Louvain School of Management

Opportunity Study of Radar-based Interaction in Multiple Orgnizations

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Abstract

Radar-based gesture recognition has become a pivotal element in the evolution of Human-Computer Interaction. This study aims to demonstrate the feasibility and transformative potential of radar technology in advancing gesture recognition systems, particularly within organizational contexts. A comprehensive market study and survey were conducted to evaluate the device's relevance across various applications documented in existing literature. Targeting a diverse audience, the survey gathered a wide range of perspectives on the potential uses of radar-based gesture recognition. To evaluate the feasibility, an extensive dataset was used, capturing gestures performed by different individuals through various materials. Testing these recorded gestures can help to confirm the system's capability to accurately recognize gestures across a diverse population. The insights obtained from this research will be invaluable for stakeholders interested in this technology. Additionally, a comparative analysis of an extensive gesture dataset is provided. This research seeks to deepen the understanding of market trends, growth prospects, and technological advancements in radar-based gesture recognition, ultimately facilitating its integration into everyday Human-Machine scenarios.

Acknowledgements

I extend my sincere gratitude to Prof. Jean Vanderdonckt for his invaluable guidance and unwavering support throughout the journey of this thesis. His trust in my abilities has been a driving force behind my continued progress, and I am truly grateful for the opportunity to work under his mentorship.

I am indebted to the numerous individuals involved in this project whose dedication and collaboration have been indispensable. I extend my heartfelt appreciation to those individuals who graciously accepted interviews and consented to be recorded for their gestures and interactions. Their willingness to share insights, experiences, and perspectives has been instrumental in shaping the qualitative aspects of this research. Their participation has not only provided valuable data but has also exemplified a spirit of cooperation and openness that is essential for advancing knowledge in our field.

Contents

Chapter 1

Introduction

1.1 Introduction

Gesture recognition plays a crucial role in improving human-machine interaction. In the healthcare sector, for example, it can enable healthcare professionals to perform remote control gestures during surgical operations, thereby reducing the risk of nosocomial infections. Another significant example can be found in the nuclear industry, where operators can use gesture recognition to manipulate objects remotely in potentially dangerous environments, reducing the need for direct physical intervention and thus contributing to worker safety. Not having to clean all objects that have not been in contact with radioactive waves also saves time and money. These examples illustrate the importance of gesture recognition in simplifying and improving various aspects of multiple industries. It shows the potential to revolutionize various aspects of daily life and professional practice, making interactions more seamless, efficient, and safe across a wide range of applications.

Radar-based gesture recognition is an emerging technology that utilizes radar waves to detect and interpret human body movements or breath. Unlike other motion detection methods such as cameras or touch, radar offers the advantage of being able to operate in a variety of environmental conditions, including total darkness and through obstacles. Moreover, the functionality of devices with screens remains unaffected even when the screen is wet, such as in rainy conditions. This technology has significant potential in many fields, from healthcare to the nuclear and automotive industries. The advantages discussed here illustrate how it can enhance effectiveness and reliability compared to other gesture recognition methods.

1.2 Objectives of the Research and Outline of the Thesis

The primary objective of this study is to conduct a comprehensive analysis of the radar-based gesture recognition market, with a focus on understanding customer needs, identifying trends, and highlighting opportunities for companies. Additionally, we aim to explore recent advancements in this domain and propose avenues for future innovation.

We aim to understand **"how can recent advancements in radar-based gesture recognition technology be leveraged to meet customer needs and identify emerging market trends and opportunities ?"**

This dissertation will be organized into several chapters. Following this introduction, Chapter 2 will delve into a literature review, discussing the theoretical bases of radar technology in gesture recognition, along with an examination of its applications and market advantages. Subsequently,Chapter 3 will outline the methodology employed to analyze the market, providing insights into the research approach adopted. Additionally, this chapter will explain the technology used for collecting data to test the efficacy of radar-based gesture technology, detailing the tools and methods used for testing and validation.

The findings of the study will be presented in Chapter 4, which will delve into the results obtained from our market analysis, with a particular focus on the consumer side. Chapter 5, on the other hand, will offer conclusions drawn from the study, emphasizing implications for companies operating in this space seeking to further explore this field.

Furthermore, chapter 6 will be dedicated to the testing using a dataset characterized by its large scale and diverse nature. This chapter aims to demonstrate the practical application of the research findings, showcasing how radar-based gesture recognition technology can be effectively utilized in real-world scenarios. By employing recognizer and validation methods, we will systematically evaluate the performance of radar-based gesture recognition across varying conditions and environments. The materials selected for this study are chosen to represent a broad spectrum of real-world applications, ensuring that our findings are robust and generalizable.

To complete this thesis, Chapter 7 will summarize the work and address the study's limitations, acknowledging any constraints and challenges encountered during the research process. This chapter will also provide a discussion on future work, highlighting potential areas for further investigation.

Chapter 2

Theoretical Background

2.1 Advancements in Radar-Based Gesture Recognition

Hand gesture recognition (HGR) is a notable enhancement to the UWB-Gestures dataset. Ahmed et al. (2021) indicate that the dataset will still be used for training the algorithms for HGR without UWB (Ultra-Wide-Band) radar. Ahmed et al. (2021) delivered a database with 12 dynamic gestures having 9,600 events. Data sets like this can serve as a database for other researchers who will perform the same experiment and they could compare their data to the results of other HGR algorithms. Radar sensors are widely favored in the HGR industry due to their endurance and versatility, making datasets like the UWB-Gestures valuable resources for researchers to compare their algorithms and results with those of others in the field.

The UWB gestures are a basis to develop image recognition algorithms with the help of machine learning which are going to help to effectively solve the problem of gesture recognition (Ahmed et al., 2021). The potential of AI and ML led to the integration of radar-based hand detection which is the key to the current AI and ML innovations in human-computer interaction (HCI). Radar-based hand detection is one of the principal breakthroughs in the field of HCI (Ahmed et al., 2021).

Dong & Qu (2021) note that radar gesture detection technology involves four steps : data recording on gesture variation, signal processing, feature extraction, and algorithm development for a machine learning classifier. Scientists have been utilizing the various frequency bands in which the radar sensors are furnished. Dong & Qu (2021) go into detail about the mm-wave and K-band covering the sensitive and compact which are broadly known for their wide bandwidth. Preprocessing techniques are the basis for methods that take advantage of Fourier transform analysis to get the maximum information from gesture features while keeping the noise at bay. Classification techniques like Dynamic Time Warping (DTW) have been used for gesture recognition to obtain high accuracy but they are less robust because of the high space and time complexity (Dong & Qu, 2021).

Template-based recognizers are lauded for high accuracy with small sample size and easy implementation but their main drawback is to be unable to recognize complex gestures and generalize to user-independent scenarios (Chioccarello et al., 2023). Conversely, deep learning needs more samples, but it is better at dealing with problems that are related to complex gestures and that are user-independent. Attygalle et al. (2021) highlight that radar sensing has an edge over vision systems as the former can still detect gestures even when the hand is covered by an object widening the scope of interactions. However, radar-based gesture detection has some drawbacks, like signal degradation for objects and calibration sensitivity. According to (Chioccarello et al., 2023), radar sensing technology provides several advantages including operational reliability regardless of the lighting conditions, privacy-friendly features, and motion detection through various layers such as fabrics and surfaces.

2.2 Radar-Based Gesture Recognition for Human-Computer Interaction

As a radar-based gesture recognition system successfully proliferates, it is increasingly being perceived as a revolutionary technology that is contributing to the improvement of human-computer interaction. Radar, by using the wave sensing principle which is electromagnetic, can detect minute hand movements with high precision and versatility which is not present in methods like Wi-Fi-based recognition (Zhou et al., 2023). Radar can capture the signals that change according to gestures allowing for dynamic recognition with accuracy rates exceeding 95% in a variety of applications, including smart homes, medical care, and sports training among others (Zhou et al., 2023). With the pandemic of coronavirus, which requires non-contact solutions for public health, this innovation has become even more important (Islam et al., 2021). The Doppler radar technology initially created for physiological sensing now aids in remote respiration monitoring, heart rate tracking, and even occupancy detection which helps in lockdown enforcement for effective implementation (Qi et al, 2023).

The significant advantage of the FMCW millimeter-wave radar (based on the RADAR technology) is that it is convenient and contactless (Galván-Ruiz et al., 2020). Unlike the wearable sensor systems that often pose users with inconvenience and cost considerations, the radar system does not have such barriers, thus being more accessible and friendly to users (Tang et al., 2023). Besides, radar technology has the advantage of delivering intuitive gesture-capturing features, which allow machines and humans to communicate fluidly and interact effectively (Qi et al., 2023). The adaptability and accuracy of this technology have also been improved thanks to the improvement in deep learning models like Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Auto Encoders (AEs). The models offer feature extraction that is automatic and therefore the system better responds to data changes making it suitable for applications like patient monitoring, robotics, and vehicle interfaces (Li et al., 2019).

2.3 Radar-Based Gesture Recognition through materials

Radar technology for mid-air gesture identification has gained popularity due to its 3D spatial data characteristics and capacity to perform in a variety of environments. Leiva et al. (2020) present in their research the use of materials-based radar gesture recognition which is a breakthrough in the field of wearables that will allow the integration of radar sensors for gesture interaction. Thus, the method used there is an hybrid deep learning model that is trained with and without occlusions created by the materials, thereby assessing the effect of fibers like leather, wool, and cotton on gesture identification. (Leiva et al., 2020). The lack of material and the large samples caused the precision score to be 95% on average even if the fabric coatings covered them up at 95% on average. The model shows good accuracy with 99% AUC (Leiva et al., 2020). Gesture recognition via Radar technology has been proven as one of the most helpful ways to improve Human-Machine Interaction (HMI) in various industries (Weis, & Santra, 2018). In the study of Weis and Santra (2018) Siamese network technique based on the distance-based similarity matrix was used for material classification. The efficacy of such a system is evident in a compact 83-GHz radar sensor that results in a strong overall accuracy of 99.23% (Weis & Santra, 2018).

The ability to perceive air gestures without the need for any specific materials opens up opportunities to develop a diverse range of real-world applications, for example, in consumer electronics, industrial and automotive sectors, and at home (Khan et al., 2013). The autonomous wireless sensor network is a radar that collects Doppler data and is composed of easily available components that can be used for a variety of sensing and classification tasks (Khan et al., 2013). Radar-based sensing for tangible interaction is proposed to be a space for extending six novel modes of sensing (Yeo et al., 2018). As pointed out by Khan et al. (2013), the best-performing machine learning techniques, such as Random Forest, Logistic Model Trees, and Multilayer Perceptron, achieve an exceptional material classification accuracy of up to 80% (Khan et al., 2013).

The effectiveness and precision of these advancements need validation. Utilizing data from lab studies and full-wave radar models, along with experimental results, holds promise in achieving this goal (Yeo et al., 2018). This approach integrates theoretical insights with practical project outcomes in a controlled laboratory setting. There's a growing interest among scientists in deploying close-range radar sensors like UWB-IR and CW units due to their versatile applications and precise motion sensing capabilities (Ahmed et al., 2021). Radar serves not only as an efficient sensing system but also integrates seamlessly with autonomous systems, unlocking numerous possibilities. Indeed, radar can measure various characteristics, including direction and velocity that can be useful in many application such as traffic monitoring systems, surveillance and security systems, and industrial automation.

The gesture sensor detects hand movements and then advances to radar detection of gestures. According to Ahmed et al.'s 2021 research, this type of sensor could fall into two categories: pulse radar and continuous radar. The ultra-short-pulse infrared radar (UWB-IR pulse radar) is a radar that works with very short pulses. Hence, they can discriminate gestures properly as they support even the diverse surroundings by filtering out any interference caused by the ambient noise (Ahmed et al., 2021). Sidelobes are undetectable with CW radars but can be found with FM and SFCW radars. The recent trend for gesture categorization methodology relies on machine learning techniques such as the use of convolutional neural networks (CNN) or other deep learning approaches (Ahmed et al. 2021). Radar-based gesture recognition systems have three key advantages: they do so by being non-invasive, fast and adaptable, and contactless, and because they do not require any contacts they can be operated without having to touch the button (Ahmed et al., 2021),. These elements include autonomy, dexterity, tactility, sensitive sensors, and mobility.

2.4 Market Trends and Growth Prospects of gesture recognition

Radar-based gesture recognition has some unique features that are specifically useful in environments where touch-based interactions are not appropriate or hygiene conditions are of high concern, e.g., healthcare, autonomous vehicles, and public places (Allied Market Research, 2023). The capability of radar technology to reveal and analyze precise hand movements and gestures in a contactless mode matches the industry trend that is characterized by contactless interfaces. It is advantageous in the automobile sector where drivers can adjust infotainment system settings or navigation by not diverting their hands from the steering wheel. Gesture recognition using radar, which is a type of touchless gesture recognition, is a sub-sector of the market, which is among the significant portions of the market (Dhapte, 2024). Radar technology enables touchless sensing of gestures by detecting changes in the radar signal caused by hand movements or gestures. The global gesture recognition market, valued at $13.9 billion in 2021 and projected to reach $88.2 billion by 2031, showcases a substantial growth trajectory driven by factors such as the increasing demand for contactless interfaces and the rising popularity of gaming applications (Allied Market Research, 2023). Moreover, the compound annual growth rate (CAGR) was nearly 30% in 2021, which is exceptionally significant. Analysts predict an average CAGR staying high with an average of 20-25% in the following yeas

The market's segmentation into touch-based and touchless gesture recognition highlights the dominance of touch-based systems currently, driven by the popularity of touch-enabled devices like smartphones. However, the touchless segment, including radar-based systems, is expected to witness significant growth, particularly in industries prioritizing contactless interactions and user experience enhancements (Allied Market Research, 2023). Regionally, North America leads the gesture recognition market,

Gesture recognition operates in a highly competitive environment, positioned in an oligopoly where 5 to 10 companies vie for market share. Key players include Microchip, Sony, Intel, Apple, and Japil. This competition drives impressive technological advancements, making gesture recognition increasingly prevalent in our daily lives.

The automotive, medical, and robotics sectors are particularly keen on these new technologies and are investing heavily. At the same time, the trend of smart and connected homes is gaining popularity among consumers, representing a significant opportunity for these companies in the coming years.

However, the adoption of gesture recognition faces a major hurdle: its high cost. It is possible that once an initial adoption phase is passed, economies of scale will allow for more affordable commercialization of this technology, facilitating its integration into everyday life.

Two continents stand out in terms of potential for gesture recognition: North America and Asia. North America is crucial for its significant market share, driven by advanced technology adoption and applications like augmented reality, while Asia is notable for the high percentage of its population adopting this new technology. In Europe, where the population is generally more hesitant, it will likely take longer before gesture recognition becomes a regular part of daily life.

The Gesture Recognition In Retail Market is experiencing robust growth, driven by technological advancements and the need for streamlined operations (Precision Pulse, 2023). Key players like Cognitec, Apple, and Crunchfish are pivotal in shaping market dynamics, focusing on product innovation and strategic collaborations. As businesses leverage these insights and strategies, the forecast for significant market expansion from 2023 to 2031 remains positive, offering boundless opportunities for growth and market positioning (Precision Pulse, 2023). However, the requirement of a continuous power source and the possible expense hurdles might influence the acceptance of radar-based gesture recognition in general (Dhapte, 2024). Also, standardization and technical protocols ought to be formulated to guarantee that the radar-based gesture recognition systems are compatible with each other and operate without malfunctioning. And even the fact that high construction costs and power usage are still the main issues. Despite the challenges of radar technology, such as sensing and algorithms, the advancements in this field, including improved sensors and algorithms, are mitigating these challenges, making radar-based gesture recognition projects more and more viable and attractive (Allied Market Research, 2023).

Chapter 3

Methodology

In this chapter, I detail the methodology used to study the radar gesture recognition market in Belgium. Our aim is to explain and understand Belgian consumers' and Companies' perception of the technology

In a second time, we delve into the methodology for evaluating the feasability of rada-based gesture recognition. Additionally, we ensured the inclusivity of individuals across different ages and body types in our dataset.

3.1 Market study design

To start our analysis, I tried to understand the consumer's perception with a particular emphasis on the use of the TAM (Technology Acceptance Model).

The TAM is a theoretical model widely used to understand and predict user adoption of new technologies. For our survey, we adapted the TAM by designing a questionnaire including specific questions on the perceived usefulness and ease of use of radar gesture recognition technology. We also included questions on other factors influencing acceptance of the technology, such as privacy and security concerns.

Using TAM to survey a representative sample of the Belgian population, we employed a Python algorithm to randomly select cities from a pool of major cities across Belgium. This algorithm ensured a randomized and diverse sample, leveraging geographic data to select cities while maintaining a balanced representation across different regions of Belgium. Even though our dataset consists of only 153 respondents, we ensure its randomness and merge it across diverse cities for analysis.

The questionnaire was also disseminated online and distributed anonymously to a diverse pool of respondents to prevent bias towards responses solely from students or personal acquaintances, such as friends or family members. This approach didn't yield a significant number of responses.

The data collected was analyzed statistically to highlight insights that might be of interest to readers and the community.

As consumers are not the only stakeholders interested in radar gesture recognition technology, I conducted interviews with key personnel in NIKE Europe and AUDI Brussels, focusing on individuals working within the supply chain. These companies were selected due to their significant presence in the Belgian market and their potential interest in radar gesture recognition technology.

The interviews were conducted individually and structured around key themes such as current supply chain challenges and prospects for technological innovation. Qualitative analysis methods were employed to analyze the interview data and identify key insights regarding the market potential of gesture recognition technology. A summary of this insight have been provided in the master thesis to allow the reader to get a smooth idea of the innovation within company's point of view.

At the conclusion of this thesis, I will discuss the steps taken to ensure the validity and reliability of the results. This will include a reflection on the potential biases of the study and the strategies implemented to mitigate them, ensuring the credibility of our findings.

3.1.1 Technology Acceptance Model

The Technology Acceptance Model (TAM) is a crucial tool forged in the 1980s, and has since informed the work of numerous researchers. Operating around two fundamental concepts - perceived usefulness and perceived ease of use - the TAM offers valuable insights into how individuals perceive the implications of a technology on their performance or productivity, as well as the simplicity and accessibility of its use.

Despite its popularity and recognition, TAM is not immune to criticism and limitations. Some researchers question its universal applicability, arguing that perceived usefulness and perceived ease of use are not enough to predict technology adoption in all situations. (Legris et al.2003)

However, TAM remains a valuable tool for researchers and practitioners in a variety of fields. It continues to offer a solid analytical framework for understanding the dynamics of technology adoption.

An illuminating example of the application and relevance of TAM is presented as an empirical study (Mohamed Benabid,2019) using technology acceptance theory". This article explores the links between online purchase intention and various cognitive variables through two separate empirical studies. The results highlight the importance of technical and psychosocial aspects in technology choice processes, underlining the imperative of understanding user needs FOR successful commercialization of new technology.

Below is an example of a number of graphs explaining purchase intent. The key ideas of perceived usefulness and ease of use can be seen.

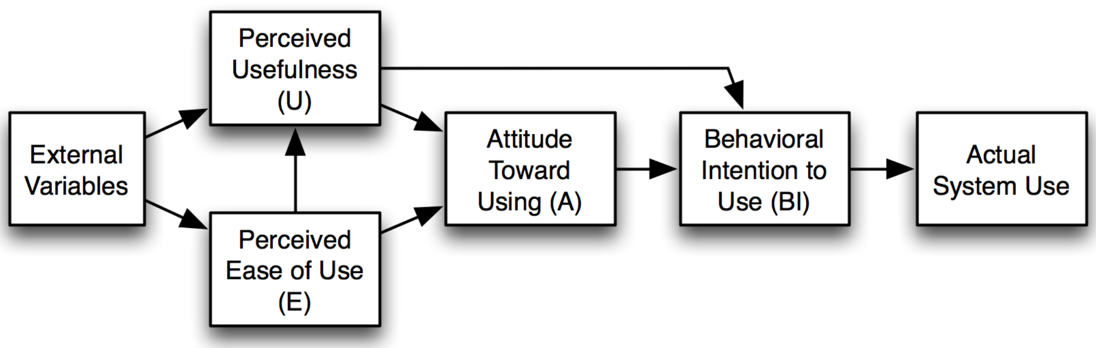


Figure 3.1: TAM Model Example

3.2 Dataset Gesture Recognition Analysis study

To evaluate our recognition algorithm, we compiled extensive datasets that simulate various scenarios involving radar signals passing through different materials, each featuring a diverse array of gestures. Moreover, our dataset is comprehensive, including individuals of different ages and body types. The following sections of this chapter are organized as follows.

Algorithm's Data Collection and Processing

To collect the dataset, I based our methodology on previous studies (Sluyters & al., 2023), I use the Walabot Developer that is a commercially available radar sensor utilizing ultra-wideband (UWB) technology with frequency-modulated continuous-wave (FMCW) capabilities. Operating in the 6.3-8 GHz range (EU/CE version), it features an array of 18 bowtie radar antennas, providing both distance and direction information that is a good advantage for analysis. With its compact size (72x140 mm) and USB connectivity, it's suitable for mobile and stationary applications.

The Walabot Developer SDK offers access to raw time-domain radar data for customization, with three profiles for different scanning needs:

1. Profile 1 (`PROF_SENSOR`): This profile operates within the 6.3-8 GHz frequency range, employing 40 antenna pairs. It captures 8192 fast-time samples per frame, achieving approximately 20 frames per second.
2. Profile 2 (`PROF_SENSOR_NARROW`): This profile also operates within the 6.3-8 GHz range but with a narrower focus. It utilizes only 12 antenna pairs, capturing 4096 fast-time samples per frame at a higher frame rate of around 41 frames per second.
3. Profile 3 (`PROF_WIDE_BAND`): This profile extends the frequency range from 3.3-10 GHz, employing 40 antenna pairs similar to Profile 1. However, it captures 8192 fast-time samples per frame at a lower frame rate of approximately 15 frames per second. This profile is only available with the US/FCC version of the Walabot.

Given our specific application requirements, we focus on Profiles 2 due to their compatibility with our experimental setup, balancing between resolution and speed for effective data acquisition and processing. The Walabot has been used in various application domains, including material identification, activity recognition, and gesture recognition, demonstrating its versatility and effectiveness across different fields of study.

The dataset comprises nine common gestures chosen based on prior research experience, with consistent numbering retained. These gestures include open hand, close hand, swipe right, swipe left, draw infinity, push fist, push palm, pull palm, and knock three times.

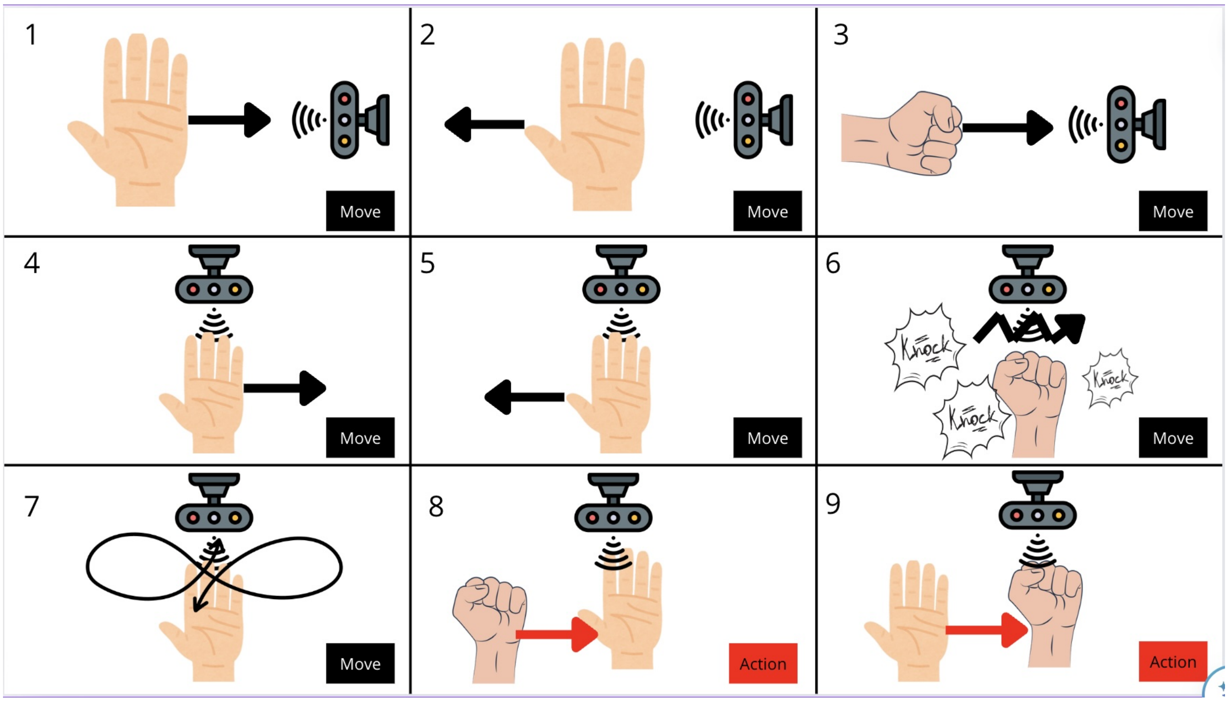


Figure 3.2: Recorded Gesture Draw

All gestures were captured using three Walabot devices affixed to the rear of 1 m × 1 m plates made of different materials: wood (1.7 cm thick), PVC (0.9 cm thick), and glass (0.5 cm thick). Though not as extensive as existing works in the field, this selection covers diverse real-world contexts and potential scenarios for hand gesture recognition applications. For example, these materials are commonly found in furniture and construction, with some also used in toy manufacturing.

Participants executed gestures while standing in front of the material, with each material mounted on an easel at a height aligning the participant's extended arm with the Walabot, maintaining a distance of 20 cm between hand and material.

Each gesture was executed five times by 36 participants within a controlled environment, resulting in a total of 1620 samples for each type of material. The recording process involved demonstrating the gesture to the participant, followed by a sequence of steps for each sample: (1) participant starts with arms by their sides, (2) recording begins, (3) gesture is performed, (4) participant returns arms to sides, and (5) recording ends with data saved to a text file. This process was repeated for every repetition of each gesture and for every type of material.

Figure 3.3: Setup for the experiment (http://hdl.handle.net/2078.1/286156)

The data processing procedure in this study closely follows methodologies described in previous research (Sluyters & al., 2023) Gestures are represented as sequences of frames, each containing timestamped radar data. Initially, this data includes distance and apparent permittivity, later transitioning to real and imaginary components of the frequency-domain radar signal. The recognition process involves several stages, including raw data capture, background scene removal, full-wave inversion, and filtering. Each stage aims to enhance gesture recognition accuracy by refining radar data. This approach draws inspiration from established practices in the field, adapting and refining them to suit the specific requirements of this study.

The Experiment

The experiment evaluates the performance of the Walabot on 9 gestures dataset, a set of 9 hand gestures produced by 36 participants on three different materials as described above. It has two main goals:

1. Evaluate the efficacy of our algorithm on a large set of gestures from multiple users in user-dependent, user-independent scenarios.

2. Explore how differentiable subsets of the gesture set affect the performance of our approach by clustering in age and morphology.

The evaluation is done using The *Jackknife* tool which ran on the same computer and used the Jackknife recognizer. The performance of Jackknife was evaluated following a K-fold cross-validation procedure. In this procedure, the dataset is randomly divided into k equally sized groups, known as folds. The model is trained using k - 1 of these folds, while the remaining fold is used for testing. This process is repeated k times, each time with a different fold serving as the test set. The overall accuracy is then calculated as the average accuracy from all k iterations.

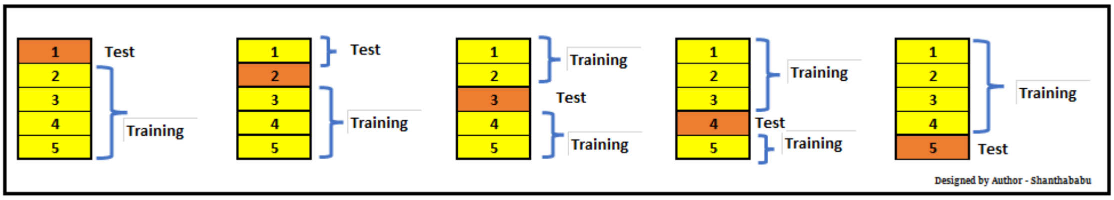


Figure 3.4: 5-Fold Example (https://www.analyticsvidhya.com/blog/2022/02/k-fold-cross-validation-technique-and-its-essentials/: :text=The%20choice%20of%20k%20(number,%3D10%20or%20k%3D20.)

The choice of k depends of several factors. Indeed, When k is smaller, the model is trained on a smaller portion of the data in each fold, leading to a higher bias. This occurs because the model has less data to learn from, resulting in a pessimistic estimate of the generalization error. Conversely, as k increases, the training set in each fold becomes larger, reducing bias. In the other hand, a lower k can be good as it reduces computational demands, making it feasible for larger datasets. In this thesis, I chose to use $k = 10$ for the k-fold cross-validation to balance bias, variance, and computational complexity. Using $k = 10$ is a common default because it is effective for assessing generalization error with a low computational time.

Chapter 4

Market Analysis : Consumer's Perception

To collect data regarding the consumer's perception, I designed a questionnaire based on the hypotheses:

Hypothesis 1: Perceived usefulness influence purchase intention
Hypothesis 2: Perceived ease of use influence purchase intention
Hypothesis 3: Security and privacy have importance in the purchasing process.
Hypothesis 4: The technology-induced creativity has an impact on purchase intention.
Hypothesis 5: The competitive advantage of cleanliness offered by radar gesture recognition compared to competing technologies is a competitive advantage over similar technologies.

By designing our questionnaire around these hypotheses, we aim to collect relevant data to assess the impact of various factors on user purchase intention.

The questionnaire items and the questionnaire itself are included in the appendix of this thesis. The different analysis steps presented in this chapter include, on the one hand, the analysis of the sample and, on the other hand, the analysis of responses to items. The latter consists of verifying the validity of our items and verifying the validity of our hypotheses. Finally, an analysis of qualitative responses from subjects is also conducted.

4.1 Sample analysis

I collected 154 responses (N = 154) from various individuals in Belgium as explained in the methodology chapters, encompassing diverse ages, genders and educational backgrounds. This subsection aims to examine the distribution of the sample and compare it to Belgian statistics. All comparisons made with our dataset are checked against the latest statistics from Statbel for the year 2024. This ensures that our findings accurately reflect the current demographic trends in Belgium.

Our dataset over-represents individuals aged 18 to 35 years. In contrast, the Belgian population aged 0 to 60 exhibits a more uniform distribution across age groups. This discrepancy should be considered in the subsequent analysis. The disproportionate representation of young individuals in our dataset is likely attributable to their greater propensity to respond to questionnaires, coupled with their heightened interest in new technologies. The subsequent statistical analysis will be based on the age range of our sample. Given that Belgium demonstrates a relatively uniform distribution across education levels and genders, these factors are not expected to significantly impact the validity of our others comparison.

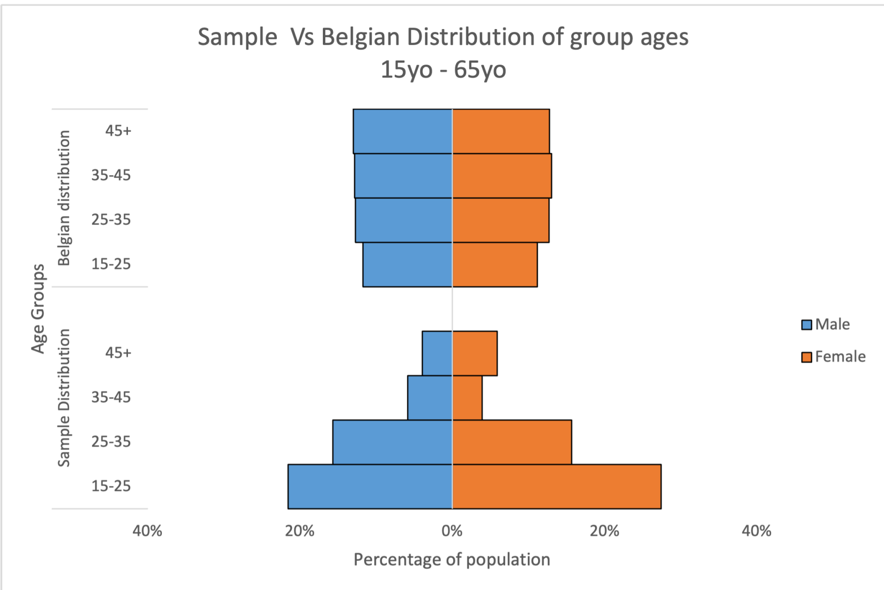
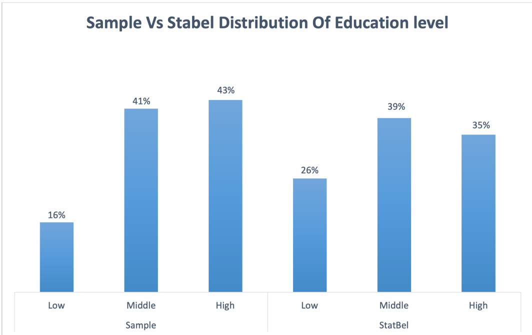
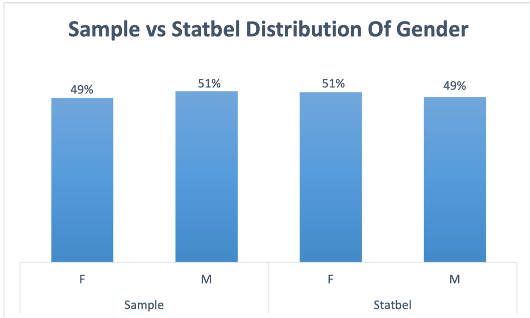


Figure 4.1: Ages Data Comparison

Upon comparative analysis of gender and education levels among participants, striking similarities emerge with national demographic data. When examined alongside comparative graphs with Statbel statistics, these findings bolster the credibility of our sample, suggesting a significant capture of national demographic trends. This statistical coherence lends support to the robustness of our methodology and the likelihood that our conclusions faithfully reflect the diversity of the Belgian population. It's noteworthy to mention that for educational level comparison, we adhere to Statbel's classification. Individuals with a low level of education are those who possess at best a diploma from lower secondary education or equivalent short-term training. Those with a medium level of education have obtained a diploma from upper secondary education but do not hold a higher education diploma. Finally, individuals classified as having a high level of education hold a higher education diploma.



((a)) Education Level Data Comparison



((b)) Gender Data Comparison

In conclusion, our analysis of the sample reveals a reasonable representation of the socio-demographic diversity of the Belgian population, with the notable exception of some imbalances, primarily related to age. We did not take active measures to correct these imbalances but observed that, overall, our sample appears to adequately represent various socio-demographic characteristics of the Belgian population. It is important to note that, due to the size and nature of our sample, no bootstrap or similar statistical correction method was employed to mitigate potential effects. However, we believe that our results provide a solid basis for meaningful analyses and interpretations, while acknowledging the inherent limitations of our methodology.

4.2 Responses: A Descriptive Overview

This chapter is dedicated to a comprehensive exploration of the collected data, with a primary emphasis on descriptive analysis. The dataset originates from responses provided by participants, rated on a Likert scale ranging from 1 to 7, reflecting degrees of agreement from "Not at all agree" to "Completely agree". These responses were structured into items, each item representing a thematic cluster of questions rather than individual questions. These thematic clusters encompass five core themes: Perceived usefulness, Perceived ease of use, Security, Creativity, Sanitary aspects of technology, and Purchase possibility. Each theme comprises between 3 to 5 questions, collectively designed to explore various facets of respondents' perceptions.

In the subsequent sections, we delve into a detailed descriptive analysis of these Likert scales, aiming to uncover a spectrum of insights embedded within the data. Furthermore, the latter part of this chapter is devoted to a qualitative analysis of responses obtained at the conclusion of the questionnaire, where participants had the opportunity to freely express their opinions. Through this comprehensive approach, we endeavor to unveil nuanced perspectives and glean valuable insights beyond numerical representation.

The initial analysis involved a frequency questionnaire. This questionnaire revealed the habits and perceptions of the surveyed population regarding the frequent use of various technological devices.

Responses regarding the frequent use of phones/smartphones and computers showed a significant prevalence, with over 90% of participants indicating scores of 6 or higher on the Likert scale ranging from 1 to 7. This finding aligns with the widespread use of these devices in our daily lives.

However, the most interesting results concerned the use of sensory radar technology. While this emerging technology is not yet widely used, about one-third of participants indicated higher scores (ranging from 4 to 7), suggesting some familiarity or interest in this innovation. The remaining two-thirds reported lower scores (ranging from 1 to 3), indicating perhaps less familiarity or reluctance to adopt this technology. These observations emphasize the importance of closely monitoring the acceptance and use of such an emerging technologies.

Our second analysis employed a comprehensive questionnaire consisting of 24 questions, aptly termed Items, meticulously organized into 6 overarching themes designated as Variables. These Variables encapsulated diverse aspects such as perceptions of usefulness, ease of use, the pivotal role of security in the purchasing process (including data privacy concerns), the paramount importance of health considerations facilitated by radar sensor technology, and individuals' purchase intentions. Notably, as this study was not conducted on a large-scale survey basis,

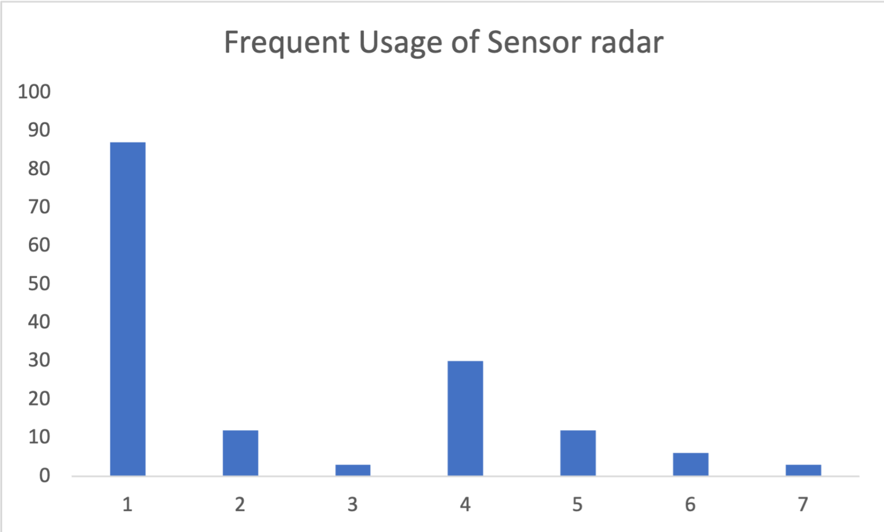


Figure 4.3: # of people using frequently a radar sensor

no pre-testing was conducted, emphasizing the exploratory nature of our analysis.

Upon conducting an initial assessment utilizing Cronbach's alpha on the myriad of Items, it became apparent that certain questions suffered from issues related to formulation or ambiguity, resulting in Cronbach's alpha values falling below the recommended threshold of 0.7.

Cronbach's Alpha is a measure of the internal consistency of a scale, which is the relationship between a group of questions used to collectively measure a latent variable that cannot be measured directly, such as intelligence or attitude. It reflects the correlation between the answers to these questions and can take values between 0 and 1, with higher values indicating greater internal consistency and reliability. Reliability refers to how accurately a test measures a true value, with fewer measurement errors. It gives an estimation of how good the measurement accuracy is

To address our low Cronbach's Alpha problem (Around 0.5), a strategic consolidation of clear and conceptually aligned questions was undertaken, ultimately reducing the number of Items from 24 to 18, with an average of 3 Items per theme. Consequently, while the Cronbach's alpha scores for most Variables exceeded 0.7, the score for security stood at 0.69. Despite this, the overall robustness and validity of the subsequent conclusions drawn from our analysis remain well-supported regarding these scores.

Table 4.1: Cronbach's Alpha Scores for Different Variables

Variable	**Cronbach's Alpha Score**
Usefulness	0.87
Ease of use	0.73
Security	0.69
Creativity	0.70
Cleanliness	/
Willing to buy	0.73

In this analysis, we computed the mean of responses (E(Item)), providing a single value X for each theme per individual. This yielded a matrix of 154 individuals by 6 items, subject to descriptive examination. Surprisingly, the distributions of these X variables closely mirrored each other, with medians and means hovering around 5-6. The distributions appeared to adhere to a normal distribution with right-skewness, although two distributions, namely security and usefulness, exhibited slightly more individuals clustered towards the center. At first glance, these distributions may imply that all X variables hold significance for individuals. However, for the two specific variables, I embarked on investigating whether there existed an overrepresentation of individuals scoring low, aiming to potentially unveil correlations or connections.

To further analyze this, I attempted to discriminate those who scored low by employing the t-test to determine if the difference in means between high Likert and low Likert responses was significant. However, none of the differences were statistically significant when considering gender, education, or age, with alpha levels set at 0.90 and 0.95. This lack of significant discrimination suggests that creating two distinct groups based on these variables is not substantiated by the data. Despite this preliminary analysis, it is conceivable that additional methods, such as more advanced statistical tests or qualitative data exploration, may be requisite to elicit deeper insights.

My last test was to see of it has a kind for relation between the variable "willing to buy", lets called it Y and the others variables X. For that I proceeded to a linear regression.

Before proceeding with linear regression, I conducted a validation test, which yielded positive results. The T-test for both the median and mean also showed positive outcomes, indicating that all the features appear significant. (Should I include additional information about linear regression?)

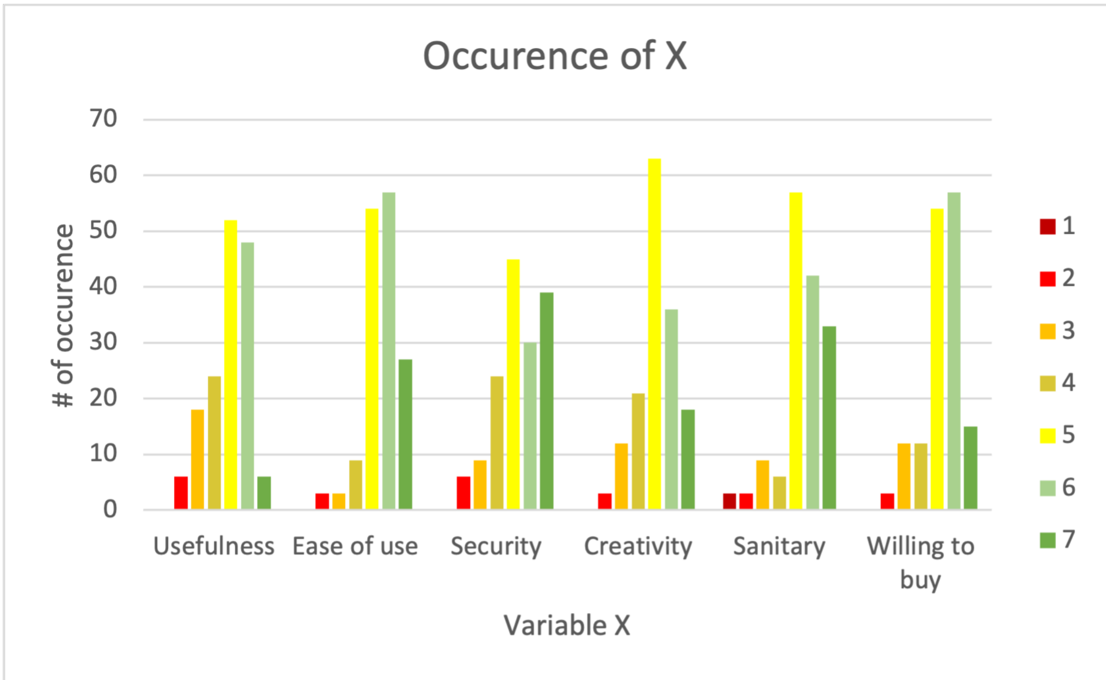


Figure 4.4: Variables Distribution Overview

4.3 Qualitative Analysis

After this quantitative analysis, I conducted a qualitative analysis. Interestingly, two of the questions posed received very mixed responses. These questions concerned compatibility with other equipment and the added value of the technology. The first statement was: "The system is not compatible with other systems I use," and the second: "I would have difficulty explaining why using the system might or might not be beneficial."

For the first statement, opinions were divided: some users struggled to imagine integrating the system with their existing equipment, while others easily saw potential for coordination.

For the second statement, several users acknowledged that they found it difficult to clearly communicate the system's advantages, even though they often seemed to perceive these benefits in their daily use.

These feedbacks suggest that improving communication about the system's compatibility and benefits could facilitate its adoption.

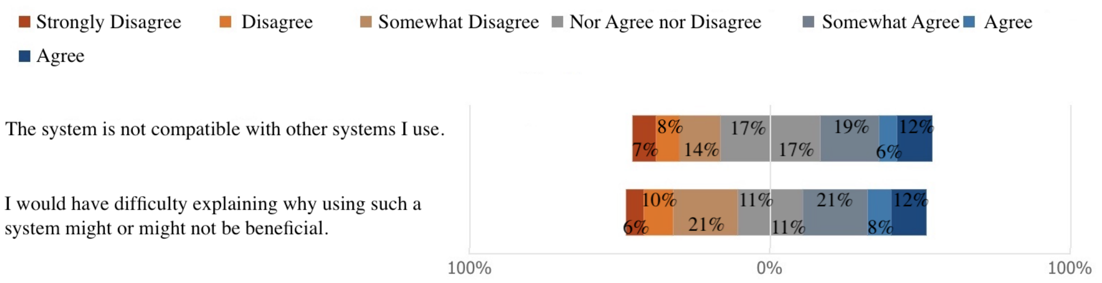


Figure 4.5: Interesting Questions Insights

While many people may not immediately see the direct benefits, a significant number have commented that they wouldn't be surprised to see this technology become part of our daily routines, such as changing the TV channel or interacting with household appliances (turning off lights, starting the microwave, etc.). Close to a quarter of individuals envision this technology being utilized in political settings, universities, or others. Another quarter sees its potential in assisting individuals with disabilities, perhaps due to its advanced capabilities in understanding and responding to human needs. A considerable portion also sees its application in enhancing workplace interactions, facilitating tasks and communication. This reflects a widespread perception that this technology represents an advancement in human-machine interaction, which is already prevalent in both our professional and private lives. Few respondents mentioned its potential in the medical and/or educational sectors, despite these being significant potential markets. However, the medical sector, in particular, holds substantial promise as a potential buyer.

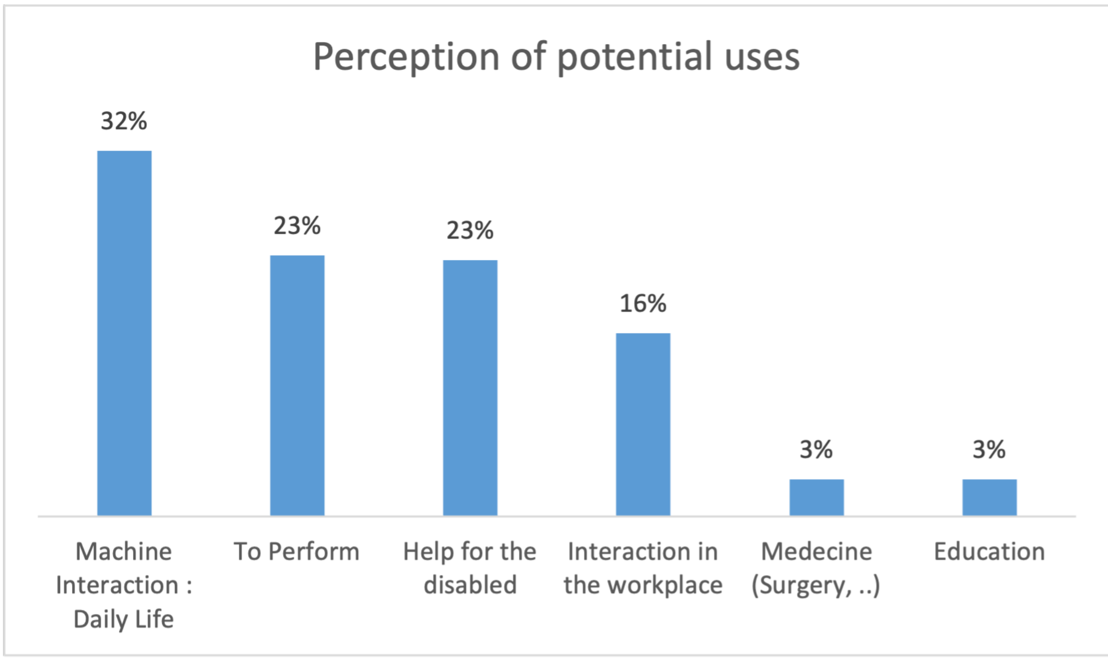


Figure 4.6: Potential Uses Perception

The rationale behind individuals scoring high on Likert scale questions, despite not perceiving tangible benefits or adaptability from a technology, likely lies in their perception of it as an advancement in interaction. They may view it as an evolution beyond tactile interfaces, akin to the progression seen in voice-activated assistants like Siri or Alexa. The prospect of seamlessly interacting with technology through simple, intuitive gestures, devoid of complexity, holds appeal as it promises to simplify and enhance daily life. This perspective is corroborated by the data depicted in the graph below, where primarily and overwhelmingly, ease of use must be high, and the number of errors made by the machine must be low. People want something that works. In second place, security slightly edges out cost, although these two aspects vie for this second position. Cost seems just as crucial as data protection, even if these two features often evolve in different directions, which might not please the companies designing such technology. Lastly, not surprisingly, recurring updates, device reliability (planned obsolescence), etc., come in last.

In conclusion, the mixed responses from both the quantitative and qualitative analyses shed light on key considerations for the adoption of the technology. While opinions varied regarding compatibility with existing systems and articulating the technology's benefits, there was a notable consensus on its potential integration into daily life, workplaces, and assisting individuals with disabilities. The data

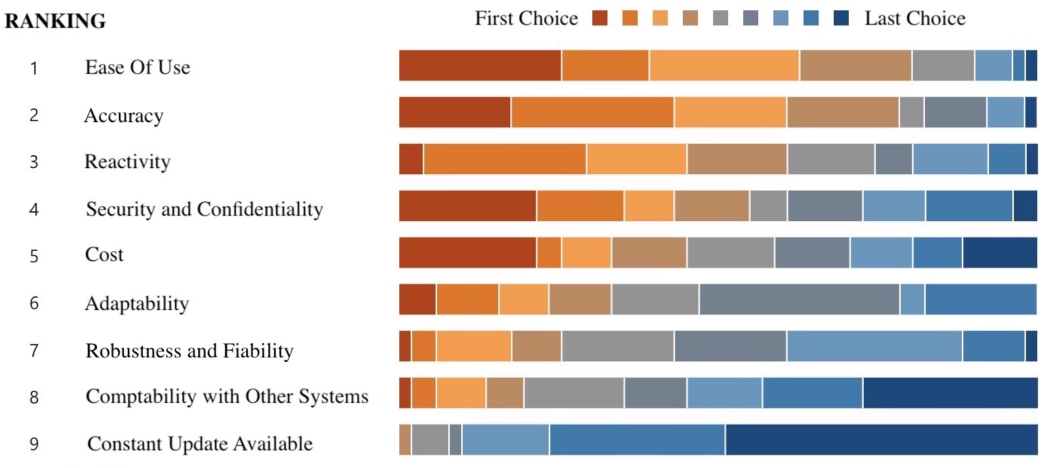


Figure 4.7: feature Ranking for Gesture Recognition Technology

suggests that improving communication about compatibility and benefits could enhance adoption rates. Additionally, respondents' prioritization of ease of use and security underscores the importance of these factors in technology acceptance.

Moreover, it's interesting to note that all findings presented in this chapter looks verifiable, as they stem from the primary questions posed and the predominant comments provided by respondents. The inquiries revolved around the practical implementation of simple commands, the integration of typing capabilities, and how the technology could replicate the tactile feedback experienced with traditional interfaces as pressure detection. These inquiries reflect the genuine curiosity and concerns of users regarding the practicality and usability of the technology in various contexts.

Chapter 5

Market Analysis : Company's Perception

In this chapter, we delve into the perspectives of two industry giants, Audi Brussels and Nike Europe, regarding the adoption and implications of radar gesture recognition technology. With a focus on enhancing user experiences and driving product innovation, both companies offer unique insights into the integration of this technology into their respective domains.

From Audi's emphasis on seamless vehicle controls to Nike's commitment to creating intuitive interfaces for consumer electronics and sports gear, we explore how radar gesture recognition is reshaping industries and shaping future advancements. Additionally, considerations of privacy, security, and employee adaptation underscore the multifaceted nature of this technological shift. Through this examination, we gain a deeper understanding of the potential impacts and opportunities presented by radar gesture recognition across diverse sectors.

5.1 Audi Brussels point of view

The interest in radar technology for gesture detection at Audi came from its ability to improve user experience and vehicle controls. Drivers may easily and non-invasively engage with navigation and entertainment systems using radar-based gesture detection without taking their eyes off the road. Jean-Claude learned about the technology around 2019 after reading an article on radar gesture detection, which demonstrated how flexible the technology is even in a variety of situations, reflecting the many interior configurations found in Audi cars.

Implementing radar technology at Audi still could pose serious technological difficulties because radar sensors must be integrated into car systems with smooth functioning and safety. Particularly in dynamic driving situations, calibration and testing should be essential to ensuring precise gesture detection and reducing false positives. But for Audi, it's enticing to see how easily and hands-free the navigation, climate control, and entertainment systems might be used.

By doing the interviews, we learned that Audi already carried out preliminary radar technology gesture recognition trials in controlled driving situations. One realization was the need for sensor positioning and calibration to guarantee precise gesture detection with the least amount of outside interference from vibrations from the road. Employing these tests, they have been evaluated the comfort and efficiency of users by testing several gestures for typical car features, such as volume adjustment and call answering. They also assessed the seamless and user-friendly integration of radar-based gesture detection with current voice and touch controls.

Audi has been interested in how they could prevent compromising important features for customers in terms of privacy and security. Then, when Audi think about implemented radar systems, privacy and security issues required a multi-faceted approach. To safeguard consumer privacy, they advise first to make sure that gesture data gathered by radar sensors was encrypted. Sensitive data must only be accessible by authorized staff, and strong cybersecurity protocols must put in place to stop illegal access or data breaches. Furthermore, crucial open lines of communication and openness with consumers about the usage of radar-based gesture recognition and the data must be gathered.

Thanks to the culture of Audi and their technology focus, staff members responded with interest and enthusiasm in gesture recognition, because Audi staff give importance to technological development being integrated into car's systems, and they are always keen to investigate its possibilities. In collaboration with companies and people that provide any new kind of technology, they use to organize training sessions and show demonstrations, staff members became acquainted with the new technology and saw right away how convenient and better the user experience was. Similarly, this kind of session should be organized with customers to get positive responses. For Audi, that's a condition for successfully commercializing a technological product.

After being really focused on cars and customers, Audi provided me some information about radar gesture recognition in a logistics point of view. The radar technology would greatly improve supply chain efficiency. By allowing more effective assembly line operations and quality control inspections, the use of this technology in the supply chain should expedite production processes. Supply chain knowledge gives an idea of that, if gesture controls are used by employees to retrieve data, therefore it would be lowering mistakes and increasing output. This effectiveness improves supply chain performance generally by resulting in faster turnaround times and a smoother production flow.

Audi thinks that radar technology is predicted to continue to change dramatically in the next few years. Improvements in the range and accuracy of radar technology may result in better inventory tracking and logistics optimization in supply chain management. Radar sensors might be included, in autonomous cars used for warehouse operations to facilitate effective inventory control and navigation. Faster order fulfillment, lower running expenses, and greater supply chain agility may all follow from this. Further enabling more complex driver assistance systems and innovative car features, developments in radar technology may also affect all cars product development.

5.2 Nike Europe Point of view

Radar gesture recognition technology can stimulate an interest in my work at Nike Europe because of its possible uses in consumer devices, especially in the creation of intuitive interfaces. Detecting gestures in mid-air without making physical touch fits with Nike's goal of giving customers creative and easy-to-use experiences. In keeping with the company's innovation and user-centric design philosophy, Nike Europe wants to improve the user experience by making interactions with gadgets more natural and responsive by using radar-based gesture detection.

With radar-based gesture detection being used in consumer electronics, Nike Europe saw chances to completely reimagine how consumers interacted with their products or the different market partner. Creating user-friendly, readily learned gestures that were resilient in a range of environments and resolving any privacy issues with gesture data were challenges. However, the possibility of designing smooth and interesting user experiences like interactive fitness apps or hands-free smart device control was tempting. As a leader in tech-infused sports gear, Nike Europe saw radar-based gesture recognition as a means of maintaining its position.

Wearables and smart clothing dominated Nike's early radar-based gesture detection experiments. They evaluated wearable device gesture-based controls for music playback,notifications, and fitness tracking. These tests revealed the need for robust algorithms to differentiate between deliberate and accidental motions and intuitive, easily remembered gesture sets. They also investigated how radar sensors might be included in apparel and accessories to provide touchless interactions in different sports situations. And it's a market they are interested in.

When it comes to put radar technology into wearables, privacy, and security, in their opinion, It's the top priorities. To stop unwanted access, they, in the same way than Audi, think that we need robust encryption techniques. The user interface must include opt-in and user permission options that let users manage the usage of gesture data and offer openness on data collecting procedures. To find and lessen possible threats to user data, they would certainly carry out routine vulnerability assessments and security audits.

Some workers at Nike expressed a real and deep interest in the use of radar technology because they see that the radar technology will significantly improve consumer experience on Nike shops. All the employees could be excited about it after receiving training and they would realize right away how much better user experiences and product development innovation might be because radar technology allowed for creativity and user-centric design.

By contrast, they don't think it will have an impact in the supply chain effectiveness, at least not here, in Hilversum. Within the supply chain, Nike does not see a full use in the distribution side of their supply chain. Product development, and Marketing within Nike shops and Market Partner would be significantly impacted by the advancement of radar technology.

5.3 Conclusion

In conclusion, both Audi Brussels and Nike Europe recognize the potential of radar gesture recognition technology to revolutionize user experiences and product innovation. At Audi, the focus lies on integrating this technology seamlessly into vehicle controls to enhance safety and convenience for drivers, while also considering privacy and security concerns. They see opportunities for improving supply chain efficiency as well. On the other hand, Nike Europe views radar gesture recognition as a way to create intuitive interfaces for consumer electronics and sports gear, aligning with their commitment to innovation and user-centric design. Privacy and security are also paramount for Nike, especially in wearable technology.

While both companies acknowledge the need for training and adaptation among employees, they foresee significant benefits in terms of improved user experiences and product development innovation. However, Nike Europe does not anticipate a direct impact on supply chain effectiveness in their specific context.

Overall, both Audi and Nike anticipate that radar gesture recognition technology will play a crucial role in shaping the future of their respective industries, offering opportunities for enhanced customer interactions and product advancements.

Chapter 6

Gesture recognition : Analysis And Results

The following chapter presents the analysis and results of our study, which involved a total of 36 participants. Our sample comprised 16 individuals who actively participated in the experiment, supplemented by archival data from an additional 20 individuals. This approach allowed us to amass a diverse dataset, inclusive of various ethnicity's, genders, and age groups, thus ensuring a comprehensive representation of the population. Specifically, our dataset encompassed individuals from Western, Asian, Sub-Saharan African, and Arab backgrounds, across four age categories (15-25, 25-35, 35-45, 45+), with at least one representative from each demographic subset.

Each participant was tasked with performing nine gestures five times on three different materials, as outlined in the methodology section. The primary objective was to assess the functionality of our gesture recognition algorithm across a broad spectrum of individuals. Prior to the main analysis, preliminary investigations were conducted using multinomial regression to explore potential associations between morphology, age, and ethnicity. (The results being unsatisfactory, this short section can be found in the appendix). Subsequently, clustering were employed to identify distinct age clusters within the dataset.

Our analyses were conducted before and after the application of filtering and background subtraction techniques. Additionally, the gesture recognition algorithm was executed on the entire dataset to capture comprehensive insights. I also clustered the DataSet depending of the materials and ages. The findings from these analyses will be comprehensively discussed in this chapter, shedding light on the performance and efficacy of the gesture recognition algorithm across diverse individuals.

The results of the testing can be found in tables below :

K=10	**Antennas**		**Computation Time**
	2	**4**	
Dataset after filtering phase	0.43	0.45	9/21
Dataset after background subtraction phase	0.71	0.73	86/192
Through wood after filtering phase	0.42	0.43	3/11
Through wood after background subtraction phase	0.88	0.93	43/142
Through PVC after filtering phase	0.40	0.44	4/12
Through PVC after background subtraction phase	0.69	0.70	38/123
Through glass after filtering phase	0.43	0.43	5/9
Through glass after background subtraction phase	0.46	0.56	32/102

Table 6.1: Accuracy - Computation Time of the dataset (Table 1)

K=10	**Antennas**		**Computation Time**
	6	**8**	
Dataset after filtering phase	0.48	/	38
Dataset after background subtraction phase	0.75	/	380
Through wood after filtering phase	0.48	0.49	15/18
Through wood after background subtraction phase	0.95	0.94	245/327
Through PVC after filtering phase	0.48	0.48	13/17
Through PVC after background subtraction phase	0.71	0.72	217/291
Through glass after filtering phase	0.44	0.45	9/16
Through glass after background subtraction phase	0.56	0.51	168/237

Table 6.2: Accuracy - Computation Time of the dataset (Table 2)

K=10	**Antennas**		**Computation Time**
	6	**8**	
Dataset after filtering phase	/	/	/
Dataset after background subtraction phase	/	/	/
Through wood after filtering phase	0.51	0.51	22/35
Through wood after background subtraction phase	0.93	0.95	417/484
Through PVC after filtering phase	0.48	0.49	26/34
Through PVC after background subtraction phase	0.73	0.72	408/456
Through glass after filtering phase	0.44	0.45	17/21
Through glass after background subtraction phase	0.53	0.55	387/398

Table 6.3: Accuracy - Computation Time of the dataset (Table 3)

The data presented in the tables illustrates the results when varying the number of antennas and different phases of processing on the performance metrics and computation time across various materials. I haven't tested every possible combination of antennas, but I have added a new antenna with each subsequent test. The general trend shows that the performance metrics maintain an acceptable average level for most materials, except for glass, where the results are more variable. The filtering phase is quicker but provides poorer results, while the background subtraction phase, despite requiring more computation time, yields significant improvements in performance. This suggests that the number of antennas does not significantly alter performance for materials like wood and PVC, where metrics remain relatively consistent. It is important to note that for the complete datasets, we stopped at 6 antennas due to computer memory limitations, as the memory was insufficient to proceed further.

When considering materials, processing through wood and PVC shows stable and acceptable performance metrics, indicating potential practical applications. For instance, in the automotive industry, where many components are made from PVC, this technology could improve the detection and monitoring of these components for maintenance and safety checks. However, processing through glass remains challenging due to the observed variability in performance metrics. As highlighted by Nike's interest in utilizing this technology through screens in their shops, enhancing performance through glass is a critical area for future development. Overcoming these challenges could enable new applications in retail environments, where transparent displays are common, providing seamless and interactive customer experiences.

Furthermore, clustering the dataset by age or ethnicity results in subsets containing only 10 people each. The performance metrics and computation times in these smaller clusters remain consistent with the overall dataset, indicating no significant changes or improvements. This suggests that the variations observed in the performance metrics are not influenced by the age or ethnicity of the subjects, but rather by the material being processed and the phases of processing.

Below, there are two confusion matrices. An interesting observation that I wanted to highlight is that the recognizers struggle with the palm push/pull, knock, and open/close hand gestures, possibly due to their similarities. For instance, a slow close hand gesture is very similar to a palm push gesture, which could explain the confusion. To avoid this, in future gesture recordings, the experimenter should focus on executing gestures more quickly and naturally. This is is more evident in the wood case.

Training Set										
TARGET / OUTPUT	Push Palm	Pull Palm	Push Fist	Swipe Right	Swipe Left	Knock Three time	Infinity	Open Hand	Close Hand	SUM
Push Palm	147 9.07%	7 0.43%	2 0.12%	2 0.12%	2 0.12%	0 0.00%	0 0.00%	18 1.11%	2 0.12%	180 81.67% 18.33%
Pull Palm	6 0.37%	157 9.69%	0 0.00%	1 0.06%	0 0.00%	0 0.00%	0 0.00%	5 0.31%	11 0.68%	180 87.22% 12.78%
Push Fist	3 0.19%	0 0.00%	177 10.93%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	0 0.00%	180 98.33% 1.67%
Swipe Right	3 0.19%	1 0.06%	0 0.00%	168 10.37%	4 0.25%	1 0.06%	1 0.06%	2 0.12%	0 0.00%	180 93.33% 6.67%
Swipe Left	1 0.06%	2 0.12%	1 0.06%	5 0.31%	166 10.25%	2 0.12%	0 0.00%	1 0.06%	2 0.12%	180 92.22% 7.78%
Knock Three time	1 0.06%	0 0.00%	0 0.00%	1 0.06%	0 0.00%	164 10.12%	2 0.12%	5 0.31%	7 0.43%	180 91.11% 8.89%
Infinity	3 0.19%	1 0.06%	1 0.06%	2 0.12%	1 0.06%	12 0.74%	150 9.26%	3 0.19%	7 0.43%	180 83.33% 16.67%
Open Hand	8 0.49%	9 0.56%	1 0.06%	2 0.12%	3 0.19%	1 0.06%	0 0.00%	142 8.77%	14 0.86%	180 78.89% 21.11%
Close Hand	2 0.12%	4 0.25%	5 0.31%	3 0.19%	1 0.06%	2 0.12%	0 0.00%	18 1.11%	145 8.95%	180 80.56% 19.44%
SUM	174 84.48% 15.52%	181 86.74% 13.26%	187 94.65% 5.35%	184 91.30% 8.70%	177 93.79% 6.21%	182 90.11% 9.89%	153 98.04% 1.96%	194 73.20% 26.80%	188 77.13% 22.87%	1416 / 1620 87.41% 12.59%

Figure 6.1: Wood - Background Subtraction - 2 antennas

Training Set										
TARGET / OUTPUT	Push Palm	Pull Palm	Push Fist	Swipe Right	Swipe Left	Knock Three time	Infinity	Open Hand	Close Hand	SUM
Push Palm	93 5.74%	21 1.30%	16 0.99%	6 0.37%	9 0.56%	4 0.25%	6 0.37%	10 0.62%	15 0.93%	180 51.67% 48.33%
Pull Palm	22 1.36%	96 5.93%	11 0.68%	9 0.56%	8 0.49%	8 0.49%	8 0.49%	9 0.56%	9 0.56%	180 53.33% 46.67%
Push Fist	8 0.49%	8 0.49%	116 7.16%	8 0.49%	10 0.62%	12 0.74%	5 0.31%	5 0.31%	8 0.49%	180 64.44% 35.56%
Swipe Right	5 0.31%	9 0.56%	12 0.74%	98 6.05%	16 0.99%	14 0.86%	5 0.31%	12 0.74%	9 0.56%	180 54.44% 45.56%
Swipe Left	7 0.43%	10 0.62%	22 1.36%	20 1.23%	81 5.00%	16 0.99%	4 0.25%	14 0.86%	6 0.37%	180 45.00% 55.00%
Knock Three time	5 0.31%	4 0.25%	5 0.31%	12 0.74%	9 0.56%	107 6.60%	9 0.56%	14 0.86%	15 0.93%	180 59.44% 40.56%
Infinity	2 0.12%	2 0.12%	15 0.93%	8 0.49%	14 0.86%	23 1.42%	79 4.88%	22 1.36%	15 0.93%	180 43.89% 56.11%
Open Hand	4 0.25%	7 0.43%	10 0.62%	7 0.43%	5 0.31%	20 1.23%	7 0.43%	97 5.99%	23 1.42%	180 53.89% 46.11%
Close Hand	8 0.49%	5 0.31%	7 0.43%	4 0.25%	9 0.56%	21 1.30%	17 1.05%	18 1.11%	91 5.62%	180 50.56% 49.44%
SUM	154 60.39% 39.61%	162 59.26% 40.74%	214 54.21% 45.79%	172 56.98% 43.02%	161 50.31% 49.69%	225 47.56% 52.44%	140 56.43% 43.57%	201 48.26% 51.74%	191 47.64% 52.36%	858 / 1620 52.96% 47.04%

Figure 6.2: Glass - Background Subtraction - 6 antennas

Chapter 7

Conclusion, Limitation and Future Work

7.1 Final Conclusion

In this chapter, we are going to conclude by discussing what we have done in each chapter from this work.

In chapter 1, I presented our research methodologies and outlined our objectives, elucidating what we aim to achieve.

In chapter 2, I explored radar-based gesture recognition, showcasing its breakthroughs in materials-based radar technology and its applications across industries. It highlights the technology's role in enhancing human-computer interaction, driving market growth, and overcoming challenges through ongoing advancements in sensor technology and deep learning algorithms.

In chapter 3, I described different methodology use in the work.

In chapter 4, I assessed a sample of 154 responses from Belgium, I've got through a quantitative and qualitative analysis revealing diverse perspectives of the technology from a consumer point of view.

In chapter 5, I evaluated the market from a corporate perspective by conducting interviews and analyzing key factors crucial for major players in the radar gesture technology sector.

In chapter 6, I assessed the effectiveness of the gesture recognition algorithm across this broad spectrum of individuals. The study encompassed 36 participants, incorporating diverse demographics across various ethnicity, ages, and genders.

As each chapter meticulously explored our research endeavors, culminating in comprehensive analyses and findings, the following summary encapsulates the breadth and depth of our work, shedding light on the efficacy and implications of my investigations.

The TAM is an essential framework for comprehending technology adoption. TAM provides an understanding of how people evaluate the effects of technology on their performance and usability through the emphasis on perceived utility and ease of use. The market study of customer perception reveals important new information on the elements affecting purchase intentions for human-computer interaction technology. The study looked at five theories on the perceived utility, usability, security and privacy, technological inventiveness, and cleanliness benefits of radar gesture recognition. The study emphasizes how important these elements are to the acceptability of technology and suggests that better communication of the benefits of the technology could promote wider adoption.

The observations from Nike Europe and Audi Brussels highlight how radar gesture recognition technology can revolutionize several sectors. Audi wants to seamlessly include this technology into the controls of the car, improving convenience and safety for the driver while also taking care of privacy and security issues. Conversely, Nike Europe, in keeping with its innovation-centric strategy, concentrates on developing touchless, intuitive interfaces for sports equipment and consumer devices.

The study on gesture recognition and its analysis offers important new information on the performance and usefulness of our system in a variety of demographics. With 36 volunteers, representing a broad spectrum of ages, genders, and nationalities, our study guaranteed a thorough representation of the general public. We evaluated the algorithm on user-dependent and user-independent datasets by rigorous testing encompassing nine movements on three different materials. By use of multinomial regression and clustering methods, we were able to investigate correlations between morphology, age, and ethnicity and to find unique clusters within the dataset.

This study's main limitations are the convenience sample bias and relatively small sample size of this study are its drawbacks. The primary objective of future studies should be to increase the sample size to increase the generalizability of the conclusions. Moreover, looking at more advanced clustering techniques and incorporating machine learning algorithms for gesture identification could improve accuracy and robustness, especially in different demographic situations. Researching how background noise affects gesture recognition effectiveness might also help to improve practical applicability.

7.2 Future Work

The primary limitation we encountered was the size of our dataset, especially in the context of market analysis and regression statistics. However, I expand the dataset for gestures testing and prove its efficacy. Delving into trends and correlations will provide significant statistical insights. Moreover, currently the dataset primarily focuses on the Belgian market due to constraints on time and resources, though it offers a glimpse into broader European trends. Nevertheless, there's immense potential in collecting data from various continents to observe convergences and time trends, which could enrich our understanding of global market dynamics.

Due to time constraints, we opted to conduct interviews with major players and large companies to gain insights from a qualitative perspective. However, it could be advantageous to complement this qualitative approach with quantitative analysis if sufficient data can be collected. Our decision to pursue interviews stemmed from the challenge of engaging big players who often face time constraints or may not respond promptly. Leveraging my internship during my master's program allowed me to establish connections and dedicate time to delve deeper into the subject matter, ensuring comprehensive insights despite these challenges.

The final limitation for the gesture testing was the inability to test the recognition ability for many pairs of antennas due to computer memory limitations. Testing all combinations of antenna pairs could also be interesting to see how accurately the recognizer can work efficiently.

List of Figures

List of Tables

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Appendix A

Appendix

Appendix B

Result of Regression

A regression between the variable "Willing to buy" with other variables gives us this result :

Willing to buy   Usefulness + Ease of use + Security + Creativity + Creativity + Cleaness

Coefficients:

	Estimate	Std. Error	t value	Pr(>$\lvert t \rvert$)
(Intercept)	-0.099109	0.487160	-0.203	0.839
R$Usefulness	0.341488	0.052552	6.498	1.18e-09 ***
R$‘Ease of use‘	0.014506	0.057322	0.253	0.801
R$Security	-0.009707	0.045636	-0.213	0.832
R$Creativity	0.460327	0.052483	8.771	4.06e-15 ***
R$Cleaness	0.244166	0.049649	4.918	2.31e-06 ***

Table B.1: Regression Results

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.6884 on 147 degrees of freedom
Multiple R-squared: 0.6381, Adjusted R-squared: 0.6258
F-statistic: 51.83 on 5 and 147 DF, p-value: < 2.2e-16

Three variables are significant; however, it is important to note that the R-squared value is slightly above 0.6, which is considered quite low in social science research. Nevertheless, readers can use this information as a starting point for future studies.

Additionally, by performing a regression analysis between ethnicity and morphology to achieve a good accuracy score, I found the following regression:

Ethnicity   Height + Weight + Body Water.

This regression yields good results; however, it is important to highlight that the sample size used is not large—only 40 people. Therefore, we cannot consider the accuracy found of 75% as reliable. Similar to the first analysis, readers should observe these results and take them into consideration for future research.

Appendix C

List of question for the interviews

Appendix D

List of question for the interviews

Q1: How interesting is it to start employing radar technology for gesture recognition in your companies?

Q2: What particular opportunities or problems did you notice when it comes to using radar-based gesture recognition?

Q3: Could you offer some observations from early radar gesture recognition experiments?

Q4: How would you handle worries regarding user acceptance, security, and privacy?

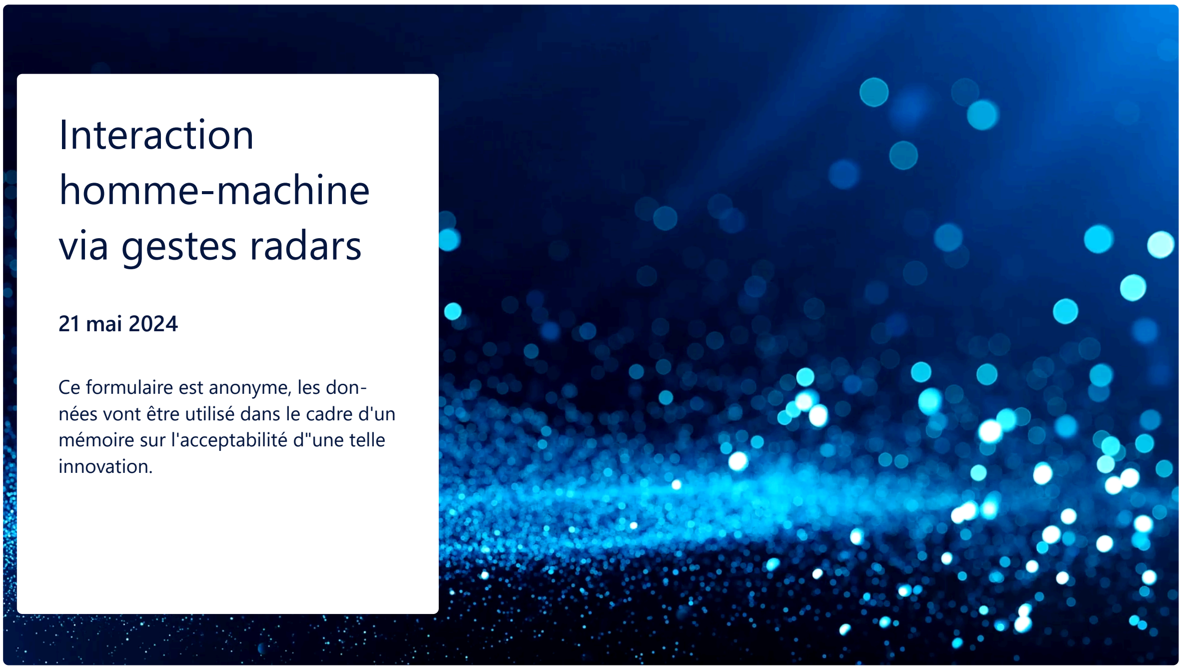
Q5: How did staff members and consumers respond to the technology? Or How do you think staff members and consumers respond to the technology?

Q6: How did/could the technology help your companies' supply chains run more smoothly and how did customers feel?

Q7: What future developments do you envision radar technology bringing about and how will it affect product development and supply chain management?

Appendix E

Tam Survey



Interaction homme-machine via gestes radars

21 mai 2024

Ce formulaire est anonyme, les données vont être utilisé dans le cadre d'un mémoire sur l'acceptabilité d"une telle innovation.

* Obligatoire

Données du répondant

Veuillez répondre à ces premières questions

1

Avez-vous participé à l'expérience "Interaction homme-machine via détection de gestes radar" qui se déroule à LLN ? *

- ◯ Oui
- ◯ Non

2

Si oui, spécifiez le numéro qui vous a été attribué durant cette expérience

3

Votre niveau d'étude : *

- CESS/Bac
- Fomation/Bac+2
- Bachelier/Bac+3
- Master/Bac+5
- Doctorant
- Post-Doctorant
- Autre

4

Vous êtes ? *

- Homme
- Femme
- Non-binaire
- Je ne me reconnais pas dans un des genres ci-dessus
- Je préfère ne pas répondre

5

Votre âge *

Veuillez entrer un nombre supérieur à 14

6

Votre profession *

7

Votre domaine d'activité *

Présentation du système d'interaction homme-machine via système par radar.

Ces vidéos illustrent comment on peut manipuler un media player par gestes de la main
Veuillez prendre connaissance de cette première vidéo (1/2)

8

Veuillez prendre connaissance de cette seconde vidéo. *

- ◯ Ces vidéos ont été utiles pour comprendre le concept de reconnaissance de gestes par radar
- ◯ Ces vidéos n'ont pas été utiles pour comprendre le concept de reconnaissance de gestes par radar

Premières questions

9

Sur une échelle de 1 (Pas du tout d'accord) à 7 (Tout à fait d'accord), évaluez ces affirmations. *

	Pas du tout d'accord	Pas d'accord	Plutôt pas d'accord	Ni d'accord ni pas d'accord	Plutôt d'accord	D'accord	Tout à fait d'accord
J'utilise fréquemment un ordinateur	○	○	○	○	○	○	○
J'utilise fréquemment un téléphone	○	○	○	○	○	○	○
J'utilise fréquemment un smartphone	○	○	○	○	○	○	○
J'utilise fréquemment un radar sensoriel	○	○	○	○	○	○	○

10

Sur une échelle de 1 (Pas du tout d'accord) à 7 (Tout à fait d'accord), évaluez ces affirmations. *

	Pas du tout d'accord	Pas d'accord	Plutôt pas d'accord	Ni d'accord ni pas d'accord	Plutôt d'accord	D'accord	Tout à fait d'accord
L'utilisation du système d'interaction homme-machine via détection de gestes radar améliorer ait ma performance.	○	○	○	○	○	○	○
L'utilisation du système d'interaction homme-machine via détection de gestes radar augmente rait ma productivité.	○	○	○	○	○	○	○
L'utilisation du système d'interaction homme-machine via détection de gestes radar améliorer ait mon efficacité	○	○	○	○	○	○	○
Globalement, je trouve que ce système à l'air utile.	○	○	○	○	○	○	○
Je pense que l'utilisation d'un tel système est importante.	○	○	○	○	○	○	○
Je pense que l'utilisation d'un tel système est pertinente.	○	○	○	○	○	○	○
Les conséquences de l'utilisation du système sont évidentes pour moi.	○	○	○	○	○	○	○
Je trouve que le système est utile car il réduit le besoin de toucher des surfaces potentiellement sales (par exemple, écrans tactiles) et contribue ainsi à une meilleure hygiène.	○	○	○	○	○	○	○
Je suis enclin à un changement vers l'interaction homme-machine via détection de gestes radar par	○	○	○	○	○	○	○

rapport à
d'autres
méthodes
similaires.

Votre avis (2/2)

11

Sur une échelle de 1 (Pas du tout d'accord) à 7 (Tout à fait d'accord), évaluez ces affirmations. *

	Pas du tout d'accord	Pas d'accord	Plutôt pas d'accord	Ni d'accord ni pas d'accord	Plutôt d'accord	D'accord	Tout à fait d'accord
L'interaction avec le système semble clair et compréhensible .	◯	◯	◯	◯	◯	◯	◯
Interagir avec le système ne nécessiterait pas un gros effort mental de ma part.	◯	◯	◯	◯	◯	◯	◯
Obtenir ce que je veux du système doit être facile	◯	◯	◯	◯	◯	◯	◯
Je pense disposer des ressources nécessaires pour utiliser le système.	◯	◯	◯	◯	◯	◯	◯
Le système n'est pas compatible avec d'autres systèmes que j'utilise.	◯	◯	◯	◯	◯	◯	◯
Je peux communiquer aux autres mon expérience du système	◯	◯	◯	◯	◯	◯	◯
J'aurais du mal à expliquer pourquoi l'utilisation du système peut être ou ne pas être bénéfique.	◯	◯	◯	◯	◯	◯	◯
Le système simplifierait l'interaction avec les appareils électroniques.	◯	◯	◯	◯	◯	◯	◯

12

Sur une échelle de 1 (Pas du tout) à 7 (Très), évaluez ces affirmations. *

	1	2	3	4	5	6	7
Dans quelle mesure seriez-vous préoccupé par la possibilité que la reconnaissance de gestes par radar puisse permettre à d'autres de visualiser vos actions sur l'écran de votre appareil ?	○	○	○	○	○	○	○
Dans quelle mesure est-ce important d'avoir le contrôle dans l'utilisation du système.	○	○	○	○	○	○	○
Dans quelle mesure seriez-vous préoccupé par la sécurité de vos données personnelles lors de l'utilisation de la reconnaissance de gestes par radar, notamment en ce qui concerne le partage ou le vol de ces données ?	○	○	○	○	○	○	○

Les différents facteurs clés

13

Sur une échelle de 1 (Pas du tout d'accord) à 7 (Tout à fait d'accord), évaluez ces affirmations. *

	Pas du tout d'accord	Pas d'accord	Plutôt pas d'accord	Ni d'accord ni pas d'acord	Plutôt d'accord	D'accord	Tout à fait d'accord
Je pense que je serais créatif ou créative en utilisant ce dispositif	○	○	○	○	○	○	○
Je pense que je serais spontané ou spontanée en utilisant ce dispositif	○	○	○	○	○	○	○
Je pense que je serais enjoué ou enjouée en utilisant ce dispositif	○	○	○	○	○	○	○
Je pense que je serais sans originalité en utilisant ce dispositif	○	○	○	○	○	○	○
En supposant que j'ai accès au système, j'ai l'intention de l'utiliser.	○	○	○	○	○	○	○

14

Classez ces éléments par ordre d'importance selon vous : *

- Précision
- Adaptabilité
- Réactivité
- Facilité d'utilisation
- Sécurité et confidentialité
- Robustesse et fiabilité
- Coût
- Mise à jour récurrente
- Compatibilité avec d'autres appareils

15

Je pourrais utiliser ce dispositif *

- [ ] Si personne n'est à mes côtés pour m'accompagner
- [ ] S'il y a un bouton d'aide pour m'assister
- [ ] Si quelqu'un me montre comment faire avant
- [ ] Si j'ai déjà utilisé un dispositif similaire avant pour faire le même travail

Dernières questions

16

Dans quel cas, voyez-vous le système d'interaction homme-machine via détection de gestes radar utile ?

17

Avez-vous des commentaires ou des suggestions ?

Abstract :

Résumé :

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