



JÖNKÖPING UNIVERSITY
School of Engineering

Licentiate Thesis

Radar Based Sensing for Psychological Monitoring

Possibilities of Emotion Recognition through
Respiratory Frequency for Adaptive Lighting

Elham Rastegari

Jönköping University
School of Engineering
Dissertation Series No. 104 • 2026



JÖNKÖPING UNIVERSITY
School of Engineering

Licentiate Thesis

Radar Based Sensing for Psychological Monitoring

Possibilities of Emotion Recognition through
Respiratory Frequency for Adaptive Lighting

Elham Rastegari

Licentiate thesis in Built Environment

Radar Based Sensing for Psychological Monitoring:
Possibilities of Emotion Recognition through Respiratory
Frequency for Adaptive Lighting
Dissertation Series No. 104

©2026 Elham Rastegari

Published by
School of Engineering, Jönköping University
P.O. Box 1026
SE-551 11 Jönköping
Tel. +46 36 10 10 00
www.ju.se

Printed by Stema Specialtryck AB 2026

ISBN 978-91-89785-41-0 (Printed version)
ISBN 978-91-89785-42-7 (Online version)



Acknowledgements

This thesis would not have been possible without the kindness and support of many people. I wish to begin by expressing my sincere gratitude towards my supervisors, *Myriam Aries* and *Bruce Ferwerda*, whose generous support and guidance carried me throughout this journey. I am especially grateful to my main supervisor, *Myriam*, for her support through difficult times and her valuable insights. I am equally grateful to *RatnaKala Sithravel* and *Anita Hurtig Wennlöf*, who supervised me during a significant part of this project, and whose support and contributions helped shape the direction of this thesis.

I would like to sincerely thank *Bertil and Britt Svensson Foundation for Lighting Technology* for providing the funding that made this research possible.

I am truly grateful to all participants who dedicated their time to be part of my experiments, as well as the caretakers and technical staff at HHJ, JTH, and HS. Your involvement helped shape this research and bring clarity to it.

To my colleagues, especially *the (not so) Young Ones* at the Department of Construction Engineering and Lighting Science. Thank you for the laughter, support, and for making this journey more enjoyable.

Special thanks to my dearest friends. To *Tanvi*, thank you for the coffee breaks and shared study moments that kept me going. To *Kiana* and *Arefeh*, though far away, thank you for your support and care.

Finally, it is my privilege to thank my beloved family who supported me every step of the way, especially my mother, *Mahbubeh*, my father, *Younes*, and my sister, *Arezou*. Thank you for being my strength and my source of comfort. Your support means more to me than words can fully express.

Elham Rastegari 🐱

Jönköping, April 2026

Abstract

Light influences human physiology beyond vision, affecting circadian rhythms, alertness, and emotional states. Emotions, in turn, shape human behaviour, cognition, and overall well-being. Despite this information, most existing intelligent lighting systems rely on basic inputs such as occupancy or daylight, with limited to no integration of physiological or emotional signals in the decision-making process. This has created a gap between advances in beyond-visual lighting research and practical lighting applications. To address this, this thesis explores the feasibility of integrating non-wearable, non-invasive physiological sensing into adaptive lighting systems, with a focus on radar-based monitoring.

A sequential research approach was used, starting with a literature review to identify suitable sensing approaches, after which mm-wave radar sensors were selected for further investigation. This was followed by three experimental studies to evaluate the radar's performance: controlled tests with Controlled Airflow Thorax robots (CAT-bots) that accurately simulated chest movement for different respiration frequencies, a pilot study with single human subjects in two different positions (sitting and supine), and a final study under varied occupancy conditions. Each stage increased in complexity to evaluate performance in realistic scenarios.

Results show that radar performs well at detecting occupancy and monitoring respiration frequency for multiple (two) occupants in varied occupancy situations. While some limitations were observed, overall accuracy remained high. The findings suggest potential for capturing physiological changes linked to emotional states, but further validation is needed.

This research provides a foundation for integrating physiological sensing into adaptive lighting. It validates radar as a practical solution, points out its weaknesses, and proposes a two-level emotion recognition strategy for future studies. The work contributes toward emotion-aware environments, with applications in home monitoring, ambient assisted living, and human-centred design.

Sammanfattning

Ljus påverkar människans fysiologi bortom synen och påverkar dygnsrytm, vakenhet och känslomässiga tillstånd. Känslor formar i sin tur mänskligt beteende, kognition och allmänt välbefinnande. Trots denna kunskap förlitar sig de flesta befintliga intelligenta belysningssystem på grundläggande indata som närvaro eller dagsljus, med begränsad eller ingen integration av fysiologiska eller känslomässiga signaler i beslutsprocessen. Detta har skapat en klyfta mellan praktiska belysningstillämpningar och framsteg inom forskning om ljusets icke-visuella effekter. För att ta itu med detta undersöker denna avhandling möjligheten att integrera icke-bärbar, icke-invasiv fysiologisk avkänning i adaptiva belysningssystem, med fokus på radarbaserad övervakning.

En sekventiell forskningsmetod användes, med början i en litteraturgenomgång för att identifiera lämpliga avkänningsmetoder, varefter mm-vågsradarsensorer valdes ut för vidare undersökning. Detta följdes av tre experimentella studier för att utvärdera radarns prestanda: kontrollerade tester med Controlled Airflow Thorax-robotar (CAT-bots) som exakt simulerade bröst rörelser för olika andningsfrekvenser, en pilotstudie med enskilda människor i två olika positioner (sittande och liggande) och en slutlig studie under varierande närvaroförhållanden. Varje steg ökade i komplexitet för att utvärdera prestanda i realistiska scenarier.

Resultaten visar att radar fungerar bra för att detektera närvaro och övervaka andningsfrekvens för flera (två) personer i varierande närvarosituationer. Även om vissa begränsningar observerades, förblev den övergripande noggrannheten hög. Resultaten tyder på potential för att fånga fysiologiska förändringar kopplade till känslomässiga tillstånd, men ytterligare validering behövs.

Denna forskning ger en grund för att integrera fysiologisk avkänning i adaptiv belysning. Den validerar radar som en praktisk lösning, pekar ut dess svagheter och föreslår en tvånivåstrategi för känsloidentifiering för framtida studier. Arbetet bidrar till känslomedvetna miljöer, med tillämpningar inom hemövervakning, assisterat boende och människocentrerad design.

Original papers

The following papers are enclosed as appendices.

Paper 1

Emotion Recognition in Residential Environments Using Non-Wearable Devices: A Mapping Review for Emotion-Responsive Lighting Systems

Submitted to LEUKOS, under review

Elham Rastegari, RatnaKala Sithravel, Bruce Ferwerda & Myriam Aries

Paper 2

Physiologically Aware Lighting for Ageing in Place: Exploring mm-Wave Radar Sensing for Embedded Health Support in Residential Environments.

Accepted for publication in Studies in Health and Information Technology

Elham Rastegari, RatnaKala Sithravel, Bruce Ferwerda & Myriam Aries

Paper 3

Radar-Based Breathing Detection for Emotion-Responsive Lighting: Laboratory Studies with Robot Simulations and Human Occupants under varied occupancy.

Submitted to Building and Environment, under review

Elham Rastegari, RatnaKala Sithravel, Bruce Ferwerda & Myriam Aries

Other Publications

Daylight Potential of Swedish Residential Environments: Visual and Beyond-vision Effects and the Relationship with Well-being Assessment

Lighting Research and Technology, 57(2), 156-180

Elham Rastegari, Mathias Adamsson & Myriam Aries

Table of Contents

1.	Introduction	1
1.1.	Background	2
1.2.	Problem area.....	4
1.3.	Research objectives	5
1.4.	Scope and delimitations	6
2.	Theoretical background	7
2.1.	Human emotions	7
2.1.1.	Emotional models	8
2.1.2.	Emotions and physiology	9
2.2.	Visual and beyond-visual effects of light.....	11
2.3.	Emotion recognition methods and ethics	12
2.4.	Millimetre-wave radar	13
3.	Research methodology	15
3.1.	Research approach.....	15
3.2.	Exploration phase	15
3.3.	Empirical evaluation phase	16
3.3.1.	Experimental study without human subjects	16
3.3.2.	Experimental study with human subjects	17
3.4.	Application of the research methodology	20
3.5.	Data analysis	22
3.6.	Quality of research	23
3.6.1.	Validity	23
3.6.2.	Reliability	24
3.7.	Ethical considerations	24

4.	Summary of findings and synthesis of the appended papers	27
4.1.	Paper 1	27
4.1.1.	Summary of identified sensors and devices	28
4.1.2.	Performance and applicability evaluation	30
4.2.	Paper 2	31
4.3.	Paper 3	34
4.4.	Unpublished work	35
5.	Discussion.....	39
5.1.	Research questions	39
5.2.	Academic and industrial contribution	41
5.2.1.	Radar and occupancy detection	42
5.2.2.	Radar and respiration frequency.....	43
5.2.3.	Radar and emotion recognition.....	44
5.3.	Study limitations.....	45
6.	Conclusions and future work	47
6.1.	Conclusions	47
6.2.	Future research	48
	References	51

Appendices

Appendix 1. Study design for human experiments

1. Introduction

Light plays a fundamental role in human existence, shaping how people see, feel, and function. Light affects human physiology and behaviour not only through visual perception but also through neural pathways that influence circadian regulation, alertness, mood, and emotional state, commonly referred to as the beyond-visual effects of light [1, 2]. These effects are influenced by light characteristics such as intensity, spectral composition, timing, and duration of light exposure, as well as individual factors such as age, chronotype, and pupil response [1, 3, 4]. As a result, lighting research increasingly emphasises the development of lighting systems that extend beyond basic illumination to support both visual performance and human well-being [5, 6]. Such systems, which integrate both visual and beyond-visual effects of light, are referred to as “integrative lighting”, defined by the International Commission on Illumination (CIE) [7]. Therefore, this thesis explores the potential for lighting systems that can adapt to occupants' psychophysiological needs by investigating sensing systems that can incorporate information regarding occupants' physiological and emotional states without disturbing or invading their privacy.

The work presented in this thesis was conducted within the framework of the Presence-sensing, User-responsive Lighting for Sensing Emotions (PULSE) project. PULSE project continues a series of prior research projects focused on intelligent illumination and sensing technologies in the built environment that consider occupant well-being. Earlier projects in this research line included Smart Illumination in Living Environments (SMILE) [8], Daylight and Occupancy Sensing System for Residential Environments (DOSE) [9] and EXtensive Tracking of Respiration Added in Daylight and Occupancy Sensing Environments (EXtra-DOSE) [10].

In the following sections of this chapter, the background and motivation for the study are outlined, the research problems and associated research questions are presented, and the research objectives together with the scope and delimitations of the study are described.

1.1. Background

Lighting control systems have evolved throughout the years, from basic manual switches to automatic sustainable solutions, including strategies such as occupancy or daylight-based solutions. However, these developments largely focused on energy efficiency and visual performance [5, 11]. As research increasingly highlights the beyond-visual effects of light, there is a growing need to integrate these effects into lighting systems [5, 7]. This has led to an increased interest in integrating physiological, psychological, and behavioural inputs into lighting design and systems [12].

Lighting is one of the environmental stimuli that can directly and indirectly influence human mood and emotions [1, 13, 14]. This influence extends across the built environment, where lighting conditions shape human experience and functioning in everyday contexts. It is particularly important in residential environments, where people spend most of their time and encounter critical periods for light exposure, such as early mornings [15-17]. During these periods, light exposure can affect physiological state and subjective responses such as mood, alertness, and emotions [18]. Human emotional state plays an important role in everyday functions, influencing human judgment [19, 20], memories [20, 21] and cognitive performance [20, 22]. In building science, well-being is often described in terms of “health and comfort” associated with “perceived quality of life”, “life satisfaction and levels of happiness”, and “subjective and emotional feelings” [23]. Within this context, emotional state is recognised as a key component of well-being, linking physiological and psychological processes to the overall human experience [24].

An adaptive monitoring system commonly includes three major subsystems: a sensing system that acquires information from the environment, a decision-making system that determines appropriate system response, and the response system that provides appropriate services [25, 26]. In the context of emotion-aware lighting systems, Figure 1 shows a simplified representation of this system, where psychophysiological and occupancy information from the sensing system is combined with environmental information (such as date, time of the day, and geographical location) to determine and provide lighting solutions that support well-being and sustainability. In this system, the sensing

component plays an important role in providing reliable and accurate information regarding occupants and their emotional states.

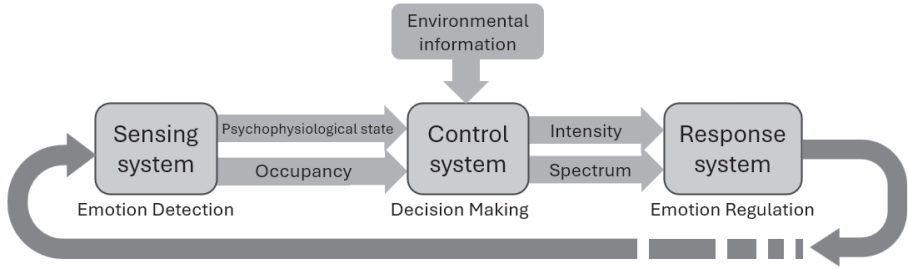


Figure 1 Simplified representation of an adaptive, user-responsive lighting system

Depending on the context, various methods exist that can be used to detect human emotional states. One established approach to detecting human emotions is through physiological signs [27-29]. Emotions are closely linked to physiological responses regulated by the Autonomic Nervous System (ANS), including functions such as heart rate, respiration, and blood pressure [29-31]. Most physiological sensing methods, such as heart rate variability, electrodermal activity, skin temperature, and respiration patterns, rely on wearable devices [29]. Although accurate, wearable sensors have limitations that hinder their practical use in indoor environments. Some of these limitations include power shortage, complications with the range of wireless communication, and reliance on occupants to remember to change and wear devices regularly [32]. Furthermore, they are not well-suited for multi-user environments and are individual-linked, as the system can only collect data from and respond to the individual wearing the device.

One of the main challenges is detecting information about occupants' physiological and emotional states without relying on intrusive methods such as video cameras or wearable devices [33]. This sensing system must balance accuracy, privacy, and practicality to form a basis for an emotion-aware lighting system.

1.2. Problem area

Despite the increasing investigations showcasing the beyond-visual effects of light and their influence on emotions [3, 34-37] and the found effects of light therapy [38, 39], lighting systems that can respond to occupants' emotions have not been well-investigated within the literature. Current lighting control systems commonly implement four main strategies: (1) Predicted occupancy control, (2) Real occupancy control, (3) Constant illuminance control, and (4) Daylight harvesting control strategies [11]. These systems often lack the full range of potential features and proper sensors for feedback, and some studies highlight the need for investigations on the practical implementation of beyond-visual effects of light [5]. Therefore, exploring a practical non-wearable emotion-sensing solution can provide more insight into the possibilities of developing lighting systems that offer much more than just visual comfort.

Concerning non-wearable emotion recognition methods, the literature review performed showed that most investigations included Facial Expression Recognition (FER) or speech analysis, both of which are not suited for primary sensors in lighting control systems. Radar sensors have fewer privacy concerns compared to video cameras, are not affected by changes or lack of lighting, and signals can penetrate through materials such as thin walls [9]. Millimetre-wave (mm-wave) radars are sensing systems operating at high radio frequencies that enable non-contact, high-resolution detection of human presence and movement. These characteristics make mm-wave radar sensors a good option for user-adaptive lighting systems. Despite these benefits, radar sensors face challenges, such as sensitivity to environmental noise and interference, processing complexity, and latency [40]. Although the possibility of vital sign detection through radar sensors has been investigated before, they normally focus on short distances [41] or single-point measurements [42]. Radar's performance across different spatial locations and under dynamic occupancy conditions remains limited [43]. Few investigations collect data in more practical [44] or multi-occupancy situations [45]. Among these investigations, most have fixed occupancy, are done in a laboratory environment with participants' chests fully exposed to the radar and involve very few subjects [46-49].

Given all these challenges, there is a growing opportunity to explore relatively non-intrusive sensing systems that effectively collect information required for recognising emotions, especially in varied occupancy environments. Finding such a system can be a stepping stone for emotion-aware lighting systems and an indoor environment that supports well-being.

1.3. Research objectives

This research aims to find emotion detection methods tailored for intelligent lighting systems by understanding the changes in physiological feedback (such as vital signs) without disturbing the end user or invading their privacy. The outcome of this research will contribute to creating more psychophysiological aware systems within controlled residential environments and concepts such as home monitoring and Ambient Assisted Living (AAL).

Main RQ: *How feasible is the use of non-wearable and non-invasive sensing to detect physiological signals for future emotion-aware lighting applications?*

RQ1- *Which emotion-detection methods and sensors are most reliable, and how well do they align with the requirements of adaptive lighting control?*

RQ2- *How accurately can the selected sensor detect simulated respiration frequency in indoor environments, and how effectively can it capture changes in respiration frequency?*

RQ3- *How can selected sensors detect varied room occupancy (zero, one, or two), and how accurately can they detect respiration frequency for each occupant?*

RQ4- *To what extent can selected sensors detect subtle changes in human respiration caused by emotional activation in variable room occupancy (zero, one, or two people)*

1.4. Scope and delimitations

This thesis documents a high-level investigation into the possibility and feasibility of emotion recognition using sensors that do not disturb individuals, have relatively low privacy concerns, and can be used effectively for lighting control systems in a residential lighting use case. The proposed method of emotion recognition is the use of non-wearable devices; therefore, emotion recognition using wearable devices such as electroencephalogram (EEG) or galvanic skin response (GSR) was not investigated.

Another restricting factor is the intended application environment for this system. Different environments have different requirements that affect the choice of sensors. For example, learning environments such as university and school classrooms may require systems that can detect a large number of students and prioritise lighting for cognitive performance. Residential environments, on the other hand, typically have fewer occupants (in this thesis, zero, one, or two occupants are assumed to be in a room simultaneously) and involve more home-monitoring purposes. Since residential environments are selected as the target environment in this thesis, investigations are narrowed to meet the requirements of this environment. Some of the investigation choices derived from the environment included assuming fewer occupants, small to medium-sized rooms, investigating sitting and supine positions, and lastly, the possibilities for monitoring well-being along with lighting control. This study focused on high-level emotion recognition, which involves considerable complexity and uncertainty. Future work could benefit from focusing on more specific objectives, such as detecting stress in indoor environments.

Lastly, this thesis focused on investigating the possibilities and performance of the selected sensor for emotion recognition in a residential lighting use case. The focus of this study was not on developing new algorithms and methods for emotion recognition. It also did not investigate the lighting priorities in contradictory physiological readings in multi-occupancy situations.

2. Theoretical background

The theoretical background is organised into four main categories to provide a comprehensive overview of the research criteria. The first section, “Human emotions”, explains what human emotions are, their physiological effects, and key emotional models. “Visual and beyond visual effects of light”, describes how light influences human physiology and emotions. The third, “Emotion recognition methods”, provides a high-level overview of available approaches to emotion recognition. Lastly, “Millimetre-wave radar” provides an overview of the sensor selected for this thesis.

2.1. Human emotions

The nature and definition of human emotions have been widely studied in psychology. Despite the ongoing debate regarding its definition, this thesis adopts a framework for understanding emotions based on the work of Oatley and Jenkins [50] and Scherer [51]:

- Emotions are states caused by an external or internal event that produce a form of neurophysiological activation or motor expression. They include cognitive processes and convey a negative or positive subjective experience [50, 51].

Based on this definition, emotions are triggered by an event and lead to neurophysiological or motor responses. These responses can be used as indicators to understand and investigate human emotional states [52]. Emotional phenomena can vary in intensity and duration, ranging from acute responses, such as fear, to more stable emotional states, such as irritability [53]. Moods and emotions are both considered part of human affective experience and are sometimes used interchangeably. However, researchers often differentiate between them and consider them distinct mental states. A mood is considered to be less intense but lasts longer and amplifies or reduces emotional intensity [53, 54].

2.1.1. Emotional models

Throughout history, there have been many attempts at categorising the nature of human emotions into different models. These models can be divided into four main categories [51], with discrete and dimensional models being particularly important for emotion recognition technologies.

Discrete emotion models

In discrete emotional models, emotions are grouped into distinct fundamental emotions, each associated with specific conditions for evocation and different patterns of response [51]. Two of the most well-known discrete models include Ekman's six basic emotions [55] and Plutchik's wheel of emotions [56]. Ekman's model is one of the most commonly used models in emotion detection systems within the concept of facial expression recognition, and body posture [57]. Ekman divides human emotions into six basic emotions: happiness, sadness, fear, disgust, anger, and surprise [58]. However, a seventh state called "neutral" is sometimes added as a separate category.

Dimensional emotion models

In dimensional models, emotions are categorised by one (unidimensional) or more dimensions (multidimensional models) [51, 58]. Some of the most well-known dimensional models are the Circumplex Model of Affect [59] and the Pleasure-Arousal-Dominance (PAD) emotional model. Russel's Circumplex model is one of the most commonly used models in studies using human physiological signs to detect emotions [28]. It proposes that all emotional states emerge from interrelated cognitive interpretations, and considers *valence* (positivity/negativity) and *arousal* (activation/deactivation) as the two basic dimensions that represent related neurophysiological pathways [59]. The PAD emotional model extends the Circumplex model by introducing a third dimension called "dominance". This model is used in many well-known emotion-oriented databases, such as IAPS (International Affective Picture System) [60], DEAP (Dataset for Emotion Analysis using Physiological signals) [61], and MAHNOB-HCI [62].

In this thesis, because emotions are evaluated through physiological responses, the main emotional model investigated in the related experiments is the Circumplex Model of Affect [59].

2.1.2. Emotions and physiology

Emotional states are supported through activation and interactions of the Central Nervous System (CNS) and the Autonomic Nervous System (ANS) [63]. The ANS is a significant part of the human nervous system, which regulates many of the body's functions at a subconscious level, including heart rate, blood pressure, digestion, respiration, pupil response, urination, and sexual arousal [64]. ANS has two subdivisions:

- 1) **Sympathetic nervous system:** Most commonly associated with the ‘fight or flight’ response, the sympathetic nervous system allows a person to engage in a more vigorous physical activity through a phenomenon known as “mass sympathetic discharge”. This includes an increase in arterial pressure, blood glucose, muscular strength, mental activity, and more. The sympathetic system can be activated in many emotional states, such as rage, fear, or stress [64].
- 2) **Parasympathetic nervous system:** The parasympathetic nervous system is often associated with activities such as resting and digesting. Unlike the mass discharge effect of the sympathetic nervous system, parasympathetic functions are more specific [64, 65].

Many studies showcased that emotions are highly associated with the activation of the ANS [30, 31]. Therefore, physiological signals such as heart rate variability, electrodermal activity, temperature, and respiration patterns are commonly analysed to recognise emotions [29].

Emotion and respiration responses:

With regards to emotional activation, some of the most noted respiratory variables reported in the literature include: Respiration Frequency (RF), Respiratory period, respiratory depth, tidal volume, and respiratory variability, with RF being the most commonly studied [31]. Using the arousal and valence framework, Gomez et al. [66] described how breathing patterns

vary across different emotional states. Generally, high-arousal states are associated with shorter breathing cycles and increased airflow, while low-arousal states tend to show slower and deeper breathing patterns. Variations in valence further influence these patterns, affecting factors such as inspiration time and flow rate. These findings are in line with the findings of Zhang et al. [67], who described “deep and fast breathing” as a sign of excitement and associated “shallow and slow breathing” with a calm or sad state. To add to this, many other studies reported significant changes in breathing pattern within different emotional states, some of which can be found in Table 1.

Table 1 Respiration variation due to emotional stimuli in the literature

Reference	Year	Population size	Emotion/Activity	Variables ^a		
				RF	VT	T _i
[68]	2001	10 (All male)	Anticipatory anxiety	↗	↘	↘
[69]	1997	10 (All male)	Mental stress	↗	↗	Not investigated
			Physical load	↗	↗	Not investigated
[70]	2007	34 (19 female) (15 male)	Fear	↗	-	Not investigated
			Sadness	-	-	Not investigated
[71]	1999	10 (All male)	Anxiety (Low anxiety trait group)	↘	↗	-
			Anxiety (High anxiety trait group)	↗	-	↘
[72]	2014	44 (5 male)	Negative high arousal (LVHA)	↗	↗	↗
			Negative low arousal (LVLA)	-	-	-
			Positive high arousal (HVHA)	-	↗	-
			Positive low arousal (HVLA)	-	-	-
			Fear	↗	↗	↗
			Depression	-	↗	-
			Desire	↗	↗	-
[73]	2002	23 (11 female) (12 male)	Relaxation	-	-	-
			joy	↘	Not investigated	Not investigated
			Anger	↗	Not investigated	Not investigated
			Fear	↗	Not investigated	Not investigated
			Sadness	-	Not investigated	Not investigated

^a RF=Respiration Frequency, V_T = Tidal volume, and T_i = Inspiratory time

Although respiration data is less investigated compared to cardiovascular responses, Jerath et al. [74] called for more research on the integration of respiratory patterns with other physiological signals to improve emotion recognition and regulation technologies.

2.2. Visual and beyond-visual effects of light

Light is detected by the human eye through different types of photoreceptors: Rods, Cones (S-cone, M-cone, and L-cone), and intrinsically photosensitive retinal ganglion cells (ipRGCs). Each of these photoreceptors has a distinct spectral sensitivity. Cones are responsible for colour vision with S-, M-, and L-cones sensitivities that peak at Short (~440 nm), Medium (540 nm), and Long (565 nm) wavelengths, respectively. Rods, responsible for supporting vision under low-light conditions, peak at 507 nm [75, 76]. Lastly, ipRGCs, which are highly connected to beyond-visual effects of light, are maximally sensitive to short wavelengths (~480 nm) [76, 77].

The impact of light on humans depends on several key characteristics of light exposure, including intensity, timing, duration, and spatial distribution [1, 3, 4, 76]. Figure 2 shows the pathways through which light influences visual and beyond-visual physical and physiological responses.

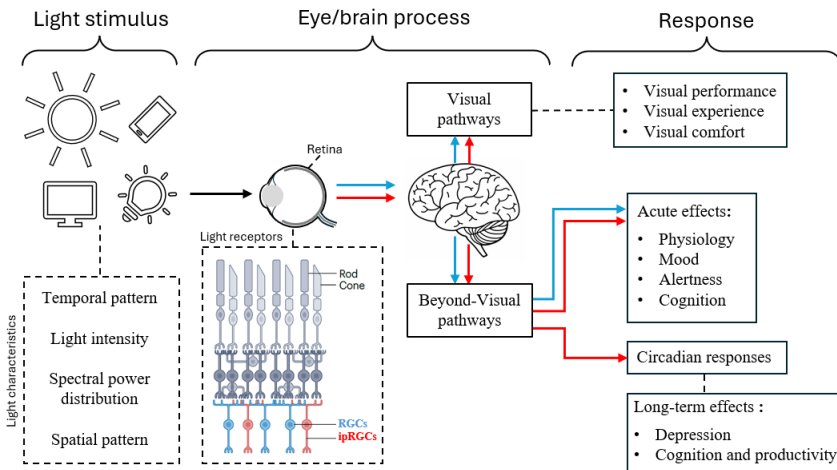


Figure 2 Overview of how light characteristics influence humans, created based on [1] and [2]

Effects of light on humans include both acute and long-term effects. The acute effects of light happen within seconds or minutes of exposure and include changes in pupil size, physiology, mood, alertness, and cognition. The long-term effects include circadian (‘nearly 24 hours’) phase shift, which, depending on disrupted rhythms, may lead to depressed mood, impaired cognition, low productivity, and poor health [1, 2].

One of the acute responses of humans to light is on human emotion and mood. Research shows that human emotional states are influenced by lighting conditions [78]. Many studies have showcased the emotional valence and arousal metrics to be highly connected to lighting characteristics such as illumination and colour [79-81] and that electric lighting can be used to improve mood and cognitive function in people with depressive tendencies [82]. Neuroimaging studies further support these findings by showing the direct influence of light on parts of the brain involved in emotional processing. For example, blue light was found to enhance functional connectivity between emotional processing regions of the brain [1, 13].

2.3. Emotion recognition methods and ethics

Emotion recognition refers to the process of identifying and interpreting human emotional states. There are three main approaches used for this purpose: physiological, physical, and self-assessment methods (Figure 3) [27].

Self-assessment methods rely on self-reported measures, such as the Positive and Negative Affect Schedule (PANAS) or the Self-Assessment Manikin (SAM), to capture subjective emotional experience [27]. Physical methods, on the other hand, focus on expression cues such as body language, facial expressions, or speech. Lastly, physiological methods use the subconscious changes in physiology to detect emotions, including heart rate, electrodermal activity, temperature, respiration patterns, or measurements of brainwaves [29]. Different emotion recognition methods require different data processing; therefore, the choice of method should be aligned with the intended use case.

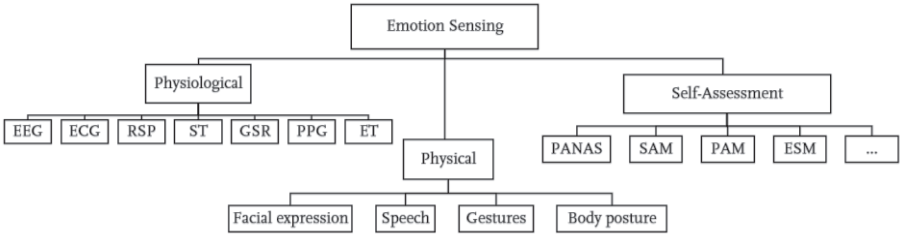


Figure 3 Classification of emotion sensing techniques [27]. EEG: Electroencephalogram, ECG: Electrocardiogram, RSP: Respiration, SKT: Skin Temperature, GSR: Galvanic Skin Response, PPG: Photoplethysmography, ET: Eye Tracking, PANAS: Positive and Negative Affect Schedule, SAM: Self-Assessment Manikin, PAM: Photographic Affect Meter, ESM: Experience Sampling Methods.

As emotion recognition technology continues to grow rapidly, the ethical challenges that arise should be considered. This includes issues related to fairness, since many emotion recognition methods rely on culturally biased data that may lead to inaccurate classifications. Furthermore, the data used in emotion recognition, as well as the emotional data, are very sensitive and may cause issues if collected or used without user consent. Lastly, there are concerns regarding the use of such technologies in workplaces or educational environments, where misuse of emotional information could lead to harmful decisions [83]. To somewhat address these issues, this thesis focuses on carefully choosing sensors and methods that do not require culturally specific data and are more privacy-preserving than methods such as facial expression recognition or speech analysis.

2.4. Millimetre-wave radar

As previously mentioned, this study employs millimetre wave radar sensors. This section, therefore, provides a high-level overview of the selected sensor used across the three experimental designs, offering the necessary background to understand its role and function. Millimetre-wave Radio Detection and Ranging (mm-wave radar) sensors are a branch of radar sensors that operate within millimetre wavelengths, corresponding to a frequency range of 30 to 300 GHz. They function by transmitting electromagnetic waves and analysing

the reflected signals to provide high-resolution spatial information [84]. They have recently gained recognition for their ability to detect vital signs with relatively high accuracy [42]. Radar sensors have fewer privacy concerns compared to sensors such as visible or thermal video cameras and audio detection sensors [33]. Furthermore, emitted radio signals can penetrate through architectural materials such as thin walls, glass, and wood [9]. Figure 4 shows how radar sensors can collect the subtle movement of the chest. After filtering out static clutter and multiple steps in data processing, an estimation of respiration frequency and/or heart rate can be achieved [42].

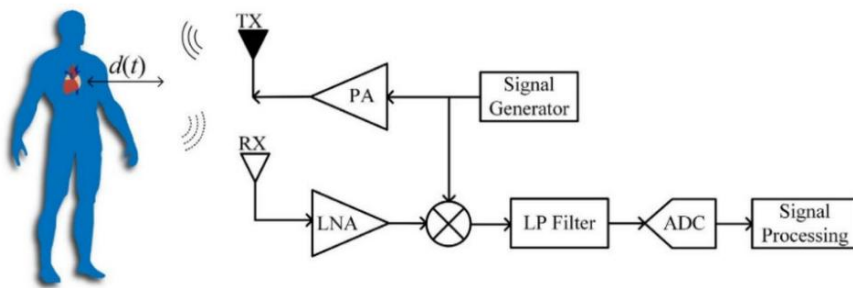


Figure 4 Block diagram of the performance of radar sensors for subtle movement detection [42]

3. Research methodology

In this chapter, the overall research approach is introduced, followed by an overview of how the literature review and the experimental studies were conducted. The appended papers are connected to the research questions, and research quality and ethical considerations are discussed in detail. Data collection and analysis are described at a high level, with additional details available in the related papers.

3.1. Research approach

This thesis follows a sequential research approach, where each experiment builds on the findings of the previous one, allowing the research to gradually explore progressively more complex conditions [85]. The study began with an exploration phase (literature review) to inform the research design and identify suitable sensing systems, leading to the selection of mm-wave radar sensors for subsequent investigation. This was followed by an empirical evaluation phase (three experimental studies) to assess radar performance under increasingly complex and realistic indoor conditions. The first experiment was a controlled laboratory validation study, and the two subsequent experiments followed a single-group interrupted time-series design.

3.2. Exploration phase

An exploratory phase was initiated first, using a structured mapping review to explore the research topic and identify suitable emotion detection methods and sensors for lighting applications. In technology-oriented research, such literature reviews are often used to inform key methodological and design decisions prior to empirical work [86]. By grounding the design decisions in existing evidence, this approach strengthens methodological rigour and reduces the risk of unjustified choices in later experimental stages. The conducted mapping literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [87] guidelines at a high level. First, suitable keywords were identified based on the three main

topics: “emotion recognition,” “non-wearable,” and “smart home”. These keywords were used to formulate search strings for four relevant databases. Inclusion and exclusion criteria were defined to ensure relevance and quality of the selected literature. The review identified common approaches and gaps in non-wearable emotion recognition methods used in residential environments. The strengths and weaknesses of found approaches were evaluated, and their performance and applicability were compared with a focus on lighting system integration.

Overall, this phase provided a solid foundation for the study by directly informing the design decisions, such as the selection of mm-wave radar sensors to ensure that the following experimental studies were based on an academically justified approach.

3.3. Empirical evaluation phase

3.3.1. *Experimental study without human subjects*

Measuring and testing sensor technology typically involves several structured steps prior to human experiments to ensure reliability, accuracy, and operational safety. The first step involves system setup and sensor calibration, followed by baseline measurements under controlled conditions to establish stable signal collection. Controlled experiments are then performed using predefined inputs or simulated scenarios to evaluate the sensor’s performance under consistent and controlled conditions [88]. Repeated trials are often performed to assess consistency and reduce random variability, in line with principles of ISO 5725-1 [89]. In the final step, the sensor is tested under varied environmental and operational conditions to test its limitations. Together, these validation steps ensure that the sensing system performs as expected before more complex experiments involving human participants [88]. Following this principle, a controlled laboratory validation study with a robotic surrogate (Figure 5) was employed to evaluate the performance, accuracy, and limitations of the radar system under highly controlled and repeatable conditions. To ensure consistent respiration frequency in all tests, two robotic breathing simulators, the Controlled Airflow Thorax robots (CAT-bots), were developed and validated against a reference medical

instrument (spirometer) to confirm their reliability as ground-truth sources for the experimental evaluation. Using CAT-bots, an experiment (Experiment 1) was conducted across multiple respiration frequencies and spatial positions, focusing on low and normal RF [90, 91], to allow for a systematic assessment of detection reliability and accuracy under key parameters such as distance and respiration rate. The system was tested under empty, single, and dual occupancy conditions to examine the system’s ability to estimate room occupancy and extract respiration signals individually. Lastly, dynamic breathing scenarios were simulated to assess the system’s ability to detect abnormalities in RF, such as irregular respiration and possible emergencies.

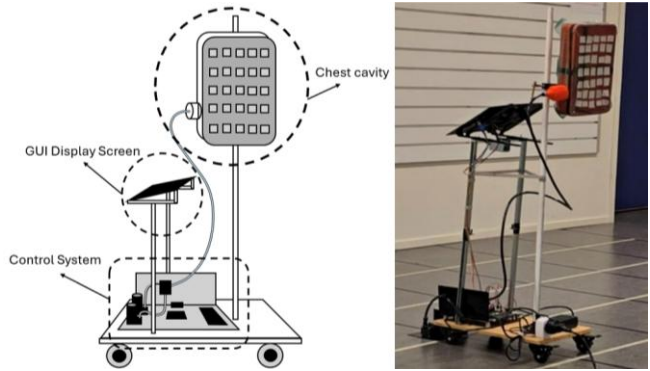


Figure 5 Controlled Airflow Thorax robot (CAT-bot) and its main modules

Overall, the controlled laboratory validation experiment allowed for a systematic evaluation of the radar system to establish initial performance and operational limits before introducing human subjects and more realistic occupancy conditions.

3.3.2. Experimental study with human subjects

Experiments involving human subjects were conducted to evaluate system performance under realistic physiological and behavioural conditions, to capture the natural variability in respiration and quasi-stationary body movement and to improve ecological validity. These studies were designed using a single-group interrupted time series (ITS) approach, in which repeated measurements are taken from the same group before and after a defined intervention [85]. This design allows identification of the changes in the

subject responses over time, where the effects of the intervention can be clearly separated from underlying trends [92]. In this case, emotional video stimuli acted as the interruption, allowing changes in physiological responses to be examined for each stimulus within the same participants, accounting for intra-individual variability.

Experiment 2 and Experiment 3 were structured within this framework, with the former serving as a pilot study for the latter (study design provided in Appendix I). A total of 29 adult participants (15 female and 14 male) were recruited from Jönköping University students and staff using a convenience sampling approach. Prior to participation, a health-based screening was conducted using lung volume tests with a medical spirometer to ensure consistent measurements by excluding conditions that directly affect human respiration. During the experimental sessions, participants were exposed to a series of emotional video stimuli that represented each quadrant of the Circumplex model [59]. Experiments were conducted in a controlled laboratory setting where physiological responses were continuously recorded using the mm-wave radar and reference medical sensors. Baseline mood was recorded through subjective questionnaires, which were administered again after each video stimulus to assess the emotional state.

Experiment 2 was conducted with single-participant sessions in a controlled laboratory setting, where physiological responses were recorded with the participant's chest fully exposed to the radar (Figure 6). Experiment 3 investigated a more complex scenario involving varied occupancy, where participants were seated individually or in pairs across different spatial configurations and distances from the radar (Figure 7). This design allowed for a systematic evaluation of the radar's ability to monitor physiological signals under increasingly complex and realistic conditions.

Within the research strategy, the ITS-based experiments with human subjects allowed the evaluation of the sensor's performance under more realistic and complex conditions while also exploring the potential for emotion detection through identifying small changes in respiration frequency associated with emotional activation.

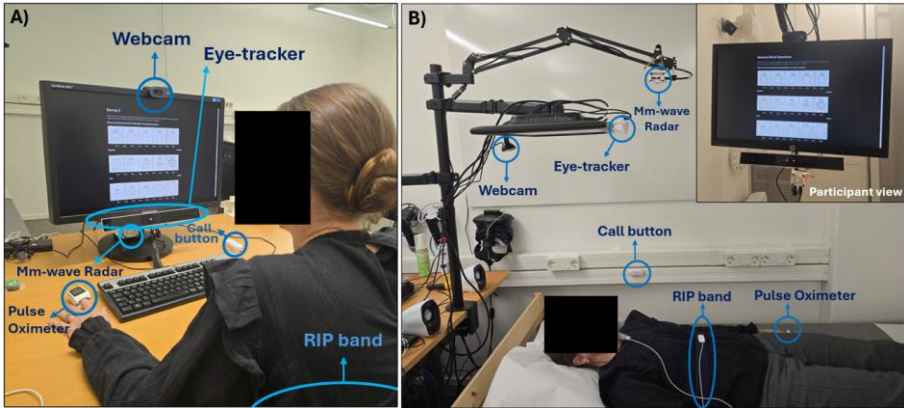


Figure 6 Experimental setup and sensors for experiment 2. A) Setup for sitting position B) Setup for supine position

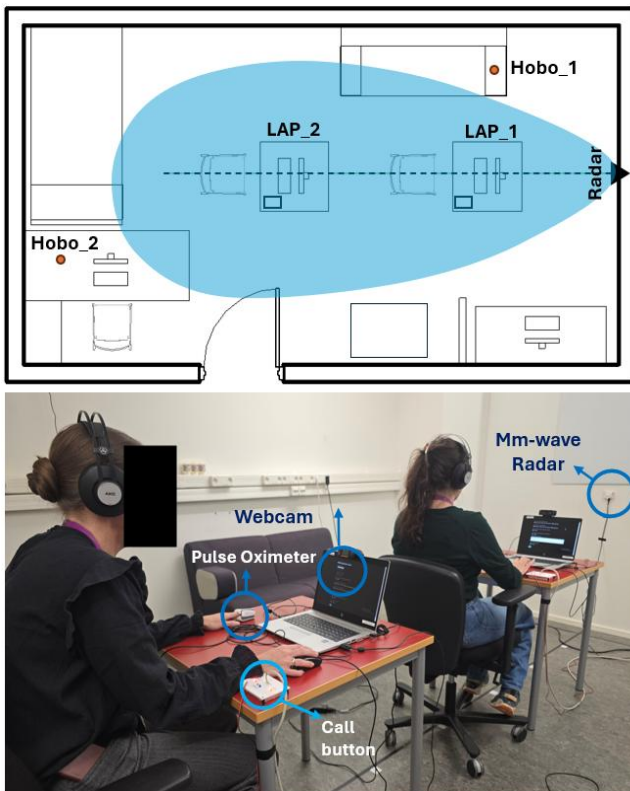


Figure 7 Experimental setup and sensors in experiment 3

3.4. Application of the research methodology

The research objectives were addressed through two main stages. The exploration phase created an overview of practical non-wearable emotion recognition, assessing available methods, sensors, and their reliability. Besides, it discussed the alignment between the emotion-detection method and the requirements of adaptive lighting control. The mapping literature review in this phase was used to support the research decisions. It was followed by an empirical evaluation phase, which further explored the selected approach and sensor. The first experimental study (without human subjects) provided insight into sensors' capabilities and limitations. It examined the selected sensor's accuracy in estimating respiration frequency and its efficacy in monitoring changes in RF. Additionally, it investigated the sensor's performance under varying room occupancy, focusing on the accuracy and separation of respiration signals between occupants. The second and third experimental studies (with human subjects) explored respiration-related factors associated with emotions and added ecological validity to the study.

The overall process and the rationale for the method choice are shown in Figure 8. The answer to the first research question (literature review outcome) is provided in Paper 1, whereas Paper 2 answers part of the second research question. Paper 3 addresses the remaining part of the second research question and the third question, using the outcomes of experiments 1 and 3. Papers 1 and 3 are currently under review by a peer-reviewed scientific journal, whereas Paper 2 has been peer-reviewed and will be published in conference proceedings. The results of Experiment 2 will be published in a future journal paper.

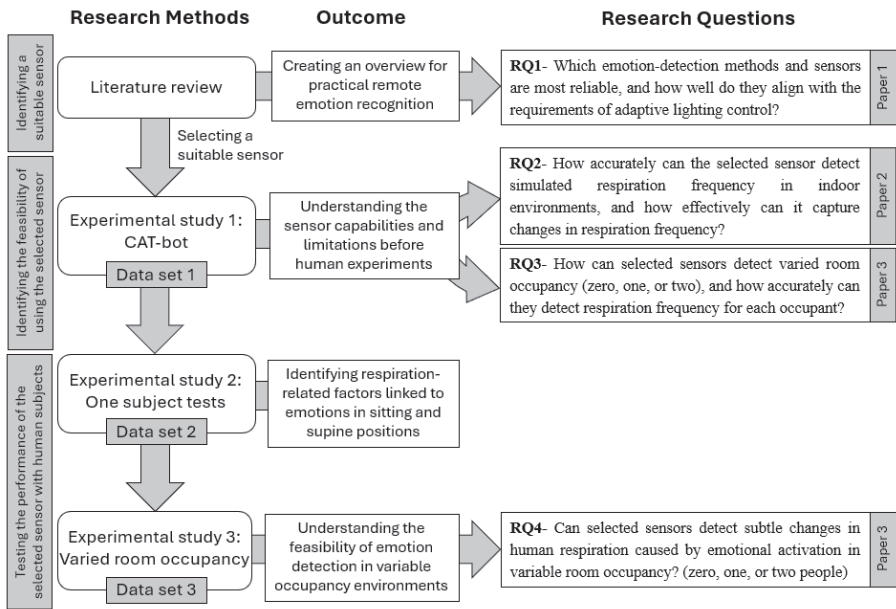


Figure 8 Overview of the research approach, connecting the chosen methods with outcomes, research questions, and associated publications.

Paper 1 included the mapping literature review and the exploratory phase of the thesis. It investigated suitable non-wearable sensing approaches for emotion recognition in residential environments, with a particular focus on integration into lighting control systems. The results indicated that widely studied approaches such as facial expression recognition, remote photoplethysmography (rPPG), and speech analysis present significant limitations for lighting control applications, primarily due to privacy, light dependency and contextual constraints. In contrast, radar-based sensing and motion capture approaches, while less extensively explored, demonstrate strong potential for integration into lighting systems.

Based on these findings, millimetre-wave (mm-wave) radar was selected as the sensing technology for further investigation in the subsequent experimental studies of the thesis.

Paper 2 represents the initial empirical evaluation phase. The aim of the study was to systematically assess the capabilities and limitations of millimetre-wave (mm-wave) radar for respiration monitoring under controlled conditions prior to experiments involving human subjects. The evaluation focused on key performance aspects of residential lighting systems, including spatial coverage, accuracy of respiration frequency estimation, sensitivity to changes in respiration frequency, and robustness under varying occupancy conditions. This study established a controlled performance baseline for mm-wave radar respiration estimation, identified operational constraints, and informed the design for the subsequent human-subject experiments presented in the next stage of the thesis.

Paper 3 investigated the respiration frequency detection in varied occupancy conditions by combining systematic data from the first experiment with natural physiological variability introduced in the third experiment. The findings demonstrate the feasibility of using millimetre-wave radar for occupancy detection and respiration monitoring, showing reliable performance across both controlled and human-based experiments. The results also indicate that respiration patterns reflect changes in emotional arousal, supporting their potential use in emotion-aware systems.

3.5. Data analysis

Data analysis was primarily quantitative and focused on system performance across scenarios. It included the probability of detection, confusion matrices for occupancy estimation, and the absolute error between radar-estimated respiration frequency and reference values. Statistical analysis and repeated-measures ANOVA were used to examine the relationship between radar respiration frequency and emotional valence and arousal. For more detailed information regarding data analysis, please refer to the appended papers.

3.6. Quality of research

High-quality research is characterised by transparent and well-aligned methods, producing valid and reliable findings that are clearly communicated and relevant to practice [93]. In this thesis, research quality was addressed by considering validity and reliability.

3.6.1. *Validity*

Validity refers to how well the results reflect what the study aims to measure, ensuring the intended concepts are properly captured [94]. Internal validity refers to how accurately a study measures what it aims to measure and whether the results are a reflection of the studied variables [95]. To ensure the internal validity of the studies, high-precision medical reference devices were used, such as a medical-grade pulse oximeter, spirometer, and respiratory inductive plethysmography band to quantify errors in the CAT-bot and mm-wave radar performance. All devices requiring calibration were calibrated accordingly. The spirometer was calibrated twice daily using a 3-litre syringe, and the eye-tracker was calibrated individually for each participant to ensure measurement accuracy. All measures, including emotion-evoking videos and surveys, were selected from established and validated databases and methods, including the DEAP database [61] and the Self-Assessment Manikin [96]. Data analysis was conducted using established statistical software, including IBM SPSS Statistics [97] and Jamovi [98]. However, due to data inconsistencies and the prevalence of neutral facial expressions among most participants, subjective SAM measurements and the labelled videos could not be validated using additional measures such as facial expression in the second experimental design. External validity refers to the extent to which the study findings can be generalised beyond the study setting [95]. In this thesis, to ensure external validity, target participants were the population representative of typical adult occupants in residential environments. The inclusion and exclusion criteria used to screen participants were ethically and medically motivated to ensure an ethical study process and improve internal validity by reducing irregular physiological data caused by underlying medical conditions. However, it should be noted that the use of convenience sampling, recruiting staff and students from Jönköping University, may limit the external validity of the study.

Ecological validity commonly refers to how well a study reflects real-life conditions [99]. Although the ecological validity of the study is not high due to testing conditions in monitored laboratory settings, a few measures were considered to address this issue. Participants were placed in quasi-stationary positions. They were asked to avoid certain movements to prevent measurement errors in the medical devices; however, their overall body movements were not restricted. Emotion-evoking stimuli consisted of music videos, which reflect everyday media consumption and induce subtle, natural emotional changes rather than extreme responses.

3.6.2. *Reliability*

Reliability refers to how consistent a measurement is, reflecting whether the results are stable and precise [94]. To ensure the reliability of the results in this study, first, the radar was tested with a CAT-bot, which allowed for consistent and repeatable breathing simulations for all different locations in the room. Furthermore, standardised procedures and consistent sensor setups helped ensure stable and reproducible results. Lastly, detailed descriptions and visual documentation of the experimental setups were provided to enhance reproducibility in future studies.

3.7. Ethical considerations

The research follows the guidelines for good research practice as well as the World Medical Association Declaration of Helsinki [100]. All procedures involving human participants were submitted for ethical review to the Swedish Ethical Review Authority (Etikprövningsmyndigheten) and approved on 3rd of February 2025 (Nr. 2024-08540-01).

The experiments were designed to avoid any harm or discomfort to participants, and all devices used are commercially available or approved medical devices. Participant privacy was protected through anonymisation using randomly generated participant IDs, along with secure data handling procedures for storage and sharing. To ensure research integrity and prevent data falsification or fabrication, all raw data is stored in PULSE shared files with restricted access only to the researchers mentioned in the ethics approval form. Data presented in the publications avoid individual-level analysis and is

presented as generalised information, such as Mean \pm SD. Participation was entirely voluntary, and participants received a clear explanation of the study procedures, both in written and/or oral form, before providing their informed consent. Lastly, participants were informed of their right to withdraw from the study at any time, without providing a reason or consequences.

4. Summary of findings and synthesis of the appended papers

This chapter presents a summary of the findings and synthesis of articles contributing to this thesis. This includes selected unpublished findings to provide a foundation for the overall discussion. The information provided in this chapter is at a high level to avoid repetition. For detailed information regarding the investigations, refer to the appended papers.

4.1. Paper 1

A mapping literature review was conducted to establish a knowledge base for practical emotion-aware lighting and to support the selection of suitable sensors for the upcoming experiments. This review identified current non-wearable sensors and methods for detecting emotions in smart home environments, resulting in the first paper, titled *“Emotion Recognition in Residential Environments Using Non-Wearable Devices: A Mapping Review for Emotion-Responsive Lighting Systems”*.

After screening 657 articles by title, abstract, and full text, 34 articles were found strategically relevant to the aim of the study. The found emotion recognition methods included (1) body language analysis (including gait, posture, gesture, and eye tracking), (2) facial expression recognition (static and dynamic FER), (3) speech analysis (including linguistic and paralinguistic analysis), and (4) physiological signal analysis (including heart rate variability, respiration, and skin temperature). The identified approaches were systematically mapped by sensor type and method of emotion recognition, resulting in two main categories of video-based devices and voice-based devices. Video-based devices (particularly regular cameras) dominated the literature, while other sensing systems, such as motion capture cameras, thermal cameras, radar sensors, eye trackers, and piezoelectric sensors, were less frequently studied (Figure 9).

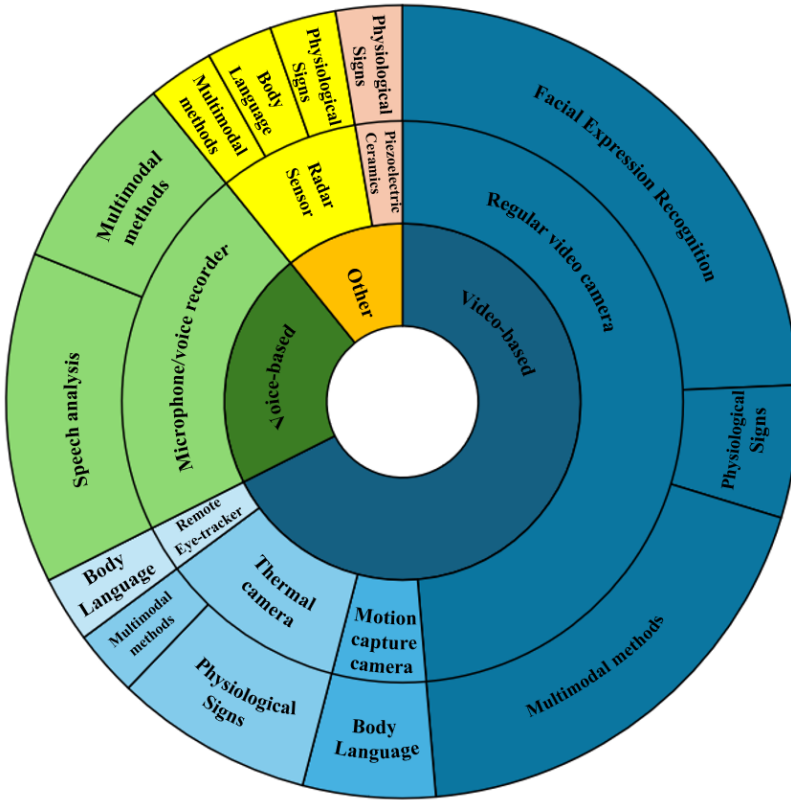


Figure 9 Distribution of sensor/device types used in selected articles and their related emotion recognition methods

4.1.1. Summary of identified sensors and devices

Video-based devices

Video-based devices included various types of cameras, such as regular video cameras, motion-capture cameras, thermal cameras, and remote eye trackers.

Regular video cameras are mainly used for two emotion recognition methods, facial expression recognition and heart rate variability using remote photoplethysmography. Facial expression recognition includes two major categories: Static FER (S-FER), which only relies on the spatial information in a single image, and Dynamic FER (D-FER), which includes both the spatial

and temporal information from consecutive images. Among the selected articles, static FER was more commonly used than dynamic FER, with both methods lacking practical studies and relying largely on secondary data. These datasets typically provide images with fully visible facial features [101-103], and databases that include non-optimal facial expressions were rarely used [104, 105]. Remote photoplethysmography is a non-contact method that estimates real-time heart rate by analysing subtle changes in skin colour caused by blood flow [106]. rPPG methods were relatively less investigated than the FER methods and provided a more limited range of emotional states.

Motion Capture Cameras are most commonly used for emotion recognition through body language, such as gait, posture, and gestures. Unlike standard video cameras, systems such as Kinect do not require lighting conditions to track body movement. Only a limited number of studies (two articles) employed this approach. The categorized emotions in both studies are discrete but do not extensively refer to any known psychological models.

Thermal cameras detect infrared radiation rather than visible light, allowing them to operate without environmental lighting. Two emotion recognition methods were associated with this device, one analysing changes in facial skin temperature in specific regions of interest, and another measuring respiration rate. The thermal camera is placed at an angle to provide a clear view of the occupant's nostrils. For respiration detection, the camera is positioned to have a full view of the nostrils, where temperature changes during breathing are used to estimate respiration.

Remote eye trackers are sensitive to near-infrared light and capture information such as gaze position, dwell time, blink rate, and pupil size by capturing images of the eyes and the reflection glints on the cornea [107, 108]. Only one of the selected studies employed this method, suggesting that this method may require more focus in the future. The study focused on identifying patterns associated with positive and negative emotions, using metrics such as mean fixation duration and mean dwell time.

Voice-based devices

Voice-based devices may include microphones or voice recorders that collect audio signals used for analysis. All articles used paralinguistic analysis, with some also incorporating linguistic features. The categorized emotions show an underlying focus on symptom detection (e.g., stress, pain, depression, frustration, and anxiety) rather than on basic emotion categories [109-111].

Other sensors

Other sensors included radar-based sensors and piezoelectric ceramic sensors.

Radar-based sensors detect subtle chest micro-movements to measure heart rate, respiration, and capture small movements such as lip and jaw motion. One study used mm-wave radar for emotion recognition through vital signs, while the other two used it to capture body movement, posture, and micro-expressions.

Piezoelectric ceramic sensors are embedded in furniture such as chairs or beds and measure ballistocardiogram signals to extract heart rate variability. Among the identified sensors, these are the only ones that require a form of physical contact.

4.1.2. Performance and applicability evaluation

Sensor performance was evaluated against the functional requirements of lighting control systems, including continuous sensing, reliable occupancy detection, support for multi-user scenarios, and compatibility with dimensional emotion models commonly used in lighting research [82]. Methods requiring active user involvement (e.g., speaking), limited fields of view, or light-dependent sensing were found to be less suitable as primary inputs for lighting systems. The applicability of approaches was also evaluated based on their integration into existing systems, considerations of privacy and user acceptance, and the cost and maintenance requirements for real-world deployment. Based on a combined evaluation of performance and real-world applicability, using decision factors adapted from Wang et al. [4], motion capture cameras and mm-wave radar sensors emerged as the most promising primary sensing technologies for emotion-responsive lighting.

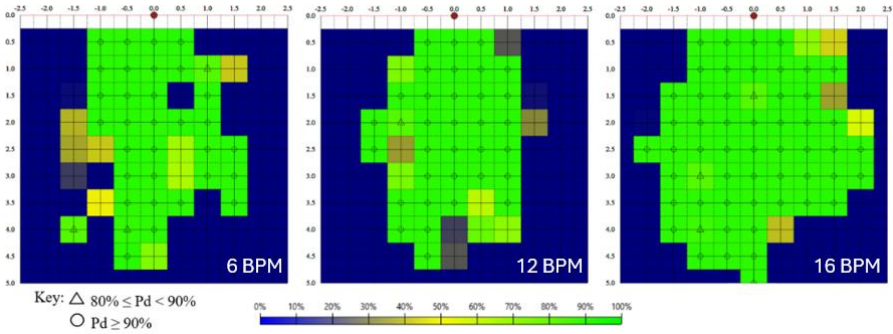
4.2. Paper 2

Based on the literature review, mm-wave radar was chosen for further study, and several investigations were conducted to test its potential for practical use in residential lighting systems. The second paper, titled “*Physiologically Aware Lighting for Ageing in Place: Exploring mm-Wave Radar Sensing for Embedded Health Support in Residential Environments*”, examined the performance of mm-wave radar for respiration monitoring in small and medium rooms, focusing on spatial coverage, accuracy, and responsiveness to changes in respiration frequency. The study aimed to go beyond short-range and single-point radar measurements to validate its potential for indoor applications before human experiments and explore its potential for physiologically aware and safety-oriented lighting systems in ageing-in-place contexts.

To ensure repeatable and homogeneous chest motion across measurement locations, a Controlled Airflow Thorax robot (CAT-bot) was developed to simulate adult human thoracic movement at controlled respiration frequencies. The CAT bot consists of a pneumatically actuated chest cavity with a functional residual capacity of approximately 3 litres [112]. The air flow is controlled through an Arduino-based system, allowing for programmable respiration frequencies. The simulated respiration was validated using a medical spirometer, demonstrating a strong agreement between the target and measured respiration frequencies.

Radar coverage and accuracy were evaluated in a 5×5 m laboratory space, divided into a 0.5 m-resolution grid. The CAT-bot was positioned at each grid point and tested at three breathing frequencies (6, 12, and 16 bpm), representing the slow and normal respiration ranges [90, 91]. Probability of detection (P_d) and absolute respiration frequency error were calculated from five-minute recordings at each location (Figure 10). Across all breathing frequencies, a large proportion of the room exceeded 80% P_d , with the highest and most uniform coverage observed at 16 bpm. For grid points with $P_d > 80\%$, two one-sided tests (TOST) showed that radar-estimated respiration frequencies were statistically equivalent to spirometer measurements within equivalence bounds of ± 0.5 bpm, confirming high accuracy in areas of stable detection.

a) Probability of detection



b) Absolute error

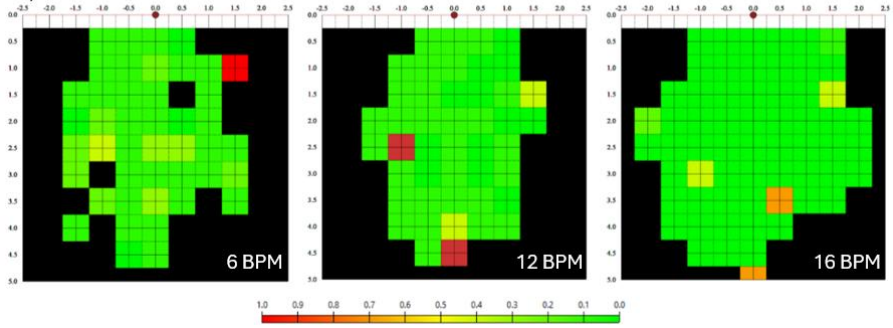


Figure 10 a) Heatmap for probability of detection for BF=6, 12, and 16 bpm, b) Heatmap of absolute error (radar BF vs target BF) for BF=6, 12, and 16 bpm

The radar's ability to detect temporal changes in respiration frequency was further assessed using five programmed breathing scenarios, including sudden increases and decreases in RF, inconsistent breathing patterns, and short-term (false alarm or sleep apnea) and long-term (emergency) stops in breathing. The radar showed strong temporal alignment with the programmed ground truth, reliably detecting transitions between respiration rates. Detection latencies ranged from approximately 10 to 20 seconds, but no critical events were missed, and system warnings for abnormal or absent breathing were consistently triggered (Figure 11).

Overall, Paper 2 demonstrates that mm-wave radar provides stable spatial coverage, high accuracy in respiration frequency, and reliable detection of respiratory changes in residential-scale environments. The findings indicate that radar-based respiration monitoring can support non-invasive detection of

physiological and psychophysiological [113-116] states and timely identification of abnormal breathing events, making it suitable for integration into adaptive and safety-oriented lighting systems for ageing-in-place applications.

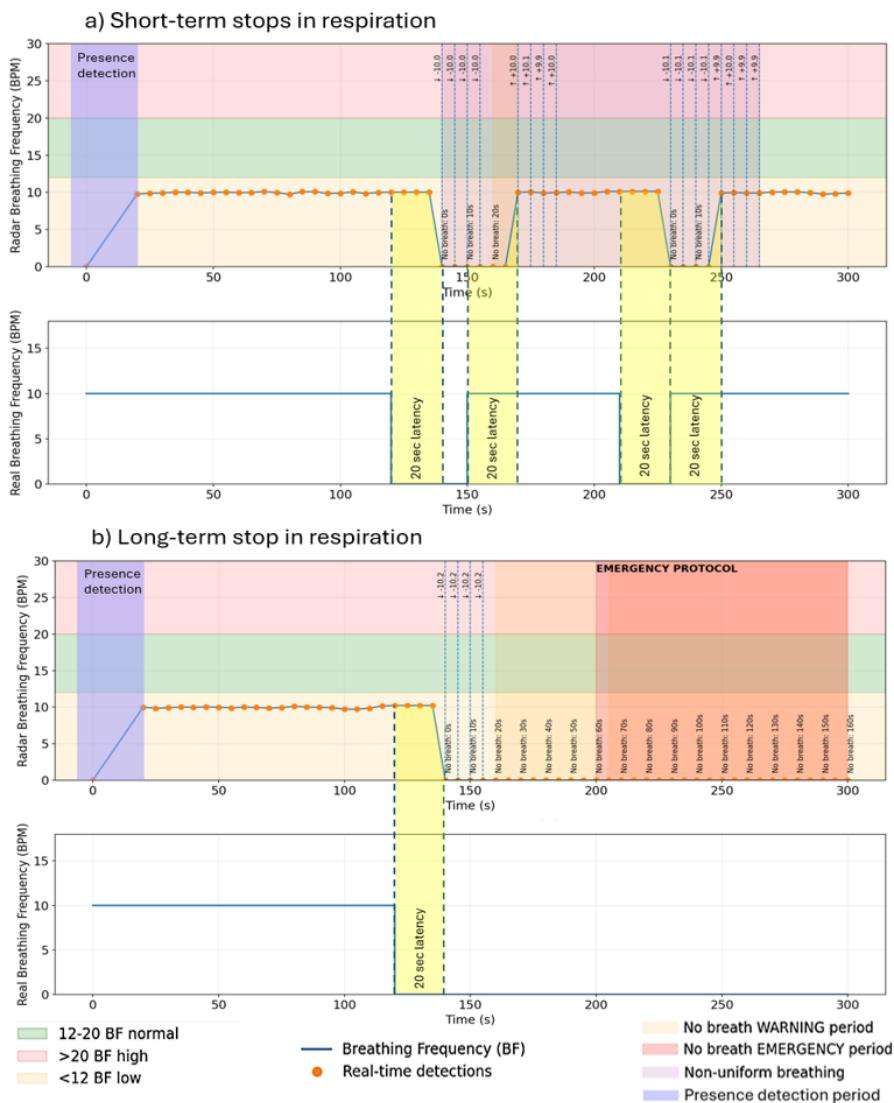


Figure 11 Time-aligned comparison between radar RF and the real-RF with real-time warnings for a) Short-term, and b) Long-term stop in respiration

4.3. Paper 3

This study investigated whether mm-wave radar can reliably estimate occupancy and respiration frequency in environments with varying (no, one, or two) occupancy. It further explored the potential for emotion-detection via radar by investigating changes in respiration frequency with emotional valence and arousal. The overarching aim was to assess the feasibility of radar-based emotion detection under more realistic conditions involving shared spaces. This paper utilised the systematically collected data from the first experiment (CAT-bot) to provide controlled and repeatable reference measurements, complemented by data from the third experiment with human subjects to incorporate natural physiological variability. Respiration frequency extraction from mm-wave radar follows a standard signal processing chain adapted from Wu et al. [117], with additional steps introduced for varied occupancy detection seen in Figure 12.

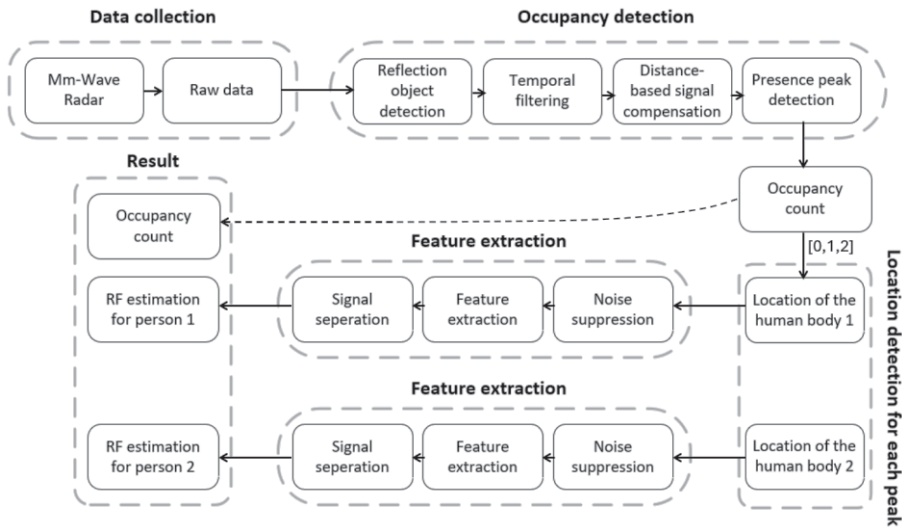


Figure 12 Signal processing chain for vital sign collection with varied room occupancy

In the CAT-bot experiment, occupancy classification achieved an overall accuracy of 89% ($macro\ F1 = 0.87$; $weighted\ F1 = 0.90$), with the highest performance in no-occupancy scenarios. Most misclassifications occurred when in two occupancy scenarios, one CAT-bot partially blocked or

overwhelmed the other CAT-bot's signal, particularly when low respiration rate (RF=6 bpm) was involved. Respiration frequency detection remained highly reliable across all conditions, achieving 100% accuracy in single-occupancy scenarios and over 95% in two-occupant scenarios.

In the third experiment with human subjects, Radar-based occupancy detection achieved an overall accuracy of 96% (macro- and weighted-F1 = 0.96), correctly classifying all empty-room and single-occupant recordings, with only one misclassification in the paired condition. Respiration frequency estimation showed an overall accuracy of 80% within a clinically acceptable tolerance of ± 3 bpm [118], with slightly reduced performance for participants seated further from the radar or partially occluded. Mean absolute error and mean accuracy were calculated as 2.18 bpm and 87%, respectively. Comparable studies reported respiration frequency estimation accuracies ranging from 70% to 94% [119-121].

Repeated-measures ANOVA confirmed significant differences in subjective arousal and valence ratings between intended video categories, and critically, a significant increase in radar-derived respiration frequency during high-arousal compared to low-arousal videos ($F(1,24) = 13.98, p = 0.001$). No corresponding effect was observed for valence. This aligned with prior work [66, 72, 73] showcasing respiration frequency changes within different emotional states. Overall, these findings suggest the potential of radar sensing in shared spaces through passive physiological monitoring and occupancy detection, with applications in emotion-responsive lighting systems.

4.4. Unpublished work

A pilot experimental study designed to investigate the feasibility of radar-based emotion recognition in a controlled, single-occupant setting served as a preparatory step for subsequent experiments. It evaluated the accuracy of radar respiration frequency measurements and their robustness across common residential body positions prior to introducing the added complexity of multi-occupancy environments. However, due to time constraints, the analysis and interpretation of the data could not be completed before the licentiate thesis. To protect unpublished data, only a small portion of the

results connected to the thesis is provided in this section to complement the information required for the discussion section.

The same participants and screening procedures were used as in Experiment 3. Data collection was conducted in two sessions separated by a one-month washout period (Appendix 1). Participants completed the experiment in both seated and supine positions, reflecting typical residential contexts, with a high difference in lung functional residual capacity [122]. To minimise repetition bias, two matched sets of emotion-eliciting videos were used across the two sessions. Participants reported their emotional states using the Self-Assessment Manikin (SAM). At the same time, data were collected using multiple sensors, including an mm-wave radar, a Respiratory Inductive Plethysmography (RIP) band, a pulse oximeter, a webcam, and an eye tracker. Environmental conditions were also continuously monitored. Radar-derived respiration frequency was evaluated against the RIP band as ground truth. Radar signals were processed to extract respiration frequency, while epoch timestamps from the video stimuli were used to temporally align data across sensors. After excluding four participants due to sensor failures or insufficient data quality, a total of 400 respiration frequency recordings were analysed (eight videos \times two positions \times remaining 25 participants).

The results showed strong agreement between radar-estimated respiration frequency and RIP measurements. Using a clinical tolerance of ± 3 bpm [118], radar respiration detection achieved an overall accuracy of approximately 90%. No significant difference in accuracy was observed between seated and supine positions, indicating consistency across common body postures in residential environments. Further analysis across respiration frequency ranges (low, normal, high, and very high) showed increased estimation error at the extremes, particularly for low and very high breathing rates, although these cases were infrequent (Table 2).

Overall, the findings from this pilot study (**unpublished paper**) demonstrate that mm-wave radar can reliably estimate respiration frequency for a single occupant across common residential postures. The results provide methodological validation for subsequent multi-occupancy studies and support the use of radar respiration sensing as a foundation for emotion-responsive and physiologically aware lighting research.

Table 2 Mean absolute error for radar respiration rate estimation across breathing ranges

Range	Count	Mean Absolute Error
Low bpm (6-11 bpm)	5	± 5.26
Normal bpm (12-20 bpm)	288	± 1.20
High bpm (20-25 bpm)	102	± 2.07
Very high bpm (25 + bpm)	13	± 5.81

5. Discussion

This chapter discusses the thesis findings in relation to the overarching aim of finding feasible sensing systems to be used in emotion-aware lighting systems. It addresses the research questions, the potential applications of mm-wave radars in the built environment, the academic and industrial contributions, and reflects on the study's limitations.

5.1. Research questions

This section addresses the four research questions by synthesising findings from across the appended studies.

RQ1- Which emotion-detection methods and sensors are most reliable, and how well do they align with the requirements of adaptive lighting control?

The literature review (**Paper 1**) mapped the available non-wearable emotion recognition methods, listed their advantages and disadvantages, and evaluated them against lighting control system requirements. The results revealed that although video cameras with FER methods and voice analysis are the most investigated and reliable modes of non-wearable emotion recognition, they are not quite compatible to be primary sensors for lighting systems. When evaluated against the requirements of adaptive lighting control, these sensors are not applicable, especially in terms of privacy, lighting dependency, and continuous operation. In contrast, motion capture cameras and radar sensors were found to be more suitable as primary options, as they allow continuous, real-time monitoring without requiring user interactions such as speaking, and are not affected by different lighting conditions. Radar sensors showed strong potential by enabling non-wearable sensing without capturing identifiable visual data, thereby offering privacy advantages over camera-based solutions while still providing both occupancy and physiological information. This highlighted the need for further investigation into less explored or emerging non-wearable sensing approaches that offer better suitability for lighting control systems.

RQ2- How accurately can the selected sensor detect simulated respiration frequency in indoor environments, and how effectively can it capture changes in respiration frequency?

This question was answered mainly by the results of **Paper 2**, and partially through those in **Paper 3** and the unpublished experimental results. The radar performance was evaluated across different points in a 5×5m room and three different breathing rates. The findings showed that, in indoor residential environments where normal breathing ranges are most common, the radar achieved stable coverage and high accuracy in respiration frequency estimation, particularly in areas with a reliable probability of detection ($P_d > 80\%$). The results also showed the radar's ability to capture sudden changes in respiration frequency over time, and detect respiration patterns, including non-homogeneous breathing patterns, as well as reliably detect periods of no breathing in emergency and non-emergency situations. Additionally, the results showed that the mm-wave radar achieved approximately 90% accuracy in detecting human respiration frequency compared to a RIP band, considering a clinical tolerance of ± 3 bpm.

RQ3- How can selected sensors detect varied room occupancy (zero, one, or two), and how accurately can they detect respiration frequency for each occupant?

This question was answered by the results in **Paper 3**. Overall, the radar showed strong performance in detecting occupancy, in both experiments with the CAT-bot and human subjects, with weighted F1-scores of 0.90 and 0.96, respectively. Respiration frequency estimation was more accurate in the CAT-bot experiment (approximately 96%), mainly because the robot's simulated breathing was perfectly homogenous, with no micro/macro movements. In the two-occupant scenarios, the person closer to the radar was usually detected more accurately than the person behind, likely because the front person partially blocked the reflected signals. The respiration frequency estimation in the human experiments had much lower accuracy, likely due to natural body movements and less regular breathing. Even so, within the clinical tolerance of ± 3 bpm, the radar still achieved about 80% accuracy when compared to the pulse oximeter as the ground truth. Overall, the results showed that the radar can reliably detect whether a room is empty, has one person, or two occupants,

and can estimate respiration frequency for each occupant individually with relatively high accuracy.

RQ4- To what extent can selected sensors detect subtle changes in human respiration caused by emotional activation in variable room occupancy? (zero, one, or two people)

Paper 3 investigated this question, and the repeated-measures ANOVA showed that the radar can detect differences in respiration frequency associated with emotional arousal. Respiration frequency increased with higher *arousal* levels, in line with previous studies [66, 73], while no effect was found for emotional *valence*. While these results point to the possibility of using radar for emotion recognition, the observed changes in respiration were relatively small and fell below clinically meaningful thresholds. This suggests that the radar may be better suited for detecting stronger emotional responses or patterns over time, rather than subtle emotional differences. Therefore, further investigations using classification approaches are needed to fully explore the radar's potential for emotion recognition in variable occupancy scenarios.

5.2. Academic and industrial contribution

This research contributed to the development of future physiological-aware lighting systems by investigating a practical sensing system to collect passive physiological data. Mm-wave radars are non-wearable sensors that can be discreetly integrated into architecture. The findings showed how radar can reliably detect occupancy and respiration frequency in varied occupancy settings, supporting both presence-based control and more advanced applications related to user well-being. Radar enables continuous passive RF monitoring without relying on methods using image processing or wearable devices, which leads to supporting user comfort and acceptance. Although the system was originally developed to fit lighting control requirements in residential settings, the approach can be used for other intelligent systems that require remote emotion recognition, supporting concepts such as residential health monitoring, ambient assisted living, and behavioural studies. Beyond residential use, radar-based occupancy and respiration sensing could support safety-critical applications in, for example, healthcare and industry. In

hospital patient rooms, passive respiration monitoring could enable early warnings for abnormal or absent breathing, while in manufacturing environments, the same capability could enhance personnel safety by detecting stationary workers in hazardous zones and triggering safety alerts independently of motion.

5.2.1. Radar and occupancy detection

For a conceptual emotion-aware lighting system, it is important that the sensing system can provide occupancy information, as in current lighting systems, to ensure sustainability. Detecting occupancy provides information for “multi-user scenarios”, one of the key decision factors for integrative lighting, described by Wang et al. [4].

Radar showed good coverage for small and medium-sized rooms, especially in normal breathing range, making it suitable for typical residential environments while allowing continuous, non-intrusive monitoring. In addition to reliable occupancy detection, as shown by both CAT-bots and human experiments, false absence detections with other occupancy classifications being classified as zero, were very rare, with only one case observed. This indicates that if the radar is placed with regard to the radar’s coverage, there is a low risk of the lighting system turning off while someone is still in the room.

Furthermore, the no-occupancy classification achieved a perfect recall score in both robot and human investigations, indicating that the radar can provide reliable information to fulfil sustainability goals. Most errors occurred in two-occupant scenarios, where the system sometimes detected only one person present. Interestingly, many of these cases occurred under atypical breathing conditions [123] (CAT-bot settings set to 6 and 16 bpm), which are unlikely in everyday residential settings. To add to this, in a study by Islam et al. [124] radar sensors were used to detect up to 10 participants. Although the referenced study did not explicitly measure or validate individual respiration rates, it demonstrated the potential for occupancy detection using respiration-induced radar signals. Similarly, the experiments in this thesis showed reliable performance and accuracy for up to two occupants. While alternative methods, such as door-based counting systems, may provide more efficient solutions

for estimating occupancy, radar sensing may offer an advantage by enabling simultaneous respiration monitoring. This additional capability can be beneficial for applications that extend beyond occupancy detection, such as context- and emotion-aware lighting, where capturing physiological signals is important.

5.2.2. Radar and respiration frequency

For physiological monitoring, the radar showed good overall performance in estimating respiration frequency. In areas with reliable presence detection ($Pd > 80\%$), the accuracy in breathing frequency remained very high. In human experiments, as expected, the system showed a good accuracy of around 90% for one person at close range, with the chest well exposed to the radar. and 80% for two participants in more complex setups where reflective objects such as laptops were present in front of them. These results indicate that the radar can reliably monitor respiration frequency, with most errors remaining within clinical tolerance.

Furthermore, the CAT-bot experiment showed the potential for detecting respiratory patterns that could be linked to psychophysiological states or used for early detection of emergencies. However, some limitations were observed when detecting low or very high breathing rates. When analysing the radar coverage, detection of the CAT-bot set at 6 bpm was less consistent, and the highest misclassifications occurred when the CAT-bots were set to 6 and 16 bpm. This was also reflected in the unpublished results, where higher errors were observed at low or very high respiration rates. These findings suggest that the system used in this investigation may be less reliable when very slow or very fast breathing is involved, likely due to the current filtering approach for respiration detection. This points to the need for improved algorithms that can better capture a wider range of breathing frequencies. Overall, these results suggest that radar may perform well for residential health monitoring, where breathing patterns are typically within the normal ranges (12-20 bpm), and environments are less complex. Respiration detection using radar in environments where RF is typically low or very high requires more (future) investigations.

5.2.3. *Radar and emotion recognition*

Although the repeated-measures ANOVA showed that the radar respiration frequency was significantly affected by emotional arousal, with most participants showing an increase in RRF at higher subjective arousal levels, the RF changes were approximately 1–2 bpm from low to high arousal, which are not clinically significant. Considering how the most common error in respiration frequency in paper 3 was 1 to 3 bpm, radar respiration frequency by itself is not recommended for detecting subtle physiological changes in less intense emotions. Other information collected via radar, such as changes in breathing pattern or heart rate, might provide more context for emotion recognition.

Furthermore, some intense emotions may involve outward bodily movement, as most people do not sit in a quasi-static position during emotional episodes. Emotional episodes may include movements such as pacing, rapidly tapping the foot, and more. Therefore, for emotion recognition via radar, a two-step emotion detection is suggested: a macro-level emotion recognition through body movement when vital signs are not reliably detected, followed by an emotion recognition in quasi-static states, using vital signs for when outward bodily movement does not exist.

From a lighting-system perspective, mm-wave radars can provide useful physiological information that could support adaptive lighting strategies while maintaining sustainability goals. However, determining optimal lighting conditions for occupants is extremely complex and cannot rely solely on emotional or physiological indicators such as respiration frequency. Human responses to lighting depend on many factors, including illuminance, spectral composition, exposure duration, time of day, and individual differences [1, 3, 34]. These parameters influence both visual and beyond-visual outcomes, including short-term responses, such as alertness and emotional state, and long-term physiological processes, including circadian rhythms and overall well-being. To add to this, in indoor environments, people are exposed to multiple light sources, including daylight as well as light from televisions, laptops, and mobile devices. As a result, even with more advanced sensing technologies, identifying the optimal lighting condition for occupants still requires consideration of multiple environmental and behavioural factors.

Therefore, while radar-based respiration monitoring shows potential as an input to adaptive lighting systems, it should be further explored and applied in combination with other contextual factors rather than relied upon as a sole control mechanism.

5.3. Study limitations

Even though the results show the potential of using mm-wave radar sensing for the control of emotion-aware lighting systems, several limitations of the sequential studies need to be considered. A first limitation is related to the use of CAT-bots in the first experimental study. While the CAT-bot enables highly controlled and repeatable breathing patterns, it does not fully represent natural human respiration. Human breathing is inherently irregular and influenced by many factors such as physiology, posture, and age, which the CAT-bot cannot replicate. Therefore, while it is useful for early-stage validation and controlled testing, the results obtained using the CAT-bot may not fully reflect real-world human behaviour. To address this, human experiments were performed afterwards; however, they did not match the exact scope and repetitions of the studies with the robots.

Secondly, the human experimental studies relied on convenience sampling, meaning that participants were selected based on availability (students and staff of Jönköping University), which limits the generalisability of the findings. In addition, participants' emotional intelligence scores were not assessed before the experiments, which may differ by age and gender [125]. Emotional intelligence refers to a person's ability to recognise and understand their own emotional state at any given moment [126], which influences the accuracy with which participants report their subjective SAM scores.

Thirdly, there were important technical limitations related to the selected radar system itself, which lacked angle detection, reducing the radar's flexibility in two occupancy scenarios, particularly when two subjects were present at the same distance from the radar. Future investigations would benefit from more advanced radar systems with improved spatial and angular resolution.

Lastly, emotions were mainly assessed using subjective self-report measures. Although the SAM survey is a rigorously researched and widely used method, it remains subjective and may not always reflect true physiological and emotional states. More objective methods, such as electroencephalography (EEG), could have provided more accurate insights, but were not used in this study to maintain participant comfort and ensure a more natural experimental setting.

6. Conclusions and future work

6.1. Conclusions

This thesis explored the potential of mm-wave radar sensing as an enabling technology for possible use in future emotion-aware adaptive lighting systems. Moving beyond traditional occupancy-based lighting control, the research explored sensing approaches that provide richer information about occupants' physiological states to support lighting that responds to human needs. The findings demonstrate that mm-wave radar can reliably estimate room occupancy under zero, one, and two-occupant conditions, while accurately capturing additional physiological information, such as respiration frequency and breathing patterns, for each occupant. Together, these results highlight the potential of radar-based sensing to support more adaptive, informative, and integrative lighting control strategies with low disturbance to occupants' privacy.

The literature review established and mapped current non-wearable emotion recognition systems, their limitations, advantages, and practicality for use in lighting control systems, creating a knowledge foundation for researchers interested in developing non-invasive, practical emotion-aware systems, especially in the lighting sector. The conducted experimental studies demonstrated that radar can reliably detect occupancy and estimate respiration frequency in indoor environments, particularly within normal breathing ranges. The system showed good coverage in small to medium-sized rooms and maintained high accuracy in both controlled robot and human experiments. In addition to presence detection, radar was able to capture temporal changes in respiration frequency, detect non-uniform breathing patterns, and identify periods of no breathing, to highlight its potential for both adaptive lighting and safety-oriented applications. However, the radar performance was affected by more complex conditions, such as macro body movement and extreme respiration rates, indicating that further improvements in signal processing and system design are needed. Regarding emotion recognition, the findings showed that radar can detect changes in respiration frequency associated with everyday emotional arousal, but the magnitude of these changes is relatively small and often falls within the system's

measurement error. This limits the use of respiratory frequency alone for detecting subtle emotional states in everyday scenarios. Therefore, a combined approach was suggested, where macro-level behavioural cues, such as body movement, are used alongside physiological signals to improve emotion detection.

Overall, this research highlighted the potential of radar as an enabling technology for future physiological-aware lighting systems, while also identifying key limitations and directions for further development toward real-world applications.

6.2. Future research

Additional data analysis will focus on analysing the relationship between physiological signals and emotional arousal and valence, to investigate which radar-derived signals can reliably reflect emotion-related physiological changes. Besides, radar emotion recognition in multi-occupant indoor environments will be investigated by using the results from experiment 2 to train machine learning tools. These tools will be used on the database from experiment 3 to compare radar-based emotion recognition with FER results from the webcams and the SAM subjective scores.

Going forward, further investigation is required into the proposed two-step approach to emotion recognition using radar to evaluate the potential and practicality of combining macro-level emotion recognition with physiological signals, like respiration, to improve the reliability of overall emotion recognition and overcome one of the major limitations of using this radar for vital sign detection: participants' macro movements.

For practical emotion-responsive lighting in indoor environments, further research is required on how lighting interventions affect emotion-linked physiological responses. It may explore, for example, if respiration frequency, caused by mental stress, returns to normal more quickly if subjects are exposed to specific lighting solutions. In continuation of this topic, another important aspect of physiological data collection across varying room occupancy is to determine how lighting should respond to occupants when more than one person is present. People in the same room may have different

or contradictory physiological or psychological needs. Therefore, investigations into how lighting systems should balance, prioritise, or simply respond to these differences are needed.

Lastly, this study focused mainly on the short-term (acute) effects of lighting. Future research should examine the long-term impact of closed-loop, emotion-responsive lighting systems on circadian (~24 hr) rhythms, well-being, and overall health. Understanding these long-term effects is essential for the practical implementation of such a system in, for example, residential (care) environments.

References

1. Mahoney, H.L. and T.M. Schmidt, *The cognitive impact of light: illuminating ipRGC circuit mechanisms*. Nature Reviews Neuroscience, 2024. **25**(3): p. 159-175.
2. Houser, K.W. and T. Esposito, *Human-centric lighting: Foundational considerations and a five-step design process*. Frontiers in neurology, 2021. **12**: p. 630553.
3. Xiao, H., H. Cai, and X. Li, *Non-visual effects of indoor light environment on humans: A review*☆. Physiology & behavior, 2021. **228**: p. 113195.
4. Wang, Y., X. Zhang, and H. Chen, *From needs to control: a review of indicators and sensing technologies for occupant-centric smart lighting systems*. Energy and Buildings, 2025. **339**: p. 115740.
5. Chew, I., et al., *Smart lighting: The way forward? Reviewing the past to shape the future*. Energy and Buildings, 2017. **149**: p. 180-191.
6. González, L.V., et al., *Towards Sustainable Indoor Lighting Design: Ensuring Energy Efficiency, Health and Human Wellbeing—A Review*. Sustainable Development, 2026. **34**: p. 1067-1095.
7. CIE, *CIE Position Statement on Integrative Lighting Recommending Proper Light at the Proper Time, 3rd Edition*. 2024, CIE Central Bureau: Vienna, Austria.
8. Moadab, N.H., et al., *Smart versus conventional lighting in apartments-Electric lighting energy consumption simulation for three different households*. Energy and Buildings, 2021. **244**: p. 111009.
9. Sithravel, R., T. Olsson, and M. Aries, *Optimizing presence sensing lighting for energy efficiency and user behavioral needs in small Swedish homes*. Leukos, 2024. **20**(1): p. 107-125.
10. Sithravel, R., et al., *Optimising presence sensor placement in small houses for accurate lighting control with vital sign detection*. Lighting Research & Technology, 2025: p. 14771535251382820.
11. Baharudin, N., et al., *Smart lighting system control strategies for commercial buildings: A review*. International Journal of Advanced Technology and Engineering Exploration, 2021. **8**(74): p. 45.
12. Alvich, A., et al. *Towards the Human-Centered Lighting Evaluation and Control: An Overview*. in *2025 IEEE International Conference on Environment and Electrical Engineering and 2025 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe)*. 2025. IEEE.

13. Vandewalle, G., et al., *Spectral quality of light modulates emotional brain responses in humans*. Proceedings of the National Academy of Sciences, 2010. **107**(45): p. 19549-19554.
14. Li, Y., et al., *Diurnal intervention effects of electric lighting on alertness, cognition, and mood in healthy individuals: A systematic review and meta-analysis*. Leukos, 2024. **20**(3): p. 291-309.
15. Klepeis, N.E., et al., *The National Human Activity Pattern Survey (NHAPS): a resource for assessing exposure to environmental pollutants*. Journal of exposure science & environmental epidemiology, 2001. **11**(3): p. 231-252.
16. Schweizer, C., et al., *Indoor time–microenvironment–activity patterns in seven regions of Europe*. Journal of exposure science & environmental epidemiology, 2007. **17**(2): p. 170-181.
17. Brasche, S. and W. Bischof, *Daily time spent indoors in German homes–baseline data for the assessment of indoor exposure of German occupants*. International journal of hygiene and environmental health, 2005. **208**(4): p. 247-253.
18. Choi, K., et al., *Awakening effects of blue-enriched morning light exposure on university students' physiological and subjective responses*. Scientific reports, 2019. **9**(1): p. 345.
19. Angie, A.D., et al., *The influence of discrete emotions on judgement and decision-making: A meta-analytic review*. Cognition & emotion, 2011. **25**(8): p. 1393-1422.
20. Storbeck, J. and G.L. Clore, *Affective arousal as information: How affective arousal influences judgments, learning, and memory*. Social and personality psychology compass, 2008. **2**(5): p. 1824-1843.
21. Laird, J.D., et al., *Remembering what you feel: Effects of emotion on memory*. Journal of personality and social psychology, 1982. **42**(4): p. 646.
22. Blair, K.S., et al., *Modulation of emotion by cognition and cognition by emotion*. Neuroimage, 2007. **35**(1): p. 430-440.
23. Altomonte, S., et al., *What is NExT? A new conceptual model for comfort, satisfaction, health, and well-being in buildings*. Building and Environment, 2024. **252**: p. 111234.
24. Alexander, R., et al., *The neuroscience of positive emotions and affect: Implications for cultivating happiness and wellbeing*. Neuroscience & Biobehavioral Reviews, 2021. **121**: p. 220-249.
25. Liu, L., et al., *Smart homes and home health monitoring technologies for older adults: A systematic review*. International journal of medical informatics, 2016. **91**: p. 44-59.
26. DiLouie, C., *Lighting controls handbook*. 2020: River Publishers.

27. Khare, S.K., et al., *Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations*. Information Fusion, 2023: p. 102019.
28. Saxena, A., A. Khanna, and D. Gupta, *Emotion recognition and detection methods: A comprehensive survey*. Journal of Artificial Intelligence and Systems, 2020. **2**(1): p. 53-79.
29. Egger, M., M. Ley, and S. Hanke, *Emotion recognition from physiological signal analysis: A review*. Electronic Notes in Theoretical Computer Science, 2019. **343**: p. 35-55.
30. Gomez, P., A. von Gunten, and B. Danuser, *Autonomic nervous system reactivity within the valence–arousal affective space: Modulation by sex and age*. International Journal of Psychophysiology, 2016. **109**: p. 51-62.
31. Kreibig, S.D., *Autonomic nervous system activity in emotion: A review*. Biological psychology, 2010. **84**(3): p. 394-421.
32. Nouman, M., et al., *Recent advances in contactless sensing technologies for mental health monitoring*. IEEE Internet of Things Journal, 2021. **9**(1): p. 274-297.
33. Debes, C., et al., *Monitoring activities of daily living in smart homes: Understanding human behavior*. IEEE Signal Processing Magazine, 2016. **33**(2): p. 81-94.
34. Cai, H., et al., *Recognition of human mood, alertness and comfort under the influence of indoor lighting using physiological features*. Biomedical Signal Processing and Control, 2024. **89**: p. 105661.
35. Wilms, L. and D. Oberfeld, *Color and emotion: effects of hue, saturation, and brightness*. Psychological research, 2018. **82**(5): p. 896-914.
36. Knez, I., *Effects of colour of light on nonvisual psychological processes*. Journal of environmental psychology, 2001. **21**(2): p. 201-208.
37. Knez, I. and C. Kers, *Effects of indoor lighting, gender, and age on mood and cognitive performance*. Environment and Behavior, 2000. **32**(6): p. 817-831.
38. Bais, B., W.J. Hoogendijk, and M.P. Lambregtse-van den Berg, *Light therapy for mood disorders*. Handbook of Clinical Neurology, 2021. **182**: p. 49-61.
39. Lam, R.W., et al., *Light therapy for patients with bipolar depression: systematic review and meta-analysis of randomized controlled trials*. The Canadian Journal of Psychiatry, 2020. **65**(5): p. 290-300.
40. Kong, H., et al., *A survey of mmwave radar-based sensing in autonomous vehicles, smart homes and industry*. IEEE Communications Surveys & Tutorials, 2024. **27**(1): p. 463-508.

41. Marty, S., et al. *Investigation of mmWave radar technology for non-contact vital sign monitoring*. in *2023 IEEE International Symposium on Medical Measurements and Applications (MeMeA)*. 2023. IEEE.
42. Chen, Y., J. Yuan, and J. Tang, *A high precision vital signs detection method based on millimeter wave radar*. *Scientific Reports*, 2024. **14**(1): p. 25535.
43. Saleh, S., et al. *Overview of mmWave Radar and Antenna Advances in Contactless Vital Signs Monitoring*. in *2025 IEEE International RF and Microwave Conference (RFM)*. 2025. IEEE.
44. Qin, J., et al., *Motion-Tolerant Measurement of Respiration and Heartbeat via mmWave Radar Across Diverse Healthcare Scenarios*. *IEEE Transactions on Instrumentation and Measurement*, 2026.
45. Singh, A., et al., *Multi-resident non-contact vital sign monitoring using radar: A review*. *IEEE Sensors Journal*, 2020. **21**(4): p. 4061-4084.
46. Lee, H., et al., *A novel vital-sign sensing algorithm for multiple subjects based on 24-GHz FMCW Doppler radar*. *Remote Sensing*, 2019. **11**(10): p. 1237.
47. Islam, S.M., et al. *Multiple subject respiratory pattern recognition and estimation of direction of arrival using phase-comparison monopulse radar*. in *2019 IEEE radio and wireless symposium (RWS)*. 2019. IEEE.
48. Lu, C., et al. *Multi-target continuous-wave vital sign radar using 24 GHz metamaterial leaky wave antennas*. in *2019 IEEE MTT-S International Microwave Biomedical Conference (IMBioC)*. 2019. IEEE.
49. Ahmad, A., et al. *Vital signs monitoring of multiple people using a FMCW millimeter-wave sensor*. in *2018 IEEE Radar Conference (RadarConf18)*. 2018. IEEE.
50. Oatley, K. and J.M. Jenkins, *Human emotions: Function and dysfunction*. *Annual review of psychology*, 1992. **43**(1): p. 55-85.
51. Scherer, K.R., *Psychological models of emotion*. *The neuropsychology of emotion*, 2000. **137**(3): p. 137-162.
52. Thanapattheerakul, T., et al. *Emotion in a century: A review of emotion recognition*. in *proceedings of the 10th international conference on advances in information technology*. 2018.
53. Davou, B., *Interaction of emotion and cognition in the processing of textual material*. *Meta*, 2007. **52**(1): p. 37-47.
54. Neumann, R., B. Seibt, and F. Strack, *The influence of mood on the intensity of emotional responses: Disentangling feeling and knowing*. *Cognition & Emotion*, 2001. **15**(6): p. 725-747.

55. Ekman, P., *An argument for basic emotions*. Cognition & emotion, 1992. **6**(3-4): p. 169-200.
56. Plutchik, R., *Emotions and life: Perspectives from psychology, biology, and evolution*. 2003: American Psychological Association.
57. Leong, S.C., et al., *Facial expression and body gesture emotion recognition: A systematic review on the use of visual data in affective computing*. Computer Science Review, 2023. **48**: p. 100545.
58. Wang, Z., S.-B. Ho, and E. Cambria, *A review of emotion sensing: categorization models and algorithms*. Multimedia Tools and Applications, 2020. **79**: p. 35553-35582.
59. Russell, J.A., *A circumplex model of affect*. Journal of personality and social psychology, 1980. **39**(6): p. 1161.
60. Lang, P. and M.M. Bradley, *The International Affective Picture System (IAPS) in the study of emotion and attention*. Handbook of emotion elicitation and assessment, 2007. **29**: p. 70-73.
61. Koelstra, S., et al., *Deap: A database for emotion analysis; using physiological signals*. IEEE transactions on affective computing, 2011. **3**(1): p. 18-31.
62. Soleymani, M., et al., *A multimodal database for affect recognition and implicit tagging*. IEEE transactions on affective computing, 2011. **3**(1): p. 42-55.
63. Hagemann, D., S.R. Waldstein, and J.F. Thayer, *Central and autonomic nervous system integration in emotion*. Brain and cognition, 2003. **52**(1): p. 79-87.
64. Guyton, A.C., *Text book of medical physiology*. 2006: China.
65. Buijs, R.M., *The autonomic nervous system: a balancing act*. Handbook of clinical neurology, 2013. **117**: p. 1-11.
66. Gomez, P., W.A. Stahel, and B. Danuser, *Respiratory responses during affective picture viewing*. Biological psychology, 2004. **67**(3): p. 359-373.
67. Zhang, Q., et al., *Respiration-based emotion recognition with deep learning*. Computers in Industry, 2017. **92**: p. 84-90.
68. Masaoka, Y. and I. Homma, *The effect of anticipatory anxiety on breathing and metabolism in humans*. Respiration physiology, 2001. **128**(2): p. 171-177.
69. Masaoka, Y. and I. Homma, *Anxiety and respiratory patterns: their relationship during mental stress and physical load*. International journal of psychophysiology, 1997. **27**(2): p. 153-159.
70. Kreibig, S.D., et al., *Cardiovascular, electrodermal, and respiratory response patterns to fear- and sadness-inducing films*. Psychophysiology, 2007. **44**(5): p. 787-806.

71. Masaoka, Y. and I. Homma, *Expiratory time determined by individual anxiety levels in humans*. Journal of applied physiology, 1999. **86**(4): p. 1329-1336.
72. Vlemincx, E., I. Van Diest, and O. Van den Bergh, *Emotion, sighing, and respiratory variability*. Psychophysiology, 2015. **52**(5): p. 657-666.
73. Philippot, P., G. Chapelle, and S. Blairy, *Respiratory feedback in the generation of emotion*. Cognition & Emotion, 2002. **16**(5): p. 605-627.
74. Jerath, R. and C. Beveridge, *Respiratory rhythm, autonomic modulation, and the spectrum of emotions: the future of emotion recognition and modulation*. Frontiers in Psychology, 2020. **11**: p. 555957.
75. Molday, R.S. and O.L. Moritz, *Photoreceptors at a glance*. Journal of cell science, 2015. **128**(22): p. 4039-4045.
76. Vetter, C., et al., *A review of human physiological responses to light: implications for the development of integrative lighting solutions*. Leukos, 2022. **18**(3): p. 387-414.
77. Bailes, H.J. and R.J. Lucas, *Human melanopsin forms a pigment maximally sensitive to blue light ($\lambda_{max} \approx 479$ nm) supporting activation of Gq/11 and Gi/o signalling cascades*. Proceedings of the Royal Society B: Biological Sciences, 2013. **280**(1759).
78. Mohammad-Moradi, A., S.A. Yazdanfar, and M.-A. Khanmohammadi, *The impact of lighting on emotions in architectural interior spaces: A systematic review*. International Journal of Architectural Engineering & Urban Planning, 2025. **35**(1): p. 1-28.
79. Li, X., R. Wang, and M. Whang, *Designing light for emotion: A neurophysiological approach to modeling affective responses to the interplay of color and illuminance*. Biomimetics, 2025. **10**(10): p. 696.
80. Li, Y., et al., *Bridging photometric parameters and emotional well-being: validating the atmosphere perception scale to optimize illuminance and CCT interactions in occupational lighting*. Building and Environment, 2025: p. 113533.
81. Lee, H. and E. Lee, *Effects of coloured lighting on pleasure and arousal in relation to cultural differences*. Lighting Research & Technology, 2022. **54**(2): p. 145-162.
82. Zhou, L., et al., *The effect of light on negative emotion and cognitive regulation in individuals with depressive tendencies*. Leukos, 2024. **20**(4): p. 367-379.

83. Katirai, A., *Ethical considerations in emotion recognition technologies: a review of the literature*. *AI and Ethics*, 2024. **4**(4): p. 927-948.
84. Wang, S., et al., *Multi-modal fusion sensing: A comprehensive review of millimeter-wave radar and its integration with other modalities*. *IEEE Communications Surveys & Tutorials*, 2024. **27**(1): p. 322-352.
85. Creswell, J.W., *Qualitative, quantitative and mixed methods approaches*. 2014: Sage.
86. Booth, A., et al., *Systematic approaches to a successful literature review*. 2021.
87. Page, M.J., et al., *The PRISMA 2020 statement: an updated guideline for reporting systematic reviews*. *bmj*, 2021. **372**.
88. Czichos, H., *Measurement, Testing and Sensor Technology*. 2018: Springer.
89. International Organization for Standardization, *ISO 5725-1*, in *Accuracy of measurement methods and results - part 1: General principles and definitions*. 1994, ISO: Geneva.
90. Parkes, R., *Rate of respiration: the forgotten vital sign*. *Emergency Nurse*, 2011. **19**(2): p. 12-7; quiz 18.
91. Russo, M.A., D.M. Santarelli, and D. O'Rourke, *The physiological effects of slow breathing in the healthy human*. *Breathe*, 2017. **13**(4): p. 298-309.
92. Linden, A., *Challenges to validity in single-group interrupted time series analysis*. *Journal of evaluation in clinical practice*, 2017. **23**(2): p. 413-418.
93. Evans, C., et al., *What constitutes high quality higher education pedagogical research?* *Assessment & Evaluation in Higher Education*, 2021. **46**(4): p. 525-546.
94. Kimberlin, C.L. and A.G. Winterstein, *Validity and reliability of measurement instruments used in research*. *American journal of health-system pharmacy*, 2008. **65**(23): p. 2276-2284.
95. Säfsten, K. and M. Gustavsson, *Research methodology: for engineers and other problem-solvers*. 2020: Studentlitteratur AB.
96. Bradley, M.M. and P.J. Lang, *Measuring emotion: the self-assessment manikin and the semantic differential*. *Journal of behavior therapy and experimental psychiatry*, 1994. **25**(1): p. 49-59.
97. Corp, I., *IBM SPSS Statistics for Windows, Version 28.0.1.0* 2023: Armonk, NY.
98. *The jamovi project (2024)*. *jamovi*. (Version 2.6) [Computer Software].
99. Schmuckler, M.A., *What is ecological validity? A dimensional analysis*. *Infancy*, 2001. **2**(4): p. 419-436.

100. Association, W.M., *World Medical Association Declaration of Helsinki: ethical principles for medical research involving human participants*. *Jama*, 2025. **333**(1): p. 71-74.
101. Langner, O., et al., *Presentation and validation of the Radboud Faces Database*. *Cognition and emotion*, 2010. **24**(8): p. 1377-1388.
102. Lucey, P., et al. *The extended cohn-kanade dataset (ck+): A complete dataset for action unit and emotion-specified expression*. in *2010 IEEE computer society conference on computer vision and pattern recognition-workshops*. 2010. IEEE.
103. Goodfellow, I.J., et al. *Challenges in Representation Learning: A Report on Three Machine Learning Contests*. in *Neural Information Processing*. 2013. Berlin, Heidelberg: Springer Berlin Heidelberg.
104. Dhall, A. *Emotiv 2019: Automatic emotion, engagement and cohesion prediction tasks*. in *2019 International Conference on Multimodal Interaction*. 2019.
105. Dhall, A., et al. *Static facial expression analysis in tough conditions: Data, evaluation protocol and benchmark*. in *2011 IEEE international conference on computer vision workshops (ICCV workshops)*. 2011. IEEE.
106. Xiao, H., et al., *Remote photoplethysmography for heart rate measurement: A review*. *Biomedical Signal Processing and Control*, 2024. **88**: p. 105608.
107. Kim, H.-C., J. Cha, and W.D. Lee. *Eye detection for gaze tracker with near infrared illuminator*. in *2014 IEEE 17th International Conference on Computational Science and Engineering*. 2014. IEEE.
108. Narcizo, F.B., J.E.R. de Queiroz, and H.M. Gomes. *Remote eye tracking systems: technologies and applications*. in *2013 26th Conference on Graphics, Patterns and Images Tutorials*. 2013. IEEE.
109. Sayeri, R., et al., *Evolutionary AdaBoost ensemble: A machine learning framework for depression detection*. *MACHINE LEARNING WITH APPLICATIONS*, 2025. **22**.
110. López-de-Ipiña, K., et al., *Feature selection for automatic analysis of emotional response based on nonlinear speech modeling suitable for diagnosis of Alzheimer's disease*. *Neurocomputing*, 2015. **150**: p. 392-401.
111. De La Fuente Garcia, S., F. Haider, and S. Luz. *COVID-19: Affect recognition through voice analysis during the winter lockdown in Scotland*. in *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*. 2021.
112. Lumb, A.B. and C.R. Thomas, *Nunn's Applied Respiratory Physiology eBook*. 2020: Elsevier Health Sciences.

113. Ashhad, S., et al., *Breathing rhythm and pattern and their influence on emotion*. Annual review of neuroscience, 2022. **45**: p. 223-247.
114. Jerath, R. and C. Beveridge, *Respiratory rhythm, autonomic modulation, and the spectrum of emotions: the future of emotion recognition and modulation*. Frontiers in psychology, 2020. **11**: p. 1980.
115. Cho, Y., N. Bianchi-Berthouze, and S.J. Julier. *DeepBreath: Deep learning of breathing patterns for automatic stress recognition using low-cost thermal imaging in unconstrained settings*. in *2017 Seventh international conference on affective computing and intelligent interaction (acii)*. 2017. IEEE.
116. Yang, C., et al., *Physiologically Explainable Ensemble Framework for Stress Classification via Respiratory Signals*. Technologies, 2025. **13**(9): p. 411.
117. Wu, Y., et al., *Non-intrusive human vital sign detection using mmWave sensing technologies: A review*. ACM Transactions on Sensor Networks, 2023. **20**(1): p. 1-36.
118. Lee, P.J., *Clinical evaluation of a novel respiratory rate monitor*. Journal of Clinical Monitoring and Computing, 2016. **30**(2): p. 175-183.
119. Sithravel, R., et al., *Optimising presence sensor placement in small houses for accurate lighting control with vital sign detection*. Lighting Research & Technology, 2025.
120. Xue, W., et al., *Accurate multi-target vital signs detection method for FMCW radar*. Measurement, 2023. **223**: p. 113715.
121. Zhao, Y., et al. *Multi-target vital signs remote monitoring using mmWave FMCW radar*. in *2021 IEEE Microwave Theory and Techniques in Wireless Communications (MTTW)*. 2021. IEEE.
122. Ibanez, J. and J. Raurich, *Normal values of functional residual capacity in the sitting and supine positions*. Intensive care medicine, 1982. **8**(4): p. 173-177.
123. Rachel, P. and D. Derrel, Graham, *Abnormal Respirations*. 2025.
124. Islam, S.M., et al., *Building occupancy estimation using microwave Doppler radar and wavelet transform*. Building and Environment, 2023. **236**: p. 110233.
125. Cabello, R., et al., *Age and gender differences in ability emotional intelligence in adults: A cross-sectional study*. Developmental psychology, 2016. **52**(9): p. 1486.
126. Mayer, J.D., D.R. Caruso, and P. Salovey, *The ability model of emotional intelligence: Principles and updates*. Emotion review, 2016. **8**(4): p. 290-300.

Appendix 1. Study design for human experiments

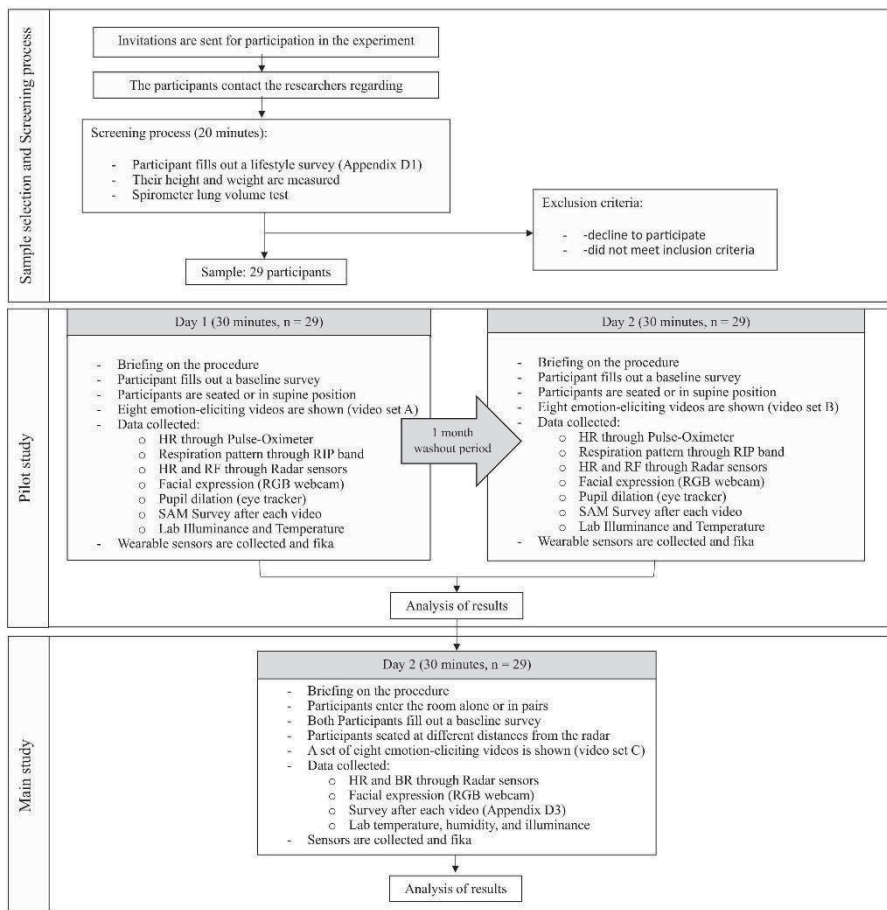


Figure 13 Study process and connections for Experiment 2 and 3

Radar Based Sensing for Psychological Monitoring

Possibilities of Emotion Recognition through Respiratory Frequency for Adaptive Lighting

Light influences human physiology beyond vision, affecting circadian rhythms, alertness, and emotional states. Emotions, in turn, shape human behaviour, cognition, and overall well-being. Despite this information, most existing intelligent lighting systems rely on basic inputs such as occupancy or daylight, with limited to no integration of physiological or emotional signals in the decision-making process. This has created a gap between advances in beyond-visual lighting research and practical lighting applications. To address this, this thesis explores the feasibility of integrating non-wearable, non-invasive physiological sensing into adaptive lighting systems, with a focus on radar-based monitoring. A sequential research approach was used, starting with a literature review to identify suitable sensing approaches, after which mm-wave radar sensors were selected for further investigation. This was followed by three experimental studies to evaluate the radar's performance: controlled tests with Controlled Airflow Thorax robots (CAT-bots) that accurately simulated chest movement for different respiration frequencies, a pilot study with single human subjects in two different positions (sitting and supine), and a final study under varied occupancy conditions. Each stage increased in complexity to evaluate performance in realistic scenarios.

Results show that radar performs well at detecting occupancy and monitoring respiration frequency for multiple (two) occupants in varied occupancy situations. While some limitations were observed, overall accuracy remained high. The findings suggest potential for capturing physiological changes linked to emotional states, but further validation is needed. This research provides a foundation for integrating physiological sensing into adaptive lighting. It validates radar as a practical solution, points out its weaknesses, and proposes a two-level emotion recognition strategy for future studies. The work contributes toward emotion-aware environments, with applications in home monitoring, ambient assisted living, and human-centred design.



ELHAM RASTEGARI is a PhD student in the Department of Construction Engineering and Lighting Science at the School of Engineering, Jönköping University. She holds a Bachelor of Engineering in Civil Engineering from Sharif University of Technology, and a Master of Science in Sustainable Building Information Management from Jönköping University. Her research focuses on radar-based physiological sensing for adaptive lighting applications, with a specific focus on investigating human-centred solutions that enhance well-being and enable more intelligent and responsive environments.

ISBN 978-91-89785-41-0 (Printed version)

ISBN 978-91-89785-42-7 (Online version)