headset and glasses. PPG data indicates blood volume changes within a subject. Data from these data sources were fused and processed to determine anxiety levels.

The applicability of leveraging electrocardiogram (ECG) features for detecting anxiety disorders using wearable devices was analysed in a recent review of state of the art [22]. Specifically, applicability across panic, post-traumatic stress, generalized anxiety, social, mixed, and obsessive-compulsive anxiety disorders was investigated.

Portable Autonomous Multisensory Intervention Device (PAMID) [23] is a proprietary device designed to monitor anxiety as well as other negative behavioural symptoms wirelessly. PAMID used automatic audio analysis to detect disruptive behaviours from PwD to prevent anxiety episodes that could escalate [23]. To support that approach, the audio was used to provide information about different levels of contexts, such as speech, activities [18], and environmental sound events [12].

The review concluded that, although much of the previous works reported in the literature has obtained satisfactory results; in many cases, the data collection method is intrusive and raises important questions regarding privacy.

It has been shown that wearable solutions are intrusive to observed users by requiring devices to be physically affixed to individuals. This physical attachment can cause issues with discomfort, unfamiliarity and notably, can cause distress within PwD. Wearable devices typically require maintenance such as charging, which must be managed. Additionally, they require a user to be remembered to wear these devices each day or employ caregivers to do this. A requirement for a PwD to maintain or remember to wear such devices cannot be assured due to the nature of the illness [24]. As such, the use of ambient sensings, such as audio is a more appropriate model when observing PwD.

The recent popularity in the use of smart microphones; which provide high-quality audio and include speech recognition algorithms, is very relevant as these are potential tools for detecting anxiety due to their ease of placement in the living environment and their intuitive interaction/operation. An important advantage of using microphones over other types of technologies is that they are an unobtrusive technology that allows capturing data from people without using wearable devices. Moreover, analysing the audio within the smart microphone addresses privacy concerns as it is not necessary to transmit recordings for further investigation but only to send notifications regarding detected anxiety episodes.

Given their potential to provide useful information and their ease of use, smart microphones can be utilised to non-intrusively monitor the wellbeing of PwD through the identification of acoustic events. Smart microphones can be installed in living spaces (*e.g.*, bathrooms, living rooms) and start collecting data from the PwD without interrupting or interfering in their daily living activities but rather non-intrusively detecting relevant acoustic events. To explore these capabilities, we conducted a non-participatory study aiming to acquire a broader understanding of the sounds occurring before and during the manifestation of an episode of anxiety. Respective outcomes provided us with design clues to develop a prototype of AnxiDetector. We then build a Neural Network model to detect acoustic patterns associated with the manifestation of anxiety in PwD.

3. Development of anxiety in patients with dementia in their daily living

Designing UbiHealth technology requires a deep understanding of the user's profile and the environmental conditions in which the technology will be deployed. Our research methodology addressed this by incorporating elements of qualitative data collection from PwD and caregivers and quantitative evaluation of machine learning models for recognising categories of sounds. In this section we describe a four-day study based on a non-participatory observation of PwD [12] and interviews with their caregivers, to better understand how anxiety is manifested within Activities of Daily Living (ADL).

This data collection informed an iterative and incremental approach to the evaluation of AnxiDetector, as described in sections 4-6, including quantitative evaluation of machine learning models for sound recognition and qualitative evaluation of prototype outcomes with caregivers.

3.1. Consultation with Domain Experts

In coordination with the AgeingLab Foundation (host entity of the European project: REMIND[†]), the observational study was conducted at the Residential Centre 'Ángeles Cobo López', located in the city of Alcaudete in Jaén, Spain. This is a residence that welcomes cognitively impaired patients who voluntary accept to be hosted by the care centre or have been clinically referred. Patients are hosted according to their level of dependency which is characterised by their impairment profile (*e.g.*, dementia, Parkinson's, bipolar disease) and impairment severity (*i.e.*, emerging, moderate, and severe). Some of the services that patients receive consist of physical treatment and psychological therapies. They are also supported with medication management and constant monitoring towards reaching the stage in which they are sufficiently healthy to temporarily leave the residence centre under the condition that they return to the facilities at night.

To conduct this study, the AgeingLab Foundation provided ethical approval under the auspices of Personal and Public Involvement, which includes the involvement of expert caregivers as specialist advisers in the evaluation. The non-participatory observation was conducted under the ethical and privacy countenance of the Residential Centre 'Ángeles Cobo López'. Note that the quotes provided in this report have been translated from Spanish by the researcher who is conducting the observational study *in-situ*.

[†] https://cordis.europa.eu/project/rcn/207045_en.html

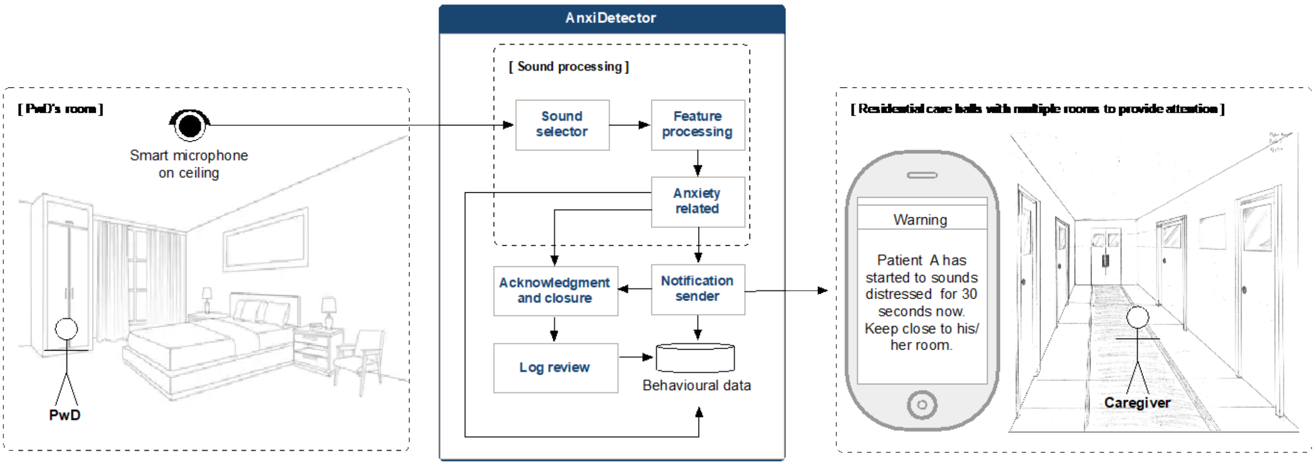

Figure 1. AnxiDetector architecture consisting of six components to collect, filter, and select audio features from the PwD's daily life environment (left side of diagram). AnxiDetector automatically monitors anxiety episodes and triggers a notification to caregivers through their smartphone or smartwatch (right side of diagram).

shared room, hence, sends a warning notification to the caregivers. While, the caregivers, understand that this is not an emergency, but rather a potential anxiety treat, they decide to prioritise and finish their ongoing task before heading to the shared room.

After a few seconds, John loses control and start shouting and violently treating them. Given the early notification sent by AnxiDetector, the caregivers arrive just in time, before John behaviour escalates further. Given the early action of the caregivers, they quickly manage to calm John down.

Previous scenarios are summarized in a use case narrated by building upon Figure 1. Here, AnxiDetector represents the sensing actor which monitors the acoustic sounds from the environment; including those emitted by the PwD (Maricela or John). The entry condition for AnxiDetector consists of an anxiety manifestation represented by a pattern of sound (see Section 4), hence, as the AnxiDetector detects a critical sound, it exits condition is satisfied by sending a notification to the caregiver's smartphone.

In these scenarios, the PwD would benefit from early care to prevent accidents, whereas caregivers would benefit from contextual information to assist PwD unobtrusively.

5. AnxiDetector

AnxiDetector is a prototypical solution that has been devised to investigate the feasibility of implementing smart microphones to anticipate anxiety episodes in PwD who live in a residential care environment.

AnxiDetector consists of a Matrix Voice ESP[‡] module, which is an array of 8 digital microphones which can sense and identify sound energy levels and location of where sounds were produced. The Matrix Voice ESP module includes a microcontroller, which enables processing of algorithms for voice detection, de-reverberation and noise cancellation, amongst other capabilities.

In this initial prototype of AnxiDetector, the Matrix Voice ESP was connected to a Raspberry Pi Single Board Computer[§]. A software component which provides interaction with the Matrix Voice ESP and performs relevant processing was loaded on the Raspberry Pi.

AnxiDetector is connected to a power supply and to a wireless Internet connection nearby where PwD spend most of their time, such as private rooms or leisure areas. To reduce privacy concerns, data is processed locally on the microphone's device. The system architecture is presented in Figure 1 and consists of the following components:

Sound processing. The smart microphone monitors sound from the environmental perimeter of the PwD.

a) A sound selector filters noise focusing on sounds produced by the PwD (*e.g.*, crying, screaming).
b) A feature processor generates features retrieved from sound frequency, amplitude, speed of sound, direction, pitch, duration, loudness, timbre, sonic texture, spatial location, and pressure level.
c) Anxiety-related sounds. It classifies the sound input to determine whether the sounds are related to anxiety. Hence, this component conceives a decision-maker that identifies the probability of an episode of anxiety occurring.

Notification sender. Two levels of notifications are available, warning and emergency. A warning notification it is sent when probabilities of an anxiety episode are low (*e.g.*, < 70%). An Emergency notification it is sent when a behavioural pattern on the PwD has been clearly identified; therefore, certainty has been calculated by the Anxiety-related component. This setup is helpful to avoid entering private rooms when a false positive anxiety episode is detected.

Intervention and notification. The notification sent to the caregiver consists of a combination of sound and visual

‡ https://www.matrix.one/products/voice

§ https://www.raspberrypi.org

information triggered on their smartphone/smartwatch device. There is no need to acknowledge the Warning notification since its purpose is only to warn of potential assistance support. However, once the Emergency notification is sent, this component will expect a caregiver to attend the PwD's location and provide adequate support. A closure mechanism will be automatically triggered once anxiety has been treated by the caregiver.

Log review. To improve the detection of future episodes, this component generates a log of behaviours in which pattern behaviour pre-episodes are recorded towards a better understanding of anxiety events.

As more data is logged into the database stored in the server and more relevant patterns are found, it is anticipated there will be a greater insight into the individual behaviour of PwD concerning their anxiety (causes and interventions). This insight will inform the early detection algorithm located within the anxiety-related component.

Note that in this paper we introduce AnxiDetector as an embedded prototype system to be installed within a Raspberry Pi Single Board Computer, its deployment is envisioned to be compatible to Linux operative system platform (*e.g.*, Java as a programming language and PostgreSQL as the database). The Sound processing is a machine learning component envisioned to be deployed utilising TensorFlow Lite[**] (for deploying a DNN model) or Firefly[††] (for deploying an SVM model). Finally, we consider that the notifications should adopt standardised SMS or MMS content; which are compatible with popular mobile devices platforms such as Android and iPhone.

To evaluate the adoption of AnxiDetector, an iterative and incremental development model is used, in which (i) a prototype is co-designed including opinions of caregivers, (ii) the prototype is developed considering the architecture detailed previously, and (iii) validation of the acceptability of the prototype is conducted. Then, a new iteration is reworked when needed until a final prototype will be achieved, as presented in Figure 2.

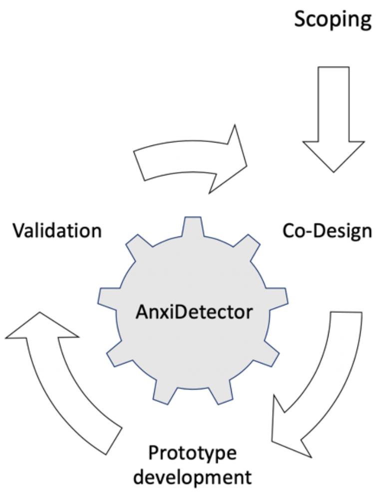

Figure 2. Prototype development model.

6. Preliminary validation

To validate the acceptability of AnxiDetector, we conducted two interviews with caregivers at the Residential Centre 'Ángeles Cobo López' in Spain. During this study, we observed that PwD expressed anxiety in different ways, given individual circumstance regarding their mental impairment and their personality.

In this work, we estimated the effectiveness of the detection by adopting nine classes of sounds as representative patterns manifested by PwD when experiencing anxiety. The variety of classes were determined as they were observed in our non-participatory study (Section 4) and as they are reported in the literature - that dementia can worsen the effects of sensory changes by altering how the person perceives external stimuli, such as noise and light [27].

Two groups of audio files were considered: (i) *disturbance* sounds, and (ii) *expression* sounds. The former are sounds that could disturb PwD and include: flushing toilet, knocking door, phone ringing, and bell ringing. The latter are sounds expressed by the PwD when experiencing anxiety, such as crying, verbal expressions (*i.e.*, wow), typing, anger, and screaming.

Due to privacy restrictions, audio recording from the Residence Centre 'Ángeles Cobo López' was not possible. Therefore, we relied on publicly available datasets to validate our methodology, as presented below.

Table 1. Relationship between the classes of sound and the open-access dataset from which they were retrieved. Description of the datasets is provided in Section 6.1.

Acoustic event	Group	Dataset
Flushing toilet	Disturbance	Mixed ES [28]
Knocking door	Disturbance	Mixed ES [28]
Phone ringing	Disturbance	Mixed ES [28]
Typing	Disturbance	Mixed ES [28]
Bell ringing	Disturbance	Mixed ES [28]
Verbal expression (*i.e.*, Wow)	Expression	Speech Commands [29]
Screaming	Expression	Zapsplat [30]
Crying	Expression	Freesound [31], Soundsnap [32]
Anger	Expression	Soundsnap [32]

To validate the capabilities of our methodology, we implemented a Deep Neural Network model consisting of 16 hidden layers, in which eight features were conceived as input neurons (energy entropy, short-time energy, spectral roll-off, spectral centroid, spectral flux, relative spectral transform filtering, and Mel-frequency cepstral). Our model was built using a sigmoid as activation function and trained upon 500 epoch iterations.

We calculated the above features creating a vector by splitting each audio file into 23 milliseconds windows with 10 milliseconds overlap, as we have previously proof effective

[**] https://www.tensorflow.org/lite

[††] https://pypi.org/project/firefly-python

[28]. Then the different length of the audio files was addressed by calculating the standard deviation from each vector.

To extend the capabilities to recognize different PwD's anxiety events, we trained our model with a small sample of instances per subject (between-subject approach) as described in Section 6.1. We hypothesise that by doing so, we build a more general model capable of identifying a wider variety of acoustic events compared to (for example) training our model by utilising instances from a single subject.

Validation was furthermore done using a Support Vector Machine (SVM) with a linear kernel and the suggested default hyperparameters (version 0.21.3 of the scikit-learn toolkit).

Features for each audio file in the data set were extracted with the openSMILE framework for acoustic feature extraction [35]. We extracted single feature vectors (statistical functionals over whole utterances) of the eGeMAPS feature set [36]. eGeMAPS is a widely used knowledge-driven multi-purpose feature set, mostly used for voice sciences.

For scaling, the mean was removed, and data points were scaled to unit variance.

6.1. Datasets description

The audio files were standardised by converting them into 16-bit little-endian PCM-encoded, and formatting them into WAVE files with a sample rate of 44.1Khz which as it has been proven to be effective in different research studies [33] [34]. Audio files were listened one by one of the authors from this paper, in order to validate the audio file annotation. The datasets used are described below.

Mixed Environmental Sound (Mixed ES). This dataset consists of 40 three-seconds audio files captured from each of the next classes: flushing toilet, knocking door, phone ringing, typing, and bell ringing. The sounds were recorded in an apartment of an older adult using a low-end mobile phone. Four anonymous subjects participated. To conduct our study, the 40 samples of each class were utilized [28].

Speech Commands. This is a set of 64,727 one-second audio files which contains a single spoken English word. The audio files were collected in uncontrolled locations by different people around the world. The number and characteristics of the participants are not reported. To conduct our study, we randomly selected 40 audio files from the verbal expression "wow" [29].

Zapsplat. It consists of free sound effects and a music library offering up to 55,446 tracks for instant download. The length of the files varies. The subjects' profile recordings are not reported nor the conditions under which they were recorded. To conduct our study, we randomly selected 40 two-seconds audio files from people screaming [30].

Freesound. This is an open-access online server that offers more than 400,000 sound and effects audio files. The length of the files varies. Neither technical information of the subjects nor recording equipment are provided. To conduct our study, we randomly selected 40 one-second audio files from adults crying [31].

Soundsnap‡‡. It consists of a server with more than 278,428 audios files. The length of the files varies, and information of the subject's producing the audio is not reported. To conduct our study, we randomly selected 40 audio files from emotion events such as adults crying and being angry. Length of the audio files is approximately 2 seconds [32].

6.2. Results

6.2.1 Caregivers interviews outcomes

The acceptability of AnxiDetector was validated by the outcomes of two scenarios presenting its functionality (Presented in Subsection 4.4). In the interviews, the caregivers expressed that the deployment of AnxiDetector could positively impact in two aspects: (i) by providing assurance that there may be no PwD in harm, and (ii) the opportunity to improve the quality of their services.

Quote from Caregiver A: *"This technology will totally make me feel more comfortable because normally I will be under stress thinking that PwD-A (whose room is located at the main entrance) could have an anxiety episode, while I am patrolling the other end of the corridor".*

Quote from Caregiver B: *"I think this can help me to run my errands quickly so that I can invest more time with the PwD. Sometimes, in tween rooms (i.e., rooms with two PwD divided by a door), it takes me up to 10 minutes to make a PwD's bed because I am (simultaneously) walking back and forth to the other room. Hence, with this technology, I can focus on a single one at the time, trusting the other PwD doesn't require my assistance".*

6.2.2 Quantitative results

The accuracy of the DNN model was estimated by validating the classification model under a 10-fold cross-validation. When classifying the two groups of classes (*i.e.*, *expression* and *disturbance*), the classification accuracy reaches 98.1% with a precision of 98.0% and 98.1% respectively. The average accuracy when classifying the nine different classes reports a classification accuracy of 92.2%, with the "Verbal expression" and the "Typing" classes having the highest precision of 100% each. The lowest precision was obtained with the class "Scream" (*i.e.*, 74.4%). Table 2 presents the confusion matrix for these results.

Table 2. Confusion matrix for the DNN on the 9 audio classes and 10-fold cross-validation.

a	b	c	d	e	f	g	h	i	Classified as:
32	4	0	0	0	2	0	0	2	a = Screaming
7	32	0	0	0	0	0	0	1	b = Anger
0	1	38	0	0	0	0	0	1	c = Verbal Expression

‡‡ Educational license was granted by the Soundsnap company.

1	0	0	37	1	0	0	0	1	d = Flushing toilet
0	0	0	0	40	0	0	0	0	e = Knocking door
3	0	0	0	1	35	1	0	0	f = Phone ringing
0	0	0	1	0	0	39	0	0	g = Bell ringing
0	0	0	0	0	0	0	40	0	h = Typing
0	0	0	1	0	0	0	0	39	i = Crying

The classification accuracy of the SVM was evaluated with 10-fold cross-validation. The distinction of the two *expression* and *disturbance* categories was made with an accuracy of 99.2% each. For the multiclass classification problem, the model achieved an overall classification accuracy of 93.0%, with the classes “Knocking door, Phone ringing, Bell ringing, and Typing” having the highest precision of 100%, and the “Scream” class reporting the lowest precision of 77.8%. Table 3 presents the confusion matrix for these results.

Table 3. Confusion matrix for SVM on the classification of the 9 audio classes and 10-fold cross-validation.

a	b	c	d	e	f	g	h	i	Classified as:
28	9	1	0	0	1	0	0	1	a = Screaming
6	32	1	0	0	0	0	0	1	b = Anger
1	0	37	0	2	0	0	0	0	c = Verbal Expression
0	0	0	39	1	0	0	0	0	d = Flushing toilet
0	0	0	0	40	0	0	0	0	e = Knocking door
0	0	0	0	0	40	0	0	0	f = Phone ringing
0	0	0	0	0	0	40	0	0	g = Bell ringing
0	0	0	0	0	0	0	40	0	h = Typing
1	0	0	0	0	0	0	0	39	i = Crying

7. Limitations and Constraints

Overall, two significant challenges to consider during the implementation stage will be to differentiate between sounds produced by a PwD from another PwD from an artificial environmental source, such as on TV. This is of particular concern as this could be misinterpreted by the AnxiDetector and PwD within the environment being observed. To address this, future work will take advantage of the directionality feature of the Matrix Voice ESP smart microphones. Specifically, this will be leveraged to map the location of appliances such as TVs or radios and filtering as appropriate. Another challenge is the characterisation of parameters according to how PwD manifest anxiety episodes, since, for example, whiles one PwD could express it by shouting, another could do so by walking. For the next step of this project, we will implement a first hardware version of AnxiDetector; hence, a more detailed architecture will be provided.

8. Recommendations

In this section, we provide a brief list of recommendations acquired during the design and development of this paper:

- **Understanding the end-user and their environment.** Which includes the qualitative analysis to understand better the relevant sounds associated with the PwD’s behaviours and anxiety episodes. We also found it useful to identify the common background sounds exposed in the living environment, in order to properly discriminate them and reduce the amount of false positives classification events.
- **Training of the model with appropriate samples.** Although publicly available datasets provide useful audio to train a classification model, it is encouraging to collect audio samples from the real-living environment in order to build a more robust model.
- **Maintaining privacy.** Given the sensitive information that can be captured by audio sensors, edge processing is recommendable, so that data can be processes in-site rather than remotely.
- **Personalising.** Given that not all sounds manifested by PwD are related to anxiety episodes, systems like AnxieDetector should be personalised.
- **Feedback.** As a personalization technique, one can adopt the active learning approach, so the model builds up as the caregivers discriminate between the different manifestations of anxiety in PwD’s.

9. Conclusion and Future work

This paper has presented a feasibility study of using environmental smart microphones to detect early stages of anxiety in PwD based on the identified auditive manifestations of anxiety. We presented the outcomes from a non-participatory observation of PwD and interviews with the caregivers from the Residential Centre ‘Ángeles Cobo López’. We identified the existence of auditory manifestation before and during anxiety episodes. The design and intended use of a low-fidelity prototype called AnxiDetector have been presented. Initial results from an evaluation of our prototype were presented. These results indicate that the use of this type of smart microphone-based technology would be of great support for caregivers. Additionally, two sound classification models based on a DNN and SVM were implemented to showcase the technical feasibility of AnxiDetector. Using the DNN model, a classification accuracy of 98.1% was obtained, whereas accuracy of 99.2% was achieved utilising the SVM for classifying the two groups of classes (*i.e.*, *expression* and *disturbances*). An accuracy of 92.2% and 93.0%, for the DNN and SVM models; respectively, when classifying the nine different classes of sound selected as an acoustic representation of disturbances and manifestations associated to anxiety episode in PwD.

As part of our future work, we will rely on transfer learning and active learning techniques, so that only a small amount of data is required to initiate the anxiety identification task. In particular, active learning techniques are envisioned to improve the quality of anxiety detection by providing annotation to describe the relevance of the notifications sent by AnxiDetector. Moreover, we are interested in carrying out trials in care homes in Northern Ireland, Mexico, Germany, and Spain to help generalise the acceptability of this approach across cultures.

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