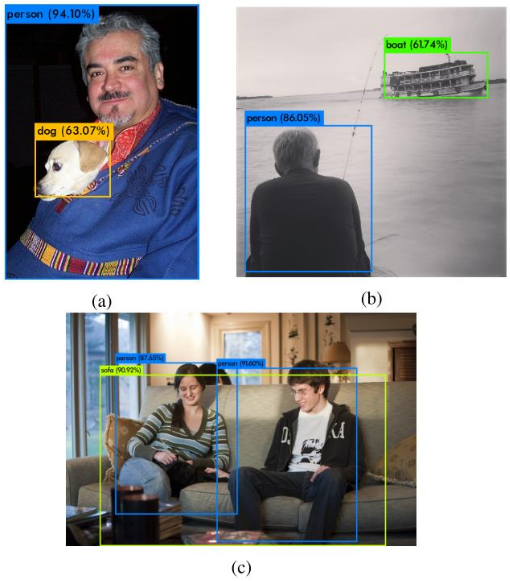


Figure 2.30: Examples of detections performed by YOLO in different datasets. (a) PASCAL VOC; (b) personal dataset; (c) COCO. Includes confidence level and class (Padilla *et al.*, 2020)

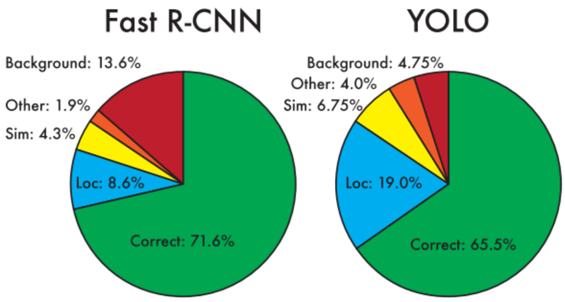


Figure 2.31: Charts showing percentage of errors (Redmon *et al.*, 2016)

To summarize, the sensing layer is of paramount importance in smart buildings, comprising the apparatus of sensors that read changes in the built environment and provide data to centralized systems which can run further analyses. In the field of occupancy sensing, while sensors can be of various modalities, modern image-based sensors have several benefits such as the ability to pinpoint occupant location with high granularity and the potential to be used with existing security camera infrastructure, with the use of artificial intelligence and deep learning with convolutional neural networks. However, this comes with its own challenges, such as the risk of privacy infringement. Although various techniques can be used to protect occupant identities in image/video data, the concept of personal privacy in modern smart buildings, and the associated legislation must be considered for this type of sensing.

2.3 Privacy in Smart Buildings

Smart buildings promise a greater quality of living, using interconnected systems that sense changes in the environment and predict the needs of its occupants. In such a dynamic, connected environment that is facilitated by the Internet, privacy risks cannot be ignored; whether they are created through the design of the smart building, the data that is collected, or usage of that data by building managers, corporate executives, real estate owners, or public entities. The following sub-chapter will describe the privacy risks, perceptions and legal frameworks pertaining to data collection in general, smart buildings, and finally, image-based occupancy sensing. However, this will not include examples relating to network security and measures enacted to prevent hacking or virtual intruders, as the vast amount of literature in that area is outside the scope of this research.

2.3.1 Definitions of Privacy

In the United States, a legal definition of privacy was first stated as “the right to be let alone” (Brandeis & Warren, 1890). This definition has formed the basis in legislation for almost a century, and it was during the period of 1960s to 1980s, with the growth of information technology, that further investigation into privacy and liberties took place (Berman & Bruening, 2001).

In his book *Privacy and Freedom*, Westin (1967) defined privacy as "the claim of individuals, groups, or institutions to determine for themselves when, how, and to what extent information about them is communicated to others." In the same book, he lists four basic states of privacy:

1. solitude, wherein an individual is alone. This is described as the most complete state of privacy achievable.

2. intimacy, the state of existing as part of a small group, whether a family, couple, or group of close friends.

3. anonymity, which occurs when the individual is out in public but expects to be free of surveillance or identification. In this state, one can enjoy the ability of 'merging into the situational landscape' and the freedom that comes with it.

4. reserve, when an individual is interacting actively with those around him or her, but withholding personal information or thoughts as they choose (Westin, 1967)

Westin's book was one of the important works of that era, pertaining to the value of information privacy in the face of a budding technological revolution and the potential threats to freedom that could appear.

The rapid progression of technology, permeating our environment faster than most people can wrap their heads around, can lead to apprehension and discomfort related to the fear of being watched. This is not a recent phenomenon; there are several related works of literature in the 20th century, of which *Privacy and Freedom* is just one example; another is *Nineteen Eighty-Four*, a book that even today is often quoted in conversations surrounding privacy and surveillance (Orwell, 1949).The book's 'Big Brother' character, who is the symbol of government supervision over citizens, is often cited in opposition to initiatives involving data collection (Hess, 2014).

Privacy in the modern era can also be defined as personal autonomy with regards to the use of information that individuals disclose or permit to be collected from them. For instance, when customers submit information to a bank, doctor or other service, they may expect the information will only be used to fulfil the service rendered to the customer. Individuals must have the right to object to further use (Berman & Bruening, 2001).

McCreary *et al.* (2016) had a more nuanced perspective, adopting the definition of the philosopher Helen Nissenbaum, which states that "privacy relates to appropriate data sharing". They state that individuals do not want absolute secrecy, nor do they desire complete control over their data; instead, they want confidence that their data would be shared according to general "context-dependent informational norms". Since there is such a diverse set of information privacy risks, ranging from hacking to unethical disclosure of customer data, the researchers clarify that privacy must not be treated as a monolithic concept but carefully considered with more granular methods.

2.3.2 Privacy-related Ethical Concerns and Perceptions of Occupants

Published over seventy years ago, George Orwell's book Nineteen Eighty-Four is widely read, and often comes up in conversations about surveillance and privacy infringements. In the dystopian world portrayed, the book features a 'telescreen': a television-like device in all houses, equipped with a camera that allowed the government to spy on its citizens. A paragraph from the book reads, "He thought of the telescreen with its never-sleeping ear. They could spy upon you night and day, but if you kept your head, you could still outwit them. With all their cleverness, they had never mastered the secret of finding out what another human being was thinking" (Orwell, 1949).

The example of Nineteen Eighty-Four might not have exact parallels with smart buildings today; but since data collection in smart buildings may involve metrics relating to the locations, habits, and identities of the users within them, the ethical concerns pertaining to privacy cannot be ignored. According to Callaghan *et al.* (2009), smart building technology is advertised as providing improved energy efficiency and quality of life, as well as greater profits for real estate owners; and yet the presence of vast amounts of sensors collecting information on users' activities warrants careful consideration.

As mentioned previously, it is essential for users to be aware of the ways their data might be used. For instance, Cascone *et al.* (2017) analyze the smart building projects attached to the Politecnico Di Torino Living Lab with a focus on privacy; namely "Wifi4Energy" and "SEEMPubs". They report that the mere presence of sensors in offices made occupants uncomfortable, since sensors could potentially monitor whether employees were at their working places; even though the occupants were not obliged to follow a strict schedule, they felt discomfort due to the possibility of surveillance. Furthermore, since the sensors also provided the possibility of workplace quality monitoring, the parties responsible for maintaining said quality also felt threatened.

Privacy concerns around smart building technology can also arise from poor practices in workplace applications, at the managerial or technology supplier level. Nappi and de Campos Ribeiro (2020) report that when companies have access to their employees' physiological data using smart wearable devices and health programs, this can lead to 'wellness syndrome'. Wellness is linked to productivity, and seen as quantifiable, through the tracking of physiological metrics. In one example of a health initiative conducted by BP America, the benefits of tracking this data, when resulting in increased physical activity through the use of health initiatives, were shown to be increased morale, improved corporate culture, better health and lower insurance rates (Lindzon, 2014).

However, Nappi and de Campos Ribeiro (2020) clarify that at the same time, such initiatives could potentially lead to biometric surveillance, or penalization of individuals who choose to opt out of such programs. Furthermore, employers had overarching access to the data generated by their employees, but employees were not able to download their own data in some cases. Of course, this data is of tremendous value to the employers, since it could help managers who would want to prevent employee sick leaves, insurance companies which can use the data to raise health insurance costs, and pharmaceutical companies that can target specific individuals with advertisements based on the profiles they create from the data.

Expanding the scale to the integration of smart local energy systems (SLES) in neighborhoods, Vigurs *et al.* (2021) described these systems as being supported by the UK government due to their potential in carbonization reduction, as well as fulfilment of various economic and energy conservation goals. SLES is an emergent concept, hence there isn't a standard definition, but some core aspects are the use of smart meters that collect data on energy use, learning and predicting user patterns, and combining with automated processes, for instance, dynamic load management in smart grids. Most importantly in the context of this research, these systems require personal data, and obtaining user permission is essential; not to mention the importance that must be placed on privacy. Through a review of relevant literature, Vigurs *et al.* (2021) found that studies related to privacy concerns in SLES suggested that data collection on energy use in homes could reveal the living patterns of users, crossing socially-acceptable boundaries when it came to privacy. Another major ethical aspect was the users' feeling of loss regarding their 'individual sense of autonomy choice and control'.

One reason for the anxiety surrounding privacy and data collection is the potential for misuse. Stepping out of the construction realm momentarily, data gathered from users on social media networks has had the potential to be used in targeted advertisements or political campaigns. In one recent, notorious example, Donald Trump's campaign was revealed to have enlisted the services of British political consulting firm Cambridge Analytica in the use of targeted advertisements towards voters (Graham-Harrison & Cadwalladr, 2018). The firm utilized personal information (extracted without authorization) from users of an app called thisisyourlife. The app appeared to be a personality test, and users agreed for the collected data from the test to be used for academic purposes; however, information on the users' Facebook friends was also extracted to create a data pool containing tens of millions of voters in the US. This information was then used by Cambridge Analytica and the Trump campaign to create politically useful profiles by analyzing personality traits linked to voter behavior; in other words, they knew which voters would be susceptible to the particular brand of advertisement they planned to show (Hal Berghel, 2018).

Privacy infringements are not limited to online platforms and data management systems. The computer vision research community at Stanford experienced a publicity blow due to the Brainwash dataset, a collection of webcam images of people in a crowded cafe in 2014, taken for a duration of three full days in the Brainwash Cafe in San Francisco, which was made publicly available and streamed on the internet, by a Stanford researcher for a research paper in 2015 (Midler, 2020). While the individuals in the cafe did not give their consent to participate in a dataset, the situation was exacerbated by the dataset being used in 2016 and 2017 by researchers associated with the National University of Defense Technology in China, for military research. In 2018, it was used in research affiliated with Megvii, the parent company of Face++ (a company blacklisted in the United States), which has provided surveillance technology to monitor the Uighur community in China (Harvey & LaPlace, 2021). In 2019, this information was made public, and the dataset was removed from the Stanford depository.

Examples like this have emphasized the need for legal frameworks to protect individuals from such misuse of private data, especially when the data itself goes on to be implemented in applications that are potentially unethical, and anti-pacifist.

2.3.3 Relevant Legal Frameworks and Regulations

Due to the high volume of data harvested from users of online websites such as social networks, as well as other forms of data collection in the physical world (for instance, physical sensors, smart devices and smart buildings) legal frameworks play a large part in regulating the use of data and protecting user privacy.

In the European Union, the General Data Protection Regulation (GDPR) was adopted on the 14th of April 2016 while it was enforceable from the 25th of May 2018. It is applicable when the data subject (person whose data is collected), controller (entity gathering data), or processor (third party that processes data on behalf of the controller) are based in the European Union (*General Data Protection Regulation*, Regulation 2016/679). The regulation aimed to give individuals right of ownership of their personal data, and to enact strict requirements for the processing of this data by other entities(Voigt & Bussche, 2017).

Holm (2018) stated that on the subject of smart buildings, there are several aspects of data collection that are sensitive to the possibility of personal identification, private habits and other individual traits. For example, even something as innocuous as a carbon dioxide sensor can detect when a person is home, and if paired with other information, an occupant's schedule may be extracted, which they may otherwise desire to keep private. Therefore, the processing of this data must then be in accordance with GDPR. The intuitive idea that the individual who 'produces' the data owns the data, is embedded in the GDPR, but this issue becomes complicated in smart buildings; particularly in homes, where data collected reveals much more about the identity of a person.

When it comes to data processing for research on smart buildings, Holm then describes three areas that must be closely observed:

- Research which involves 'personal data'. This must be done with a legal basis found in Article 6 of the GDPR (*General Data Protection Regulation*, Regulation 2016/679), of which the first (Article 6.1.a) is consent from the subject.Holm noted that in Swedish law, if the entity conducting the research is public, for instance, a public university, then the research can be said to be in the public interest, which is a legal basis as per Article 6.1.e.

- Research which involves ‘sensitive personal data’. This must be vetted by an ethical board, whether the research is undertaken by a public or private entity.

- Research which involves databases. These databases can be managed by public research entities on the same basis as the first point, while private research entities must be approved by an ethical vetting board, which in turn must observe specific, explicit consent of the data subject.

In Turkey, the equivalent regulation for the protection of personal data was established by the Turkish Data Protection Authority or in Turkish, *Kişisel Verileri Koruma Kurumu*. The Law on the Protection of Personal Data (KVKK) No. 6698 was published on the 7th of April 2016 (a week before the adoption of GDPR). KVKK was in fact prepared in line with the repealed EU directive 95/46/EC (with the exception of a few customized points) which was itself a predecessor of the GDPR (Geden & Bensghir, 2018).

2.3.4 Legislative Compliance and Anonymization

One category of data collected from the users of a building is referred to as biometric data. This is data that can identify a person based on their behavioral or physiological trait, and Onu *et al.* (2020) classified these traits as facial image, gait, voice, retina and fingerprints. In buildings, biometric readers use the aforementioned biological information to verify the identity of users, and are often used in buildings for access control, as an alternative to keycards (Sinopoli, 2009).

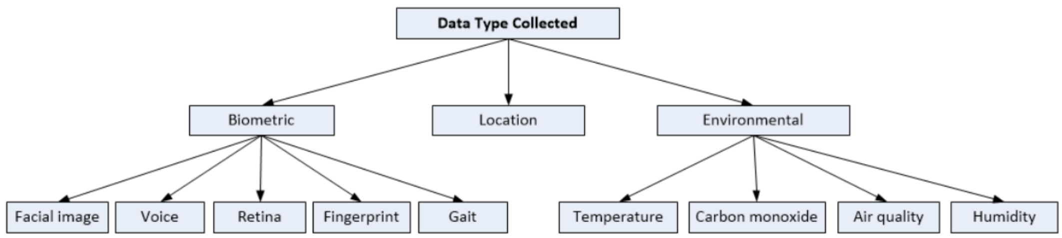


Figure 2.32: Data types collected in smart buildings (Onu *et al.*, 2020)

Article 4 of the GDPR defines personal data as “any information relating to an identified or identifiable natural person”. This information can be the name of the person but also other details such as race, political inclination, religion, biometric and genetic data (*General Data Protection Regulation*, Regulation 2016/679).

Since image or video data retrieved by cameras inherently contains facial data, it constantly records the biometric data of any individual it captures. This presents certain privacy risks, as described by Rajpoot and Jensen (2015). They refer to facial recognition with the use of cameras as ‘remote biometric sensing’ systems and warn that when these algorithms are applied onto integrated security camera systems, individuals can be tracked without their consent throughout the area that the camera network covers. According to the researchers, this can facilitate cyber stalking if irresponsible or malevolent parties gain access to the camera network. Callemein *et al.* (2019) stated that occupants may also feel uneasy if a camera is watching their movements.

The processing of video data is illegal until one of six conditions are met, as detailed in Article 6 of GDPR (*General Data Protection Regulation*, Regulation 2016/679). These conditions are:

1. Consent of the data subject,

2. Carrying out a contract to which the data subject is party to,

3. Complying with legal requirements that the controller is subject to,

4. Protection of the vital interests of the subject,

5. Public interest,

6. Legitimate interests of controller, except when these override the fundamental freedoms of subject, especially if the subject is a child.

Barnoviciu *et al.* (2019) reported on the GDPR compliance of video cameras used for surveillance and image processing. They describe the most common of these in practical applications as consent and legitimate interest, an example of which is the use of surveillance cameras to protect the security concerns of a business against theft or vandalism.

The GDPR also defined seven principles to adhere to when processing public information in Article 5.1 (*General Data Protection Regulation*, Regulation 2016/679). These are:

1. Lawfulness, fairness and transparency

2. Collected for specific, legitimate and explicit purposes (purpose limitation)

3. Collection adequate and limited to what is necessary (data minimization)

4. Accuracy

5. Limited time of storage

6. Ensuring security of confidential data

7. Accountability remaining with the controller

Barnoviciu *et al.* (2019) used these to make certain interpretations in the context of video processing:

- According to the principles of purpose limitation and data minimization, cameras should capture as little of the public space as possible.

- According to the GDPR, anonymization of video data is defined as techniques through which the data subject is no longer identifiable; therefore, true anonymization places the processing of the data outside the scope of the GDPR.

- Article 4 of the GDPR defines pseudo-anonymization as processing of data in a way that it cannot be identified as belonging to any specific individual without further information. This also lowers the degree of restrictions placed on processing.

Kjærgaard and Sangogboye (2017) presented a categorization framework for data collected by occupancy sensors, classified as information type, occupant relation, and sensing strategy, shown in Figure 2.33. In the context of this image-based sensing, the information type must be restricted to presence (whether people are occupying a space and how many), the occupant relation anonymous (identity to remain unknown), and the sensing strategy to augment the environment (placing sensors in the environment instead of on occupants' person or on equipment).

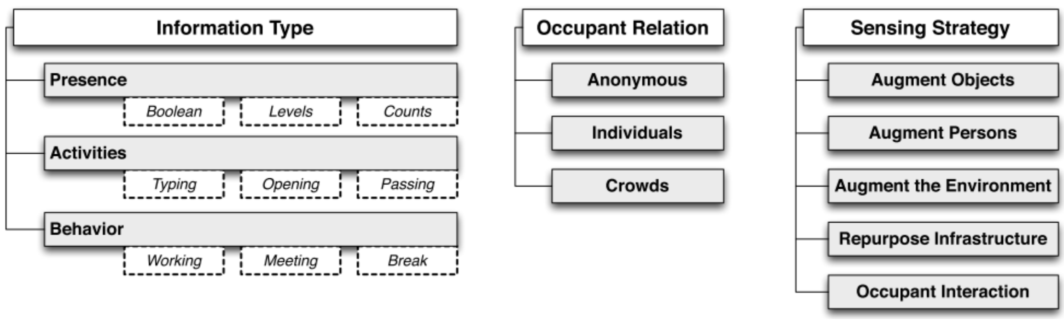


Figure 2.33: Information type, occupant relation and sensing strategy (Kjærgaard & Sangogboye, 2017)

Callemein *et al.* (2019) reported that facing similar governmental restrictions on processing video data, they would apply the anonymization technique of reducing the resolution of the video data to the point that people would not be identifiable any longer; however, they still needed to keep it high enough that a person-detection algorithm could recognize the presence of a person. The reduction of the original resolution is shown in Figure 2.34.

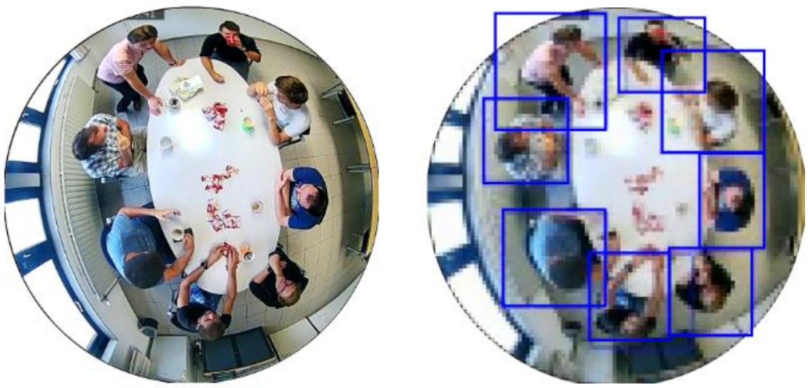


Figure 2.34: Original resolution and reduced resolution
(Callemein *et al.*, 2019)

Barnoviciu *et al.* (2019) also attempted to anonymize video data, but instead of lowering resolution for the entire image, they created a system to recognize the presence of faces and blur them to the point where they could not be identified, as shown in Figure 2.35. The researchers state however, that de-anonymization techniques also exist which can be used to reverse the anonymization process, leaving this vulnerable both to malicious agents and to the accountability mandated by the GDPR.

Hsu *et al.* (2017) attempted to preserve privacy in video-based person detection by using cameras that were pointed straight down from above and by using depth cameras instead of traditional RGB cameras, with the results shown in Figure 2.36.

Another advantage of this was that top-down cameras were not as noticeable as cameras in top corners of rooms, so occupants did not feel as uneasy.

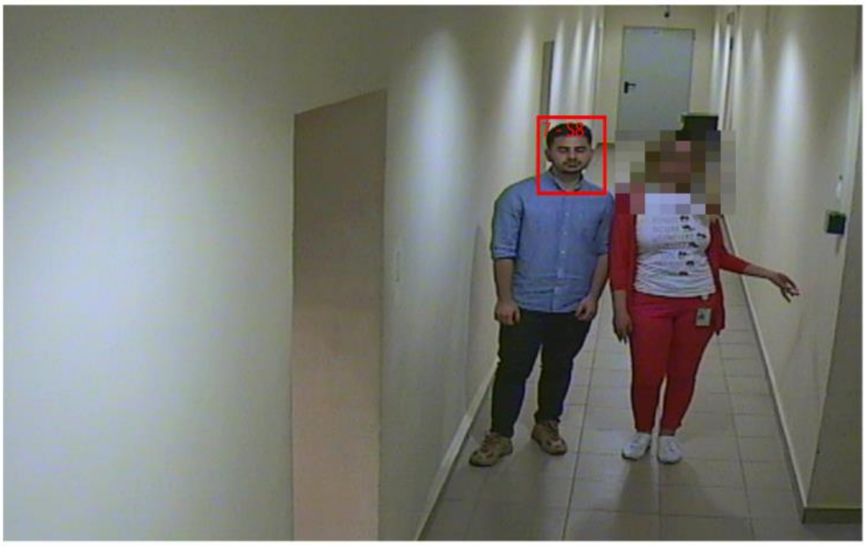


Figure 2.35: Example of facial recognition and blurring (Barnoviciu *et al*, 2019)

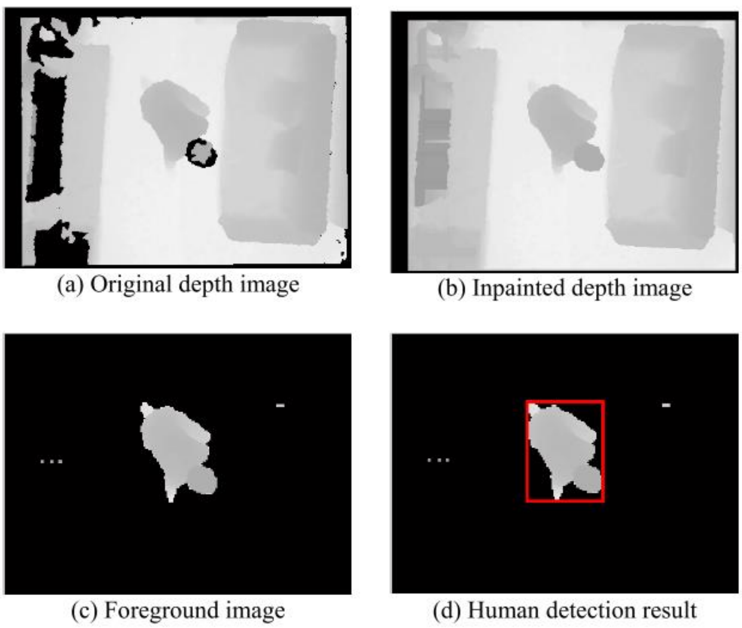


Figure 2.36: Action detection using top-down depth cameras (Hsu *et al*, 2017)

In conclusion, this sub-chapter has presented the importance and context of privacy in a world where data collection is the norm. In the realm of smart buildings, while occupancy sensing has several benefits, the major risk of privacy infringement cannot be ignored, especially in the case of image-based occupancy sensing. It is important to implement legislative compliance in occupancy sensing frameworks, which can be accomplished by anonymization techniques.

CHAPTER 3

MATERIAL AND METHOD

This chapter explains the research material and methodology used for the image-based occupancy sensing technique comparison, as well as the smart office occupant survey.

The former is used in lieu of image-based occupancy sensing inside a room; this is because most meeting places within the campus were unused due to the coronavirus pandemic situation. Instead, people passing along an outdoor pathway underneath a building were recorded using cameras placed at different angles, to compare the accuracy of both.

While the image-based experiment approaches the privacy problem from a technological perspective, the questionnaire queries respondents to find which camera angle they prefer.

3.1 Material

The intention of the research was to simulate fixed security camera recording, which could then be analyzed to determine foot traffic and occupancy counts inside the area above which the recording took place. To compare levels of privacy and subsequent people-counting accuracy, two cameras were to be placed in the same location above head height, one pointing straight downwards to not capture facial data, while the other was to be aimed forward and downwards, to capture frontal images of people passing below.

This experiment was initially planned to be conducted inside an active building in the Middle East Technical University campus; however due to the coronavirus epidemic, university classes were online and therefore the population of the campus was limited. For this reason, most gathering places and restaurants within the campus were closed. This meant the potential number of areas for the research were narrowed down. One of these buildings was the Faculty of Engineering building, (henceforth referred to as the MM building, an abbreviation of Merkez Mühendislik) due to its large size, functioning canteen, and various offices of the Engineering Faculty. The location of the MM building is of prime importance (Figure 3.1). Situated adjacent to the main pedestrian artery (referred to henceforth as the allée) that runs north to south, connecting the departments, it contains several departmental offices, a canteen and other gathering points. The building serves as a point for meeting, various institutional functions and passing through from one side of the building to the other.

While this research pertains to image-based sensing in entryway areas, the MM building has 5 entryways (Figure 3.2): the main entrance facing north, the tower entrance to the northeast (which accesses the tower elevators), the northwest entrance under the bridge, southwest entrance to the canteen from the open-air dining place, and the southeast entrance which leads to the offices from the southern part of the campus. This means that the concentration of passersby through each entrance is diluted, which is especially exacerbated due to the coronavirus situation.

Therefore, the most appealing location of camera placement was the first-floor bridge that connected the amphitheater section to the main building, which resulted in an open passageway underneath that is used as a passage between the main cafeteria and north section of the campus, to the MM building cafeteria and various areas of the south side of the campus on the other side of the building. It was observed that activity under this passageway was greater than people entering the MM building through any one entrance.

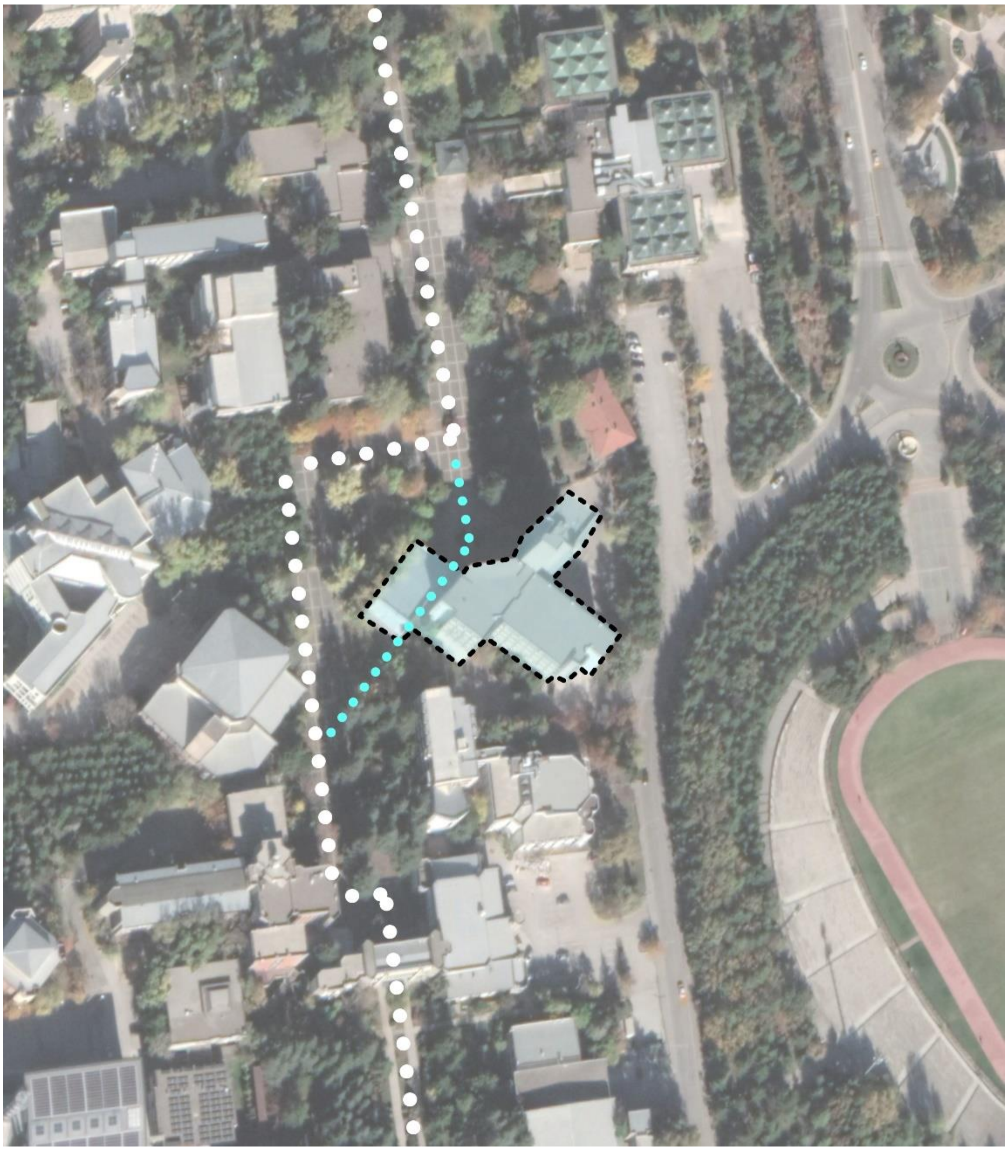


Figure 3.1: Location of MM Building relative to allée, highlighted in light blue, allée of the campus as white dotted line, and secondary passageway under the bridge of the MM building as cyan dotted line

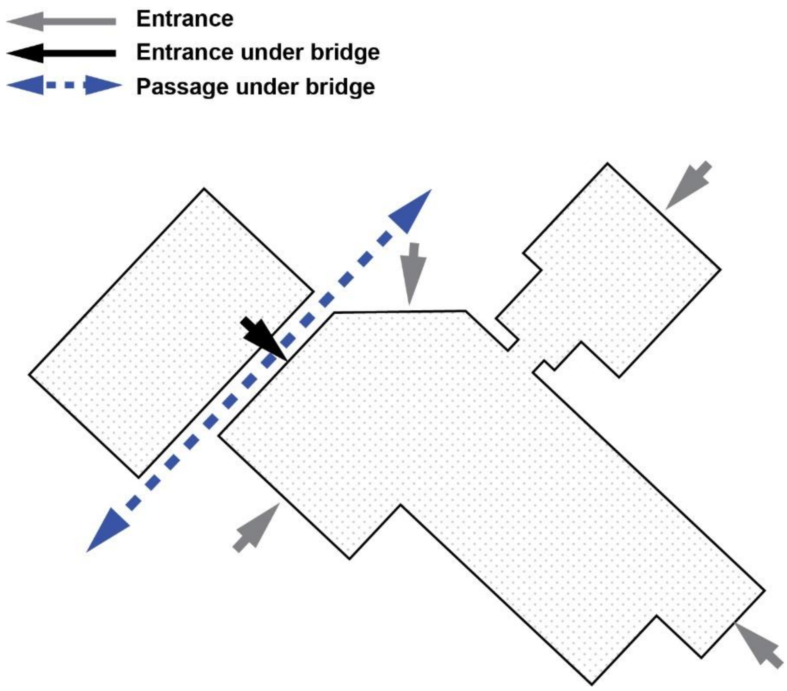
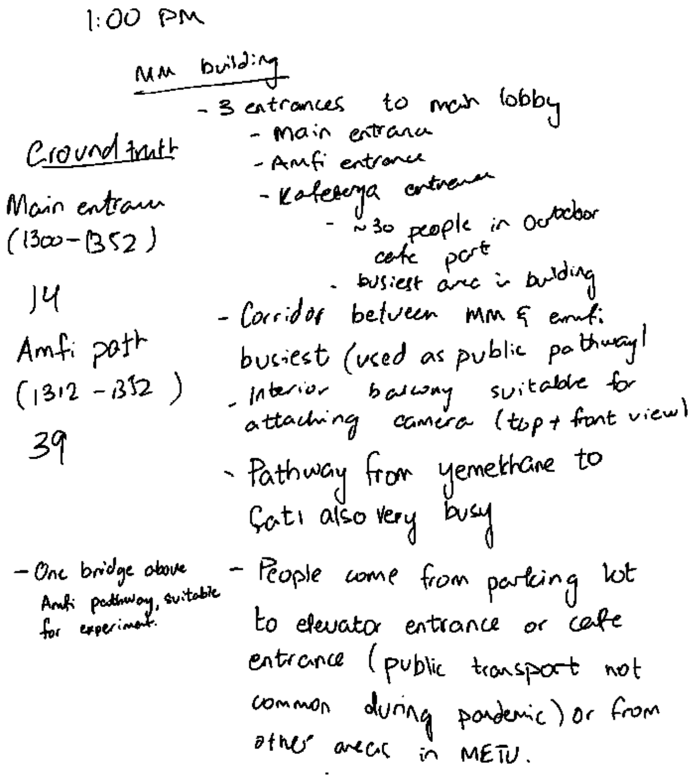


Figure 3.2: Footprint of MM Building (not to scale) with entrances and passage shown

As a preliminary investigation, the researcher compared the activity through the north-facing main entrance with the activity adjacent to the northwest entrance (people either using that entrance or passing under the bridge to get to the other side of the MM building). Passersby were counted on a Wednesday on 14th April 2021, between 1:00 PM to 1:52 PM, a time slot selected due to assumed activity at the end of lunch break and the beginning of the afternoon workday (Figure 3.3). While 14 people used the main entrance, 39 people passed under the bridge. Similar activity was observed during the time when the primary research was carried out.



1:00 PM

MM building

- 3 entrances to main lobby
  - Main entrance
  - Amfi entrance
  - Kafeterya entrance
    - ~30 people in outdoor cafe part
    - busiest area in building
- Corridor between MM & amfi busiest (used as public pathway)
- Interior balcony suitable for attaching camera (top + front view)
- Pathway from yemekhane to Cati also very busy
- People come from parking lot to elevator entrance or cafe entrance (public transport not common during pandemic) or from other areas in METU.

Ground truth

Main entrance (1300–1352)

14

Amfi path (1312–1352)

39

- One bridge above Amfi pathway, suitable for experiment.

Figure 3.3: Excerpt of notes taken during observation

The primary research was undertaken on the 12th of July 2021, Monday, with the two cameras attached at 11:45 AM. Recording took place from 12:00 PM to 4:00 PM.

The location of the research was the first-floor bridge space spanning approximately 3 meters in length, with a width of 2 meters. The bridge runs northwest to southeast, with glass and aluminum framing encasing one bottom hung casement window on either side, as shown in Figure 3.4 and 3.5.

The equipment used comprised of two GoPro Hero 4, action recording type cameras (Figure 3.6), containing memory cards with storage capacities of 64 gigabytes. These were attached to phone glass mounts (products which use suction cups to attach mobile phones to car windshields), which in turn were attached to the outside of the glass on the bottom hung casement window on the northeast side of the bridge

(Figure 3.7). Since the battery life of the cameras was approximately one hour long, the cameras were plugged into portable battery packs of 10,000 mAh to enable uninterrupted usage throughout the four-hour period, with the camera batteries removed to prevent overheating.

Figure 3.4: Bridge from MM Building to amphitheater section

Figure 3.5: Interior of bridge with bottom hung casement window

Figure 3.6: GoPro Hero 4 action recording type camera used for recording

Figure 3.7: Camera attachment using suction phone mounts

To prioritize memory efficiency, cameras were programmed to record video with quality set to 720p and a framerate of 25 frames per second. Narrow field of vision was used to prevent image distortion. GoPro cameras automatically segment recorded video files to protect against loss of data due to interrupted or corrupted recording. This resulted in 9 individual video files, each approximately 27 minutes long and 3.9 gigabytes in size, from each camera. The resolution of these files was 1280 by 720 pixels with a total bitrate of 20128 kbps (kilobits per second).

The camera recording a frontal view was attached to a fixed glass mount, pointing perpendicular to the angle of the window, which was itself approximately 30 degrees from a vertical state when open. The camera recording the top view was attached to a mount with adjustable angle of rotation and a longer arm, allowing it to be suspended approximately 20 centimeters away from the window and pointing downward. The angles are shown in Figure 3.8, with the recorded images from each camera shown in Figure 3.9. The experiment being conducted in the early afternoon meant a range of lighting conditions and occasionally harsh contrast conditions were captured in the video.

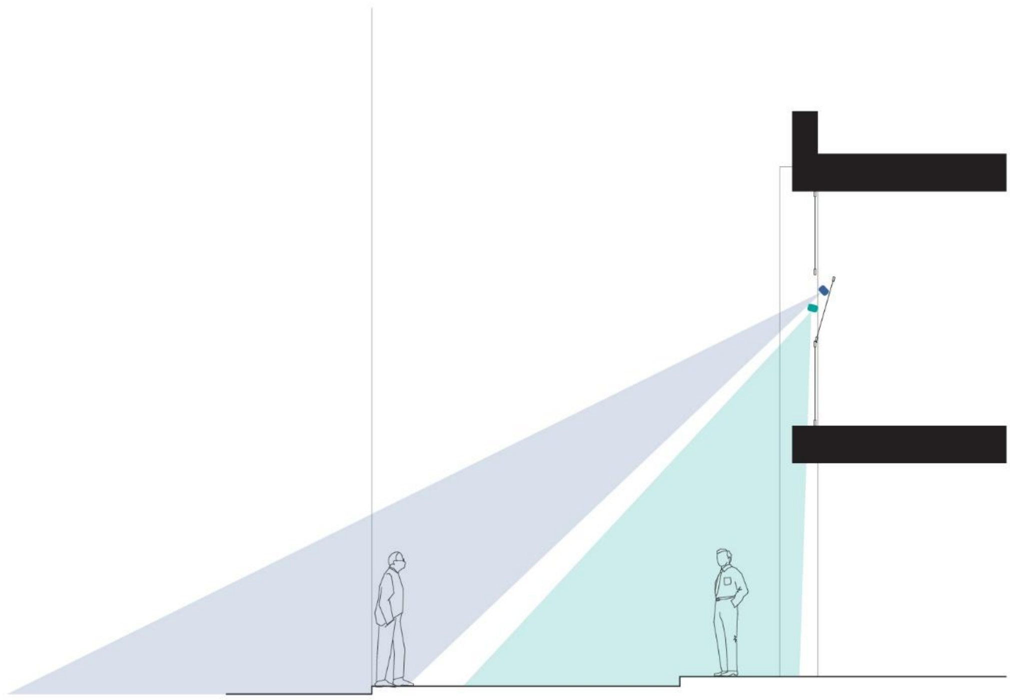


Figure 3.8: Section of bridge and camera angles (not to scale). Frontal angle shown in blue and top-down angle in green.

Figure 3.9: Top view image, top view with subject, frontal view image, frontal view with subject (Top to bottom)

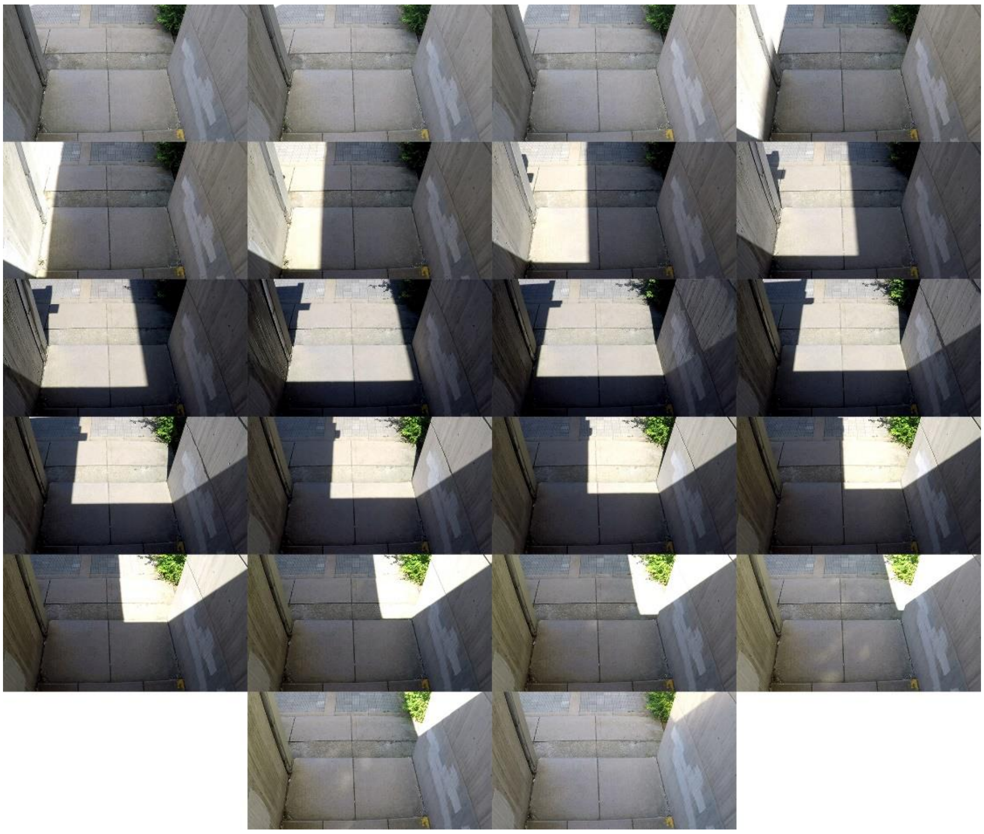


Figure 3.10: Light conditions at each 10-minute interval, as captured on frontal camera

This experiment is followed by a survey that queries respondents which camera angle they are more comfortable with. This is part of a larger survey which can be viewed in Appendix A and B. An official permission for the survey was obtained from METU Ethics Committee (Protocol number: 272-ODTU-2021).

As the literature review demonstrates, there is a lack of comparable research on building occupants' perceptions towards the growth of the smart building sector, advances in sensors, and use of artificial intelligence in vision-based technologies. This may be a potentially revealing area of research considering privacy attitudes towards corporate data collection in general throughout the 20th and 21st century, and recent events which have been brought to the forefront of people's awareness concerning privacy irregularities by technology companies.

The survey starts with an introductory text which identifies the survey as part of research, introduces the intention, and imparts some context pertaining to smart building technologies, data collection, and image-based occupancy sensing. This text is written in both English and Turkish.

The complete survey is composed of 21 questions, divided into four categories, as shown in Figure 3.11.

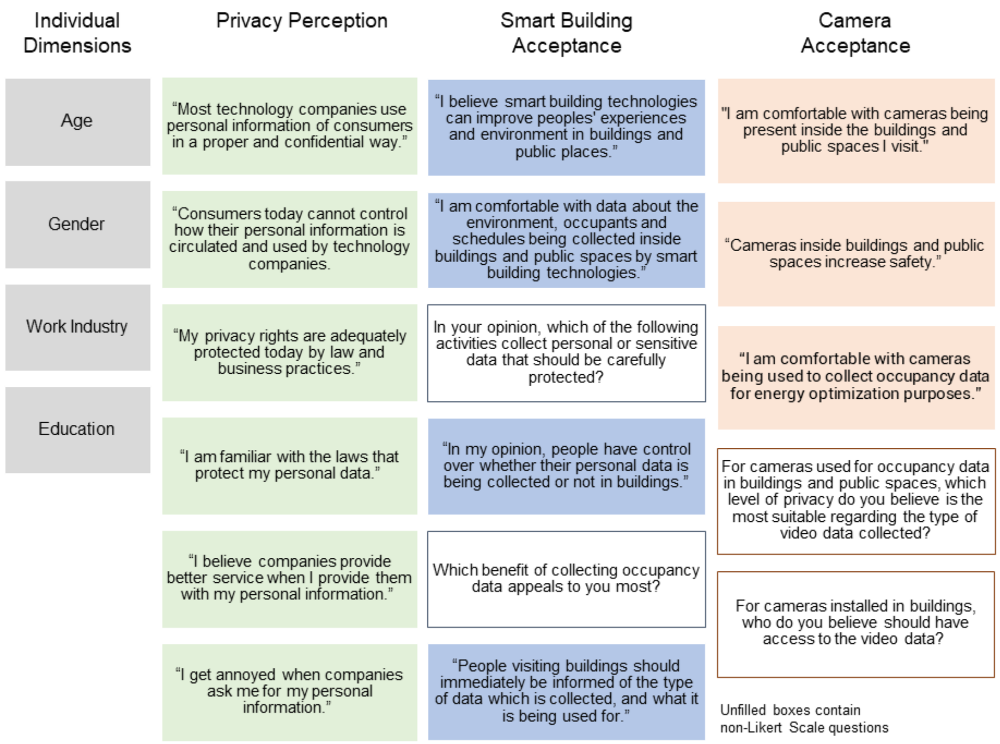


Figure 3.11: Category-wise breakdown of all survey questions

In Category A, four questions query the respondent's age, gender, work industry, and education (last completed degree).

In Category B, the respondent's perception of privacy as a concept is addressed, asking the respondent their level of agreement with a set of statements. These do not pertain to smart building technologies or data collection using sensors, but towards a general perception of corporate/institutional data use and the concept of mutual benefit between consumer and corporation.

Category C contains questions that narrow the focus to data collection in buildings specifically, while Category D pertains to cameras used for occupancy data collection.

The relevant question to this thesis (numbered question 18), can be seen in Category D and relates to the camera experiment, investigating the preference of the respondent towards the type of camera data captured for occupancy sensing.

- For cameras used for occupancy data in buildings and public spaces, which level of privacy do you believe is the most suitable regarding the type of video data collected?

    A. Normal video showing faces

    B. Normal videos but with faces blurred

    C. Videos recorded from top (showing the presence/location of a person but not their face)

    D. No preference

A supplementary image featuring the researcher is shown of all three types of images.

Figure 3.12: Three images from different angles shown to respondents

3.2 Method

Before analysis, the video files were first stitched together to an uninterrupted four-hour recording. Due to an adjustment in one of the camera's angles needed near the beginning of the recording process, the first 20 minutes of the front-facing camera were at a different angle than the rest of the footage. To preserve consistency, 20 minutes were trimmed from the beginning of both cameras' footage.

Ground truth data was then extracted by manual observation for comparison purposes.

As the application of this use-case was intended to be using low-cost hardware, and implementation in existing security camera infrastructure, the resolution of the videos was down-sampled to a square aspect ratio of 600 by 600 pixels, which had the added benefit of increasing computational efficiency.

Considering that the remaining footage contained large periods of no movement in an empty area, it was more computationally efficient to only carry out object-detection on the time periods where movement occurred in the area, which has the added advantage of minimizing storage space, and reducing video duration for easier viewing (Alano *et al*, 2016). This was accomplished by using background subtraction and extracting only the clips in which there was pedestrian movement (hereafter referred to as key event clips). This was activated when the background subtraction mask created contours larger than a set number of pixels.

For the implementation of motion detection, background subtraction with the MOG2 Background Subtraction node in the OpenCV library (Bradski, 2000) was used). Background subtraction is a preprocessing stage for vision-based applications, which allows the segmentation of foreground objects from a static background (Piccardi, 2004).

Figures 3.13 and 3.14 show visual outputs for the top-view camera at each stage of preprocessing, for instance, the original frame, the output of the background subtraction mask, and a depiction of the contours around the blobs produced in the mask. Figure 3.13 shows the output when there is no movement; due to inconsistencies in light or image noise, there are some variations in the image towards the left of the frame, which are recorded in the background subtraction mask and produce the contours as shown. When a person enters the frame as shown in Figure 3.14, the mask output registers a higher change in the image, creating contours with areas large enough to start recording. The contour areas recorded during various time events were observed to determine a benchmark value, as shown in Figure 3.15.

Figure 3.13: No movement state. Left to right; recorded frame, background subtraction mask output, and contours created by mask output

Figure 3.14: Movement detected state. Left to right; recorded frame, background subtraction mask output, and contour created by mask output

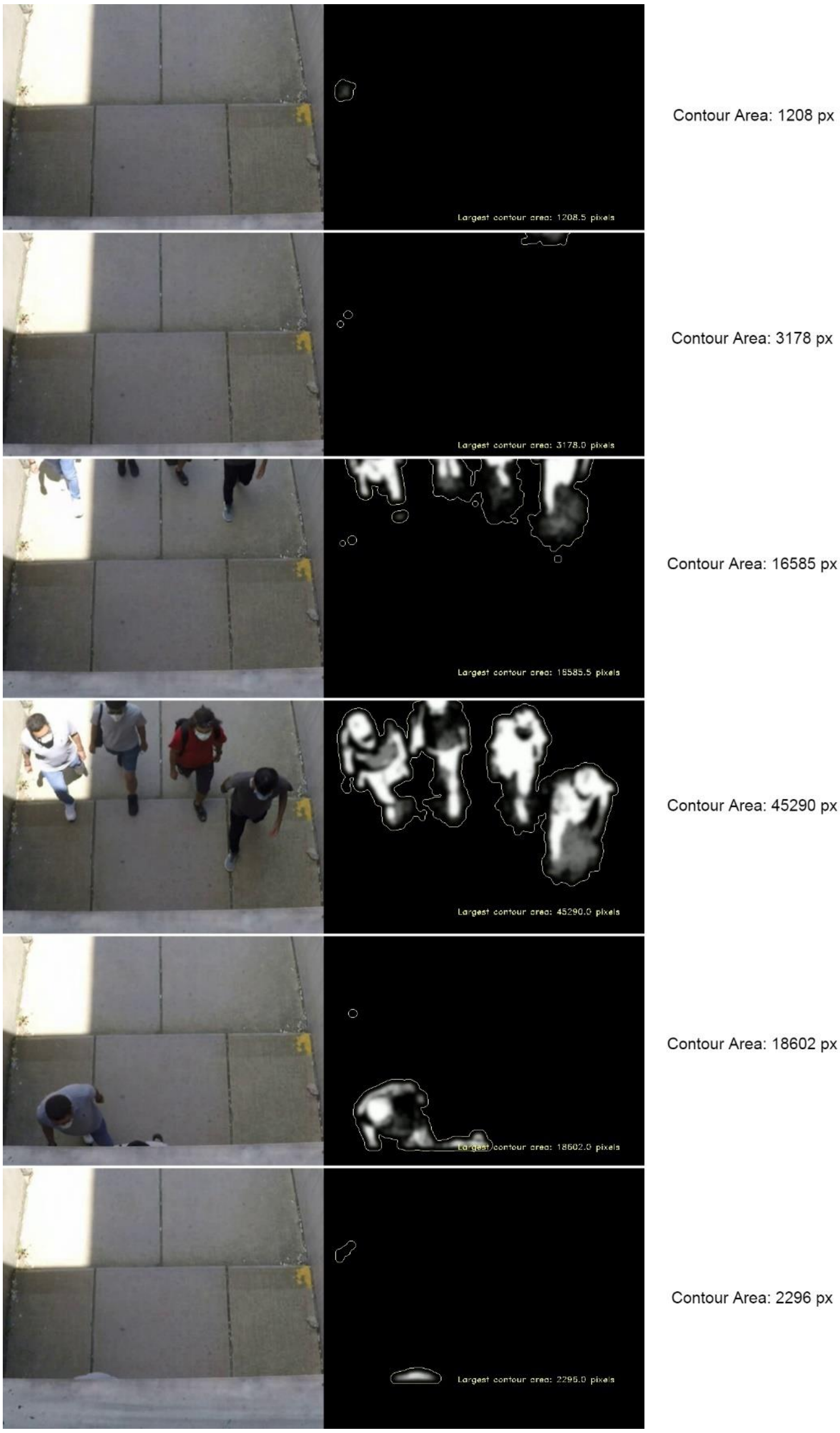


Figure 3.15: Various contour areas during pedestrian passage

After examining the contour area outputs, a value of 15,000 pixels was chosen to signify the presence of a person and activate the key event clip recorder.

The key event clips were processed through an implementation of YOLOv3 with OpenCV. The YOLO model was used with the configuration file and pre-trained weights available on the founder's Github page (Redmon, 2013). The first process is blob extraction, a process by which blobs (Binary Large Objects) that are groups of connected pixels are extracted through background subtraction, thresholding, and contouring. This process also provides single or multiple bounding boxes around each blob, to which non-maximum suppression is applied to suppress weak and overlapping bounding boxes, leaving only one around each blob.

The bounding boxes are then processed to find possible IDs of detections, and if those exist, then the ID name is returned as a detection along with the confidence percentage. For each key event clip, a .csv file was created with the timestamp, frame number, number of detections and number of people recorded for each frame. This was done for both the top and front angle cameras, and the number of detections at each timestamp compared to the ground truth recorded by manual observation.

The key event clips were then manually observed to tabulate any errors in the detection. The data for number of persons detected in each frame was tabulated and graphed, to view any errors. The graphs of both camera angles for each key event were then examined to observe false negatives or misclassifications.

This was followed by the survey, which was uploaded on the METU Survey system in Turkish and English, with two separate links for each. These links were sent to various office occupants in the sectors of construction and information technology, through convenience sampling.

For this thesis, the responses by each participant of Question 18, are observed with the demographic parameters. The responses were initially tabulated and organized according to a score system assigned to each question category, but to narrow the focus to the camera angle question posed by the field experiment, only the response to Question 18 is used in this thesis.

This is tested to find any statistically significant relationship between each specific demographic parameter of the respondents, and their preferred camera angle used for occupancy sensing.

To find whether age, gender or education were associated with camera angle preference, null and alternative hypotheses were created as follows for each.

- Null hypothesis: The specific demographic parameter has no statistically significant relationship with the camera angle preference,
- Alternative hypothesis: There is a relationship between the specific demographic parameter and the camera angle preference.

The Pearson Chi-square test is used for this purpose in Microsoft Excel. Pearson's chi-square test is used to find whether there is a statistically significant difference between the expected frequencies and the observed frequencies in one or more categories (in this case, the demographic parameter and the camera angle preference) of a contingency table.

A conventional p-value of 0.05 is used to compare with the p-value found by applying the test on the camera angle preference values with each specific demographic parameter. If the p-value found is lower than 0.05, the parameter is deemed to have a statistically significant relationship with the camera angle preference. If higher, than there is no statistically significant relationship of the parameters with the camera angle preference.

CHAPTER 4

RESULTS

This chapter outlines the results of the image-based comparative experiment as well as the survey.

The method for the image-based experiment led to the creation of key event clips containing each major movement event based on contour area outputs of each frame. For the entire period of recording, which was approximately 12:15:00 PM to 3:45:00 PM, ground truth data of the number of pedestrians passing in the video was obtained via manual observation with a ten-minute resolution, as shown in Figure 4.1.

The contour area outputs of each frame are shown in Figure 4.2 according to the time. Outputs above 15,000 pixels are shown in blue and signified a major amount of movement or change in the image, leading to a key event clip being recorded. Contour area outputs below 15,000 pixels, shown in orange in the figure, were not deemed useful to record since they were generally due to light fluctuations, small object movements (leaves and other debris), and automatic light adjustments by the camera.

In total, 212 people passed through the area, with 105 going up (towards the north-east) and 107 going down (towards the south-west). This data was segmented into 10-minute intervals, for a total of 220 minutes, and recorded.

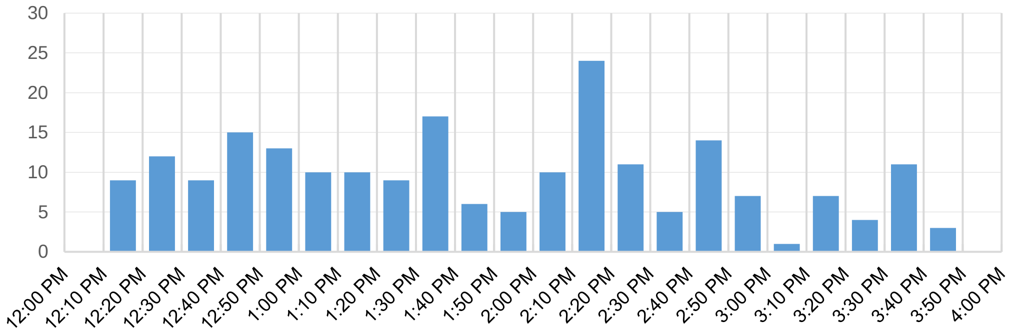


Figure 4.1: Number of pedestrians passing recorded by manual observation of video data, in ten-minute increments

After the key event clips were processed through the pedestrian detection stage, each clip was manually examined to find any irregularities in the detections. These were either noted to be a 'false negative', a single frame where a person was not detected despite being present, and 'false positive' referred to here as 'misclassification', which signified a single frame where a person was labelled as another class (such as a bird, or a skateboard). These are shown in Figure 4.2.

In many key event videos, these irregularities often occurred for a single frame, and these were made more obvious once graphs were created for each key event video with frame-count on the x-axis and number of people detected on the y-axis. To demonstrate, Figure 4.3 shows an example of a misclassification in a key event video labelled with the starting time '13:45:59'. This error only occurs for a single frame, as shown in Table 4.1, and Figure 4.4.

Figure 4.2: Examples of the errors, misclassification or false positive (top) and false negative (bottom)

Figure 4.3: Example of single-frame misclassification

Table 4.1: Excerpt of data record

Frame Number	*Number Of Detections*	*Number of People Detected*
61	2	2
62	2	1
63	2	2

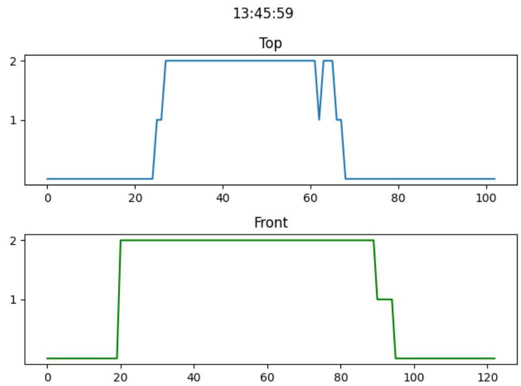


Figure 4.4: Graphs of frame-count (x-axis) and people detected (y-axis) for key event video (both cameras)

Similar graphs were created for all key event videos from both cameras, observed for irregularities, manually checked, and then tabulated.

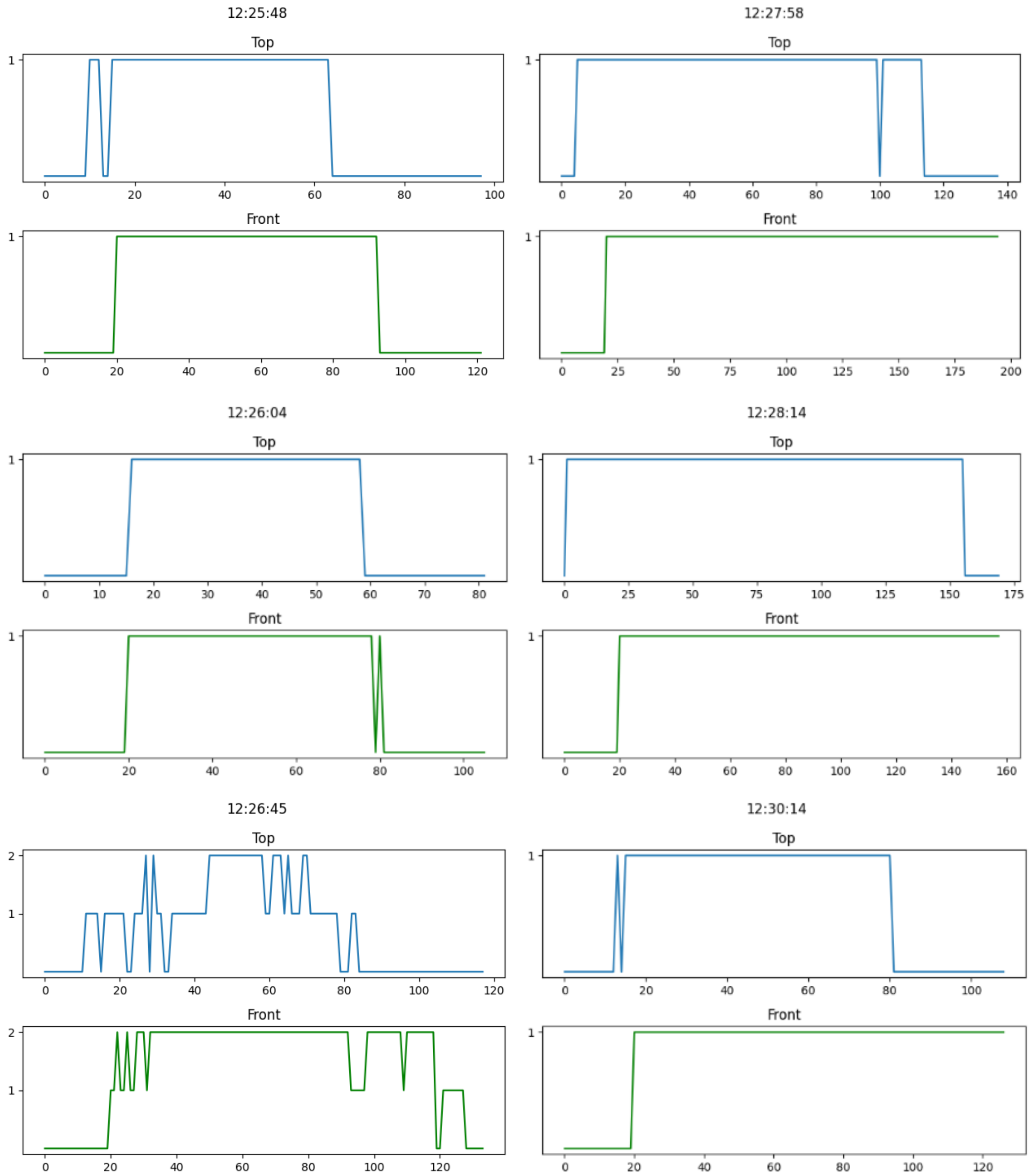


Figure 4.5: Examples of graphs of frame-count by persons detected for six key event videos from both cameras

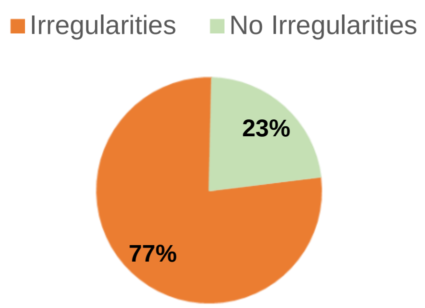


Figure 4.6: Percentages of irregularities of a single frame in graphs of key event videos captured from the top-view camera

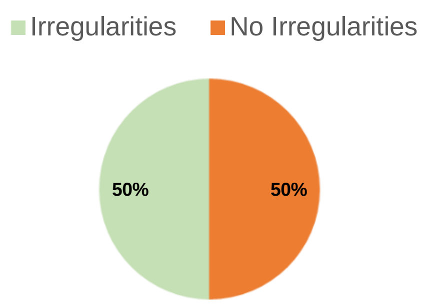


Figure 4.7: Percentages of irregularities of a single frame in graphs of key event videos from the front-view camera

The chosen method to smooth the data was by using the mode of a previous number of frames. For each frame, the mode of persons detected in the previous set number of frames was referred to as the 'sustained' count at the frame, as opposed to the 'instant' count which was the number of persons detected on the current frame. Sustained counts juxtaposed on instant counts are shown in the graphs in Figure 4.8.

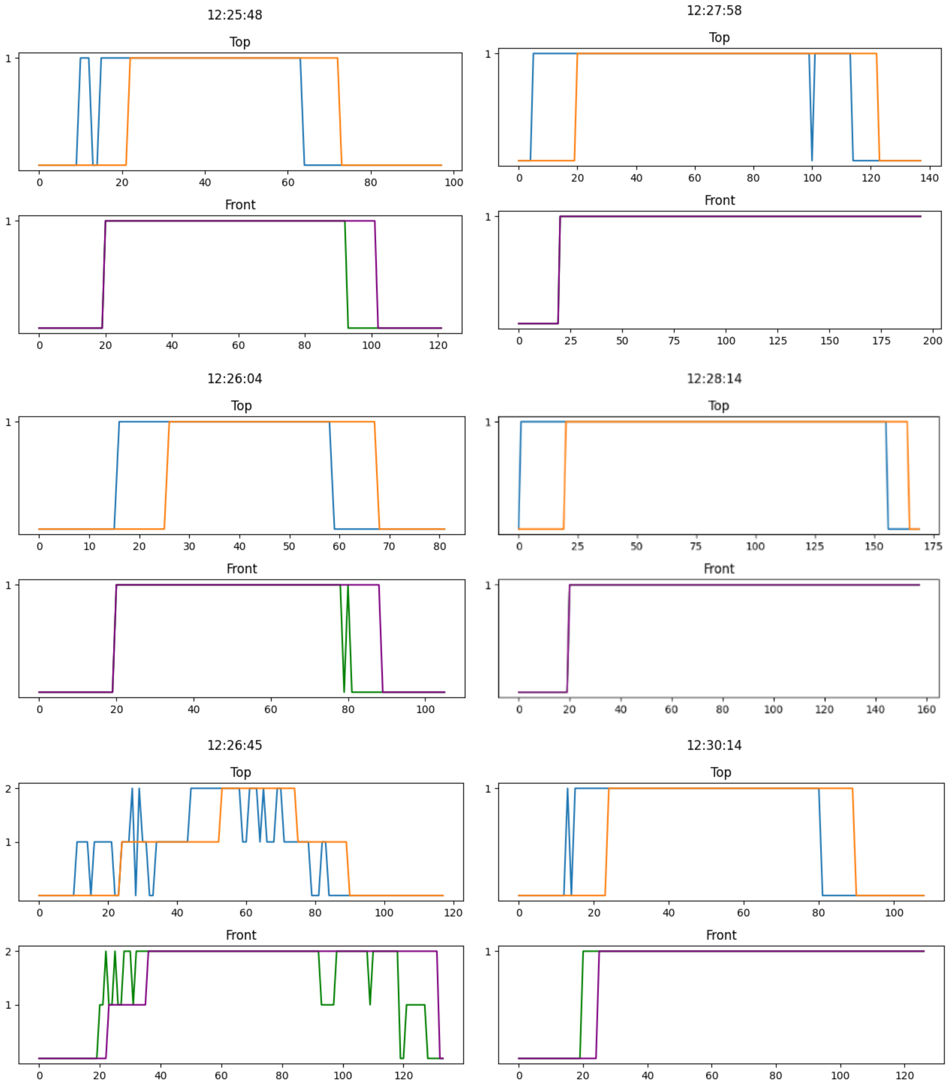


Figure 4.8: Graphs of frame-counts by ‘sustained’ (orange and purple) person counts overlaid on ‘instant’ (blue and green) person counts

Using the sustained count data from the top camera, it was possible to create an occupancy graph for the entire recorded period, with a one-second data resolution, as demonstrated in the hourly occupancy graphs in Figure 4.9.

Figure 4.9: Occupancy graphs of each hour of the recorded period with a resolution of one second

In the survey, data from 31 respondents were used for analysis. For this thesis, the descriptors of the respondents and the preferences of camera angle are used. The complete survey can be read in Appendix A and B while the responses are listed in Appendix C.

Demographic parameters such as age, gender, education of the respondents are displayed in Figure 4.10.

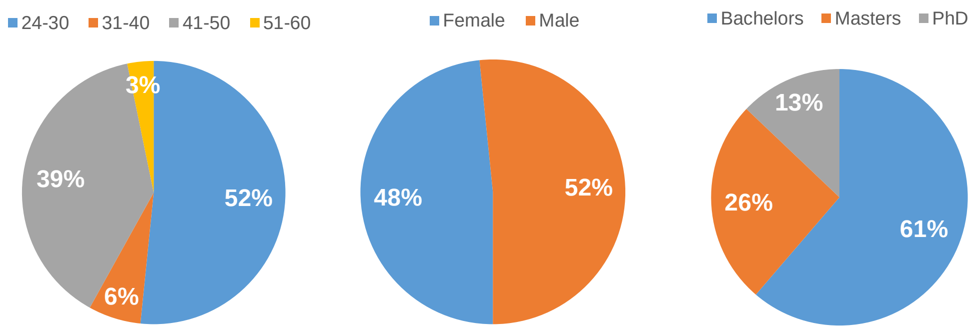


Figure 4.10: Age, gender and education level of respondents (left to right)

Figures 4.11 depicts the responses with regards to privacy perception ranges, for multiple-choice questions querying the preferred level of privacy for occupancy data collection cameras.

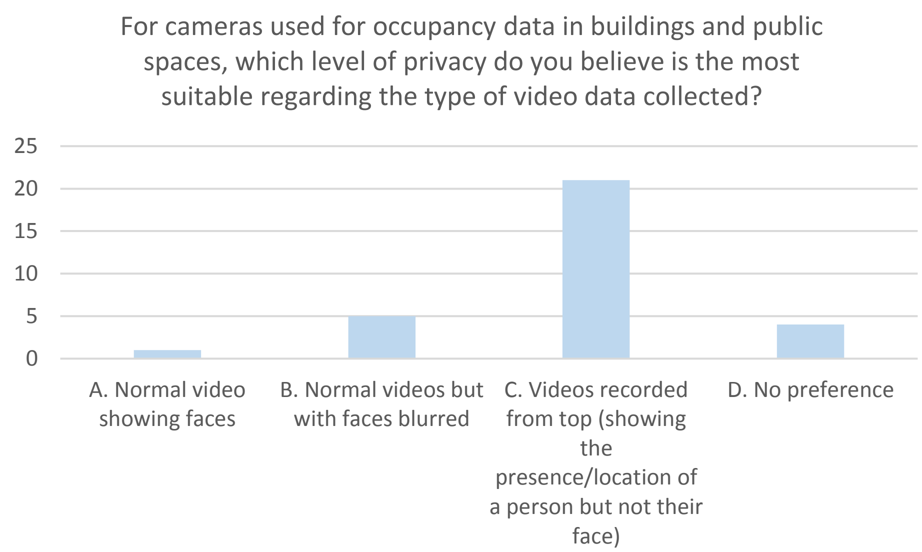


Figure 4.11: Preferred privacy level for occupancy detecting cameras, as chosen by respondents

When it came to privacy level preserved by cameras used for occupancy sensing, a vast majority of respondents preferred videos recorded from the top, showing location and presence of a person as opposed to videos recorded from the front, or blurred. The figures below illustrate the distribution of each parameter in camera angle preferences.

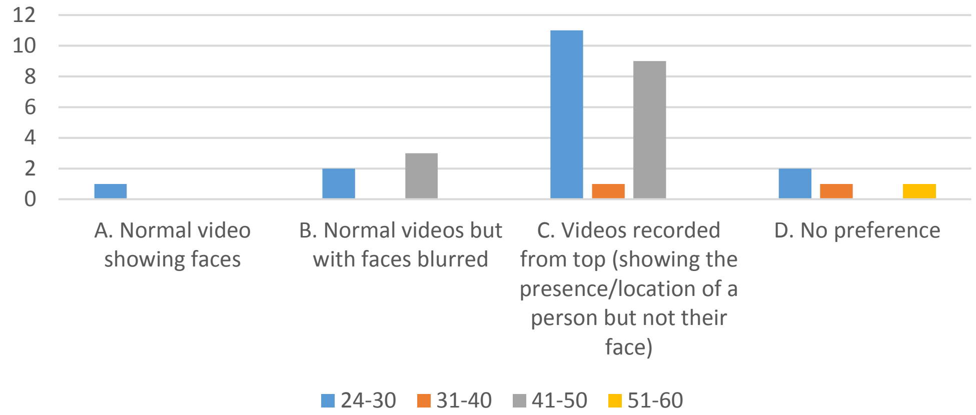


Figure 4.12: Age - Camera Angle Preference

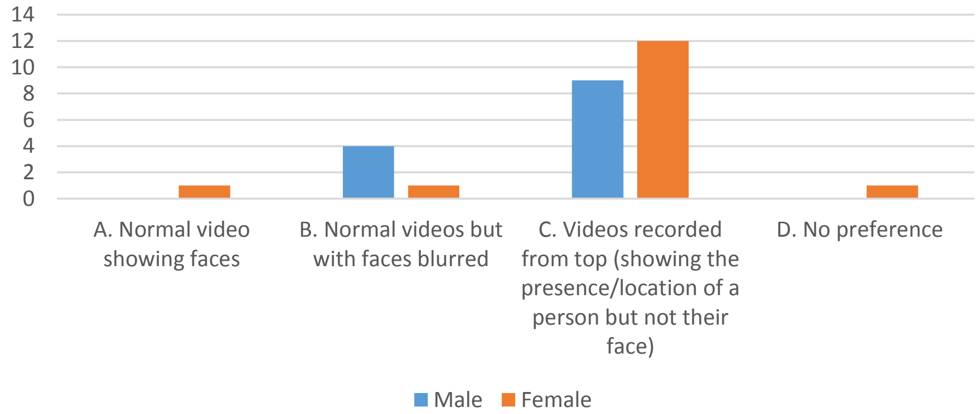


Figure 4.13: Gender - Camera Angle Preference

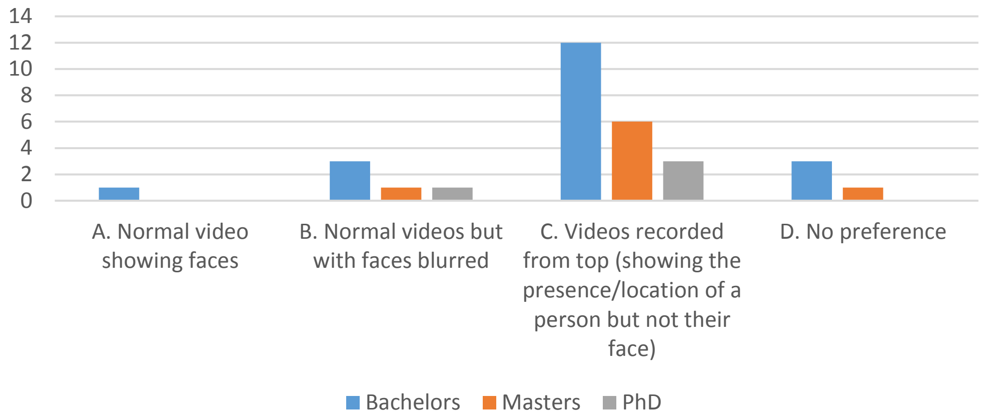


Figure 4.14: Education - Camera Angle Preference

It is necessary to understand whether this preference is typical across the sample, or whether it differs based on the demographic parameters. To find whether there is a statistically significant relationship, the Chi-square test for independence was applied. For each parameter, the actual and expected counts are tabulated. The Chi-square test was applied via taking the camera angle preferences with the age, gender, and education level. The results are tabulated as follows:

Table 4.2: Chi-square test results for each parameter compared to camera angle preference

Parameter	**Value**	**P-value**
Age	12.57	0.18
Gender	4.20	0.24
Education Level	1.69	0.95

As shown, the p-value for each parameter is greater than 0.05. Therefore, the null hypothesis cannot be rejected. It can be said that for the current sample, no statistically significant relationship could be found between the age, gender and education level of the respondent and their camera angle preference.

CHAPTER 5

DISCUSSION

The image-based occupancy sensing comparison experiment and survey, in conjunction with the literature, relates to the role of privacy in the implementation of smart building technologies, specifically image-based occupancy sensing using cameras.

The image-based experiment aimed to show how image-based occupancy sensing can be accomplished by less invasive and privacy-infringing methods, by using cameras situated on higher elevations with steeper angles. To lower the number of variables, a pre-trained object-detection algorithm was used. This had the added effect of demonstrating a lower entry barrier for these technologies, as the algorithm (YOLO) can be downloaded and run 'out of the box'. For the same reason, the same pre-trained algorithm was used for both top and frontal camera angles, rather than training the algorithm on top-view images.

A strict criterion was used to assess the accuracy of the algorithm on both cameras, and any processed video that included one or more frame containing a false negative was judged as containing an irregularity. This was the case in 50% of the frontal view videos, and 77% of the top view videos. This can be attributed to the fact that object-detection algorithms are trained for the 'person' class with frontal view images, so that while a person is moving, the algorithm can potentially misidentify their form.

Despite these figures, it must be noted that this did not indicate serious errors in detection; a misdetection in one frame was enough to label the video as irregular, but in a total period of 3 seconds (75 frames), the error lasts only 1.3% of the time duration.

Regardless, such irregularities were visible in high resolution graphs (people counted per frame) occupancy visualization and could potentially with systems that react in real-time. Therefore, the data was cleaned of the irregularities by taking the mode of a previous set number of frames, for instance 25 frames (equal to one second) which resulted in a smoother graph free of irregularities, albeit with a delay equal to the set number of frames. This data could then be used to create occupancy profiles or used in conjunction with reactive building systems.

This experiment demonstrated that the top view camera data resulted in more irregularities in detection when processed in the pre-trained YOLO algorithm, in comparison with frontal view camera data. Despite this, using the mode method to smooth data resulted in more regular occupancy graphs for individual videos.

This comparison of occupancy-sensing camera angles was then referenced in the survey, which was propagated amongst office workers working in the construction industry or adjacent fields, chosen for their domain-specific knowledge regarding building energy use as well as their proximity to the author.

Respondents were shown three images of the researcher collected from both cameras in the camera angle comparison experiment (displayed in Figure 3.17). A large majority selected Option C: ‘Videos recorded from top (showing the presence/location of a person but not their face). This could potentially be due to the privacy preserving method being integrated into the hardware itself, as well as a mistrust of software post-processing techniques, *i.e.* blurring faces as in Option B.

The Chi-square test implied that for the surveyed sample, no statistically significant relationship could be found between the age, gender, education level of the respondents and the camera angle preferences, that regardless of these parameters, the sample group largely preferred the top-view angle. At the same time, the experiment showed that this method does not hold a disadvantage in an off-the-shelf object-detection algorithm after smoothing methods have been applied.

CHAPTER 6

CONCLUSION

As technological augmentations to the built environment have grown in previous years with the advancement of sensor technology and the growing value of data collection, it is important to understand how this change relates to the users of buildings. Buildings which accommodate multiple users of disproportionate levels of ownership and agency, may be useful sites for data collection for the purpose of energy optimization and analysis.

In this thesis, the literature survey section explored the history of smart buildings, various technologies used in sensing layers, image-based occupancy sensing and a subsequent historical approach to privacy, in order to provide relevant information about the historical and current context of using cameras for low-cost image-based occupancy sensing.

After reviewing various sensing technologies, image-based occupancy sensing stood out as being potentially the most flexible and accurate in terms of location and number of occupants detected. At the same time, this type of sensing technology also presented risks in terms of harvesting identification data. Like other sensing technologies, due to popular attitudes towards privacy as well as legislation such as the GDPR, image-based sensing provides complications with the implementation, storage and processing of the data. However, in its most common form, that of frontal view cameras, image-based sensing inherently records people's biometric data, *i.e.,* their faces. To that end, alternative avenues of privacy protection were explored from literature, such as blurring faces in post-processing, reducing resolution drastically in post-processing, recording video from the top of spaces, and using depth cameras instead of RGB cameras.

Since one aim of the thesis was to explore a low-cost system for image-based occupancy sensing with minimal infrastructural and customization cost, readily available RGB GoPro cameras were used in tandem with a free, out-of-the-box YOLO v4 object detection algorithm, using the default training data that comes with the weights downloaded online. The privacy preservation approach used was recording from the top, due to the added benefit of implementing identification privacy by design in the raw data, instead of using post-processing.

A top view camera recording was used with a control dataset derived from a front view recording. These were then processed through YOLO and compared to see whether the top-view camera recording was effective in detecting how many people were in a space. As a result, the top-view camera performed with more irregularities than the frontal-view camera; while it managed to detect all occupants which passed beneath it, there were more instances of false-negatives, or non-detections of a person. It should be noted that these mostly lasted the duration of a frame, or $1/25^{th}$ of a second. However, an approach was used to clean up this data by taking the mode of the previous 25 frames for each frame: the resulting graph created of people in the space by index number of frames proved an accurate indicator of the population inside the frame at the given time, albeit with a delay of 25 frames (1 second).

It should also be noted that this delay could present issues in situations where instantaneous reactions are required in building systems, for instance, if a low-light camera must switch on lights when a person enters the recording frame, it might not be suitable for the person to have to wait a second.

6.1 Limitations

Due to burgeoning advances in computer vision in the fields of autonomous machines and self-driving cars, the biggest limitation of research and implementation in the field of image-based occupancy sensing are not related to the technology, but the social and legal implications due to potential infringements of privacy and anti-social data collection practices. As people gain further awareness of these issues and experience these practices themselves, they may be less likely to welcome these technologies into their workplaces, unless they can also be aware of, or reap the tangible benefits.

Strict applications of the GDPR may also make certain implementations difficult, however this is positive in the sense that it forces technology companies and building management to adhere to GDPR compliance which is designed to force anonymization of user data.

However, this issue also presents itself with regards to training data in certain cases. It presents a challenge to ethically acquire training data, since individuals need to expressly consent before their data is collected. The Brainwash dataset is a good example of this, as explained in Section 2.3.2. Therefore, strict guidelines need to be followed to ensure ethical research practices.

6.2 Future Work

For future experiments, one solution could be to train the object-detection algorithm with top-view person image data, creating less frame-long irregularities and effectively removing the need for cleaning the data after the fact. However, at the same time it should be noted that the frontal-view data also contained irregularities (albeit less so than the top-view data), which indicates that extra training on top-view data still would not be a complete solution. Different approaches for cleaning the data could then be used depending on the context, so that resulting irregularities and instances of non-detection do not interfere with the smooth operation of building systems.

It should also be mentioned that from a GDPR-compliance perspective, any data that leads to the identification of an individual is a violation. Therefore, any occupancy-sensing approach implemented in a space with a small number of known individuals (*e.g.*, less than three) would inherently lead to the knowledge of who exactly is in that room. Also, even top-view RGB video data can give descriptions of an individual, such as their gender, rough age, ethnicity, etc. To that end, further experiments could use hardware appendages to decrease identifiability, or even depth cameras. For smaller spaces with specific inhabitants, the data relating to the space can be anonymized in database systems for later analysis.

In the case of the survey, future studies can improve on the sampling, by increasing the pool of respondents, by only focusing on respondents who work in smart buildings, or by querying individuals who all work in the same smart office. A larger sample could be more illuminating as to the reasons why people prefer a certain camera angle, as it could incorporate more statistical methods.

The main factor to consider however, is the inclusion of opinions, attitudes and concerns of individuals when implementing such technologies. It is important to understand that in the context of smart building technologies, data collection apparatuses such as image-based sensing can benefit organizations and stakeholders via value addition, or cost-saving through energy optimization, but coming at the cost of occupant privacy infringement, or by lowering transparency, is not a sustainable approach. The literature review has described several examples attesting to this.

In conclusion, it is imperative to actively strive for increased privacy while preserving accuracy, and gain insight as to the opinions of the occupants of a space to implement these technologies in a way that benefits all stakeholders, from owners down to occupants.

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APPENDIX

A. The Survey in Turkish

Bu anketin amacı, ofis kullanıcıların akıllı bina ortamlarında veri toplamaya dair bilinç ve algılarını ortaya çıkarmaktır.

Araştırmanın özel odak noktası, güvenlik kameralarının bu amaçla kullanımı ile doluluk algılamasıdır. Doluluk algılama, en basit haliyle bir mekânda bir kişinin bulunup bulunmadığını tespit edebilen doluluk verilerinin toplanmasını ifade ederken, toplanan veriler yüksek çözünürlüklü ise, kişi sayısını, kimlikleri ve etkinlikleri ortaya çıkarabilir. Doluluk algılama, aşağıdakiler de dahil olmak üzere çeşitli faydalar edebilir:

- Çevresel faydalar (aydınlatma ve HVAC sistemlerinin otomasyonu: enerji maliyetlerinden tasarruf etmek için),
- Kolaylık (mekân planlaması: hangi masaların/odaların boş/mevcut olduğunu uzaktan görme),
- Mali tasarruflar (daha düşük enerji faturaları),
- Güvenlik (acil durum senaryoları sırasında bina sakinlerini izleme: örn. kurtarma operasyonları için).

Anket, veri toplama, kameralar ve potansiyel faydalar konusundaki algılarını anlamak için inşaat veya teknoloji ile ilgili sektörlerde çalışan ofis kullanıcılarına yöneliktir.

Bu araştırma, Orta Doğu Teknik Üniversitesi Mimarlık Bölümü Yapı Bilimleri Yüksek Lisans Programı'nda Hammad Haroon tarafından tez çalışması olarak yürütülmektedir.

Yaş:

- 24 yaşından küçük
- 24-30
- 31-40
- 41-50
- 51-60
- 60 yaşından büyük

1) Cinsiyet:
2) Çalışma alanı:
3) Son tamamlanan eğitim:
   - Lise
   - Lisans
   - Yüksek lisans
   - Doktora
   - Yanıt yok

Lütfen ifadeye katılma derecenizi belirtiniz.

4) "Çoğu teknoloji şirketi, tüketicilerin kişisel bilgilerini uygun ve gizli bir şekilde kullanır."
   - Kesinlikle katılmıyorum
   - Katılmıyorum
   - Emin değilim
   - Katılıyorum
   - Tamamen katılıyorum

5) "Günümüzde tüketiciler, kişisel bilgilerinin teknoloji şirketleri tarafından nasıl dağıtıldığını ve kullanıldığını kontrol edemiyor."
   - o Kesinlikle katılmıyorum
   - o Katılmıyorum
   - o Emin değilim
   - o Katılıyorum
   - o Tamamen katılıyorum

6) "Gizlilik haklarım yasalar ve ticari uygulamalar tarafından yeterince korunmaktadır."
   - o Kesinlikle katılmıyorum
   - o Katılmıyorum
   - o Emin değilim
   - o Katılıyorum
   - o Tamamen katılıyorum

7) "Kişisel verilerimi koruyan yasalara aşinayım."
   - o Kesinlikle katılmıyorum
   - o Katılmıyorum
   - o Emin değilim
   - o Katılıyorum
   - o Tamamen katılıyorum

8) "Kişisel bilgilerimi verdiğimde şirketlerin daha iyi hizmet verdiğine inanıyorum."
   - o Kesinlikle katılmıyorum
   - o Katılmıyorum
   - o Emin değilim
   - o Katılıyorum
   - o Tamamen katılıyorum

9) “Şirketler benden kişisel bilgilerimi istediğinde rahatsız oluyorum.”

- o Kesinlikle katılmıyorum
- o Katılmıyorum
- o Emin değilim
- o Katılıyorum
- o Tamamen katılıyorum

10) "Akıllı bina teknolojilerinin binalardaki ve halka açık yerlerdeki deneyimimi ve çevreyi iyileştirebileceğine inanıyorum.”

- o Kesinlikle katılmıyorum
- o Katılmıyorum
- o Emin değilim
- o Katılıyorum
- o Tamamen katılıyorum

11) "Akıllı bina teknolojileri tarafından binalarda ve halka açık yerlerde toplanan çevre, kullanıcılar ve zamanlamalar hakkındaki veriler konusunda içim rahattır."

- o Kesinlikle katılmıyorum
- o Katılmıyorum
- o Emin değilim
- o Katılıyorum
- o Tamamen katılıyorum

12) Aşağıdakilerden hangilerinin dikkatli bir şekilde korunması gereken kişisel veya hassas veriler topladığını düşünüyorsunuz?

- ▪ Oturum açma sayfası / anahtar kartı ile kullanıcıların tanımlanması
- ▪ Güvenlik kamerası ile kullanıcıların tespiti
- ▪ Biyometrik verilerle kullanıcıların tanımlanması (parmak izi kilitleri, yüz tanıma)

- Doluluk (sayı / konum / kullanıcıların kalabalığı)
- Kullanıcı ajanda / takvim verileri
- Hava kalitesi (CO_2, Nem, Basınç, Kirleticiler)
- Hava sıcaklığı
- Işık seviyeleri
- Hiçbiri hassas değil

13) “Bence insanlar kişisel verilerinin binalarda toplanıp toplanmadığını konusunda kontrole sahiptirler.”
   - Kesinlikle katılmıyorum
   - Katılmıyorum
   - Emin değilim
   - Katılıyorum
   - Tamamen katılıyorum

14) “Ziyaret ettiğim binaların ve kamusal alanların içinde kameraların bulunmasından dolayı içim rahattır."
   - Kesinlikle katılmıyorum
   - Katılmıyorum
   - Emin değilim
   - Katılıyorum
   - Tamamen katılıyorum

15) “Binaların ve kamusal alanların içindeki kameralar güvenliği artırıyor.”
   - Kesinlikle katılmıyorum
   - Katılmıyorum
   - Emin değilim
   - Katılıyorum
   - Tamamen katılıyorum

16) “Enerji optimizasyonu amacıyla doluluk verilerini toplamak için kullanılan kameralardan memnunum.”

- o Kesinlikle katılmıyorum
- o Katılmıyorum
- o Emin değilim
- o Katılıyorum
- o Tamamen katılıyorum

17) Binalarda ve kamusal alanlarda doluluk verileri için kullanılan kameralar için, toplanan video verilerinin türüne göre hangi gizlilik düzeyini tercih edersiniz?

- o A. Yüzleri gösteren normal video
- o B. Normal videolar ancak yüzler bulanık
- o C. Üstten çekilen videolar (bir kişinin varlığını/konumunu gösterir ancak yüzünü göstermez)
- o D. Tercih yok

18) Binalarda kurulu kameralar için, hangi tarafların video verilerine erişiminden memnun olursunuz? Geçerli olanların tümünü seçin.

- ▪ Sadece videolarda yüzleri görünen kişiler
- ▪ Veri analizi yapan kişiler
- ▪ Ofis yönetimi
- ▪ Ofisin tüm sakinleri

19) Doluluk verilerinin toplanmasının hangi faydaları sizi daha çok hitap ediyor?

- Çevresel faydalar (aydınlatma ve HVAC sistemlerinin otomasyonu: enerji maliyetlerinden tasarruf etmek için)
- Kolaylık (mekân planlaması: hangi masaların/odaların boş/mevcut olduğunu uzaktan görme)
- Mali tasarruflar (daha düşük enerjı faturaları)
- Güvenlik (acil durum senaryoları sırasında bina sakinlerini izleme: örn. kurtarma operasyonları için)
- Diğer:

20) "Binaları ziyaret eden insanlar, toplanan verilerin türü ve ne için kullanıldığı konusunda derhal bilgilendirilmelidir."

- Kesinlikle katılmıyorum
- Katılmıyorum
- Emin değilim
- Katılıyorum
- Tamamen katılıyorum

B. The Survey in English

The intention of this survey is to reveal the awareness and perception of office occupants regarding data collection inside smart buildings.

The specific focus of the research is on occupancy sensing with the use of security cameras for that purpose. Occupancy sensing refers to collection of occupancy data, which in its simplest form can detect whether a person is present in a space, while it can also reveal the number of people, their identities and activities. There are several benefits of occupancy sensing, including:

- Environmental benefits (Automation of lights/heating to save energy)
- Convenience (room scheduling)
- Financial savings (lower energy costs)
- Safety (tracking occupants during rescue operations)

The survey is directed towards office occupants who work in construction or technology related industries to understand their perceptions of data collection, cameras and potential benefits.

This survey is conducted by Hammad Haroon, at the Department of Architecture, Graduate Program of Building Science in the Middle East Technical University in Ankara, Turkey, as part of thesis study.

1) Age:
    - o Younger than 24
    - o 24-30
    - o 31-40
    - o 41-50
    - o 51-60
    - o Older than 60
2) Gender:
3) Work industry:
4) Last completed education:
    - o High School
    - o Bachelors
    - o Masters
    - o PhD
    - o No answer

5) "Most technology companies use personal information of consumers in a proper and confidential way."
    - o Strongly Disagree
    - o Disagree
    - o Impartial
    - o Agree
    - o Strongly Agree

6) "Consumers today cannot control how their personal information is circulated and used by technology companies.”
   - Strongly Disagree
   - Disagree
   - Impartial
   - Agree
   - Strongly Agree

7) “My privacy rights are adequately protected today by law and business practices.”
   - Strongly Disagree
   - Disagree
   - Impartial
   - Agree
   - Strongly Agree

8) “I am familiar with the laws that protect my personal data.”
   - Strongly Disagree
   - Disagree
   - Impartial
   - Agree
   - Strongly Agree

9) “I believe companies provide better service when I provide them with my personal information.”
   - Strongly Disagree
   - Disagree
   - Impartial
   - Agree
   - Strongly Agree

10) “I get annoyed when companies ask me for my personal information.”

- Strongly Disagree
- Disagree
- Impartial
- Agree
- Strongly Agree

11) "I believe smart building technologies can improve peoples' experiences and environment in buildings and public places.”

- Strongly Disagree
- Disagree
- Impartial
- Agree
- Strongly Agree

12) "I am comfortable with data about the environment, occupants and schedules being collected inside buildings and public spaces by smart building technologies.”

- Strongly Disagree
- Disagree
- Impartial
- Agree
- Strongly Agree

13) In your opinion, which of the following activities collect personal or sensitive data that should be carefully protected?

- Identification of occupants by sign-in sheet / key card
- Identification of occupants by security camera
- Identification of occupants by biometric data (fingerprint locks, facial recognition)

- Occupancy (Number / location / crowdedness of occupants)
- Occupant schedule data
- Air quality (CO_2, Humidity, Pressure, Pollutants)
- Temperature
- Light levels
- None of these are sensitive data

14) "In my opinion, people have control over whether their personal data is being collected or not in buildings."
    - Strongly Disagree
    - Disagree
    - Impartial
    - Agree
    - Strongly Agree

15) "I am comfortable with cameras being present inside the buildings and public spaces I visit."
    - Strongly Disagree
    - Disagree
    - Impartial
    - Agree
    - Strongly Agree

16) "Cameras inside buildings and public spaces increase safety."
    - Strongly Disagree
    - Disagree
    - Impartial
    - Agree
    - Strongly Agree

17) "I am comfortable with cameras being used to collect occupancy data for energy optimization purposes."

- o Strongly Disagree
- o Disagree
- o Impartial
- o Agree
- o Strongly Agree

18) For cameras used for occupancy data in buildings and public spaces, which level of privacy do you believe is the most suitable regarding the type of video data collected?

- o A. Normal video showing faces
- o B. Normal videos but with faces blurred
- o C. Videos recorded from top (showing the presence/location of a person but not their face)
- o D. No preference

19) For cameras installed in buildings, who do you believe should have access to the video data?

- ▪ Only the individuals whose faces are visible
- ▪ Individuals carrying out data analysis
- ▪ Management of the building
- ▪ All occupants of the building

20) Which benefit of collecting occupancy data appeals to you most?

- Environmental benefits (for example, automation of lights/heating to save energy costs)
- Convenience (for example, room scheduling for remotely finding out which desks/rooms are empty/available)
- Financial savings (due to lower energy costs or more efficient maintenance)
- Safety (for example, tracking occupants during disaster scenarios for rescue operations)
- Other:

21) "People visiting buildings should immediately be informed of the type of data which is collected, and what it is being used for."

- Strongly Disagree
- Disagree
- Impartial
- Agree
- Strongly Agree

C. Survey Responses

1) Age:

24-30	16
31-40	2
41-50	12
51-60	1

2) Gender:

Female	15
Male	16

3) Work Industry:

Public	2
Construction	3
Academia	3
Software	3
Finance	3
Engineering	4
Architecture	13

4) Level of education:

Bachelors	19
Masters	8
PhD	4

5) “Most technology companies use personal information of consumers in a proper and confidential way.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
4	12	9	4	2

6) "Consumers today cannot control how their personal information is circulated and used by technology companies.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	0	2	16	13

7) “My privacy rights are adequately protected today by law and business practices.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
9	13	8	0	1

8) “I am familiar with the laws that protect my personal data.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
3	14	9	3	2

9) “I believe companies provide better service when I provide them with my personal information.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
5	11	11	4	0

10) “I get annoyed when companies ask me for my personal information.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	3	2	14	12

11) "I believe smart building technologies can improve peoples' experiences and environment in buildings and public places.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	2	4	20	5

12) "I am comfortable with data about the environment, occupants and schedules being collected inside buildings and public spaces by smart building technologies.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
3	5	13	10	0

13) In your opinion, which of the following activities collect personal or sensitive data that should be carefully protected?

Identification of occupants by sign-in sheet / key card	Identification of occupants by security camera	Identification of occupants by biometric data (fingerprint locks, facial recognition)	Occupancy (Number / location / crowdedness of occupants)	Occupant schedule data
20	26	28	3	14
Air quality (CO_2, Humidity, Pressure, Pollutants)	Temperature	Light levels	None of the above	
1	1	1	2	

14) “In my opinion, people have control over whether their personal data is being collected or not in buildings.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
6	14	8	3	0

15) “I am comfortable with cameras being present inside the buildings and public spaces I visit."

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	3	11	17	0

16) “Cameras inside buildings and public spaces increase safety.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	1	4	24	2

17) “I am comfortable with cameras being used to collect occupancy data for energy optimization purposes.”

Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
1	3	9	15	3

18) For cameras used for occupancy data in buildings and public spaces, which level of privacy do you believe is the most suitable regarding the type of video data collected?

A. Normal video showing faces	B. Normal videos but with faces blurred	C. Videos recorded from top (showing the presence/location of a person but not their face)	D. No preference
1	5	21	4

19) For cameras installed in buildings, who do you believe should have access to the video data?

Only the individuals whose faces are visible	Individuals carrying out data analysis	Management of the building	All occupants of the building
4	22	6	2

20) Which benefits of collecting occupancy data appeal to you most? (multi-response)

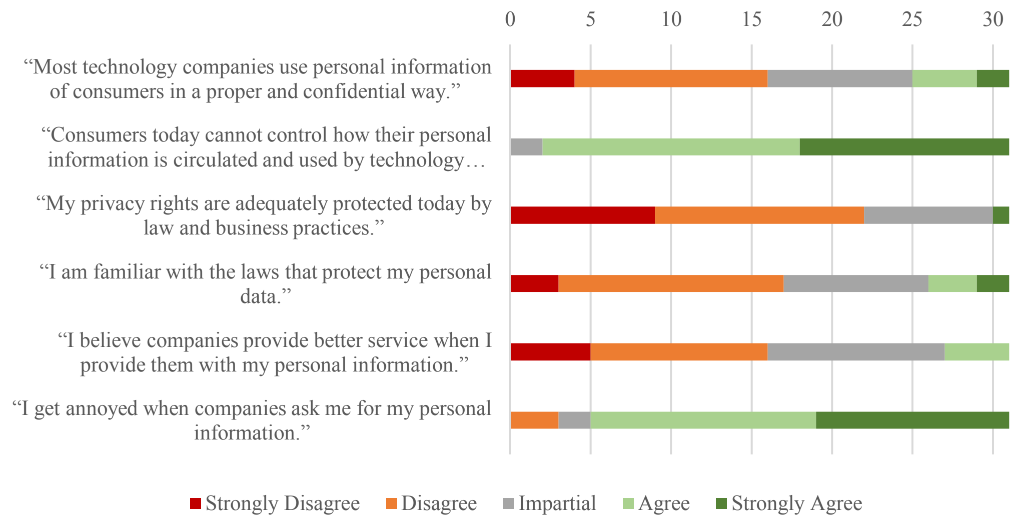
Environmental benefits (for example, automation of lights/heating to save energy costs)	Convenience (for example, room scheduling for remotely finding out which desks/rooms are empty/available)	Financial savings (due to lower energy costs or more efficient maintenance)	Safety (for example, tracking occupants during disaster scenarios for rescue operations)
27	19	19	21

21) "People visiting buildings should immediately be informed of the type of data which is collected, and what it is being used for."

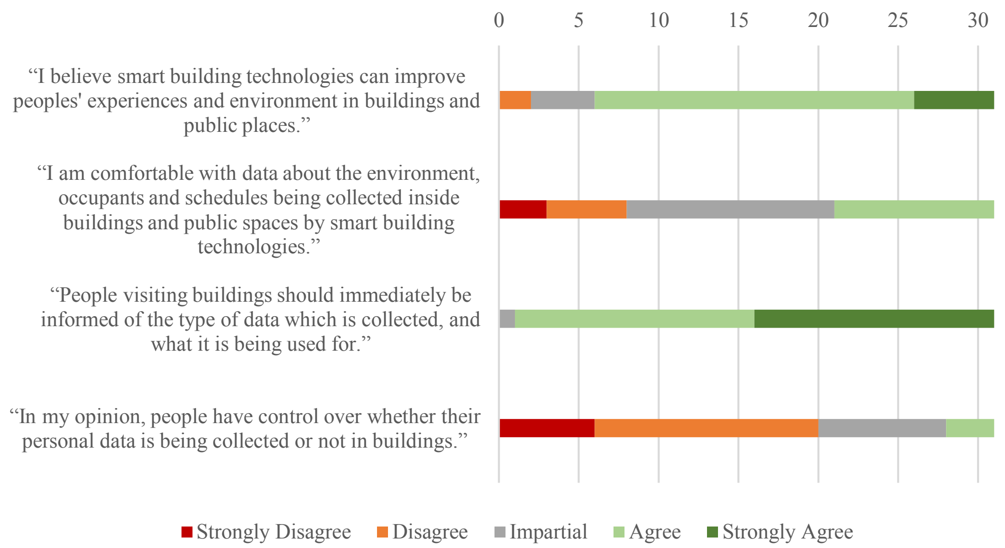
Strongly Disagree	Disagree	Impartial	Agree	Strongly Agree
0	0	1	15	15

The following figures display the responses grouped by each category after the initial demographic questions, in stacked bar chart form.

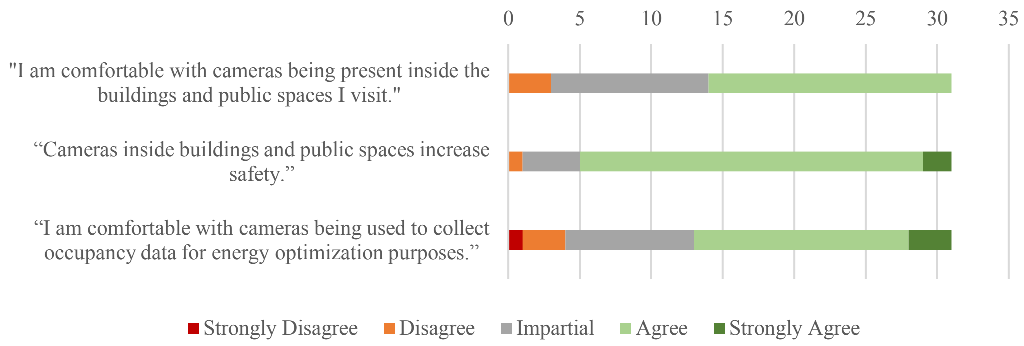
Category B (Privacy Perception) responses:



Category C (Smart Building Acceptance) responses:



Category D (Camera Acceptance) responses:



D. Image-Based Occupancy Sensing Ground Truth

Start Time	End Time	Up	Down	Total
12:20 PM	12:30 PM	5	4	9
12:30 PM	12:40 PM	7	5	12
12:40 PM	12:50 PM	4	5	9
12:50 PM	1:00 PM	7	8	15
1:00 PM	1:10 PM	4	9	13
1:10 PM	1:20 PM	4	6	10
1:20 PM	1:30 PM	7	3	10
1:30 PM	1:40 PM	3	6	9
1:40 PM	1:50 PM	8	9	17
1:50 PM	2:00 PM	3	3	6
2:00 PM	2:10 PM	2	3	5
2:10 PM	2:20 PM	5	5	10
2:20 PM	2:30 PM	10	14	24
2:30 PM	2:40 PM	5	6	11
2:40 PM	2:50 PM	4	1	5
2:50 PM	3:00 PM	7	7	14
3:00 PM	3:10 PM	3	4	7
3:10 PM	3:20 PM	1	0	1
3:20 PM	3:30 PM	5	2	7
3:30 PM	3:40 PM	2	2	4
3:40 PM	3:50 PM	7	4	11
3:50 PM	4:00 PM	2	1	3
		105	107	212

E. Person-Detection Algorithm with YOLO in Python

The following Python code was used to write video files with YOLO annotations, as well as create .csv tables for the instant and sustained person count per frame, for each key event clip.

```
import numpy as np
import argparse
import imutils
import time
import cv2
import os
import pandas as pd
import datetime

key_event_files = []
key_event_directory = (…)
for i in os.listdir(key_event_directory):
	if i[-4:] == ".mp4":
		key_event_files.append(os.path.join(key_event_directory, i))

main_csv_per_second_name = (…)

# MAIN LOOP

# construct the argument parse and parse the arguments
	ap = argparse.ArgumentParser()
	ap.add_argument("-c", "--confidence", type=float, default=0.5,
		help="minimum probability to filter weak detections")
	ap.add_argument("-t", "--threshold", type=float, default=0.3,
		help="threshold when applying non-maxima suppression")
	args = vars(ap.parse_args())
	args["output"] = outputname
	args["yolo"] = "yolo-coco"

# load the COCO class labels our YOLO model was trained on
	labelsPath = os.path.sep.join([args["yolo"], "coco.names"])
	LABELS = open(labelsPath).read().strip().split("\n")

# initialize a list of colors to represent each possible class label
	np.random.seed(42)
	COLORS = np.random.randint(0, 255, size=(len(LABELS), 3),
		dtype="uint8")

# derive the paths to the YOLO weights and model configuration
	weightsPath = os.path.sep.join([args["yolo"], "yolov3.weights"])
	configPath = os.path.sep.join([args["yolo"], "yolov3.cfg"])

# load our YOLO object detector trained on COCO dataset (80 classes)
# and determine only the *output* layer names that we need from YOLO
	print("[INFO] loading YOLO from disk...")
	net = cv2.dnn.readNetFromDarknet(configPath, weightsPath)
	ln = net.getLayerNames()
	ln = [ln[i[0] - 1] for i in net.getUnconnectedOutLayers()]

# initialize the video stream, pointer to output video file, and
# frame dimensions
	vs = cv2.VideoCapture(filename)
	writer = None
	(W, H) = (None, None)
```

```
# try to determine the total number of frames in the video file
	try:
		prop = cv2.cv.CV_CAP_PROP_FRAME_COUNT if imutils.is_cv2() \
			else cv2.CAP_PROP_FRAME_COUNT
		total_framecount = int(vs.get(prop))
		print("[INFO] {} total frames in video".format(total_framecount))
# if an error occurred while trying to determine the total
# number of frames in the video file
	except:
		print("[INFO] could not determine # of frames in video")
		print("[INFO] no approx. completion time can be provided")
		total_framecount = -1

	dicts_per_frame = []
	dicts_per_second = []

	for frame_number in range(0, total_framecount):

		print(f"{frame_number}/{total_framecount} frames")

# read the next frame from the file
		(grabbed, frame) = vs.read()
# if the frame was not grabbed, then we have reached the end
# of the stream
		if not grabbed:
			break
		frame_dictionary = {}
		frame_dictionary["FrameNumber"] = frame_number

# if the frame dimensions are empty, grab them
		if W is None or H is None:
			(H, W) = frame.shape[:2]

# construct a blob from the input frame and then perform a forward
# pass of the YOLO object detector, giving us our bounding boxes
# and associated probabilities
		blob = cv2.dnn.blobFromImage(frame, 1 / 255.0, (416, 416),
			swapRB=True, crop=False)
		net.setInput(blob)
		start = time.time()
		layerOutputs = net.forward(ln)
		end = time.time()

# initialize our lists of detected bounding boxes, confidences,
# and class IDs, respectively
		boxes = []
		confidences = []
		classIDs = []

# loop over each of the layer outputs
		for output in layerOutputs:
# loop over each of the detections
			for detection in output:
# extract the class ID and confidence (i.e., probability)
# of the current object detection
				scores = detection[5:]
				classID = np.argmax(scores)
				confidence = scores[classID]
# filter out weak predictions by ensuring the detected
# probability is greater than the minimum probability
				if confidence > args["confidence"]:
# scale the bounding box coordinates back relative to
# the size of the image, keeping in mind that YOLO
# actually returns the center (x, y)-coordinates of
# the bounding box followed by the boxes' width and
# height
					box = detection[0:4] * np.array([W, H, W, H])
					(centerX, centerY, width, height) =
box.astype("int")
```

```
# use the center (x, y)-coordinates to derive the top
# and and left corner of the bounding box
                                    x = int(centerX - (width / 2))
                                    y = int(centerY - (height / 2))
# update our list of bounding box coordinates,
# confidences, and class IDs
                                    boxes.append([x, y, int(width), int(height)])
                                    confidences.append(float(confidence))
                                    classIDs.append(classID)

# apply non-maxima suppression to suppress weak, overlapping
# bounding boxes
               idxs = cv2.dnn.NMSBoxes(boxes, confidences, args["confidence"],
                                                      args["threshold"])

               frame_dictionary["NumberOfDetections"] = len(idxs)
               frame_dictionary["People"] = 0
               DictionaryText          =          f"""NumberOfDetections          =
{frame_dictionary["NumberOfDetections"]}"""

# ensure at least one detection exists

               if len(idxs) > 0:

                       for (num, i) in enumerate(idxs.flatten()):
# extract the bounding box coordinates
                               (x, y) = (boxes[i][0], boxes[i][1])
                               (w, h) = (boxes[i][2], boxes[i][3])
# draw a bounding box rectangle and label on the frame
                               color = [int(c) for c in COLORS[classIDs[i]]]
                               boxco = ((x, y), (x + w, y + h))

                               label = LABELS[classIDs[i]]
                               if label == "person":
                                       frame_dictionary["People"] += 1
                               DictionaryText += f""", Detection {num+1}: {label}"""
                               cv2.rectangle(frame, (x, y), (x + w, y + h), color, 2)
                               text = "{}: {:.4f}".format(LABELS[classIDs[i]],

confidences[i])
                               cv2.putText(frame, text, (x, y - 5),
                                                      cv2.FONT_HERSHEY_SIMPLEX,   0.5,
color, 2)
# print(f"boxco: {boxco} and label: {label}")

               if len(dicts_per_frame) > 5:
                       last_five_frames = dicts_per_frame[-5:]
                       last_five_people_counts    =    [i["People"]    for    i    in
last_five_frames]
                       max_people_counts     =     max(set(last_five_people_counts),
key=last_five_people_counts.count)
                       sustained_counter                                         =
last_five_people_counts.count(max_people_counts)

                       if sustained_counter >= 4:
                               frame_dictionary["Sustained Count"] = max_people_counts
                       else:
                               frame_dictionary["Sustained Count"] = dicts_per_frame[-
1]["Sustained Count"]

               else: frame_dictionary["Sustained Count"] = 0

               dicts_per_frame.append(frame_dictionary)
               cv2.putText(frame, DictionaryText, (15, 35),
                                    cv2.FONT_HERSHEY_SIMPLEX, 0.5, (0, 0, 0))

               if frame_number % 25 == 0:
                       frame_dictionary["Time"] = current_time.strftime("%H:%M:%S")
                       current_time = current_time + datetime.timedelta(seconds=1)
```

```
                      dicts_per_second.append({"Time":
current_time.strftime("%H:%M:%S"),
                                                                   "PeopleCount":
frame_dictionary["Sustained Count"]})

               cv2.imshow("frame", frame)
               key = cv2.waitKey(1) & 0xFF
# if the `q` key was pressed, break from the loop
# ensure at least one detection exists
               if key == ord("q"):
                      break
# check if the video writer is None
               if writer is None:
# initialize our video writer
                      fourcc = cv2.VideoWriter_fourcc('P','I','M','1')
                      writer = cv2.VideoWriter(args["output"], fourcc, 25,
                                                                    (frame.shape[1],
frame.shape[0]), True)
# some information on processing single frame
                      if total_framecount > 0:
                             elap = (end - start)
                             print("[INFO]     single     frame     took     {:.4f}
seconds".format(elap))
                             print("[INFO]   estimated   total   time   to   finish:
{:.4f}".format(
                                    elap * total_framecount))
# write the output frame to disk
               writer.write(frame)
# release the file pointers
        df = pd.DataFrame(dicts_per_frame)
        df_second = pd.DataFrame(dicts_per_second)
        csv_per_frame_name = (…)
        writer.release()
        vs.release()
```

F. Person-Detection Algorithm Error Count

The below table has been created by checking the person count-frame graphs for each key event video for irregularities, which mark the key event video as ‘Error’. For instance, in the video with index number 1, the top view contains an irregularity while the front view does not.

Key Event Video Index Number	Timestamp	Number of People in Key Event	Top View Error	Front View Error
1	12:25:48 PM	1	✓	
2	12:26:04 PM	1		✓
3	12:26:45 PM	2	✓	✓
4	12:27:25 PM	1		✓
5	12:27:58 PM	1	✓	
6	12:28:14 PM	1		
7	12:30:14 PM	1	✓	
8	12:32:14 PM	2	✓	✓
9	12:33:10 PM	2	✓	✓
10	12:36:33 PM	1		
11	12:37:13 PM	2	✓	✓
12	12:39:35 PM	2	✓	✓
13	12:40:04 PM	3	✓	
14	12:44:04 PM	2	✓	✓
15	12:44:22 PM	1	✓	
16	12:45:32 PM	1	✓	
17	12:45:49 PM	1		
18	12:46:10 PM	1		
19	12:46:21 PM	1	✓	
20	12:47:35 PM	1		
21	12:47:46 PM	1	✓	
22	12:49:27 PM	1	✓	
23	12:49:53 PM	1	✓	
24	12:50:25 PM	1	✓	
25	12:51:26 PM	1		
26	12:51:30 PM	2	✓	✓
27	12:51:56 PM	1	✓	✓
28	12:53:26 PM	1		✓

29	12:54:09 PM	1		✓
30	12:55:19 PM	1		
31	12:56:11 PM	1		
32	12:57:30 PM	1	✓	
33	12:57:52 PM	1	✓	
34	12:58:11 PM	1	✓	
35	12:58:48 PM	1		
36	1:01:17 PM	1	✓	
37	1:04:07 PM	1	✓	
38	1:05:06 PM	2	✓	
39	1:05:48 PM	3	✓	✓
40	1:07:42 PM	3	✓	✓
41	1:09:47 PM	2	✓	✓
42	1:11:55 PM	2	✓	✓
43	1:14:30 PM	4	✓	✓
44	1:16:23 PM	1	✓	
45	1:17:08 PM	1	✓	
46	1:21:11 PM	2	✓	✓
47	1:22:15 PM	1	✓	✓
48	1:22:45 PM	1		
49	1:24:10 PM	2	✓	✓
50	1:25:30 PM	1	✓	
51	1:25:55 PM	1	✓	
52	1:29:35 PM	2	✓	✓
53	1:31:45 PM	1		
54	1:32:28 PM	1		
55	1:32:57 PM	1	✓	✓
56	1:33:05 PM	2	✓	✓
57	1:35:41 PM	1	✓	
58	1:36:15 PM	2		
59	1:39:41 PM	1		
60	1:42:03 PM	2	✓	
61	1:42:19 PM	2	✓	✓
62	1:45:12 PM	3	✓	✓
63	1:45:39 PM	3	✓	✓
64	1:45:59 PM	2	✓	
65	1:46:41 PM	2	✓	✓
66	1:50:50 PM	1	✓	✓
67	1:51:53 PM	1	✓	✓
68	1:54:43 PM	1	✓	✓
69	1:55:00 PM	2		✓
70	1:55:35 PM	1	✓	✓
71	1:58:52 PM	1	✓	✓
72	2:06:48 PM	1		✓

73	2:07:13 PM	3	✓	✓
74	2:07:43 PM	1	✓	✓
75	2:11:28 PM	1	✓	✓
76	2:12:00 PM	1		✓
77	2:12:42 PM	1	✓	
78	2:13:14 PM	1	✓	✓
79	2:14:35 PM	2	✓	✓
80	2:17:31 PM	1	✓	✓
81	2:19:20 PM	1	✓	✓
82	2:20:54 PM	2	✓	✓
83	2:21:25 PM	2	✓	✓
84	2:23:05 PM	1	✓	
85	2:23:39 PM	3	✓	✓
86	2:24:29 PM	1	✓	
87	2:24:34 PM	2	✓	
88	2:24:48 PM	2	✓	✓
89	2:25:00 PM	1	✓	✓
90	2:27:58 PM	1	✓	
91	2:28:29 PM	2	✓	
92	2:29:06 PM	3	✓	✓
93	2:30:01 PM	1	✓	✓
94	2:30:52 PM	2	✓	
95	2:31:20 PM	2	✓	
96	2:32:34 PM	1	✓	✓
97	2:33:31 PM	1		
98	2:33:49 PM	2	✓	
99	2:34:13 PM	2	✓	
100	2:36:09 PM	2	✓	
101	2:40:55 PM	2		✓
102	2:41:00 PM	2	✓	
103	2:42:31 PM	1	✓	
104	2:42:40 PM	1	✓	
105	2:44:34 PM	2	✓	✓
106	2:46:15 PM	1	✓	
107	2:52:39 PM	4	✓	✓
108	2:54:08 PM	1	✓	✓
109	2:54:55 PM	1	✓	✓
110	2:55:25 PM	1	✓	
111	2:58:31 PM	1	✓	✓
112	2:58:46 PM	1		
113	2:58:54 PM	1	✓	
114	3:00:05 PM	2	✓	✓
115	3:01:55 PM	2	✓	✓
116	3:05:34 PM	1		

117	3:05:54 PM	1	✓	
118	3:06:50 PM	1		
119	3:08:22 PM	1	✓	
120	3:09:24 PM	1		✓
121	3:20:04 PM	1	✓	
122	3:21:02 PM	1		✓
123	3:23:02 PM	3	✓	✓
124	3:26:00 PM	1	✓	
125	3:26:34 PM	1	✓	
126	3:28:39 PM	1	✓	
127	3:31:06 PM	1		
128	3:36:04 PM	1	✓	
129	3:39:47 PM	1		
130	3:39:53 PM	1	✓	
131	3:44:16 PM	2	✓	✓
132	3:44:32 PM	1	✓	✓
133	3:46:01 PM	1	✓	✓
134	3:46:36 PM	1	✓	✓
135	3:46:46 PM	2	✓	✓
136	3:47:03 PM	2	✓	✓
137	3:50:34 PM	1	✓	✓
138	3:51:13 PM	1	✓	✓
139	3:55:03 PM	1	✓	
140	3:55:13 PM	1		✓