Sensing with Earables: A Systematic Literature Review and Taxonomy of Phenomena

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Earables have emerged as a unique platform for ubiquitous computing by augmenting ear-worn devices with state-of-the-art sensing. This new platform has spurred a wealth of new research exploring what can be detected on a wearable, small form factor. As a sensing platform, the ears are less susceptible to motion artifacts and are located in close proximity to a number of important anatomical structures including the brain, blood vessels, and facial muscles which reveal a wealth of information. They can be easily reached by the hands and the ear canal itself is affected by mouth, face, and head movements. We have conducted a systematic literature review of 271 earable publications from the ACM and IEEE libraries. These were synthesized into an open-ended taxonomy of 47 different phenomena that can be sensed in, on, or around the ear. Through analysis, we identify 13 fundamental phenomena from which all other phenomena can be derived, and discuss the different sensors and sensing principles used to detect them. We comprehensively review the phenomena in four main areas of (i) physiological monitoring and health, (ii) movement and activity, (iii) interaction, and (iv) authentication and identification. This breadth highlights the potential that earables have to offer as a ubiquitous, general-purpose platform.

CCS Concepts: • **General and reference → Surveys and overviews**.

Additional Key Words and Phrases: earables, hearables, earphones, headphones, earbuds, ear wearable, earpiece, ear-worn, ear-mounted, ear-attached, ear-based

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1 INTRODUCTION

Earables are wearable computing devices that are worn in or around the ear. Ear-worn devices evolved for isolated purposes, as hearing aids and personal speakers. In using the notion of "earables", we refer to devices that integrate wider capabilities, as a new type of ubiquitous computing platform. In consumer electronics,

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earphones have already become wireless at large scale, and increasingly integrate diverse types of sensors to extend their functionality [286]. Conversely, hearing aids integrate sensing to personalise sound amplification but also converge toward wireless integration with other devices [179]. These trends are mirrored in research, where earables (and synonomously "hearables") have emerged as a distinct area of investigation [77, 165, 276]. At the heart of much of the research in this new field are questions of sensing - what can be detected and observed with earables, and what interactions and applications are enabled by sensing in or on the ear?

Earables, with their specific positioning on the human body, provide a distinct platform for sensing of a wide range of properties, processes and activities. They are portable and their small and lightweight form factor allows them to be worn for prolonged periods throughout the day. The shape of the ear affords a variety of mechanical anchoring points [134, 166, 261] and the ears are less susceptible to motion disturbance and artefacts as the body stabilises the head during locomotion [121, 162]. The proximity to the brain and blood vessels enables the accurate measurement of brain activity, cyclic blood flow and related properties [98], and the inner ear cavity acts as an echo chamber to amplify internal body sounds [11]. The position of the ears on the head allows for a multitude of facial, neck, and eye muscle activations to be sensed [14] and input from head movement [14], facial gestures [221], mouth movements [320], and eye gaze to be detected [46, 272]. The ear itself is easily and comfortably reached by the hands [171, 361], while the distinctive surface area creates opportunities for a variety of touch interactions [192]. In sum, earables are capable of sensing a wide variety of processes of the skeletal (e.g., gait [27]), muscular (e.g., facial expressions [221]), nervous (e.g., brain activity [85]), endocrine (e.g., emotions [29]), cardiovascular (e.g., blood pressure [62]), respiratory (e.g., breathing [292]), and digestive (e.g., food intake [111]) systems.

We have conducted a systematic literature review of 271 peer-reviewed research articles to advance understanding of sensing with earables. Each article reviewed was classified with respect to sensing principles applied or investigated, types of information gained, and purposes to which sensing was used. Through iteration, this process resulted in the development of a taxonomy of *phenomena* sensed with earables. At the lowest level, we identified and characterised phenomena that are directly sensed with sensors placed in or on the ear as *fundamental phenomena*, including for instance motion, body temperature and blood perfusion. Other phenomena are identified as indirectly observable and derived from fundamental phenomena, ranging from physiological parameters (e.g., heart rate) and lower-level cues (e.g., earable state; in or out of ear) to conditions (e.g., stress), actions (e.g. gestures), activities (e.g. daily tasks) and other context (e.g. user identity). In total, we identified and categorised close to 50 phenomena. We show how higher-level phenomena build on fundamental phenomena, and relate this to different sensors and sensing principles that have been investigated for their observation. The result is a taxonomy that is open-ended (new sensors might emerge, and further phenomena explored) but complete in providing a clear end-to-end structure for classification of earable sensing work, from sensors employed to fundamental and higher-level phenomena and their application.

A number of recent articles have also reviewed earables research. Plazak and Kersten-Oertel reviewed the properties and affordances of earables and how they are distinct from other wearables, for input and output [276]. Choudhury provided a reflection on earable computing that draws out key opportunities and challenges [77]. Our work, in contrast, is more specifically focussed on sensing with earables, and grounded in a systematic literature review. Two other systematic reviews have been published recently. Masè et al. reviewed 39 studies of in-ear monitoring of physiological parameters, focussed on temperature, heart rate, and oxygen saturation [216]. Ne et al. also focussed on earables for health monitoring but considered a wider range of bio-signals, reviewing 92 studies to capture device characteristics versus study outcomes [243]. In contrast, we consider earable sensing broadly, not limited to health monitoring, and inclusive also of research that has been less experimental, for example demonstrating novel forms of interaction enabled by earable sensing. Our review is organised by phenomena, in four main areas of (i) physiological monitoring and health, (ii) movement and activity, (iii) interaction, and (iv) authentication and identification. For each of the phenomena we provide a clear definition and review work on how they are sensed and on applications they enable. As such, we contribute a uniquely comprehensive survey of the state of the art in earable sensing.

The remainder of the article is organised as follows. In section 2, we briefly report on our review methodology. Section 3 presents our work to structure the field with a taxonomy of phenomena. Figure 2 provides an overview of phenomena and sensors for their capture, grouped into the four main areas. Section 4 to 7 follow to provide the detailed review, for each of the four areas. This summary is followed by a discussion of cross-cutting aspects, future opportunities and challenges, and a conclusion.

2 METHODOLOGY

Informed by prior work [40, 61, 120, 174, 366], the systematic literature review was undertaken by collecting and filtering papers from the ACM and IEEE digital libraries using a set of defined inclusion and exclusion criteria and a four-eyes principle, followed by backward chaining with the same criteria applied. This process resulted in 271 relevant articles which we analysed and clustered based on a newly introduced earable taxonomy.

2.1 Paper Retrieval

We applied an initial keyword-based search on the ACM Digital Library (ACM-DL) and IEEE Xplore (IEEE-X) libraries which, to the best of our knowledge, contain the majority of wearable and HCI publications. We formulated the following definition as the overarching guideline of our survey:

> **Earables** are devices that attach in, on, or in the immediate vicinity of the ear to offer functionalities beyond basic audio in- and output.

Research areas that apply to earables but are not targeted by our survey include voice and audio interfaces as well as the technical design of audio earphones (e.g., speaker and antenna design or noise cancelling algorithms). These topics have been summarised elsewhere (e.g., voice interfaces [314], audio interfaces [104], soundscapes [140], or sonification [176]) or are not specific to the location on the ear (e.g., algorithms to translate speech to text).

We performed the queries listed below to match keywords against title, abstract and author keywords. We identified keywords by assembling a list that was expanded with additional relevant keywords found in the first 50 papers returned by both libraries. The search resulted in 210 ACM-DL and 695 IEEE-X publications. For reference, the original queries and links can be found in the supplemental material. A final query of both libraries was performed at January 21st 2022.

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query target: Title, Keywords, Abstract (ACM-DL) / Document Title, Index Terms, Abstract (IEEE-X)
keywords: earable(s), hearable(s), ear-worn, ear AND wearable(s), earbud(s), earphone(s),
          headphone(s), earpiece(s), ear(-)mounted, ear(-)attached, ear(-)based
filter: Research Article OR Short Paper (ACM-DL) / Conferences, Journals (IEEE-X)
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2.2 Selection Criteria, Filtering and Backward Chaining

As the keyword-based search does not result in a set of papers with clear definition boundaries, we agreed on explicit inclusion and exclusion criteria to manually select the relevant papers returned by the queries. First, selected papers have to fulfill the basic properties of earables in that:

(1) the device attaches in, on, or in the immediate vicinity of the ear; and
(2) sensing occurs in, on, or in the immediate vicinity of the ear.

Additionally, we exclude articles that:

(1) are not peer-reviewed, e.g. workshop proposals, theses, patents, technical reports
(2) are a bigger head-worn or off-body system (e.g., VR headsets)
(3) focus on animals
(4) are not written in English

main objective was to show the full breadth and depth of earable research contributions to date. Hence, we did not exclude papers based on number of citations, impact factor of the venue, or number of study participants.

The search produced 906 results. Two of the authors reviewed the initial results separately by reading the titles and abstracts before screening the papers by applying the above criteria. After removing 24 duplicates and one broken cross-site link the articles with positive agreement were selected for the the review (75 ACM-DL, 112 IEEE-X). Performing this step yielded an initial set of 187 papers. We then applied backward-chaining to the selected papers to account for publications that are not available in the ACM-DL and IEEE-X library or were missed by the keywords, resulting in the inclusion of papers from other publishers including Springer, Frontiers, and MDPI. Two authors scanned the references of the papers (4,854 incl. duplicates) according to the same criteria. All references were split in half and one author confirmed the selection of the other. In total, 82 additional papers were identified through this process. We added 3 further papers that the authors were aware of but that did not appear in the search process, which is a common practice [61].

After going through all papers in depth, we later excluded 10 papers – five because of severely flawed experiments and five because no evaluation was done but the claims of the paper would demand it. The described procedure resulted in our final set of 271 papers.

Venues with more than three papers were the IEEE International Engineering in Medicine and Biology Conference (EMBC) (N=28), EarComp (N=15), Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies (IMWUT) / Ubicomp (N=14), ACM International Symposium on Wearable Computers (ISWC) (N=13), IEEE Sensors (N=13), IEEE-EMBS BSN International Conference on Wearable and Implantable Body Sensor Networks (N=10), IEEE Transactions on Biomedical Engineering (N=10), MDPI Sensors (N=7), ACM Conference on Human Factors in Computing Systems (CHI) (N=6), ACM Symposium on User Interface Software and Technology (UIST) (N=6), BioCAS (N=5), Mobicom (N=4), and SenSys (N=4).

2.3 Analysis and Survey Structure

To structure the identified papers' content in a unified format, a *Google Sheets* document was assembled. Two authors went through 15 different papers each and came up with an initial suggestion for a table structure. This structure was reviewed with the remaining authors to distill the final table for data extraction (46 different columns spanning varying aspects). Then, we split all the collected papers between co-authors to fill the table accordingly, as basis for development of the taxonomy.

At the highest level, we identified four main areas of research into which we grouped papers to provide us with a top-level structure for the survey. The grouping is pragmatic and based on larger overarching themes. The largest area, in number of articles published, is physiological sensing and health monitoring. Research in this space is pursued across disciplines and has a strong measurement focus but also includes work on detection of distinct phenomena, such as teeth grinding (bruxism) and coughing. Movement and activity forms an area that is more defined by a common ground in activity analysis than any specific application domain, with most of the research stemming from the wearable and ubiquitous computing community. Interaction forms another distinct area, where research tends to be exploratory in pursuit of new means for input and interaction enabled by earable sensing. Authentication and identification is our smallest area but distinct with a research focus on biometrics captured at the ear, including physical properties of the ear itself. Figure 1 shows how the four main research areas have evolved over time. The field has grown over the past 20 years with a significant rise in activity in

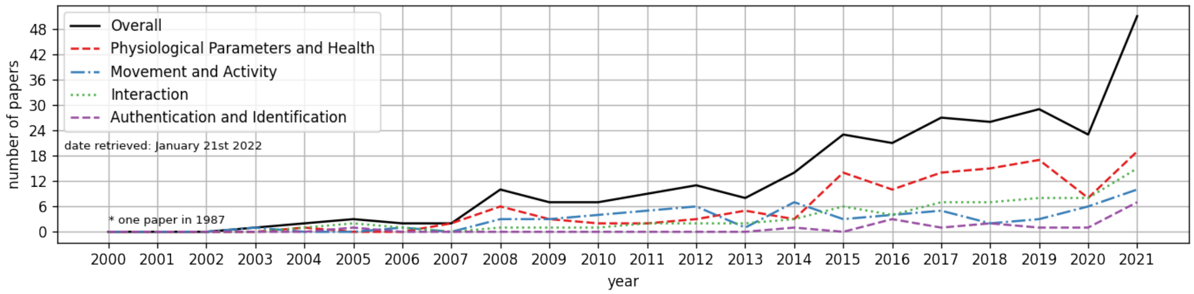

Fig. 1. Total number of papers published overall and per research area over time from 2000 to 2021.

the last 6-7 years. In every of the four main areas identified, most papers per year so far were published in 2021, underlining the growing interest in earable sensing.

For the discussion of the state of the art in this survey, we prioritise works with more study participants and signal preliminary findings where appropriate. Additionally, we list the exact number of study participants of different studies in the appendix tables. Works from the same authors with overlapping contents (e.g., follow-up paper) or the same underlying system are not filtered. Instead, we attribute overlapping contributions by citing all relevant papers while highlighting specific contributions through citations of the specific paper.

3 EARABLE SENSING TAXONOMY

There are many ways in which the research space of earables can be structured, for example by affordances [276] or features of earable platforms [288]. In our review we started by classifying work by types of sensor and purpose to which sensors were employed. In iteration, we identified phenomena, in the sense of "something that can be observed" as central for structuring the body of work, as it provides the link between sensors as the means for observation, and applications as the target. Our use of "phenomena" is comparable to the use of "context" as abstraction in sensing-based applications, however we chose "phenomena" to better encompass observation of anything from low-level physiological parameter to higher-level condition, event, state, or activity.

Figure 2 provides an overview map of the phenomena we identified, clustered into related themes and grouped into the four main areas we identified. For example, heart rate, blood oxygen saturation, blood pressure and respiration are all distinct phenomena but clustered as relating to the cardio-respiratory system. For each of the phenomena, our map captures the types of sensors that have been investigated for their observation. Our overview map also shows how many articles we found that have studied the various phenomena. For example, 49 articles have studied earable sensing of heart rate, while other phenomena have only been studied in single works (e.g., earable detection of sleep apnea, or repetition counting in fitness).

3.1 Definition of Phenomena Sensed with Earables

Table 1 provides the list of phenomena that we distilled from the earable research literature. In many cases, higher-level observations build on lower-level observations that often remain implicit. In developing our taxonomy, we have therefore analysed all selected articles in depth, to clearly identify the actual phenomena observed as well as phenomena that are derived. For each of the phenomena thus identified, we provide a clear description as point of reference for future research.

We list phenomena from lower to higher levels of observations in our table, as that allows us to show how phenomena build on each other. Phenomena that can be directly captured by a sensor are shown in boldface, and we refer to them as *fundamental phenomena* that enable observation of other phenomena. For example, blood perfusion and cardiac action potential can be sensed directly at the ear, whereas heart rate is derived from lower-level observations. We consider fundamental phenomena in more depth below.

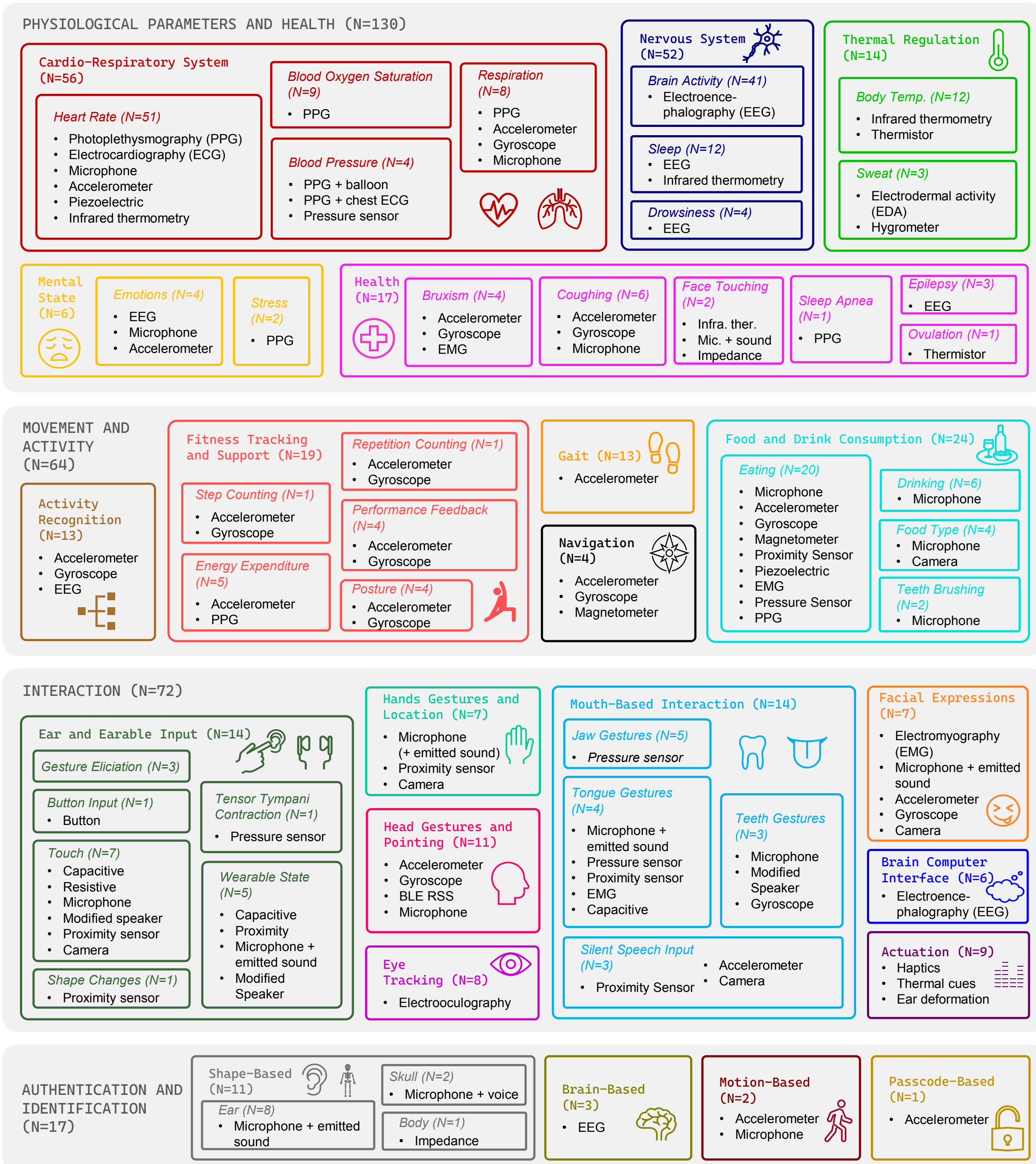

Fig. 2. Overview map of earable sensing. The map is organised by phenomena that can be captured with earable sensors. For each phenomenon, we list the number of articles found in our survey, and the different types of sensor used. Phenomena are clustered in relating to common themes or systems, and grouped into four main categories.

Table 1. Definition of phenomena investigated with earables. Boldface denotes fundamental phenomena that can be observed by sensors and that enable observation of higher-level phenomena.

Category	Phenomena	Description
Body Functions	**Blood Perfusion**	passage of blood through organs and tissue to deliver oxygen and nutrients
	Cardiac Muscle	muscles involved in the contraction of the heart stimulated by cardiac action potential
	Heart Rate	heart contraction frequency varying upon physiological and psychological conditions
	Blood Pressure	pressure created by the heart pushing blood against the walls of the arteries
	Oxygen Saturation	percentage of oxygenated hemoglobin relative to the overall hemoglobin in blood
	Respiration	gas exchange through breathing characterized by inhalation of oxygenated air and exhalation
	Brain Activity	neural activity of the brain emitting electrical signals in response to stimuli or conditions
	Body Temperature	safe range that varies slightly during activities or physiological states (e.g., sports, illness)
	Sweat	water secreted on skin for thermoregulation and in response to psycho-physiological arousal
	Energy Expenditure	energy burned by physical activity and by sustaining human life (e.g., heating the body)
	Sleep, Drowsiness	different stages during sleep, the daily change from wakefulness to sleep, and drowsiness
	Ovulation	can be associated with the highest fertility during the menstrual cycle
Sound	**External Sounds**	sounds occuring externally of the user's body e.g., in public settings by others
	Emitted Sounds	sounds that are emitted by the earable and are then sensed (e.g., sound reflection in ear canal)
	Body Sounds	sounds occuring inside or by the wearer e.g., while chewing or when tapping the ear
Movement / Location	**Motion**	change of position and orientation of an object in space over time, mostly the body
	Navigation	track the movement of a user to compute past and future path or give directions
	Head	movement of the head in different directions limited by the anatomical abilities of the body
	Facial Muscles	contraction of facial muscles to move different parts of the face (e.g., lips, jaw)
	Facial Expressions	conscious and subconscious positioning of facial muscles (e.g., to express emotions)
	Jaw, Teeth, Tongue	conscious and subconscious movement of the jaw, teeth, and tongue (e.g., eating, clenching)
	Eyes	conscious and subconscious movement of the eyes (e.g., gazing, sleep)
	Hands	positioning of the hands and fingers in space over time
Ear	**Shape**	unique shapes of the outer, middle and inner ear and skull around the ear specific to a person
	Deformation	possibility to deform the soft auricle by hand and also ear canal during, e.g., facial activities
	Touch	bring the hands or earable in contact with the skin on and around the ear
	Proximity	distance measured from the ear to other objects (e.g., hands) or ear canal and changes thereof
	Manipulation	manipulation of the ear or earable to perform input
	Earable State	position and status of an earable (e.g., in-/outside the ear, ready for input, etc.)
Mental State	Emotion	feelings and thoughts of a person associated with their physical and psychophysiological state
	Stress	overload of a person's ability to cope with mental or physical demands effectively
Health Conditions	Bruxism	grinding of teeth and clenching of the jaw, many times during the night
	Coughing	ejection of air from lungs with sudden noise to free the lungs from mucus and other particles
	Sleep Apnea	involuntary interruption of breathing during sleep from a few seconds up to minutes
	Epilepsy	commonly associated with episodic abnormal neural activity resulting in, e.g., body shaking
Activities	Posture	static position held by a person while standing, sitting or laying down
	Gait	motion of limbs during locomotion which may be impaired, e.g., due to skeletal malfunctions
	Fitness Activities	activities related to personal fitness or higher physical exertion to track repetitions and execution
	Everyday Activities	activities that occur or are executed daily that can be tracked (e.g., desk work)
	Eating	consumption of foods by bite, chew, and swallow and the detection of foods and intake progress
	Drinking	consumption of liquids (incl. liquid foods) sip and swallow
	Tooth Brushing	brushing of the teeth for oral hygiene to prevent caries
Identity	User Identity	uniqueness of an individual among others based on person-specific properties (e.g., ear shape)
Action	Gestures	movement of parts of the body (e.g., head, hands, jaw) to accomplish input
	Silent Speech	speak words and sentences by moving the mouth and tongue without vocalizing speech sounds
Vision	**Body Appearance**	looks of the user's body which give information about presence, state, or identity
	Object Appearance	looks of surroundings which give information about presence or state of objects

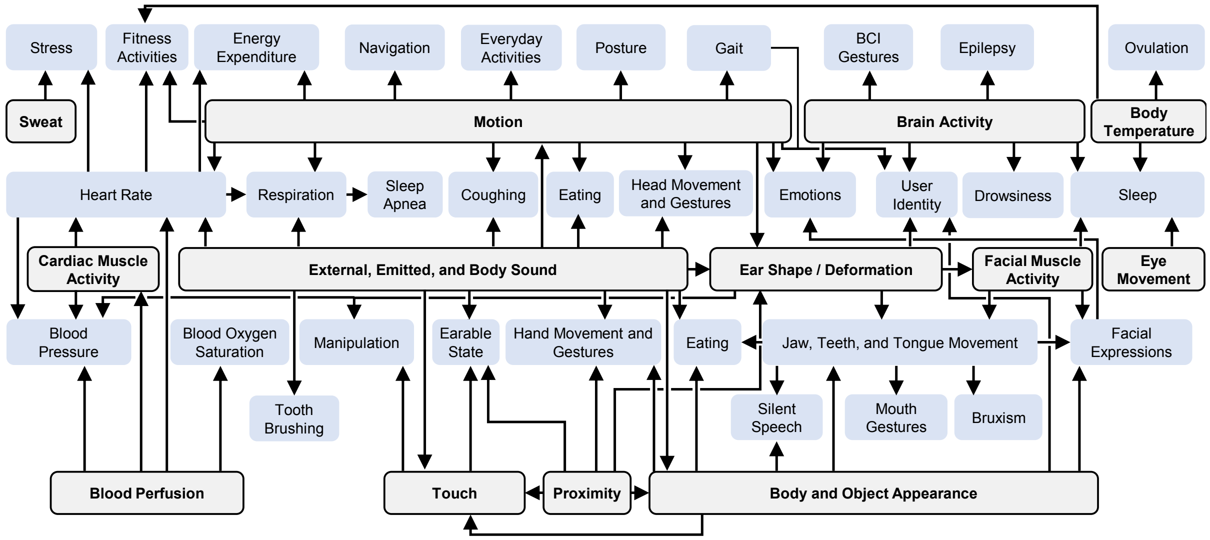

Fig. 3. Flow diagram showing how different phenomena can be inferred. The arrows indicate how lower-level phenomena support higher-level observation. The grey boxes represent "fundamental" phenomena that can be directly sensed and from which all other phenomena can be derived.

We also identify categories to capture the principal types of phenomena. A wide range of earable sensing work is, for instance, focused on monitoring of body functions. These are interesting as they focus on physiological parameters as observations at a lower level of abstraction that directly underpin applications concerned with their monitoring. Other categories relate to sensing modalities such as sound, movement and vision, with sound listed at a lower level as it contributes to observation of a wide range of other phenomena. A category of particular note is "Ear" as it encapsulates phenomena that relate to the ear or earable device as such, for example the unique shape of the ear channel, or the manipulation of either the ear or the ear-worn device.

In the ubiquitous computing field, lower-level observations are often referred to as "cues" that contribute to inference of "higher-level context". We see similar relationships in our schema, where other categories such as mental states, health conditions, activities and identity describe higher-level contexts. However, across the body of work we examined, phenomena of interest are viewed at different levels of abstraction and we therefore avoid any layering into cue versus context. The same phenomenon may be considered low level in one application and high level in another.

Figure 3 shows the relationships we identified between phenomena. Fundamental phenomena that can be directly sensed are shown as grey boxes, with other phenomena in blue. For a range of phenomena, the relationship appears straightforward, for example with posture or gait derived from motion. However, phenomena build also in less obvious ways on each other. Observation of heart rate, for instance, can be based on observation of cardiac muscle activity, blood perfusion and sound but in turn also contributes to observation of a spread of phenomena including blood pressure, respiration and fitness activity. Another example is ear canal shape deformation which feeds into detecting jaw, teeth, and tongue movements which enables the observation of higher-level phenomena such as eating, bruxism or silent speech detection. Simultaneously, the ear's distinct shape can also reveal the user's identity. While changes of ear canal shape can be quantified directly using piezoelectric or pressure sensors, it may also be sensed indirectly by measuring motion changes over time or by characteristic sound reflections emitted in the enclosed ear canal.

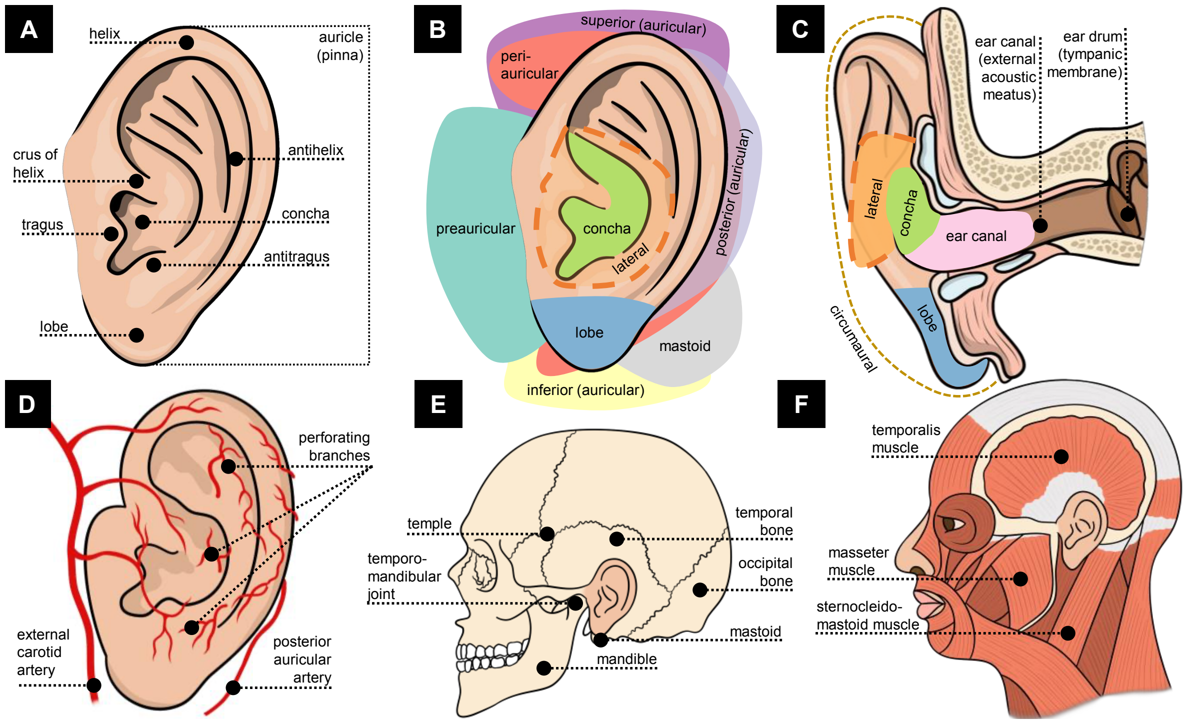

Fig. 4. (A - C) ear anatomy and unifying positioning terminology; (D) arterial network; (E) skull bones; (F) muscles.

3.2 Fundamental Phenomena and Sensing Principles

Figure 3 highlights how the observation of a wide range of phenomena is grounded in a relatively small set of fundamental phenomena. These fundamental phenomena are sensed either directly or indirectly from different sensors attached in, on or in the immediate vicinity of the ear. However, the phenomena labelled as fundamental may also be inferred from other fundamental phenomena in addition to being (in)directly sensed. For instance, "Touch" is classified as a fundamental phenomenon because it can be captured directly with specific sensors (see Table 3). However, we also found "Touch" to be inferred indirectly, for example from sound captured with a microphone or visual appearance of body and hand captured with an ear-mounted camera.

Table 2 provides a detailed definition for the fundamental phenomena we identified, explaining the physiological mechanisms on which their observation is based. The description makes reference to the anatomy of ear and head, for which we refer the reader to Figure 4. The table provides a comprehensive overview of the foundations on which earable sensing is based. Note also specifics, for instance how external, emitted and body sound leverages earable sensing differently.

Table 3 provides a list of the different types of sensors that we found reported in the earables literature, grouped into general categories. For each sensor, we provide a description of the sensing principle for reference. Each sensor directly relates to sensing at least one of the fundamental phenomena, however some fundamental phenomena can be sensed with a wide variety of sensors. For example, ear canal deformation can be sensed using a barometer to detect the in-ear pressure, through proximity sensors which measure the in-ear distances, or through accelerometers and gyroscopes as the ear canal deforms during jaw movements.

The list of sensors also completes the circle to the overview map of our taxonomy (Figure 2), where we mapped out the range of phenomena with the different types of sensors used for their observation. The taxonomy provides

Table 2. Fundamental phenomena from which all other phenomena can be derived on the earable platform.

Fundamental Phenomena	Description and Underlying Physiological Mechanisms
Blood Perfusion	The ears are characterized by thin tissue and visible blood vessels (see Figure 4 D) enabling the observation of cyclic blood flow and related properties [42]. The perfusion of the middle ear is excellent in comparison to the peripheral perfusion of other body parts [343].
Cardiac Muscle Activity	Due to the conductive characteristics of the body, the cardiac action potential created by the heart is propagated throughout the body up to the ear [127, 306, 369].
Brain Activity	The area around the ear, the concha, and the ear canal are closely located to the brain, which allows capturing its electric activity, commonly resulting in sinusoidal waves that are also called brain waves [46, 157, 330]. It provides access to the brain's response upon auditory and visual stimulation [157, 245]
Body Temperature	The close proximity to the carotid artery results in the tympanic membrane having a temperature close to core body temperature [51] (see Figure 4 C and D). Additionally, the ear canal and an earbud create a confined space in which temperature stabilizes [202].
Sweat	The area around the ear has high sweat-gland density relating to stress and physical exertion [313]. Sweat gland activity is not symmetric and different between both ears [274].
External / Emitted / Body Sound	Activities occurring close to the ear (e.g., chewing sounds or tapping around the ear) are transmitted by body sounds, or bone conduction [11, 361]. The cavity created by the ear and an earable generates a natural echo chamber that amplifies body-internal sounds [182, 261], while external sounds are dampened [261, 263]. Sounds that are actively emitted from a device at the ear result in characteristic sound reflections that are utilised by different phenomena, including detection of ear canal deformation [10]. Compared to smartwatches and smartphones, earables are less susceptible to motion-induced sound artifacts [232].
Motion	The ear provides a robust and stable attachment point [65] with few vibrations and random movement artifacts [96] when detecting motions across the body and at the ear. This includes motion induced by the ear canal deforming (e.g., during facial expressions [344]).
Facial Muscle Activity	Sensing of facial and neck muscles can be achieved via electrical potential changes in the area around the ear [221], which is closely located to the temporalis, masseter, and steroncleodmastoid muscle (see Figure 4). Facial muscles deform the ear canal [14].
Ear Shape / Deformation	The fine structures of the ears are unique enough between different users (see Figure 4 A) for the purpose of biometrics [31, 275]. Additionally, the ear canal deforms during head, face, mouth, teeth and jaw motions and muscular activity [14, 39, 119, 255], e.g. upon movement of the temporomandibular joint (see Figure 4 E).
Touch	The unique structure of the ear and the earable itself create a surface for interaction and are easily reached by the hands which affords touches by the user [171, 192].
Proximity	The ear offers a fixed reference point from which distance to external objects can be measured, or their presence inferred [227]. In addition, in-ear based proximity sensors can be used to detect ear canal deformation [39].
Eye Movement	The standing potential of the eyes and, upon movement of the eyes, changes thereof can propagate to the ear [46].
Visual / Object Appearance	The location at the ears can capture the field of view of the wearer and also the broader area around them which contains visual information about the appearance of the surroundings [193] and can also determine touch [171].

Table 3. Sensors can quantify or measure different fundamental phenomena that were identified in Table 2 and Figure 3. Some fundamental phenomena can still be inferred from other fundamental phenomena.

	Sensor	Description	Fundamental	Inferred Fund.
Motion	Accelerometer	Inertial acceleration of a body on one or more axes to measure body motion changes and ear canal deformation motions relating to facial muscle activity.	Motion	Ear Deformation, Facial Muscle Activity
	Gyroscope	Angular rotation of a body on one or more axes to measure body motion changes and ear canal deformation motions relating to facial muscle activity.	Motion	Ear Deformation, Facial Muscle Activity
	Magnetometer	Magnetic field on one or more axis relating to body motion changes	Motion	-
Audio	Microphone	Sound transmitted through air or occurring within the body of the user. Such sounds can relate to touching.	External and Body Sound	Touch, Motion
	Microphone + emitted sound	Reflected sound signals of an emitted sound (e.g., constant tone) corresponding to ear shape and deformation with facial muscle activity	Emitted sound	Ear Shape / Deform. Appearance, Facial Muscle Activity
	Modified Speaker	Modification of a speaker to sense sounds that actuate the speaker's membrane. Such sounds can be leveraged to sense touch.	External and Body Sound	Touch
Optical	Photoplethysmography (PPG)	Absorption of emitted light corresponding to blood perfusion (possibly at different light frequencies).	Blood Perfusion	Cardiac Muscle Activity
	Infrared Thermometry	Temperature based on thermal radiation without physical contact, commonly obtained at the tympanic membrane.	Body Temperature	Blood Perfusion, Appearance, Touch
	Proximity Sensor	Distance to objects in close proximity with no physical contact to observe appearance which can sense deformation and touch.	Proximity	Ear Deformation, Touch, Appearance
	Camera	Capture images to sense visual appearance of surroundings (e.g., hands), contact to the skin, or deformation of the face.	Visual Appearance	Touch, Facial Muscle Activity
Biopotential	Electroencephalography (EEG)	Electrical potential changes of the brain created by neurons in response to external stimuli (e.g., visual) or internal processes (e.g., sleep, emotions).	Brain Activity	Motion
	Electrooculography (EOG)	Movement of the eye's standing potential (dipole) and eye lid by change of potential around the eyes measured at the ear.	Eye Movement	-
	Electrocardiography (ECG)	Electrical potential of the heart produced by cardiac muscle contraction that propagates through the body.	Cardiac Muscle	-
	Electromyography (EMG)	Electrical potential generated by muscle cells during contraction to sense the activity of muscles around the ear and of the face.	Facial Muscles	-
	Electrodermal Activity (EDA)	Changes of skin lead resistance upon secreted sweat in response to psychological or physiological arousal.	Sweat	-
	Impedance	measures the impedance of current influenced by tissue	Touch	Appearance
Environmental	Thermistor	Temperature as resistance change, commonly attached on the object to be sensed, or inside a confined space such as the ear canal.	Body Temperature	-
	Hygrometer	Measures humidity as the concentration of vaporized water in air which corresponds to sweat secreted by the skin in the ear canal	Sweat	-
	Barometer	Measure air pressure in the ear canal to sense deformations that corresponds to facial muscle activity.	Ear Deformation	Facial Muscle Activity
Electrical	Piezoelectric/ -resistive	Sense change of electric charge / resistance upon mechanical stress relating to motion of ear deformations and facial muscle activity.	Touch, Motion, Ear Defor.	Facial Activity
	Capacitive	Sense change by capacitive coupling to a conductor or materials with different dieletric properties, such as the finger.	Proximity, Touch	-
	Button	Outputs a binary state or pressure force level.	Touch	-
	BLE RSS	Bluetooth signal strength between two devices.	Proximity	-

a clear structure based on sensors, fundamental phenomena, higher-level phenomena, and their relationships. In the remainder of this article, we draw on the overview of phenomena to structure our review of earable sensing literature. For future research, we expect our taxonomy to provide a reference scheme for new work in the field, for which the taxonomy will naturally be extensible for other sensors and phenomena of interest.

4 PHYSIOLOGICAL PARAMETERS AND HEALTH

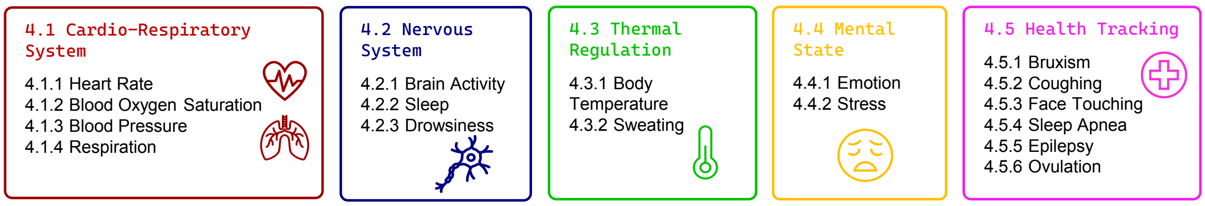

Fig. 5. Structure of the *Physiological Parameters and Health* section according to different functions of the human body.

Physiological parameters are indicators of an individual's health status, which has been explored heavily together with earables. The following sections are structured according to functions of the human body (see Figure 5). They describe the technical realization and applications of various bodily phenomena detected by sensors attached to the ear motivated by tracking and maintaining personal health.

4.1 Cardio-Respiratory System

The cardio-respiratory system resembles a close coupling process between two biological phenomena: blood flow and breathing cycles. The following sections will introduce the technical realization and applications of heart rate, blood oxygen saturation, blood pressure, and respiration sensing on the ear.

4.1.1 Heart Rate. Heart rate (HR) is an indicator of the cardiovascular and the autonomic nervous system and, therefore, a vital sign that is influenced by physical fitness, diets, and the overall health [339]. It describes the frequency at which the heart contracts and relaxes. A typical heartbeat consists of multiple characteristic waves (most importantly P-, QRS-, and T-waves [127]). Typically, the heart rate is identified from the R-wave and reported in beats per minute (bpm), with adults having an average resting heart rate of 60-100 bpm [368]. Heart rate variability (HRV) is the variability in the beat-to-beat time intervals which can predict cardiovascular diseases and mortality [332, 333]. HRV is reported in milliseconds (ms), with adults typically having an average resting HRV of approximately 20-200 ms [177, 251].

Heart Rate - Sensing. Table 4 compares seven earable heart rate sensing principles based on the results of 44 studies (for details, see Appendix A). The different sensor locations, experimental protocols, experimental conditions, and performance metrics reported across papers only allow an ordinal comparison of accuracy and robustness (low, medium, high). In our work, we define "high accuracy" as medical-grade accuracy in the resting condition (e.g., mean error < 10% [18, 254]). Robustness refers to the stability against motion artifacts. The following paragraphs will describe the advantages and disadvantages of the different sensing principles in further detail.

Photoplethysmography (PPG) measures the blood volume change by illuminating the skin and then tracks changes in the reflected or transmitted light. The proximity between the brain and ears offers an arterial network that is ideal for heart rate sensing in comparison to other locations that are subject to peripheral perfusion (see Figure 2). At the same time, PPG affords sensing other phenomena such as blood pressure (see subsubsection 4.1.3), blood oxygen saturation (see subsubsection 4.1.2), and even respiration (see subsubsection 4.1.4). In general, a

Table 4. Comparison of heart rate sensing principles. Accuracy based on comparison to medical gold standard under resting conditions. Robustness refers to the robustness against body movements. PPG = Photoplethysmography, ECG = Electrocardiography, Mic. = microphone, Acc. = Accelerometer. N = Number of studies

Sensor	Accuracy	Robustness	Advantages	Disavantages	Best Location	N
PPG	high	moderate	supports pulse oximetry, blood pressure, and respiration rate	sensitive to motion but can be filtered up to some degree	ear canal	29
ECG	high	moderate	gold standard for HR & HRV, most detailed heart activity	does not work for everyone, obtrusive, requires multiple electrodes	ear canal, mastoid	8
Mic.	medium	low	off-the-shelf	sensitive to motion but can be filtered up to some degree	ear canal, circumaural	5
Acc.	medium	low	off-the-shelf, filter movement supports activity tracking	highly sensitive against movement	posterior	2
Piezo	high	low	configurable ear shapes robust against temperature	highly sensitive against movement, requires pressure to the skin	ear canal	1

PPG sensor location in the ear canal is preferable even though it may be sensitive to jaw motions [98, 347]. Other non-ear-obstructing locations with sufficient accuracy are at the tragus, the ear lobe, and the area posterior to the ear (see Appendix A). Accuracy-wise, earable PPG devices can meet official medical standards in resting and moving conditions. Most resting state studies reported error scores of less than 1 bpm mean error [98, 270, 309, 334, 341, 343, 345–347] which even outperforms wrist-worn PPG [273, 282]. Within-subject studies showed that PPG performance decreases with motion artifacts introduced by body movement [98, 279, 309, 334, 365], facial movement (e.g. talking) [134, 204, 279], or music listening [278]. While several studies report accuracy scores of less than 10% mean error under motion noise [204, 270, 309, 309], other studies exceed the acceptable range of medical standards (e.g., [98]). Two promising pathways for reducing earable PPG motion artifacts are the use of accelerometers [70, 201, 270] and machine learning based calibration procedures [201, 323, 369].

Electrocardiography (ECG) measures the contraction of the cardiac muscle and the resulting electrical activity with electrodes on the skin surface [316]. ECG provides the highest resolution of heart rate activity and is, therefore, considered the gold standard for conventional medical measurement. A handful of studies on earable ECG reported acceptable performance (see Appendix A) with peak delays of only 50 ms [322]. The ear canal was recommended as the best location for earable ECG [348]. Still, some evidence exists that ECG waves can also be measured at the mastoid [145, 369] and posterior ear position [69]. However, Jacob et al. [145] could not identify the fundamental heart beat frequencies for 6 out of 13 study participants. Additionally, multiple ECG-electrodes are required on the skin (not necessarily on the head), which leads to the conclusion that earable PPG offers significant advantages over ECG with regards to obtrusiveness, generalizability, and possible accuracy.

Microphones, in most cases electret condenser microphones [93, 215], record air-conducted (and by modification also bone-conducted [117]) sound pressure waves elicited by mechanical pulsation of the ear-canal blood vessels. The recorded audio signal is processed with filtering algorithms for low (<24Hz) and recurring frequencies [93, 248], or other denoising algorithms [57, 215]. One advantage is that microphones are commonly built into commercial earbuds. Fan et al. [93] developed a device that plugs in between a smartphone and any off-the-shelf headphone to derive heartbeats from small voltage changes. Most studies report errors below the 10% range (Appendix A). However, the performance of microphone-based heart rate sensing is generally lower than earable PPG. Moreover, it has low robustness against motion artifacts (ME=7.5 bpm) [248]. As a result, microphones should only be considered as a cost-efficient and off-the-shelf alternative to PPG sensors.

Accelerometers measure heartbeats through recurring mechanical vibrations that result from the blood volume change [134, 256]. Similar to microphones, they are built into several off-the-shelf earables (e.g., eSense [166]). He et al. [134] found high regression coefficients for the R- and J-waves but lower coefficients for the PPG-measured stroke volume. Such accelerometers are also useful for filtering out motion artifacts of other heart rate sensors [70, 133, 201, 270] (see above).

Moreover, Park et al. [262] used piezoelectric sensors for measuring the heart rate via the variance of surface pressure in the ear canal. The authors found showed high accuracy scores on a large sample size when the user is at rest.

None of the sensing principles have high robustness against body movements. PPG and ECG are evaluated as moderately robust because they had less decline in accuracy compared to other sensing principles and still enabled an overall identification of the heartbeats. Overall, a combination of PPG sensors in the ear canal and accelerometers that control for motion artifacts seems most promising for earable heart rate sensing.

Heart Rate - Applications. Most earable heart rate publications were motivated by the possibility to continuously monitor cardiovascular functions (e.g., [127, 262, 278]). Other use cases are monitoring of stress ([126, 201, 323, 323], see subsubsection 4.4.2), energy expenditure ([183], see subsubsection 5.2.2), and exercising [248, 335]. Heart rate measured at the ear also gives insights into respiration-related events (see subsubsection 4.1.4 and subsubsection 4.5.4).

4.1.2 Blood Oxygen Saturation.

Delivering oxygen-bound hemoglobin to different cells of the body is vital to human life [355]. The proportion of oxygenated hemoglobin (saturated) to the total amount of hemoglobin molecules in the arteries (saturated and unsaturated) is defined as blood oxygen saturation, and is reported in percent (%).

Non-invasive methods commonly measure the peripheral oxygen saturation (SpO_2) based on computing the difference of absorbed light at two wavelengths by Photoplethysmography (PPG). In medicine, the earlobe is a popular and reliable location to obtain transmissive PPG-based SpO_2 measurements as light can be emitted on one side of the ear, whereas the absorption is determined on the other side of the tissue [355]. However, transmissive PPG is limited to the auricle, as the emitting LED and the light sensor are placed on opposing sides of the skin. Therefore, earables commonly use reflective PPG sensors that measure the amount of light reflected back to the emitting probe.

Appendix B shows that acceptable accuracy can be achieved by reflective PPG at rest on the earlobe [204], and in the ear canal [42, 98] based on ground truth finger SpO_2 measurements (< 2% error according to FDA [**?**]). Besides, PPG sensors posterior of the ear could also measure reliable values in a range between 70% - 100% evaluated according to gold standard arterial blood gas values (SaO_2) [58]. PPG to sense blood oxygen saturation suffers from the same problems as described in the previous heart rate section (see subsubsection 4.1.1), such as degraded performance by motion artifacts when walking or during jaw movement [98, 347].

Based on the blood oxygen saturation of the wearer, it was suggested to perform sleep apnea detection [343], see subsubsection 4.5.4. Other possible applications include vital signs tracking and alerting [32, 42, 204] foreseeing diseases [125, 347], and unobtrusively monitoring the oxygen dosage of patients [175].

4.1.3 Blood Pressure.

The circulatory system transports nutrients to all parts of the body while the pressure generated by the heart pumping plays a decisive role as the driving force. This pressure is known as blood pressure [224]. High blood pressure (hypertension) is a known risk factor of cardiovascular diseases and even death which makes it an important vital sign to track [253]. The blood pressure during systole (contraction) and diastole (relaxation) is called systolic blood pressure (SBP) and diastolic blood pressure (DBP), respectively. Historically, medicine reports blood pressure in millimeters of mercury (1 mmHg = additional pressure by 1 millimeter of mercury).

In related work, Teng and Zhang [329] showed a strong relationship between blood pressure and the time of pulse propagation from the heart to other locations of the body. Therefore, a PPG sensor worn on the ear and a traditional chest-worn ECG makes it possible to compute the Pulse Transit Time (PTT) and hence, blood pressure [125]. Selvaraj [305] demonstrated by regression analysis that PPG measured on the earlobe gives about similar results as the finger to compute PTT yielding a weak correlation between PTT and SBP / DBP ($r < 0.3$, see Appendix C).

In a concept study it was suggested to measure blood pressure in the sealed ear canal based on pressure sensing with initially encouraging results [367]. The feasibility and precise performance of the principle remains to be evaluated.

The aforementioned approaches prerequisite chest-worn ECG or sealing the ear canal which reduces everyday wearability. Bui et al. [62] introduced *eBP* to measure blood pressure using an ear-worn device only. Very similar to cuff-worn blood pressure sensing [113], eBP places an inflatable balloon in the ear canal of the user. An evaluation with 35 users showed that eBP yields an average error of 1.8 mmHg and −3.1 mmHg and a standard deviation error of 7.2 mmHg and 7.9 mmHg for SBP and DBP, respectively). Though these results are promising, the acceptable accuracy for at-home blood pressure devices was defined to be ±3 mmHg in other works [137].

The primary purpose of ear-worn blood pressure is a frequent assessment throughout the day as diseases may be episodic and related to specific activities [62, 125, 305]. Compared to traditional cuff-based monitors, ear-worn blood pressure monitoring minimizes the impact during regular activities while maximizing comfort [62, 305].

4.1.4 Respiration. For oxygen gas exchange, the human chest rhythmically expands to perform inspiration (breathing in), followed by passive relaxation of the chest wall for expiration (breathing out) [60]. This process is referred to as *respiration*. Two key characteristics of respiration are inhaled and exhaled volume of air as well as rate. The number of breath cycles per time interval is commonly reported as cycles per minute (CPM). From medical research, it is known that particularly high or low breathing rates (< 8 CPM, > 24 CPM) can be associated with underlying health problems [80]

Respiration rate was quantified by earables based on inertial-, audio-, and heart beat-based sensing which will be introduced in the following (see Appendix D).

As breathing is a biomechanical process, it produces tiny body movements and friction-induced sounds when the air enters and leaves the lungs. Röddiger et al. [292] initially reported 2.62 and 2.55 CPM mean absolute error (MAE) by filtering respiration-related body motions at the ear from accelerometer and gyroscope data. This inertial sensing approach was highly dependent on the underlying motion and only suitable when the user is at rest. Therefore, Ahmed et al. [2] improved the performance by automatically selecting the best sensor and filtering out windows with too much motion which reduced the MAE to 1.62 CPM. Alternatively, a microphone embedded in the ear canal could sense sounds propagating through the body during the respiratory cycle at 2.7 CPM MAE [215]. It was reported that such acoustic respiration rate measurements were reliable above approximately 12 CPM [117]. Subtle respiration-induced changes in the cardiac cycle may be measured on the ear to indirectly derive respiration rate through PPG amplitude changes, blood oxygen variations, or the respiratory sinus arrhythmia [42, 341, 343]. From earable heart beat PPG signals, respiration rate was predicted at -0.558 ± 1.406 CPM mean error at the ear canal at rest [42] and around 3 CPM error in the ear canal, concha, and posterior auricular under varying motion activities [98]. With increasing motion, the performance of PPG-based respiration rate estimation decreased [98]. PPG-based sensing then could also be used to classify the more granular inspiration, and expiration phases at 81.5% sensitivity and 86% specificity [341].

The performance differences across sensing principles are relatively small. The U.S. Food and Drug Administration (FDA) acceptance criterion for non-vital signs respiration monitors requires a maximum error of ± 2 CPM [191] (or 10-20% of typical human CPM frequency). While sound-based respiration rate prediction with earables can not achieve such accuracy, inertial and PPG-based respiration rate estimation appears to be acceptable when the user is at rest.

From the application perspective, reasons to obtain respiration from the ear include the detection of interruption of breathing during sleep (see subsubsection 4.5.4) [292, 343] and more generally monitoring the vital respiratory state of the user for alerting [42, 341] or of workers in hazardous environments by embedding the sensor in hearing protection for faster intervention [215].

4.2 Nervous System

The nervous system sends and receives electrical and chemical signals to control body functions and cognitive processes [236]. The resulting electrical fields can be measured on the skin surface by Electroencephalography (EEG) to extract a user's response to external stimuli internal states. Such states include sleep stages and the sleep-wake cycle. The following two sections will introduce earable brain activity sensing and sleep tracking.

4.2.1 Brain Activity. Sensing the brain activity of a person based on standard testing protocols is used for diagnosing a number of neurological and psychological disorders [129, 237]. Additionally, brain activity sensing enables higher-level applications such as sleep (see subsubsection 4.2.2) and emotion (see subsubsection 4.4.1) tracking, seizure detection (see subsubsection 4.5.5), brain-based authentication and identification (see subsection 7.3), as well as brain-computer interfaces (see subsection 6.7).

Brain Activity - Sensing. EEG measures the electric field potential caused by characteristic brain rhythms (also called brain waves) that correspond to a user's internal state or response to external stimuli [49]. The standard procedure to capture brain waves is Electroencephalography (EEG). Conventional EEG relies on a full-scalp setup worn all around the user's head which is obtrusive and not easily portable. In contrast, a smaller number of electrodes in (e.g., [117]) or around (e.g., [46]) the ear can still capture a subset of interesting brain waves. Generally speaking, related ear EEG works have shown that in comparison to scalp EEG, brain activities primarily occurring in the temporal and occipital lobe around the ear can be recorded successfully [46, 47, 170]. Overall, the reduced size of earable EEG compared to conventional EEG results in several advantages by being more discreet, unobtrusive, robust, user friendly, and feasible [46, 197].

Slight performance differences with regards to impedance and usability aspects specific to the possible electrode positions and accompanying form factors have emerged. For example, 9 out of 10 devices in the posterior and periauricular region have a generic form factor that fits on the skin around the ear. Similarly, 10 out of 12 devices in the ear canal are implemented as generic soft earplugs. In contrast, 19 out of 21 concha-placed ear EEG devices are custom fit to the wearer as the unique structure of the concha creates a challenging fit across users. Still, electrodes placed in the concha were more prone to lose contact than in the ear canal [160]. Furthermore, EEG placed inside the ear leverages it as a mechanical anchoring point (e.g., [47, 117, 229]), whereas EEG around the ear often demands gluing the electrodes onto the user's skin (e.g., [46, 213, 250]). While generic in-ear EEG can fit many different users, there is some preliminary evidence that custom-fit earplugs are more sensitive than generic ones [163, 168]. At the same time, generic ear EEG worn around the ear was found to be more sensitive than generic in-ear EEG [41].

Across ear EEG locations and styles, 23 dry and 21 wet electrode setups were identified. Dry electrodes improve the comfort of the user and simplify attachment. However, they have reduced impedance or sensitivity depending on the electrode material and compared to wet electrodes [28, 156, 158]. Additionally, the presence of cerumen was found to increase dry-contact impedance by 86% [268]. In general, the close vicinity of the ear to facial muscle potentials [35], as well as eye movement and blinking artifacts [46, 92, 164] can result in noise which was recommended to filter out in related earables works.

Table 5. Standard EEG protocols that have been evaluated on the ear using generic form factors that can fit any ear and devices that have to be custom fit to the user. Ear EEG applies wet and also dry electrodes. The feasibility of standard EEG protocols shows the general feasibility and enables higher-level applications. In brackets is the number of studies that confirmed the paradigm. A detailed overview of ear EEG papers and placements can be found in Appendix E.

Electrodes		**Auditory Stimulus**				**Visual Stimulus**		**Task**
		P300	MMN	ASA	ASSR	P300	SSVEP	AAR
Generic	Dry	✓(3)	✓(1)	-	✓(7)	✓(1)	✓(4)	✓(5)
	Wet	✓(3)	-	✓(1)	✓(4)	✓(3)	✓(6)	✓(4)
Custom	Dry	-	✓(1)	✓(1)	✓(6)	✓(1)	✓(5)	✓(6)
	Wet	✓(3)	✓(2)	-	✓(6)	✓(2)	✓(3)	-
Example Application		psychological / neurological disorders [129]	psychological / neurological disorders [237]	spatial audio hearing aids [100]	brain-computer interfaces [136]	psychological / neurological disorders [129]	brain-computer interfaces [3]	sleepiness / drowsiness detection [46]

Note: Other applications based on EEG are introduced in subsubsection 4.2.2 (sleep), subsubsection 4.4.1 (emotions), subsubsection 4.5.5 (seizures), subsection 7.3 (brain-based authentication and identification), and subsection 6.7 (brain-computer interfaces). P300=Positive deflection in brain potential; MMN=Mismatch Negatively; ASA=Auditory spatial attention; ASSR=Auditory steady state response

As to be expected, no works looked into the feasibility of ear EEG on the auricle. Overall, the different design aspects of ear EEG allow to make trade-offs between form factor, fit, ease of application, comfort, and desired accuracy.

Brain Activity - Applications. Table 5 gives an overview of earable EEG implementations and lists standard protocols that were conducted to show the general feasibility of EEG on the ear (see Appendix E for details). It also links to other sections that summarize more concrete applications. Generic, dry ear EEG is most generally applicable in day-to-day usage, while custom-fit ear EEG devices with wet electrodes are more likely to be relevant for clinical usage.

In EEG research and clinical practice, auditory, visual, and somatosensory (i.e., haptic) cues are applied to trigger an expected response of the patient's brain [299]. As it stands, little insights are available about the response to somatosensory stimuli. However, it was initially shown that skin impedance decreases in response to tactile stimulation [268]. Nonetheless, a variety of auditory and visual stimulus paradigms have been confirmed to be feasible in and around the ear, which will be described in the following.

In a clinical diagnostic context, the P300 response has been associated with dementia, schizophrenia, anxiety disorders, and more [129]. Presenting a deviant stimulus among continuous auditory or visual signals triggers a so-called transient P300 response which is a positive deflection in brain potential approximately 300ms after the deviant stimulus is presented [321]. Auditory P300 was confirmed by multiple earable studies even several hours after initial attachment [46]. Visual P300 with ear EEG was visible in response to letters [47], words [250], symbols [197], LED lights [116, 117, 170], and black/white checkboards [123]. Similarly, Mismatch Negativity (MMN) has clinical relevance for diagnosing schizophrenia or aging [237] and represents a negative EEG amplitude deflection. It targets the lower-level discrimination abilities without the user having to actively focus their attention on a stimulus. Kappel et al. [160] found that a reference electrode on one ear is required to capture a significant MMN response on the other. As such, visual attention or resting may be predicted directly from ear EEG at >70% accuracy [269]. In sum, earables potentially give easy access to diagnosing or monitoring neurological and psychological disorders without the need for a full-scale scalp EEG setup.

Presenting auditory and visual stimuli at a high repetition rate creates an overlap of transient responses, the so-called steady-state response. As the steady-state response depends on the frequency of the presented stimulus, it is ideal for selection tasks of brain-computer interfaces (see subsection 6.7). The auditory steady-state response (ASSR) was confirmed with ear EEG in and around the ear with amplitude modulation frequencies ranging from 40 Hz [197] up to 90 Hz [157]. The steady-state visual evoked potential (SSVEP) was also confirmed in and around the ear at many different frequencies ranging from 5.4 Hz [188], up to 20 Hz [170].

Extracting the direction of a user's auditory attention creates a compelling use case for hearing aids that could amplify the sounds from an attended source [100]. In that regard, the auditory spatial attention (ASA) tests the response of a person attending to simultaneous sounds coming from different directions [76]. Wet periauricular ear EEG could achieve similar performance to scalp EEG [48]. The feasibility of ASA in the ear canal with dry electrodes depended on the positioning of the reference electrode [100].

The alpha attenuation response (AAR) describes an increase of alpha frequency power in the EEG signal once a person closes their eyes. The alpha power (brain waves at 8 - 12 Hz) can be associated with the sleepiness of a person [315]. It is well possible to observe a statistically significant alpha attenuation response with in-ear and around-the-ear electrodes. Alpha power increase can also be associated with drowsiness [46], see subsubsection 4.2.3.

4.2.2 Sleep. It was reported that up to 40% of the U.S. adult population struggles with sleep annually which results in morbidity and mortality [142], which makes sleep an interesting parameter to track. Sleep can be divided into four reoccurring stages (N1, N2, N3, REM), which are repeated up to six times per night [267]. Each stage is characterized by physiological patterns across the body, that are commonly analyzed in professional sleep labs by polysomnography (includes scalp EEG, EMG, nasal airflow, etc.). State-of-the-art sleep stage classification from full-scale polysomnography achieves up to 97% F1 score on diverse datasets [124]. In contrast, earable computing research aims to reduce the number of required sensors to perform sleep analysis from biopotential signals at the ear, making it feasible even at the patient's home [239].

Automatic sleep stage classification from biopotential signals at the ear ties in deeply with the general feasibility of sensing brain activity (see subsubsection 4.2.1), facial muscles (see subsection 6.5), and movement of the eyes (see subsection 6.6). Sleep stage prediction in the ear canal (see Appendix F) was performed with wet electrodes using different evaluation strategies and classifiers. Accuracies between 66% and 95% in comparison to gold standard polysomnography were achieved [231, 239, 245]. Sleep latency (the time it takes to fall asleep) was predicted at less than three minutes error [8]. Based on the presence of sleep spindles in ear-EEG, it was initially shown, that sleep staging with dry electrodes may be feasible [211, 228]. With data captured over 80 nights from 20 participants, Mikkelsen et al. [230] then showed that custom-fit, dry ear-EEG allowed automatic sleep scoring at 0.73 Cohen's kappa in comparison to gold-standard full-scalp EEG. Their results suggest that ear-EEG may be a real alternative to full-scale Polysomnography, especially for long-term monitoring.

Additionally, the relationship of changes in body temperature from ear-worn infrared thermometry and the circadian sleep-wake rhythm was initially shown based on a single subject [50] motivated by the possibility to measure body temperature at high accuracy on the ear (see subsubsection 4.3.1).

From a wearability perspective, sleep-related earables should place "rigid parts behind the ear and [...] soft materials at the concha and in the ear canal" [291]. While Röddiger et al. [291] found that commercial earbuds for daytime usage negatively impacted sleep quality, Mikkelsen et al. [230] reported that custom-fit ear-EEG concha-plugs had little negative effects.

4.2.3 Drowsiness. Drowsiness is the feeling of being abnormally sleepy. Drowsiness during the day affects 10-20% of the population and can have an adverse influence on physical and mental health, especially when operating vehicles or heavy machinery [350]. A summary table of drowsiness works can be found in Appendix G. Bleichner and Debener [46] initially found that alpha power measured around the ear increased in the afternoon compared to recordings in the morning, indicating that the ear may be a suitable position for sensing drowsiness. Since then, drowsiness has also been detected by classifying light sleep onset with an accuracy of 80% when using in-ear EEG recorded in 20 minute sleep sessions [238]. Researchers have also explored multimodal sensing for microsleep detection. Pham et al. [272] designed a behind-the-ear device which collects data from EEG, EOG, EMG, and electrodermal activity sensors before streaming them to a mobile phone for classification. They demonstrated that microsleep can be detected on an unseen subject with average precision and recall of 76% and 85% respectively using a leave-one-subject-out cross-validation design with subjects suffering from sleep deprivation and narcolepsy [272]. More generally, Mikkelsen et al. [230] envision that earable drowsiness tracking methods may support long-term monitoring of daytime sleepiness disorders such as narcolepsy or hypersomnalence.

4.3 Thermal Regulation

One of the most important processes in humans is thermoregulation which refers to the ability to sustain a steady core body temperature (CBT) such as under different climate conditions or while exercising [358]. The ear can support measurements of body temperature and sweating, which will be described in the following.

4.3.1 Body Temperature. Under normal circumstances, body temperature ranges around 37.0°C ± 1°C [59]. In medical care, core body temperature is commonly measured in the ears as the tympanic membrane is located close to the carotid artery and, therefore, accurately reflects its temperature [51].

An infrared thermophile sensor pointing at the eardrum may be used for measuring body temperature according to medical standards. Bestbier and Fourie [42] applied the principle to an earable form factor and achieved a small mean error of only 0.02 ± 0.52 °C. However, multiple works found that the principle requires per-user calibration because of ear canal shape differences and orientation of the sensor toward the tympanic membrane [42, 201, 217]. Alternatively, a thermistor measures surface skin temperature at the mastoid with high accuracy (0.03 °C mean error) [21]. According to Matthies et al. [221] the sensing principle requires an average heat-up time of 7 minutes and is easily influenced by environmental changes [144].

Across earable research, changes of body temperature in response to external weather conditions [32, 50, 212] and while exercising [50, 71, 212, 217, 319] were confirmed. This relationship enables various applications such as alerting or vital signs and parameter tracking based on the identified relationships. Additionally, the relationship between ear-recorded body temperature and ovulation (see subsubsection 4.5.6) as well as sleep (see subsubsection 4.2.2) has been shown.

4.3.2 Sweating. Commonly, sweating occurs in response to physical exertion, heat or psychophysiological arousal [308]. In general, the preauricular area has relatively high sweat gland density [313].

Matsumoto et al. [217] presented an earbud-type wearable prototype with a sweat rate sensor based on humidity sensing in the ear canal. They showed the relationship to physical exertion and amount of sweat based on a single user which they envision to apply for early detection and prevention of heat-strokes. Pham et al. [272] introduced a posterior ear device with integrated electrodermal activity (EDA) sensing. The normalised cross correlation between the ear EDA signal and a wrist-worn ground-truth evaluated with a single user was 0.37 [272]. As sweat gland activity is not symmetric between the two halves of the body it may be necessary to place electrodes on each ear to reliably capture sweating [274]. Overall, sweat sensing appears to be feasible on the ear but more research is necessary.

4.4 Mental State

A person's mental state entails, among others, emotions and stress, which trigger physiological changes that can be measured at the ear.

4.4.1 Emotion. Emotions include the feelings and thoughts of a person, which are commonly associated with their physical and psychophysiological state. In related literature, emotions are measured either dimensional (e.g., according to the valence-arousal model [296]) or categorical (e.g., happy, sad, angry, etc. [337]).

Based on in-ear EEG (see subsubsection 4.2.1 for the general feasibility), valence has been classified from low to high at 71.07% [29] to 94.1% [190] and arousal at 72.89% [29] accuracy (see Appendix H). This accuracy is close to state-of-the-art performance of full-scale EEG [258]. Dimension-based scales can be applied to derive categorical emotion classes, which has been done based on in-ear EEG to predict happiness, sadness, calmness, fear at 53.72% accuracy [29]. Similarly, excited, relaxed, and negative emotions were predicted from in-ear EEG at 58.8% accuracy [190]. Interestingly, higher valence could also be associated with higher movement measured by an earable accelerometer [106]. Some models suggest up to eight basic emotions that can be observed in humans [277] which greatly over-exceeds what is currently possible to predict with data obtained from the ear.

Earable-based emotion tracking could enable monitoring patients and elderly remotely for more effective care-taking [29]. Additionally, facial expressions (e.g., facial action units) may be associated with emotions which are introduced separately in subsection 6.5.

4.4.2 Stress. Stress is triggered when an individual's mental or physical ability to cope with a situation effectively is over exceeded. It is commonly known that stress is associated with changes of heart rate and heart rate variability [325]. The previous subsubsection 4.1.1 gives an overview of the general feasibility of different heart rate sensing principles.

With earables, increasing heart rate and decreasing heart rate variability at the beginning of stress exposure elicited by a mathematical addition task was confirmed [201]. In a similar experiment, Suzuki et al. [323] also showed that higher heart rates at the ear are associated with stress using multivariate regression.

From the literature, the relationship between stress and skin impedance caused by sweat is well known [55]. Even though sweat sensing is possible with earables (see subsubsection 4.3.2), no earable works looked into the relationship between EDA measured at the ear and stress.

4.5 Health

The principle feasibility of the physiological parameters introduced in the previous sections can be applied to identify an individual's health status directly. Meanwhile, the location and phenomena of the ear also make it possible to derive insights into more specific bodily occurrences such as bruxism, coughing, sleep apnea, seizures, and even the reproductive system.

4.5.1 Bruxism. Bruxism is a movement disorder that is characterized by grinding of teeth and clenching of the jaw [307]. Tooth damage and headaches are common symptoms associated with bruxism. An initial evaluation with a single user successfully investigated the possibility to sense teeth grind and jaw clenching using electromyography on the ear (EMG) [92]. As jaw movements are closely related with ear canal shape deformations [275], jaw clenching and teeth grinding may be sensed from inertial sensors in the ear canal [52, 295]. Bondareva et al. [52] concluded that gyroscope-based sensing outperforms accelerometers when mixing with in-the-wild activities - achieving 76% and 74% accuracy for jaw clenching and teeth grinding, respectively.

4.5.2 Coughing. Cough describes the voluntary or involuntary rapid expulsion of air from the lungs to clear the airways. A variety of severe viral infections and diseases such as COVID-19, influenza, or COPD are accompanied by cough symptoms [115, 234]. Detecting respiratory illness from cough allows quicker isolation of infectious patients [289] and monitoring disease activity [244]. The sounds and motion of cough create cough detection opportunities that may be leveraged by sensing at the ear.

Röddiger et al. [289] initially evaluated predicting simulated weak and strong cough from earable accelerometer and gyroscope data and achieved 68% sensitivity and 72% specificity under a variety of noise conditions, including laughing, clearing the throat, swallowing, speaking, walking, and fidgeting. They present a statistical meta analysis that describes how to distinguish episodes of increased cough for a sick individual with the relatively weak classifier. Zhang et al. [370] later introduced an algorithm based on template matching that allows tuning sensitivity and specificity to the desired use case with about similar performance under noise-predicated situations. Interestingly, the ear had the best performance to predict simulated cough from accelerometer data in comparison to the chest, stomach, shirt pocket, and upper arm [90, 91].

Combining audio and motion data obtained at the ear decreased the false positive rate of cough detection and achieved 83% sensitivity, and 91.7% specificity, which is an increase by 55% compared to audio-only [244]. An advantage of audio-based cough prediction is the availability of audio cough datasets, even for specific diseases such as COVID-19 [246].

It remains to be evaluated how the proposed earable-based techniques perform based on real-world cough sounds and motion data.

4.5.3 Face Touching. Earables have also been used for detecting unconscious face touching which increases the risk of passing and spreading pathogens into the body, especially pertinent given the COVID-19 pandemic [153, 293]. Kakaraparthi et al. [153] used a hybrid sensing approach of thermal sensors embedded into an earable combined with facial skin impedance to monitor the user's face touching behavior. Using a deep learning model to combine the two signals resulted in an F1 score of 84.4% for touch detection and 70.1% for touch zone identification (rising to 90.1% for personalised models). Rojas et al. [293] introduced *Saving Face* which uses unmodified commercial earphones to sense the face touches through the distortion patterns in an ultrasound signal. The user's earphones are transformed into a sonar system with one earbud (positioned on the collar) emits the ultrasound signal which is captured by the microphone. The system was evaluated in a number of activities, achieving a sensitivity of 93.7% and precision of 91.5%.

4.5.4 Sleep Apnea. The interruption of breathing for 10 seconds or more during sleep is referred to as sleep apnea which, if not treated, poses a serious health risk [99]. As breathing results in subtle changes of the pulse wave in the PPG signal (see subsubsection 4.1.1), the interruption of breathing can be sensed with earables. In a whole-night study, 94.6% sensitivity and 93.4 % specificity was achieved for three out of six patients based on a PPG sensor worn at the tragus [343].

4.5.5 Epilepsy. As described in subsubsection 4.2.1, the brain activity of a person can be well quantified from ear-worn EEG. Epilepsy often entails seizures which are episodic abnormal neural activities that can result in body shaking or awareness loss. Given the high portability and unobtrusiveness of ear EEG, a natural application is the detection of seizures from ear-worn EEG for better health management and intervention [122, 152]. Bleichner and Debener [46] initially presented a periauricular EEG setup revealing epileptiform brain activity of a patient. Gu et al. [122] applied EEG posterior to the ear and reported 94.5% sensitivity and a false detection rate of 0.52 per hour to detect seizures of patients with focal epilepsy. Juez et al. [152] identified inter-ictal spikes in the EEG trace of a pre-diagnosed patient wearing an in-ear device. These spikes are known to occur in epilepsy patients.

4.5.6 Ovulation. Reproduction is critical to sustaining the human species. The possibility to capture core body temperature at the ear (subsubsection 4.3.1) and its relationship to ovulation creates a compelling use case for the earable platform. During the menstrual cycle, ovulation can be associated with the highest fertility, making it an important event to track when seeking pregnancy. It is well known that ovulation can be associated with basal body temperature changes [33]. In an earable context, Luo et al. [202] recorded body temperature every 5 minutes during the night using a thermistor placed in the ear canal with 34 study participants. They could correctly predict ovulation within three days at 82.35% accuracy when tracking multiple cycles.

5 MOVEMENT AND ACTIVITY

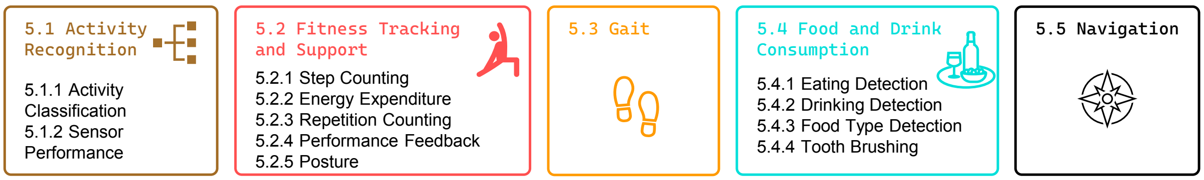

Fig. 6. Structure of the *Movement and Activity* section according to different activities.

Researchers have explored how the earable platform can be used to sense user movement and infer information about activities the user is performing; see Figure 6. Movement detected at the ear can be classified into discrete classes to infer a user's pose, how they are moving, or what type of activity they are undertaking. Beyond just classifying the sensor data, researchers have also explored how physical quantities can be derived from the user's movement to provide useful information for a wide variety of applications including fitness tracking, gait analysis, food and drink consumption, and inertial navigation.

5.1 Activity Recognition

Sensor-based activity recognition has been a staple of the of the ubiquitous computing community for many years, both as a technical pursuit focused on improving recognition rates but also as a means to understand activity context that can be used to personalise devices and systems. Earables are compelling for activity recognition because many people wear ear-based devices, such as earphones or hearing aids, as they perform their everyday activities. In contrast, other wearables are commonly abandoned as activity trackers due to their inability to be incorporated into a person's everyday life (e.g., knee or waist trackers) [30, 130].

5.1.1 Activity Classification. Prior research has explored how ear-based devices can successfully recognise a wide variety of activities. For basic activity recognition tasks, such as determining whether a user is walking or running, earable-based accelerometers on their own provide an almost perfect accuracy of 99% [65]. Similarly, Min et al. [232] reported an F1-score of 95% when determining the mobility of a user (stationary, walking, stepping up, stepping down) and 80% when performing a head gesture (nodding, shaking) by utilising both the accelerometer and gyroscope and using a nearest-neighbour classifier. Hammour and Mandic [128] show that motion artefacts from in-ear EEG can be used to classify four basic activities (sitting, walking, speaking, and chewing) with 85% testing accuracy. For estimating a user's understanding of an online lecture, Kim et al. [172] classified whether a user is gazing at a monitor or looking down at the desk based on the accelerometer and gyroscope of the earable, achieving F1-scores of ≈ 0.92 and ≈ 0.90 respectively. These results demonstrate how earables can detect simple movements and gestures with high accuracy.

However, more advanced activity recognition tasks show more variable results. Atallah et al. [25] explored one-versus-all classification rates for ear-based accelerometer sensing using different activities groups based on the "compendium of physical activities" [5]. Activity recognition using a nearest neighbour classifier was similar for the high-level (running and cycling) and low-level (preparing and consuming food, socialising, reading, and getting dressed) activities with approximately 65-70% F1-score. However, medium level activities (walking and cleaning) performed much worse than both with approximately 50% F1-score. Similar results were also found in previous research by Atallah et al. [24], although Nirjon et al. [248] reported 96.8% accuracy when classifying only the level of activity (i.e., physical intensity) rather than the activity itself.

Advances in the underlying classifiers may also increase recognition performance on the ear. More recent work has explored how end-to-end deep learning can classify five scripted activities (nodding, speaking, eating, staying, and head shaking) with an F1-score of 82% [181] and physical exercises with 82% accuracy (squats, lunges with dumbbells, alternating bicep curls, sit-ups, push-ups, sitting overhead dumbbell triceps extensions, standing dumbbell rows, jumping jacks, sitting dumbbell shoulder press, and dumbbell lateral shoulder raises) [318]. Across these works, we see how earables are able to achieve good recognition performance despite the difficulty in detecting movements of other parts of the body.

Researchers have addressed the difficulties of using earables to detect complex movements by combining them with other devices in a complementary manner, leading to greater recognition rates than are possible with any single device. Strömbäck et al. [318] recorded motion data from ten participants performing ten different exercises while carrying commodity wearable devices – a smartphone, smartwatch, and earbuds equipped with inertial sensors. Fusing the data using deep-learning techniques across wearables achieved 96% activity recognition accuracy, which was significantly higher compared with using the data from only a single wearable (earbuds - 82%, smartwatch - 94%, and smartphone - 85%) [318]. Radhakrishnan et al. [284] pair earables with dumbbells, both augmented with an accelerometer and a gyroscope, in order to classify the free-weight exercise a user is performing with a test-set accuracy of 96.85% from 3 exercises (bicep curls, triceps extension, and lateral raises), 93.72% from 6 exercises (also including squats, lunges, and side bend), and 88.6% from 12 exercises (also including seated barbell shoulder press, inclined chest flyes, weighted crunch, dumbbell triceps kickback, barbell deadlifts, and alternating bicep curls). Other work suggests fusing accelerometer and gyroscope data from an earable with optical flow from cameras can also improve classification accuracy for basic gestures including reaching for items and dressing oneself [222].

5.1.2 Sensor Performance. Accelerometers and gyroscopes are the main sensors used to detect motion of the earable for activity recognition, with the exception of one paper which explored the motion artefacts of in-ear EEG [128]. For many applications it is only the accelerometer that is used [25, 324]. Min et al. [232] found that the accelerometer significantly outperformed the gyroscope, and that fusing the two sensors resulted in a marginal performance increase over the accelerometer-only approach (only 1% for head gestures). Using only the accelerometer is compelling because they are more energy-efficient than gyroscopes [232]. However, despite finding the same relative performance differences between the three conditions, Laporte et al. [181] found the difference in performance between accelerometer-only and hybrid approach to be larger, and between accelerometer and gyroscope to be smaller, when using end-to-end deep learning with F1 scores of 75% (accelerometer), 69% (gyroscope), and 80% (both).

Comparisons between the ear and other locations show it to be among the best positions for activity detection. Atallah et al. [25] compared accelerometer placement of seven different locations on the body whilst tracking different high-level activities (including preparing food, getting dressed, cleaning, and socializing) of eleven users. The ear was second best after the knee, without significant loss in classification accuracy, and better than the chest, arm, wrist, waist, and ankle. More recent work has also shown similar results with only the knee and shin outperforming the head for activity classification for activities including climbing stairs, jumping, lying, standing, sitting, running/ jogging, and walking [324].

However, more recent work that uses deep learning suggests that other commodity wearables may outperform earables when classifying physical exercises. Earables achieved an accuracy of 82%, lower than both a smartwatch (94%) and smartphone (85%) [318]. Earables are also susceptible to falling out during heavy movements, even when adjusted correctly, and therefore certain activities may be less suitable for ear-based devices [138]. In addition, earables produce greater wearing variability in comparison to a smartwatch, with differences of roll and pitch of about 10-20 degrees in earables compared with 3-8 degrees [233] in smartwatches. Despite these disadvantages, earables provide good recognition performance across a wide range of activities, and when used in combination with other wearable sensors can further improve recognition accuracy [318].

5.2 Fitness Tracking and Support

Sedentary lifestyles account for 25% of all medical expenses and cause millions of deaths worldwide [13]. Beyond just classifying physical activities or sports, as we saw in the previous sub-section, earables can help to improve and manage a user's fitness and health [25, 32, 53, 65, 139, 183, 280]. To date earable research has covered a range of different fitness activities ranging from weight-lifting [284] and general exercise routines [235, 318], to sports including cycling [23, 25, 53], rowing [23], climbing [259], and basketball [138].

5.2.1 Step Counting. Counting how many steps a user takes is one of the most commonly used metrics for tracking and assessing physical activity, and for encouraging users to stay active [34]. Earables are ideally suited for step counting because the body acts as a filter which stabilises the head during locomotion [121, 162]. Prakash et al. [280] show the initial feasibility of step counting at the ear with a variety of walking speeds including very slow, slow, normal, and running that can be tracked with 95% accuracy [280]. They also propose to detect and measure jumping to assess the physical health of a user, with a limited user trial reporting jump heights of within 1-3cm of the ground truth.

5.2.2 Energy Expenditure. Motion of the human body measured on the ear directly relates to physical activities performed by the user, and this relationship can be used to infer a user's energy expenditure [105]. This approach provides a more generalised way of measuring a user's activity in comparison to step counting. Energy expenditure can be estimated from acceleration forces measured at the ear with high correlation confirmed by calorimetry (r=0.92 [183], r=0.74 [53]). This relationship was confirmed for lying down, standing, computer work, vacuuming, walking stairs, slow walking, fast walking, slow running, fast running, cycling, and rowing [23, 53]. Consequently, a mean absolute deviation of only 27 kcal per day was achieved [53]. Beyond tracking a user's activity to monitor their fitness, energy expenditure prediction can be combined with dietary measures to maintain long term weight loss [183] or to monitor patients remotely [24]. Also, Nirjon et al. [248] used the concept of energy, derived from the accelerometer, to detect the activity level of a user which was then used to control music being played.

5.2.3 Repetition Counting. Strömbäck et al. [318] used earables for counting the number of repetitions performed whilst exercising for a variety of ten physical exercises. Whereas accelerometers are favoured for activity classification, the authors found that gyroscope data results in better performance for repetition counting, although only marginally. Earables achieved a mean absolute repetition counting error of 1.31 (all results reported are for gyroscope), outperforming a smartphone (1.61), but significantly worse than a smartwatch (0.34). Interestingly though, the percentage of exercise sets within two repetitions of the actual number of repetitions was slightly higher for the smartphone (82.95%) than for the earable (81.33%). Again the smartwatch significantly outperformed both with 98.70% of exercise sets within 2 repetitions.

5.2.4 Performance Feedback. Earables can also be used to provide feedback to users whilst performing a physical activity in addition to analysing their form afterwards. Radhakrishnan et al. [284] not only classified the type of exercise a user was performing, but also developed a feedback system for use during weight-based exercises that combined earable motion data with motion data of a dumbbell which detected exercise mistakes (94%) of 33 users which helped to reduce subsequent mistakes by more than 10%. Similarly, Motokawa et al. [235] explored how acceleration data from the ear and chest can be combined to provide real-time corrective feedback during planks. Rather than providing real-time feedback, Pansiot et al. [259] used the accelerometer in an earable to collect data so that climbers could assess the fluidity, speed, strength-to-weight ratio, and endurance of their performances and to provide insights into their proficiency level. Hermann et al. [135] applied earables to support life-saving cardiopulmonary resuscitation (CPR). Based on an evaluation with twenty users on a test dummy, acceleration data measured at the ear of the rescuer can predict chest compression depth and rate at 5.9 mm and 1.6 cycles per minute median absolute deviation. Though that was worse than on the rescuer's wrist or chest, the performance of earables was still within the acceptable range for real-world feasibility of CPR.

5.2.5 Posture. Poor posture when sitting at a desk can cause back pain and poor circulation that can lead to other health issues [81, 131]. Earables equipped with an accelerometer and a gyroscope can be used for corrective posture feedback by detecting when a user leans forward with their head while sitting down [283, 326]. An initial simulated experiment based on five participants using their smartphone or laptop 30 minutes each yielded perfect precision at 89% recall to detect a forward-leaning posture [283].

5.3 Gait

Gait describes the motion performed by a user when walking. Earables can accurately detect several temporal and spatial gait parameters including heel contact time, toe off event, swing time, stance time, stride time, step cycle time, and step asymmetry [27, 146, 148]. The relationship between gait-specific motion data and acceleration measured at the ear has been confirmed in conjunction with gold standard procedures including an in-shoe pressure measurement system [146], a force-plate instrumented treadmill [26, 27], and a high-speed camera [148, 149]. Extracting these precise gait parameters provides clinicians with the opportunity to monitor rehabilitation from either surgery or a stroke, or progression of pathologies including osteoarthritis [27]. Ear-worn devices are a much cheaper and simpler platform for detecting gait patterns and parameters than traditional gait platforms and force plates, and have the added advantage that they can be deployed in-the-wild.

Gait parameters have been successfully extracted using earables and applied to assess health outcomes of an individual. Appendix I details all earable papers that have explored gait-related parameters. Recovery after surgery can be tracked using acceleration signals at the ear which capture the irregularity of a user's gait pattern [22]. Atallah et al. [22] used this possibility to both assess the recovery over time as well as approximating the user's gait to a healthy control group. Similarly, Jarchi et al. [147] conducted a validation study which showed that stride time, amplitude asymmetry, and step time measured at the ear improved one year post-surgery. The amplitude asymmetry level was also found to correlate with the Knee Injury and Osteoarthritis Outcome Score [146].

Impairment of gait, e.g., because of skeletal malfunctions or due to aging, can also be extracted directly using earable devices. Accuracy of more than 95% was achieved for predicting truncal [19] and lower limb impairment [19, 20] using an accelerometers on the ear. Lorenzi et al. [199] used an inertial measurement unit consisting of an accelerometer, gyroscope, and magnetometer to measure the freezing of gait of Parkinson's disease patients. The choice of an ear-based sensor was motivated through wearability and also the need to provide auditory feedback to feedback to the patient. The risk of falls in elderly people has been clinically measured using the Tinetti Gait and Balance Assessment (TGBA) [340]. King et al. [173] discovered that certain aspects of TGBA can be assessed base on motion data from the ear (2 out of 17 test-related activities), however this small fraction is likely not enough for practical use. Similarly, ear-based devices have been equipped with accelerometers for detecting fall events aimed at elderly patients [349].

5.4 Food and Drink Consumption

Dietary monitoring involves detecting both when someone consumes food or drink and, ideally, also what they are consuming. The ability to automatically monitor dietary activity can take the burden of self-reporting away from a user or patient and assist with mindful eating, tackling unhealthy behavior, and preventing diseases by supporting healthier diets [11, 12, 37]. Earables are suitable for automatic dietary monitoring because they are non-invasive [111, 260, 263, 266, 303], socially acceptable [39, 45, 303] and can be worn throughout the day [111, 249, 266]. Appendix J details all of the work that has explored how to detect when and what a user is eating or drinking on the earable platform.

5.4.1 Eating Detection. The first step of dietary monitoring is detection of eating events. The repetitive nature of jaw movement when chewing and eating is beneficial when trying to predict eating phases under real-world conditions [37] and can be detected using several sensing principles. Air- and bone-conduction microphones sense chewing sounds; proximity, piezoelectric, and inertial sensors track ear canal deformations induced by mouth motions; and electromyography (EMG) quantifies chewing-based muscle activity directly. On their own these different sensing modalities achieve roughly similar accuracy rates ranging from 80-90% in field experiments, however fusing multiple sensors can further improve recognition accuracy [44, 200, 261].

Each sensing principle used to detect eating behaviour has advantages and trade-offs. For audio-based eating detection, body-internal vibrations and sounds can be measured due to the ear cavity that are amplified by the ear's physiology [11, 45]. However, external and background sounds not relating to the chewing activity should be dampened for optimal recognition [261], which remains a critical challenge for audio-based approaches [111]. This issue is further exacerbated when chewing softer foods as the amplitude of the chewing signal is much lower compared with crunchier foods [200]. An additional microphone which measures and filters sounds from the surroundings can improve performance [225, 263], and deep learning approaches have also been shown to increase recognition accuracy up to 77-94% even with ambient noise [111]. Audio-based approaches are still an active research area because they possess a key advantage to other sensing modalities as microphones are already commonly embedded in many commercial ear-worn devices.

Motion-based approaches sense movement of the jaw when eating. They do not face the same privacy concerns and are more robust against soft food types than audio-based approaches [200]. Similar to audio-based approaches, motion-based eating detection also suffer from signal noise induced by unrelated body movement [200]. Bedri et al. [37] showed how it is possible to filter out undesired motions by using additional body-worn sensors, in the form of an IMU behind the user's neck, resulting in an F1-score of 80.1% based on field experiments. However, having the additional IMU in a form-factor that a user is likely to use is still an open challenge.

Proximity sensors can be used to detect ear canal deformation as a result of jaw movements when eating. They are compelling as they require less power and do not suffer from the same level of privacy concerns in comparison to audio-based approaches [39]. Bedri et al. [39] measured ear canal deformation using three orthogonal proximity sensors and a gyroscope embedded in an off-the-shelf earpiece which resulted in 95.3% accuracy when detecting eating events. Also, Bedri et al. [37] explored the use of an in-ear proximity sensor but found that users found it uncomfortable when wearing for prolonged periods and especially when eating.

Other sensing principles have been used to detect eating at the ear via jaw movements. Wet EMG electrodes located behind the ear on the mastoid detect the jaw's muscle activity [44], PPG senses the changes in blood flow as a result of the jaw movement [260, 261], and piezoelectric strain gauges located on the lower jaw directly measure jaw movement [101, 303]. EMG and PPG were both significantly outperformed by audio-based detection, yet when fused resulted in an overall increase in accuracy [44, 260].

Multiple lab studies investigated how to predict individual bites and chew strength on the ear using pressure, bend, and piezoelectric strain sensors [141, 302]. However, individual chews are more complicated to predict than general eating activity due to the higher temporal resolution that is required [261].

5.4.2 Drinking Detection. Staying hydrated is important for cognitive function and overall health [287]. Tracking the consumption of liquids (including liquid foods) is a challenging detection task for earables because it lacks the characteristic chewing information (e.g., [111, 200, 263, 302]). Some works reported good results based on sound sensing for a subset of study participants [311], however drinking detection can not be reliably detected with earables (see Appendix J).

5.4.3 Food Type Prediction. In addition to detecting when the user eats, automatic dietary monitoring should detect what food the user is consuming, and how much of it they are eating. The amount and type of consumed food are key contributors to the success of weight loss maintenance [178]. Research to date has focused on distinguishing foods of different textures in a lab setting using audio data collected at the ear, with a success rate of 79% [266]. Alternatively, cameras located on the ear can be triggered by a microphone when chewing is detected and images are taken of the meal which can be later analysed for an overview of the user's food-intake [193]. No field studies or studies involving food type predictions of complex meals have been undertaken.

5.4.4 Tooth Brushing. Closely related to food and drink consumption is tooth brushing, as sugary diets in particular can lead to cavities and problems with dental hygiene. Researchers have explored how tooth brushing location can be tracked using earables in order to help form better tooth brushing habits [257, 281]. Prakash et al. [281] modified an off-the-shelf earphone speaker to detect the vibrations from tooth brushing with 89% accuracy over 7 locations of the upper and lower teeth. Ouyang et al. [257] explored a larger number of locations (16) and achieved a similar prediction accuracy by using a combination of throat and ear microphones.

5.5 Navigation

Navigation can be achieved by leveraging the inertial sensors in an earable to track the position and orientation of the user over space and time without having to rely on a GPS connection [4, 360]. Listening to music or wearing earphones is common when travelling and the stable attachment and fewer random movements of earables in comparison to other locations on the body makes them a suitable platform for inertial navigation [96, 114].

However, the accuracy of inertial navigation is dependent upon a fixed global reference point which is commonly the magnetic field of the earth and detected by a magnetometer. In earable devices, the close proximity of communication circuitry and the speaker introduce significant electromagnetic noise which has so far proved problematic for inertial navigation on the earable platform [96]. To overcome this problem, Ferlini et al. [96] developed an automatic magnetometer calibration method in combination with the user's smartphone that reduces the average error from 30 degrees to less than 5 degrees at any given time. Based on a 9-axis inertial measurement unit and the described magnetometer calibration method, an inertial navigation drift of 0.15m/s when using one earable and 0.11m/s when using two earables could be achieved [4]. Gong et al. [114] presented a deep learning based pipeline that fuses the inertial data from a smartphone and earables. This pipeline takes into account the reliability of each sensor at any given point in time prior to fusing, and only relies on the earables accelerometer and gyroscope readings for inertial navigation, achieving accuracy improvements in comparison to other state-of-the-art navigation models.

To navigate indoors, Schindler et al. [304] proposed an ear-based device that tracks footsteps from acceleration data and doorways through proximity sensing. From this data, a topological graph of the environment is generated which is applied to localise the user based on a particle filtering approach with preliminary success.

6 INTERACTION

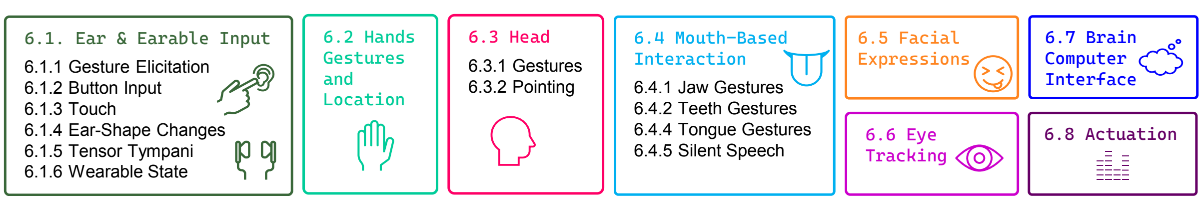

Fig. 7. Structure of the *Interaction* section according to different research topics.

Earables present an exciting opportunity for unique and novel interaction techniques given the rich and diverse sensing capabilities available on the earable platform. To date, researchers have explored how input can be provided on the ear or earable itself, as well as how the earable platform can be used to detect other modalities which can be used to provide input.

6.1 Ear and Earable Input

The location of the earable device makes it compelling as an interaction device that can be directly manipulated by the user to provide input. This enables common basic interactions including tap and double tap on and around the ear, however researchers have also investigated how more complicated sliding gestures or manipulation of the ear itself can be utilised for interaction purposes, see Appendix K.

6.1.1 Gesture Elicitation on the Ear. Abstracting from any specific sensing modality, Chen et al. [74] used an elicitation study (N=28) to explore user-defined gestures for ear-based interactions for a number of smart device tasks. The majority of user-defined gestures involved mid-air interactions (57%), with 39% involved touches directly on the ear. Of those touch-based gestures, the most common part of the ear for touch-based gestures was the helix (8.4%), followed by the tragus (and cheek) (6.8%), the lobe (4.7%), the back (4.4%) and finally the center (2%). The remaining touch-based gestures involved multiple ear parts (0.9%) or the location did not matter (11.6%). The study's user-defined gesture set contained a number of touch-based inputs involving single and double taps on different parts of the ear, covering of the ear itself, sliding gestures on the helix, and pinching of the ear lobe. They also discuss the design space of deforming the ear through manipulation, similar to Kikuchi et al. [171]'s *EarTouch*, however these gestures did not feature heavily and the authors speculate that these could cause physical discomfort.

Xu et al. [361] also introduce and explore a rich set of 27 gestures on and around the ear which include single and double tap, as well as simple and complex sliding gestures. They then proceeded to select 8 gestures based on technical properties (signal-to-noise ratio and similarity) of their acoustic-based sensing principle, and user preference based on simplicity, social acceptance and fatigue. Their final gesture set included single and double taps on the cheek, mastoid, and middle ear, as well as two sliding gestures (one on the ear rim and one below the mastoid).

6.1.2 Button Input. Pressing a button on an earable device is one of the most basic forms of input. However, the action of pressing inherently requires force to be applied in order to depress the button. In comparison with other parts of the body the ear can be more sensitive to pressure and force which can cause discomfort, especially when applied to the inner canal. Buil and Hollemans [63] found that users (N=16) were split on their preference for the amount of force required to depress a button on an earable, with 85 grams being within the acceptable range of most users.

6.1.3 Touch. In contrast, touch-based gestures enable a similar input bandwidth without requiring the same levels of physical force to be applied to the ear. Capacitive sensing has been applied to detect explicit user input using the hands [64, 192, 356]. Buil et al. [64] demonstrated how simple interactions of tap, double tap, and hold could be implemented on the earable platform using capacitive antennas built into the earphones. Lissermann et al. [192] extended this concept to 12 electrodes spanning from the beginning of the ear helix to the ear lobe. They sought to answer how well one can touch their own ear and discovered that users (N=27) are capable of detecting four salient points on the ear arc, with greater precision found at the extrema of the ear arc. Weigel et al. [356] introduced iSkin which demonstrated how capacitive sensing can go beyond traditional capacitive form factors and be achieved using a low-cost, thin, stretchable form factor made up of two layers. Light touch is sensed using the capacitive principle, while firm touch can be detected using the resistive principle when the two layers are in contact due to the pressure exerted. This sensing concept is operationalised in an application called *EarSticker* which consists of a five-element slider located behind the ear, however the sensor itself was not evaluated on the ear.

Due to the importance of real estate in such a small form factor, researchers have explored innovative solutions to detect input by using the built-in components of commodity earphones [209, 361]. Manabe and Fukumoto [209] developed an external adapter which allowed taps on the shell of commodity earphones to be detected through the speaker unit. They tested this technique on ten different pairs of earphones with six users, finding promising results for some earphones, while others did not work due to residual sound. In contrast, *EarBuddy* uses the built-in microphone from earphones to detect a wide range of touches and sliding gestures with an accuracy of $> 90\%$ by utilising deep learning based on mel spectrograms [361]. Input was not limited to just on the ear, but also included interactions around the ear including cheek and mastoid. Similarly, Fan et al. [93] leverage the coupling effect of headphone drivers detected using a peripheral device attached to unmodified headphones. Using this principle, they sense touch and sliding gestures on the earphone enclosure using a cumulative sum algorithm. As a proof-of-concept they found success rates of >99% when audio is off and >97.7% with audio signal with gestures performed 300 times.

In contrast to detecting manipulation of the sensing device, Lee et al. introduced *EarTouch* which uses a camera to detect touches on the ear [184]. The proposed technique was designed to be obfuscated, i.e. hidden from an observer by turning the head, miniaturized due to the small size of the ear, and camouflaged as common actions such as scratching. Their evaluations showed high (approx. 40%) error rates for tapping detection using a “land on” strategy, similar to those found by Lissermann et al. [192], however detection using a “lift off” or “dwell” approach resulted in much lower error rates (approx. 10%).

6.1.4 Ear-Shape Changes. Sensing dynamic changes in the shape of the outer ear and ear canal can also be used in the context of interaction. Kikuchi et al. [171] introduced *EarTouch* which uses photo reflective sensors to detect shape changes of the ear caused by physical manipulation of the helix with the hands. A support vector machine classifies four directional gestures of moving the ear helix, which in turn can be used to classify five symbolic gestures (line, check mark, inverted caret, square, and stairs) with an average accuracy of 77.43%.

6.1.5 Tensor Tympani Contraction. Researchers have also explored novel methods of that leverage the ear’s unique physiology. Röddiger et al. [290] introduced *EarRumble* which uses pressure sensing to detect changes in the shape of the ear canal when the tensor tympani (a middle ear muscle) contracts. They leverage the ability that some people can voluntarily contract the tensor tympani (43.2%, N=192) to provide subtle input and demonstrate that three ear rumble gestures can be detected with 95% accuracy.

6.1.6 Wearable State. Researchers have also explored how the location of the earables relative to the user can be sensed for both implicit and explicit interactions. Sensing whether the earables are located in the ear can be used for locking the on-ear controls to prevent accidental activation [64], pausing music or answering phone calls [182], or detecting whether the earphones are positioned correctly (i.e. left ear bud in left ear, right ear bud in right ear) [219].

The wearable state of the earables can be detected using capacitive sensing [64], proximity sensors [219], ultrasound frequency sweeping [182], and the coupling effect through the headphone drivers [93]. *HeadFi*, introduced by Fan et al. [93], provide an extensive study on detecting the wearable state of the earphones using 54 pairs of earphones grouped into five types. By leveraging the coupling effect through the headphone drivers they achieved success rates per group between 97.9% and 99.8%.

Beyond detecting just whether the user is wearing the earables or not, *EarphoneTrack* uses acoustic motion tracking to find out where the earphones are located in 3D space with millimeter level accuracy [66]. The system leverages an inaudible single frequency acoustic signal and can be used with commercial earphones. They propose self-interference and frequency offset techniques to allow for the tracking of both wired and wireless earphones respectively. This approach creates an interesting and untapped design space where the earables themselves can be used for spatial input.

6.2 Hand Gestures and Location

Besides direct manipulation of the earable or the ear for input, hand movements can also sensed and leveraged for input. Using an elicitation study (N=28), and abstracting from any specific sensing modality, Chen et al. [74] found that the majority of user-defined gestures for ear-based interactions involved mid-air hand interactions (57%) around the ear. Other researchers have operationalised sensing mechanisms which can detect motion of the hands using earables, see Appendix L.

Metzger et al. [227] introduced *FreeDigiter* which allows rapid, contact-free entry of digits based on finger gestures. To enter a digit, the user spreads their fingers to show the desired number and then slide it over a proximity sensor embedded in the earbud to encode the digit. The earbud detects the digit by the reflections of the infrared light emitted by the proximity sensor which can be used for selecting a numbered item from (e.g.) a list of tracks or to manage phone calls. *SonicASL* by Jin et al. [151] uses deep learning techniques to classify reflections of a sonic wave into 42 different sign language words. This technique enables mid-air input in front of the earable that can be used to enable communication with hard-of-hearing individuals. Tamaki et al. [327] presented *Brainy Hand* which embeds a mini-projector and a color camera inside an earbud capable of detecting hand gestures. The projector gives the user feedback where input can be performed (camera field of view), and in another configuration the projector displays words and images on the user's palm for richer feedback.

Beyond detecting mid-air hand movement for explicit user input, hand movements have also been detected in more subtle and novel ways. Yan et al. [362] introduced *PrivateTalk*, a subtle interaction technique to activate voice input by partially covering the mouth with the hand from one side. This action causes differences of the audio signals arriving at the left and right ear which can be used to signify that the user intends to interact with the voice assistant when the hand covers the face. This removes the necessity to use wake-up words or pressing a button while increasing the privacy of the user by reducing the spread of voice and concealing lip movements.

6.3 Head Gestures and Pointing

Head movement provides a hands-free input mechanism when the hands are busy or unavailable. The head has been used for input by either semantically mapping pre-defined gestures to system commands (e.g., [363]), or by using the direction as a pointing device to select targets spatially (e.g., [301]). Earables are perfectly situated to detect head movements, and researchers have explored how sensing on the earable can be used to operationalise both of these interaction paradigms.

6.3.1 Head Gestures. In addition to being hands-free, head gestures, such as nodding or shaking, are compelling because they can also be invoked in an eyes-free manner due to proprioception, and do not require visual feedback. The inertial sensors within an earable can be used to detect different head gestures intended for interaction. Gashi et al. [112] combines a hierarchical classification with transfer learning to detect typical activities including head shaking and nodding from accelerometer and gyroscope data. They achieved an F1-score of 88.24%. Similarly, Laporte et al. [181] detected nodding and shaking (and three other activities) with an end-to-end deep learning approach with an F1-score of 82%. Rather than using inertial sensors, Ando et al. [14] leveraged the fact that the ear canal changes shape when the sternocleidomastoid muscle is used to move the head. They used in-ear pressure sensing to recognize six head gestures (rotate left/right, rotate up/down, tilt left/right) with a recognition accuracy of 87.6% (which also included five facial gestures). While these paper show a promising future direction for earables interaction, they also highlight a common challenge with semantic gestures – distinguishing movement intended for interaction versus natural head movement.

6.3.2 Head Pointing. Pointing is a fundamental interaction principle that is at the core of graphical user interfaces. An inertial measurement unit that can track yaw, pitch, and roll can be used as a pointing device with three degrees of freedom. However, a magnetometer is required to measure the absolute yaw position which has proved problematic for earables due to electromagnetic noise in such a small form factor [96]. Odoemelem et al. [252] used head motion to control a robot arm, however due to the lack of yaw information of the head they map the roll of the head to the yaw of the robot. Two research threads have emerged due to the difficulties with the magnetometer: the first seeks to understand the source of the error and overcome it using calibration techniques, and the second thread seeks alternate ways of detecting the yaw position of the head.

Ferlini et al. [97] aimed to compensate for the lack of magnetometer by utilizing an additional gyroscope. Instead of detecting a specific yaw angle of the head, they classified from 30 degrees to 90 degrees in 15 degree increments. They demonstrate errors of between 5 - 15 degrees between the ground truth and proposed approach, which increases when the user is chewing or speaking. The prediction error also increases when the user maintains their position due to sensor drift. More recently, Ferlini et al. [96] demonstrated how an automatic magnetometer calibration method can overcome the electromagnetic interference resulting in an error of less than 5 degrees over a wide range of yaw angles. This approach may be key to future opportunities for earable-based head pointing.

As a result of difficulties with head pointing on the earable platform, other work has looked at innovative ways of leveraging the earables relationship to other devices to infer head direction. Hashem et al. [132] introduced the *Look&Lock* system which determines which device a user is looking at by using the Bluetooth received signal strength (RSS) on a set of earables.In a single subject study, the system was capable of 100% accuracy when detecting objects on the walls or in the corner, spaced by 15 degrees, at short distances of less than 3m. Closely related, Pfreundtner et al. [271] used the same principle with audio signals instead. They used four microphones (two on each ear) to estimate the direction of a sound source in relation to the head with an accuracy of 14 degrees on the horizontal and 5 degree on the vertical plane. Whereas the previous two papers used fixed devices in the environment, Gamper et al. [108] tracked the head orientation between multiple earable wearers by taking the speaker's voice as sound emission source and estimating the relative head angle to the listener using binaural microphones with an accuracy of around 10 degrees. This set of approaches may provide interesting opportunities for cross-device interactions, however they do not provide the accuracy required for pointing selection on a single device.

6.4 Mouth-Based Interaction

Similar to head movements, mouth-based movements afford hands- and eyes-free opportunities for input. The mouth provides a surprisingly rich input space for interaction [73] involving movement of the jaw, clicking of the teeth, and positioning of the tongue. Appendix M provides details on the different systems that have been used for explicit input using the jaw, teeth, tongue.

6.4.1 Jaw Gestures. Physiologically, jaw movements can be detected on the ear due to changes in the shape of the ear canal, however the magnitude of these changes can strongly vary between users [119, 275]. More specifically, when the jaw moves the shape of the ear canal changes depending on the position of the mandibular condyle [14]. Researchers have explored how the resultant ear canal deformations can be sensed using in-ear pressure sensing [14], proximity sensors [36], or piezoelectric bending sensors [68].

Ando et al. [14] explored how sensing in-ear pressure can be used to detect a wide variety of facial and head gestures due to the ear canal changing shape. They showed that gestures involving sliding the jaw left and right, as well as basic open and closing of the mouth, can be detected with >88.2% accuracy against other head movements (which also cause ear canal deformation). They also explored how different levels of mouth open can be detected, with four levels (closed, slight, open, wide) showing a minimum accuracy of 79.2%.

In contrast, Bedri et al. [36] used three orthogonal proximity sensors to detect the change in shape of the ear canal, and Carioli et al. [68] used bend sensors on a custom fitted ear piece. Proximity sensors were used in the context of silent speech recognition [297] and eating detection [38], but in theory both sensing modalities could be used for interaction.

6.4.2 Teeth Gestures. Movement of the jaw can also involve clicking the teeth together which results in vibrations and an audible sound. Tooth-based interaction has been used as an activation gesture [320] as well as for navigating menus [17, 281], answering phone calls [320], and typing on a keyboard in both assistive and non-assistive use cases (e.g., while working out) [17]. Such smaller interactions reduce the effort required to perform short input tasks [17] and maintain the privacy of the user [281], however users reported issues of jaw muscle fatigue when using teeth for typing [17].

Tooth-based interaction is commonly sensed using audio-based approaches to classify the distinctive sounds and vibrations from teeth clicking, similar to eating detection in subsection 5.4. Ashbrook et al. [17] reported a recognition accuracy of 96% for five different tooth pairs using bone conduction microphones, showing that the location of the click can be determined. Prakash et al. [281] expanded the input space for tooth-based interaction by exploring sliding gestures and found that these can be distinguished from taps with >90% accuracy (using six gestures). Sun et al. [320] used a fusion of audio-based and inertial sensors to detect 13 gestures, consisting of hold gestures combined with single, double, and triple taps with 90.9% accuracy in a lab environment.

6.4.3 Tongue Gestures. Interestingly, movement of the tongue can also be sensed on the ear as a result of the deformation of the ear canal [67, 205, 328]. This principle can be used for private input techniques when in a public setting [247, 328], and provides an accessible means of input for users who have a speech impairment [67, 205, 247] or physical disability [67, 247]. Interaction can be based upon pointing with the tongue in pre-defined directions within the mouth, or by detecting whether the tongue is protruding or retracted in the mouth [67, 205, 247, 328].

Earable form factors have shown how detecting tongue movements is possible. Maag et al. [205] use in-ear pressure sensing to detect ear canal deformation of three tongue gestures (left, right, and front) and two interfering movements (removing device and moving head) with comparable accuracy but significantly lower power requirements than other audio-based approaches. Taniguchi et al. [328] use a miniaturised optical sensor to detect when the tongue pushes the roof of the mouth in a small (N=5) feasibility study which shows promising results.

Other work, has explored how sensing more advanced tongue movement is possible at the ear. Nguyen et al. [247] built a more complex setup from multiple sensors including EEG, EMG, and skin surface deformation and demonstrated the feasibility of detecting ten different touch points using the tongue that can be used to provide input. Their setup achieved >85% accuracy for eight out of ten locations including four on the tongue-side (lingual) of the teeth, and six on the cheek-side (buccal). Participants found the cheek-side movements easier than the tongue-side, however many found the technique difficult to use. Finally, Cao et al. [67] use a smartphone held to the ear to sense ear canal deformation by sensing acoustic reflections measured using the microphone. Both of these are promising avenues, however it is unclear how well they can be translated to a practical earable form factor.

6.4.4 Silent Speech Input. Silent speech recognition is a unique use case of detecting both jaw and mouth movement in synergy on an ear-based device. Silent speech offers the user a privacy-preserving, socially acceptable interaction technique [72, 167] which can be used in noisy environments [72, 297] and by users with medical conditions [297].

Ear canal deformation can be used to detect silent speech, similar to jaw and tongue movements. Khanna et al. [167] developed *JawSense*, an accelerometer-based approach that uses ear canal deformations to classify 9 phonemes with 92% accuracy (N=6). Sahni et al. [297] combined an earable equipped with proximity sensors and a magnet attached to the tongue, sensed by a magnetometer, to detect 11 sentences at 90.5% accuracy (N=6). Chen et al. [72] opted to sense cheek deformation instead of ear canal deformation. They used a camera attached on the ear of a user to predict eight words with 84.7% accuracy (N=6). These early works demonstrate how silent speech recognition is possible on the ear, however there are still open research questions and challenges with regards to using and deploying this technology in-the-wild.

6.5 Facial Expressions

Facial expressions can either be voluntary or involuntary. Voluntary facial expressions are a form of non-verbal communication and can be used for explicit input for mobile and wearable devices [10, 72, 221, 300]. Involuntary facial expressions can be used in affective computing to capture the underlying feelings, mood, or emotions of a user and can be used as implicit context Verma et al. [344]. Additional insights into emotion detection with earables can be found in subsubsection 4.4.1). Appendix N details a complete list of the different sensing principles and facial expression gestures explored with earables.

The muscles which control facial expressions (i.e., sternocleidomastoid, masseter, and temporalis muscles – see Figure 4) all run close to the ear. Preliminary work has shown how in-ear EMG can be used to sense the muscle contractions in the ear when someone performs a facial expression [300]. Facial expressions can also be sensed indirectly using the deformation of the ear canal. Matthies et al. [221] explored the use of electrical field sensing which, based on a single user, performed similar to EMG in a lab environment, but when studied in a mobile context with 3 users, the electrical field sensing approach was more robust resulting in better performance. They also found that placing non-insulated electrodes in a vertical arrangement produces better results for detecting the in-ear deformation caused by facial expressions

Amesaka et al. [10] sensed the deformation of the ear canal using reflected sound, by measuring the ear canal transfer function with a microphone in the earable device. They show that it is possible to achieve a recognition accuracy of 62.5% when classifying 21 gestures, increasing to 90.0% with a smaller subset of 6. This approach of exploring a larger number of facial expression gestures (20+) before deciding on a smaller subset to increase the recognition accuracy is common in the literature [10, 187, 221].

Similarly, inertial data was applied to extract characteristic motions during facial expressions [112, 187, 344]. Verma et al. [344] reported very high accuracy (89.9%) for up to 32 facial expressions when training a user-specific classifier, however this performance decreased to 42.1% for a user-independent model. Ear-mounted miniature cameras can also be used reconstruct the outline of the cheeks with a mean square difference of 0.77mm and 0.74mm for both earphones and headphones respectively, with little degradation in performance when the user wears a mask (0.717mm) or glasses (0.824mm) [72]. Despite these promising results, the applications of camera-based approaches may be limited as they require significant power and raise potential privacy concerns of passers-by.

6.6 Eye Tracking

Eye movement requires less energy and effort than movement of the head or hands [180, 312]. Eye tracking has been used in the field of HCI and ubiquitous computing as both a method of explicit input [207] and as a means to understand user behaviour [364]. Detecting eye movement from the ear can be achieved using electrooculography (EOG) – which detects electric field changes when the eyes move because the eyeballs have a negative charge on the retina and a positive charge on the cornea [208]. EOG provides relative information about the relative movement of the eyes, but does not allow one to know what the user is looking at. In general, qualitative results have shown that EOG traces are visible when electrodes are attached in the ear canal [164, 245], posterior [272], periauricular [46, 351], preauricular [208], and close to the temple [94] at the ear. Some early results suggest that preauricular electrodes achieve gaze angle prediction with an error of 4.4° (horizontal) and 8.3° (vertical) [208]. Manabe et al. [210] introduced three sequential eye gestures measured by wet in-ear electrodes to control a music player (play/pause, next, previous), however an error rate of up to 33% was reported for some users. Work on interaction techniques using ear-based EOG are still in their infancy, but other work has leveraged the movement of the eyes measured at the ear for sleep detection [245, 272], see details in subsubsection 4.2.2.

6.7 Brain Computer Interfaces

Brain-computer interfaces (BCI) offer input based on brain activity alone. Commonly, users have to execute a specific task or follow a stimulus that triggers an expected response of the brain which can be quantified by electroencephalography (EEG), which was evaluated broadly with earables (see subsubsection 4.2.1). In the context of BCI, the steady-state response of the brain plays a critical role as it creates a response in the EEG trace that matches the frequency of an auditory or visual stimulus attended by the user. By offering multiple stimuli at the same time and at different frequencies, a user can select a desired option by attending the specific stimulus [47, 196]. Accuracies of 79.9% (six visual stimuli, [3]), and 87.92% (four visual stimuli, [353]) were achieved with in-ear electrodes. Based on the principle, text-spelling was possible at 2.4 characters per minute [250]. Brain activity also depends on the task a user is performing. Up to 90% binary selection accuracy was achieved when selecting the two ideal tasks among a list of 5 activities (breath, imagine song, listen to tone, imagine a face, imagine a cube rotating shown on screen) [226].

6.8 Actuation

Earables commonly use auditory output to share feedback with the user, or rely on visual feedback from an external device. Visualisations on the earable can not provide information to the wearer directly during use due to the location of the ear, however visual cues, such as colour-changing LEDs, have been used to provide feedback to other users [75]. Beyond these common output modalities, researchers have explored how ear-based devices can provide alternative output mechanisms based on haptics, thermal cues, and mechanical deformation.

6.8.1 Haptics. The ear is one of the best body locations for perceiving vibrating stimuli based on research which has shown that vibrations on the ear had the highest perceivability compared with other body parts including the hand, foot, and neck [88]. However, other work suggests that users could better perceive vibration stimuli at the ear because they could hear them [357]. To make full use of the ear as a tactile display, Lee et al. [186] performed a thorough investigation of vibration stimuli at the lobe, concha, and superior crus (under the helix) on each ear. Across all locations, users perceived 15 Hz to be the clearest and most unobtrusive vibration frequency. Additionally, sequential stimuli were easier to perceive and distinguish than simultaneous stimuli, while 25 spatio-temporal dual-ear patterns yielded 58.2% recognition accuracy with 4.8 seconds average response time. Vibrotactile feedback at the ear may also give hard-of-hearing users the ability to understand the sound of their surroundings better. For example, they could identify simple words and environmental sounds from vibrations at different intensities depending on the frequency of the incoming sound [357].

6.8.2 Thermal Cues. Hot and cold sensations can be created around the ear using Peltier elements [6, 241, 242]. Akiyama et al. [6] initially presented how thermal sensation changes around the ear may enhance the excitement and comfort of users listening to music. An in-depth evaluation of the thermal cues revealed that four periauricular thermal cues could be distinguished reliably by users at >99% recognition accuracy, while 5 parallel cues significantly reduced recognition performance to 86% [241]. Superior auricular cues were perceived less accurately due to the user's hair, while the posterior auricular area was most sensitive. Spatio-temporal combinations of cues on one or two ears resulted in 14 patterns with 85.3% recognition accuracy and 2.3 seconds average response time.

6.8.3 Ear Deformation. Inspired by the movement of the ears during communication of animals, Huang et al. [143] introduced a system that applies mechanical actuators to deform the ear with a view to extending the body language of disabled users. They propose 22 static and dynamic auricular postures which they link to different emotions based on an online survey. Closely related, Shirota et al. [310] applied linear actuators behind the ear to change the opening angle of the ear which could successfully manipulate the perceived direction of sound.

7 AUTHENTICATION AND IDENTIFICATION

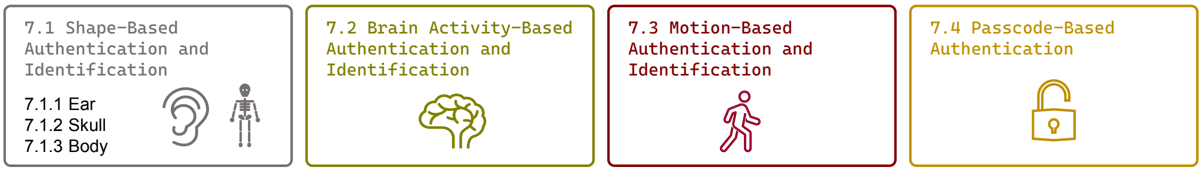

Fig. 8. Structure of the *Authentication and Identification* section according to different principles.

Protected access to sensitive data on mobile devices is commonly based on the biometrics of the user (e.g., fingerprints). Biometric earable methods have been explored based on the unique shape of the ear, skull, or body and through brain activity or body motion (see Figure 8). More traditional passcode-based authentication methods based on rhythmic patterns have also been proposed. A general distinction is made between verification, where a user claims to be a person and the system decides if the user is accepted or rejected, and identification, with the goal to "find" the user from a set of pre-enrolled users [240]. Throughout the following sections, performance is commonly reported in equal error rate (ERR), which is the threshold at which the false acceptance rate (FAR) and false rejection rate (FRR) are the same.

7.1 Shape-Based Authentication and Identification

Unique inter-participant differences between the characteristic shape and tissue softness of the ears, surrounding skull, and the overall body can be utilized for verification and identification purposes [9, 89, 194, 275, 285]. The performance across papers in this area is summarized in Appendix O.

7.1.1 Ear. In-ear and over-ear devices can determine user identity by measuring the characteristic reflections of the sound of the static enclosed ear canal [7, 16, 110, 206] or covered ear [7, 87] based on both - audible and inaudible frequencies. Additionally, authentication may be performed based on the dynamic shape of the ear canal while talking [354] or by the response of the basilar membrane in the cochlea to a sound stimulus [195].

When measuring sound reflections of the complete ear an audible chirp gave better results than an audible sequence (14.9% vs. 0.8 - 5% EER, N ≈ 30, [7, 87]). No works explored inaudible sound reflections to sense the complete ear. For the ear canal, inaudible chirps outperformed audible chirps (< 0.01% vs. 0.28 - 1% EER, N ≈ 30, [7, 206]). In contrast to existing results from sensing the complete ear, an audible sequence could still achieve comparable performance to a chirp in the ear canal with < 1% EER at = 45 users [16]). Instead of just sensing the static shape of the ear canal, dynamic changes of the ear canal while speaking can be combined with an inaudible probing tone which achieves 4% EER at 24 users [354].

Multiple authors reported that wearing variability degrades performance between wearing sessions [16, 110, 206]. Audible probe signals were identified to be more robust against wearing variability, but inaudible signals could achieve better performance [206]. Additionally, different background disturbances (room, cafe, mall, street) were found to decrease performance by only 2% FRR [110]. Still, a higher sound pressure level of the probe tone improves performance in loud environments [110]. In general, inaudible frequencies have the advantage of not disturbing the user [206, 354]. Verification performance converged at 3 seconds audible probe tone duration [110]. Moving, walking, running, and eating degrades the verification performance [93, 110], by an absolute increase of up to 6% FAR and 26% FRR for ear canal based verification [110].

In contrast to the previous approaches that sense ear canal or ear shape, Liu and Hatzinakos [195] introduced the biometric principle of transient evoked otoacoustic emission (TEOAE) to the earable platform. Originally introduced by Grabham et al. [118], TEOAE is a 20ms response of the basilar membrane in the cochlea after a low-level click sound. According to the authors, the principle is very hard to falsify because replication of the auditory system is almost impossible, and replay attacks are unlikely to be feasible. The technique outperforms all previous approaches at 0.02% EER evaluated on 54 users. The same principle can be applied for identification at high accuracy (99.4%).

7.1.2 Skull. The face is a common biometric property to authenticate or identify a user. While the ears can not directly observe the face, sounds produced by the body are propagated by the unique structures and tissue of the skull, which can be leveraged for authentication. In an initial study, air- and body-conducted sounds on both ears employ the voice of the wearer as a probing signal of skull bones and tissue [109]. The principle is independent of the spoken text and achieves 3.64% EER at 23 subjects. Also, it is relatively robust against environmental noise, wearing variability, and user movement (< 5% EER) and appears to be resistant against multiple replay attacks. Instead of audio signals, Liu et al. [194] employ an accelerometer attached to the ear canal to measure vibrations propagating from the mandible to the ear upon voicing an 'EMM' sound. An evaluation with 34 participants reveals 1.28% EER. The technique is also robust against food intake and wearing variability.

7.1.3 Body. Expanding upon the idea of sensing the unique bone and tissue structures of the user, Ding et al. [89] introduced an authentication method that measures the leakage current propagated through the body by an earable as the user touches a metal-encased laptop. The principle achieves 93.6% identification accuracy based on 15 users. Additionally, performance is hardly influenced by replay or mimicry attacks.

7.2 Motion-Based Authentication and Identification

The way a person moves is a common soft-biometric in wearable computing [214]. Ferlini et al. [95] introduced a gait-based method based on the low-frequency sounds propagated through the body, which are amplified in the occluded ear canal when walking. The principle achieves 3.23% false acceptance rate and 2.25% false rejection rate. Soft grounds such as a carpet or wearing slippers decreased the performance slightly but was still always < 8% FAR and FRR. The technique is stable against speech and playing music because it occurs in lower frequencies (< 50Hz). Additionally, merging data from both ears was beneficial over using one ear alone. For identification, Clarke et al. [78] introduced a spontaneous device association method which matched the acceleration of an earable to the movement of a user's head in the camera view to allow for private audio channels in public settings. They conducted a lab study with seven different movements (including random movements) at three speeds, which revealed an accuracy of 86% to identify an individual from a set of 10 participants.

7.3 Brain-Based Authentication and Identification

The ability to sense the brain activity of a user with earables (see subsubsection 4.2.1) has led to the development of novel biometric verification and identification systems. Commonly, the user is asked to perform a specific task during which the individual EEG response is captured. Curran et al. [82] have investigated this principle with a small group of seven users. They conclude that the approach could achieve perfect false acceptance and false rejection rate (0% = FAR = FRR) when choosing the most distinctive mental task for every user among a selection of nine different tasks (e.g., open / close the eyes, think of a personal secret, react to external stimulus). An evaluation of 5 mental tasks with 12 users revealed that the best general task across all participants was "listening to 40Hz tone", which achieved 19.9% FAR and 25.8% FRR [83]. Identification based on the unique patterns in alpha waves after closing the eyes (see subsubsection 4.2.1) resulted in a 67.8% identification rate [240].

7.4 Passcode-Based Authentication

In comparison to the aforementioned biometric principles, Bi et al. [43] introduced an authentication method based on rhythmic tapping on the earbud measured by an accelerometer. They analyzed the tap energy, tap interval, and rhythm timing for different users-chosen rhythms, which they found were sufficiently different for authentication. An evaluation with 20 users yields < 5% FAR and FRR even when the system is attacked by brute force or imitation. Introducing motion by train riding and wearing variability degrade the performance but FRR and FAR was still <10% and <5%, respectively. The main advantage of the technique compared to other earable methods is that it does not rely on biometrics which may be subject to change.

8 DISCUSSION

We have demonstrated how earables have great potential in four main research areas. Earables present a unique opportunity to leverage a platform already embedded in our everyday lives through ear-based devices such as earphones and hearing aids. As a result, earables are socially acceptable to wear [36] and have the potential to be unobtrusive (e.g., [82, 187, 221]), discreet (e.g., [163, 187, 196]), inconspicuous (e.g., [79, 117, 138]), concealed (e.g., [85, 110]), privacy preserving (e.g., [185, 187, 278]), and non-stigmatizing [170, 278].

Earables can sense a multitude of body functions from 9 (out of 11) major systems of the human body, including skeletal (e.g., gait [27]), muscular (e.g., facial expressions [221]), nervous (e.g., brain activity [85]), endocrine (e.g., emotions [29]), cardiovascular (e.g., blood pressure [62]), respiratory (e.g., breathing [292]), reproductive (e.g., ovulation [202]), immune (e.g., coughing [289]). and digestive (e.g., food intake [111]) systems. Earables are already showing promising results in the health domain, and as the sensing and processing capabilities continue to advance we are likely to see earables playing a vital role in at-home monitoring and even possibly diagnosis.

The location of the earable presents a relatively stable platform from which to sense a wide range of movements and activities, in turn enabling recognition of exercises, sports, and other daily activities. Despite earables not achieving the best performance when used in isolation, they can support and complement other devices in the wider wearable eco-system [318], and the everyday use of ear-based form factors make them easier to integrate into everyday life than many other devices – an important factor for successful habit formation [30]. Beyond just classification, quantification of sensed phenomena can also support users to self-regulate healthy behaviours in their everyday life, from monitoring their levels of physical activity to tracking what food and drink they consume. Combined with the physiological parameters and health data available on the platform, earables have the potential to be a powerful self-tracking tool in the quantified self movement [203].

In the context of human-computer interaction (HCI), earables present an exciting opportunity for unique and novel interaction techniques given the rich and diverse sensing capabilities available on the earable platform. The ear itself is easily and comfortably reached by the hands [171, 361], while the distinctive surface area creates opportunities for targeted interactions [192]. The possibility to bend the ear and its unique shape as well as flat surface area around it also opens up an interesting interaction design space [171, 361]. Even the physiological nature of the ear has been harnessed for interaction by using the tensor tympani, a small inner ear muscle, which can be sensed and used as a discreet, eyes- and hands-free binary switch [290]. Beyond the ear itself, the earable platform can also be used to detect other modalities for interaction, including head position [14], facial gestures [221], mouth movements [320], and eye gaze [46, 272].

Fingerprint and face-based biometrics of smartphones are reported to have a false acceptance rate of 1 in 50,000 or lower [15]. Earable authentication techniques were evaluated with 50 users and less while most have a false acceptance rate of ≈ 1-5% [16, 95]. This performance suggests that earable-specific authentication principles currently can not compare to methods available on other mobile platforms, however they have great potential for providing seamless authentication and identification by integrating the process into common everyday tasks. Earables are also well positioned to provide “continuous” authentication which are capable of repeatedly checking to see if the correct user is still wearing the earable device, which may compensate for the lower accuracy rates as evidence accumulates over time. In addition, these continuous authentication methods have the potential to be combined with traditional passcode-based authentication at the beginning of a session.

8.1 Future Opportunities and Challenges

Earables are a growing research area, as demonstrated in Figure 1. Despite technological advances, the limited space of the earable form factor creates, and will remain, an engineering challenge as components need to be miniaturised (e.g., [29, 54, 262]). The need for miniaturisation and small form factor introduces a number of potential constraints on the available computational performance, storage, and power on the earable device itself. From our review, we have identified several overarching opportunities and challenges to overcome in order for earables to realise their full potential across the four research areas identified.

8.1.1 Self-contained Platform. Earables have the potential to be a self-contained, light-weight wearable platform that does not depend on other devices due to the vast array of sensing principles available on the platform and the audio, and potentially haptic, output capabilities. However, in part due to the currently available computing resources on-board, it is common that other devices are used for further processing of the earable sensor data. Out of the research papers we examined, only 12 (4%) reported processing of sensor data on the earable device itself, with 22 studies (8%) using a smartphone for processing. The vast majority of research papers used higher powered computing devices (e.g., laptops and desktop computers). While this does not necessarily mean the systems developed could not run on lower-powered devices, it highlights a lack of research into earables as a self-contained platform.

8.1.2 Power Consumption. In addition to maximising the computational resources on the platform, power sources are also required to fit into the earable form factor which makes power consumption an important consideration (e.g., [181, 196, 205]). This requirement can be a considerable barrier for applications requiring frequent computationally expensive operations (e.g., machine learning models) or large and/or continuous data throughput which can quickly drain the battery. However, because the earable form factor is commonly used in wearable, mobile contexts there is the potential for energy to be harvested on the device itself, with preliminary research showing the feasibility of harvesting energy from jaw movements [54, 86] and thermoelectric generators [1]. Energy harvesting technologies may be required to supplement earable's on-board power capacity and extend battery life as the platform matures.

8.1.3 Wearable and Smart Device Ecosystem. Earables are ideally placed to, and will likely become, part of the commodity wearable and smart device ecosystem alongside smartphones and smartwatches. Earables can, and often do, offload processing onto other devices which can be beneficial for many applications and usage contexts in which other devices would likely be present anyway. Offloading sensor data provides access to additional computing resources, helps to extend the battery life of the earables, and allows earables to benefit from other devices providing higher-level contextual information about the user and their location. Researchers have also started to explore how earables can work in synergy with other wearables and smart devices. This emerging research space has yielded promising results which have shown how combining earables with other devices results in improved performance compared with the devices in isolation (e.g., [114, 225, 318]). It is important that the research community explores and understands how earables best fit into and complement the current and future wearable and smart device ecosystems. We also note that the "self-contained" and "device ecosystem" research directions are not mutually exclusive, and each will play an important role in unlocking the potential of the earable platform.

8.1.4 Integration of Multiple Sensors. Earables can come in many different form factors, from subtle in-ear hearing aids to over-the-ear headphones and mechanically anchored earphones for exercising. In this survey we have seen multiple sensing principles (see Table 3) that have been demonstrated on the earable platform. However, different sensors and their required methods of attachment present a challenge when considering what can be simultaneously sensed on the ear by one device. An earable than encompasses multiple sensing modalities will inherently be limited by what attachments are viable for a given combination of sensing principles. This introduces trade-offs between the sensing capabilities and method of attachment, and we have shown how some sensors have different performance characteristics that are dependent on the form factor (e.g., electrode placement for EMG and EEG).

To date, research into earables equipped with multiple sensing modalities or solutions that span different application domains is limited. However, commercial offerings such as the eSense[1] or more recently Cosinuss Two[2] provide platforms that remove the need for bespoke hardware to be created and may allow researchers to consider the relationship of multiple solutions on a single platform. Further research into this area will open up opportunities for novel multi-modal sensing applications and/or solutions to other common issues on the platform, such as suppressing unwanted motion artefacts.

8.1.5 Assessment Heterogeneity. The ability to understand and compare the performance of different sensing principles on the earable platform is crucial. However, both Masè et al. [216] and Ne et al. [243] noted in their hearable reviews that the literature suffers from a wide variety of protocols and measurements that made comparisons between studies difficult [216, 243]. We found this issue extends to the research papers reviewed in this work and is evidenced in the Appendices. For example, research into heart rate (Appendix A) and blood oxygen saturation (Appendix B) shows multiple performance metrics being used across research groups.

Not only does assessment heterogeneity make it difficult to compare sensors across the earable literature, but it also limits and obfuscates our understanding of earables compared to other wearable and smart devices (e.g., smartphones or smartwatches) and gold standards. In this review, we have attempted to bridge this gap where possible by providing gold standard comparison points, as does Ne et al. [243] in their review. However, it should be of primary importance moving forward for researchers investigating new and novel sensing principles on the earable platform to make a concerted effort to establish standard protocols for specific sensing principles and phenomena.

8.1.6 Ecological Validity. On top of assessment heterogeneity, earable research to date generally suffers from a lack of ecological validity. Work showing preliminary results and proofs of concepts is common, with over half (52%) of the papers surveyed having a study with less than 10 participants, and 48 (18%) papers' evaluations are based on a single user only. While preliminary research is important for the laying the foundations and exploring what is capable on the platform, there are significant questions being raised as to whether these innovations, often studied in limited lab conditions, will hold up in-the-wild during the mobile use cases and scenarios that earables will likely be used in.

We found only 26 (< 10%) papers included field experiments in their evaluation. Researchers need to take into account the context of use which is likely going to be varied, dynamic, and possibly on-the-move in noisy environments or for prolonged periods. Researchers should consider any discomfort created by exerting force on the ear canal (e.g., [63, 209, 291]) or through blocking the hearing abilities of the user (e.g., [79]). Similarly, the form factor of the earable will affect the stability during different activities, but there also exists variability between wearing sessions (e.g., [110, 233]) and earables are susceptible to motion artefacts (e.g., [46, 134, 200, 292]), audio noise (e.g., [10, 205, 357]), and environmental weather conditions (e.g., [50]). Filling in these research gaps and embracing the opportunities they present will support and accelerate the transition from experimental prototypes to impactful, real-world products.

8.1.7 User Variability. Another issue related to ecological validity, which is also highlighted in this review, concerns user variability. Ergonomics research has shown that anthropometric differences exist between different genders and populations, including differences in upper ear height, concha width, lower ear height, and ear

[1]eSense earable computing platform: https://www.esense.io/
[2]Cosinuss: https://store.cosinuss.com/

protrusion [31, 107, 189]. Another source of variability between users involves varying ear canal conditions which includes earwax blockages, ear infections, or other skin conditions that could affect the ear canal. These may affect some sensors more than others, for example those that require line-of-sight. Similarly, it is common for people to have ear piercings that may affect attachment. This is in addition to the potential problems introduced by attaching and maintaining contact with the sensors. Users may not be able to attach the sensors correctly first time (e.g., [37, 182, 233]) and there is the possibility that skin contact of a sensor is lost during use (e.g., [144]). This highlights the need for diverse research participation, and to understand how these factors affect wearability over long periods, and in the use contexts in which they were intended.

9 CONCLUSION

This paper systematically reviewed 271 earable publications, resulting in a taxonomy of phenomena and a comprehensive, in-depth overview of what can be sensed and inferred using the earable platform. Four overarching research areas demonstrate the versatility and wide variety of applications that earables enable, from detecting a user's physiological state for health monitoring, to interacting with devices in an eye- and hands-free manner. The anatomical properties and location of the ear create unique sensing opportunities that provide distinct advantages compared to other parts of the body, resulting in a wide variety of phenomena that can be detected. Our analysis shows how these can be derived from 13 fundamental phenomena and sensed using 21 different sensors. Further sensing developments will likely expand the already rich set of phenomena sensed by earables, and new applications will emerge that leverage those currently available. While the number of sensors and phenomena available on the ear will continue to grow, some will start making the transition to commercially-viable products. However, to-date most earable sensing research has not been rigorously tested in-the-wild. As the technology transitions out of the lab and into real-world deployments, a whole host of new research questions will emerge. Future work will have to demonstrate ecological validity and overcome robustness and engineering challenges to unleash the full potential that earables have to offer as a ubiquitous, general-purpose platform.

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A HEART RATE

Heart rate sensing with earables is summarized in subsubsection 4.1.1. The appendix Table 6 lists the papers that developed heart rate sensing earables according to the sensor used, the activity level and context they have been evaluated with (e.g., while sleeping, speaking, etc.), where the sensor is located, and what was the achieved performance. Additionally, the reference device and number of study participants are listed.

Commonly, earable prototypes for heart sensing are evaluated in comparison to a gold-standard ECG or PPG on other parts of the body (e.g., a fingertip PPG [145, 248] or chest-ECG [127, 309]). Most studies cannot be directly compared because of different sensors, experimental contexts, and performance metrics. Performance is assessed based on correlations (e.g., [305, 345]) mean or median deviations (e.g., [248, 345, 346]), or standard deviations (e.g., [341, 343]). Several studies applied more unconventional metrics. For example, Wang et al. [352] measure the accuracy of the movement detection and the effects of motion artifacts with the HR spectrum fidelity index (fHRS), which is the ratio of the HR frequency spectrum density over the full-spectrum strength for their respective device. The activity levels for the evaluation context of the studies were adapted from [248], ranging from activity level 1 (resting state) to activity level 3 (high effort). A large share of the studies did not report standardized performance scores, but reported proof-of-concept evaluations (e.g. [175, 365, 365]).

Table 6. Heart rate obtained from the ear according to different sensing principles and activity levels (ALVL: 1 = resting pulse expected, 1* = resting activity with head movement, 2 = mild effort activity, 3 = high effort activity). PPG = Photoplethysmography, ECG = Electrocardiography, Mic. = Microphone, Acc. = Accelerometer, Cap. = Capactior, ITS = infrared thermophile sensor. SD = Standard Deviation, MD = mean value of difference difference in means, RMSE = root mean square error, MAE = mean absolute error, ME = mean error, fHRS = HR spectrum fidelity index, ER = Error Rate, SNR = signal-to-noise-ratio, MAPE = error as a percentage of overall mean, PAT = pulse arrival time, PTT = pulse transit time, PPV = positive predictive value, IPC = impedance cardiogram.

Sensor	**ALVL**	**Context**	**Location**	**Performance**	**Ref. Device**	**N**	**Ref.**
PPG	1	resting	lobe	ER=0.6%	ECG	13	[309]
PPG	1	resting	posterior	$f_H RS$ = 35±15	PPG	10	[352]
PPG	1	resting	ear canal	ME=1.04 bpm	ECG	11	[270]
PPG	1	resting	unspecified	Peak-to-Peak amplitude=0.38, 70 bpm, same as ref.	ECG	1	[365]
PPG	1	resting	ear canal	ME= 0.66 bpm	PPG	12	[98]
PPG	1	resting	concha	ME=-0.19 bpm	PPG	12	[98]
PPG	1	resting	posterior	ME=-0.28 bpm	PPG	12	[98]
PPG	1	sleeping	ear canal + lobe	show principle	ECG	6	[343]
PPG	1	sleeping	ear canal	MAE=7.01 ms	ECG	7	[56]
PPG	1	sleeping	concha	show principle	-	3-5	[323]
PPG	1	sitting	concha	MD=-0.03 bpm, 95%CI = [-2.94 and 2.88 bpm]	ECG	28	[334]
PPG	1	sitting	mastoid	MD=-0.25 bpm, SD=0.5 bpm, RMSE=1.3 bpm	PPG	10	[79]
PPG	2	standing	lobe	MD±SD= 0.62%±4.51%, r= .97	ECG	14	[279]
PPG	1	music listening	concha	0.63%<ME<0.56%	PPG	4	[278]
PPG	1*	speaking	ear canal	ME=12.52%	PPG	12	[98]
PPG	1*	speaking	concha	ME=58.29%	PPG	12	[98]
PPG	1*	speaking	posterior	ME=62.60%	PPG	12	[98]
PPG	1*	chewing	ear canal	show principle	PPG	4	[347]
PPG	1*	resting+running	lobe	Max. absolute deviation = 2.5%	PPG	1	[175]
PPG	1*	running+walking	concha	RMSE=5 bpm	ECG	1	[70]
PPG	2	walking	ear canal	ME=27.14%	PPG	12	[98]
PPG	2	walking	concha	ME=58.66%	PPG	12	[98]
PPG	2	walking	posterior	ME=105.98%	PPG	12	[98]
PPG	2	walking	posterior	ME=105.98%	PPG	12	[98]
PPG	2	walking	ear canal	ME=2.77 bpm	ECG	11	[270]
PPG	2	walking	ear canal	show principle	PPG	4	[347]
PPG	2	walking	ear canal	show principle	-	2	[335]
PPG	2	walking	lobe	ER=1.7%	ECG	13	[309]
PPG	2	walking	lobe	MD±SD=-0.49%±8.65%, r= .82	ECG	14	[279]

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Sensor	ALVL	Context	Location	Performance	Ref. Device	N	Ref.
PPG	2	walking	lobe	Max. absolute deviation = 2 bpm	PPG	6	[204]
PPG	2	walking	posterior	$f_{H}RS = 25\pm10$	PPG	10	[352]
PPG	2	walking	unspecified	show principle	ECG	1	[365]
PPG	2	moving freely	ear canal	ME=0.031±0.717 bpm	ECG	16	[42]
PPG	2	moving freely	ear canal	0.21 % false positives , 1.23 % false negatives	ECG	16	[42]
PPG	2	moving freely	ear canal	r= .87	ECG	16	[42]
PPG	2	moving freely	ear canal	MAE=8.23 ms	ECG	7	[56]
PPG	3	jogging	lobe	ER=0.7%	ECG	13	[309]
PPG	3	running	ear canal	ME=29.84%	PPG	12	[98]
PPG	3	running	concha	ME=44.00%	PPG	12	[98]
PPG	3	running	posterior	ME=56.62%	PPG	12	[98]
PPG	3	running	concha	ME=-0.003 bpm, SD=2.84 bpm	ECG	1	[336]
PPG	3	running	lobe	ER=5.7%	ECG	13	[309]
PPG	3	running	lobe	MD±SD=-0.32%±10.63%, r= .76	ECG	14	[279]
PPG	3	treadmill	ear canal + concha	HR<90 bpm: MAE=1.5 ± SD = 1.8 bpm, MAPE = 2.5%	ECG	20	[265]
PPG	3	treadmill	ear canal + concha	HR<90 bpm: MAE=2.0 ± SD = 2.5 bpm, MAPE = 3.2%	ECG	20	[265]
PPG	3	treadmill	ear canal + concha	HR>100 bpm: MAE=1.8 ± SD = 2.8 bpm, MAPE = 1.3%	ECG	20	[265]
PPG	3	treadmill	ear canal + concha	HR>100 bpm: MAE=1.8 ± SD = 2.8 bpm, MAPE = 1.4%	ECG	20	[265]
PPG	other	stress test	ear canal	MD=-1.67 bpm, 14.87 bpm<SD<24.0 7bpm	PPG	3	[201]
PPG	other	stress test	concha	improving accuracy of 11.11 to 17.2 percentage points	-	20	[126]
PPG	other	Valsalva test	lobe	PAT: 0.15<r<0.21; PTT: 0.14<r<0.31	IPC+ECG	14	[305]
PPG	other	handgrip exercise	lobe	PAT: 0.15<r<0.29; PTT: 0.16<r<0.33	IPC+ECG	14	[305]
PPG	other	thermal stress	concha	show principle	PPG	6	[342]
PPG	other	simulated altitudes	posterior	RMSE=2.61%, r= .96	PPG	12	[58]
PPG	-	unspecified	ear canal	SD=1.2 bpm, R^2>0.99	ECG	26	[341]
ECG	1	sitting	concha	R-, T-, P-, & S-waves: 10.92<SNR<17.27	PPG	1	[212]
ECG	1	sitting	mastoid	HR-waves: ME=1.3 bpm, 2.9<SNR<12.4	PPG	2	[145]
ECG	2	treatmill	mastoid	QRS: ME=2.7 ms, SD=7.8 ms, MAE=5.1 ms, RMSE=8.2 ms	PPG	8	[369]
ECG	-	unspecified	ear canal	R-wave: SD=0.94 ms, 0.59 ms delay	PPG	10	[127]
ECG	-	unspecified	ear canal	P-, QRS-, and T-waves: r= .96	PPG	5	[348]
ECG	-	unspecified	posterior	P-, QRS-, and T-waves: show principle	PPG	1	[69]
ECG	-	unspecified	beyond auricle	percentage RMS deviation=2.2-3.3%	ECG	6	[306]
Mic.	1	sitting	unspecified	1.37%<ER<1.64%	PPG	1	[93]
Mic.	1	sleeping	ear canal	r= .99	ECG	4	[117]
Mic.	1	sitting	ear canal	ME=5.6% (MAE=4.3 bpm), SE=51.2% (2.2 bpm)	ECG	25	[215]
Mic.	1	lying, sitting	concha	r= .85	ECG	37	[248]
Mic.	1	music listening	unspecified	1.42%<ER<2.42%	PPG	1	[93]

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Table 6 – continued from previous page

Sensor	ALVL	Context	Location	Performance	Ref. Device	N	Ref.
Mic.	2	treadmill	concha	r= .84	ECG	37	[248]
Mic.	3	jogging	concha	r= .75	ECG	37	[248]
Mic.	other	breathing	ear canal	MAE=4.3 bpm (2.7 cpm)	ECG	25	[215]
Acc	1	sitting	beyond auricle	show principle	PPG+ECG	8	[256]
Acc	other	Valsalva test	posterior	R^2= .66 for stroke volume	ECG	13	[134]
Acc	other	Valsalva test	posterior	R^2= .96 for R- & J-waves	ECG	13	[134]
Piezo	1	sitting	ear canal	MAD=0.62, ER=0.68%	ECG	58	[262]
Cap.	other	Valsalva test	posterior	show principle	ECG	1	[133]
ITS	-	unspecified	concha	ER=±10.5 bpm for 70% of the samples	ECG	5	[84]

B BLOOD OXYGEN SATURATION

Measuring blood oxygen saturation with earables is summarized in subsubsection 4.1.2. In that regard, appendix Table 7 introduces the sensor, attachment location of the sensor, reported performance, range of ground-truth blood oxygen saturation captured by the study dataset, and the number of study participants. Compared to traditional PPG, which applies LEDs to emit light, VCSEL measures the reflected light of vertical-cavity surface-emitting lasers.

Table 7. Performance of earable prototypes measuring the fraction of oxygenated hemoglobin in blood by measuring peripheral blood oxygen saturation.

Target	Sensor	Location	Performance	Evaluation Range	N	Ref.
SpO_2	PPG	earlobe	1% mean absolute error	93% - 98%	6	[204]
SpO_2	VCSEL	earlobe	≈ 6% mean absolute error	≈ 93% - 98%	1	[175]
SpO_2	PPG	posterior	2.61% root-mean squared error	70 - 100% (SaO_2)	12	[58]
SpO_2	PPG	ear canal	-0.22±1.50% mean error	96.38% - 100%	16	[42]
SpO_2	PPG	ear canal	show principle	unspecified	4	[347]
SpO_2	PPG	tragus	show principle	unspecified	11	[343]
SpO_2	PPG	ear canal	< 2% mean absolute error	96% - 100%	12	[98]
SpO_2	PPG	posterior	< 2% mean absolute error	96% - 100%	12	[98]
SpO_2	PPG	concha	< 2% mean absolute error	96% - 100%	12	[98]

C BLOOD PRESSURE

Measuring blood pressure with earables is summarized in subsubsection 4.1.3. In appendix Table 8 the underlying principle to measure blood pressure, the metric used for evaluation, the achieved performance of systolic and diastolic blood pressure, and the number of study participants are listed.

Table 8. Blood Pressure using different principles. *ECG is attached on the user's chest. SBP = systolic blood pressure, DBP = diastolic blood pressure.

Principle	Sensor	Metric	SBP Performance	DBP Performance	N	Ref.
Pulse Transit Time	PPG + ECG*	correlation	r=0.25 ± 0.30	0.33 ± 0.32	14	[305]
Pulse Transit Time	PPG + ECG*	-	show principle	unspecified	1	[125]
Pulse Amplitude	PPG + balloon	mean error	1.8 ± 7.2 mmHg	−3.1 ± 7.9 mmHg	35	[62]

D RESPIRATION

Sensing the respiration rate of a user is summarized in subsubsection 4.1.4. The appendix Table 9 lists earable respiration based on the sensor applied, the measure obtained, the performance achieved, the number of study participants recruited, and the range in which ground truth respiration data was collected.

Table 9. Respiration rate and ins-/expiration phases measured by different sensors at the ear. MAE = mean absolute error, ME = mean error.

Sensor	**Measure**	**Performance**	**N**	**Range (≈)**	**Ref.**
accelerometer	respiration rate	2.62 cycles per minute MAE	12	8 - 22 CPM	[292]
gyroscope	respiration rate	2.55 cycles per minute MAE	12	8 - 22 CPM	[292]
accel. / gyro.	respiration rate	1.64 cycles per minute ME	30	no reported	[2]
microphone	respiration rate	2.7 cycles per minute MAE	20	6 - 25 CPM	[215]
PPG	respiration rate	-0.558 ± 1.406 cycles per minute ME	16	7 - 28 CPM	[42]
PPG	respiration rate	≈ 3 cycles per minute error	12	no reported	[98]
PPG	ins- / expiration	81.5% sensitivity, 86% specificity	36	4 - 21 CPM	[341]

E BRAIN ACTIVITY

Brain activity sensing with earables is summarized in subsubsection 4.2.1. The appendix Table 10 lists different locations at which earable EEG has been evaluated with dry and also wet electrodes with generic and custom fit ear-EEG devices. The different EEG paradigms are described in subsubsection 4.2.1.

Table 10. EEG paradigms evaluated at different locations on the ear. ✓= paradigm feasible, ✗ = paradigm not feasible.

Location	Fit	Electrode	P300	MMN	ASA	ASSR	P300	SSVEP	AAR	Ref.
posterior	generic	wet	-	-	-	-	✓	✓	-	[250]
posterior	generic	wet	-	-	-	-	-	✓	-	[213]
periauricular	generic	dry	-	-	-	✓	✓	✓	✓	[123]
periauricular	generic	dry	-	-	-	✓	-	-	-	[41]
periauricular	generic	wet	✓	-	-	-	-	-	✓	[46]
periauricular	generic	wet	✓	-	-	-	-	-	✓	[85]
periauricular	generic	wet	✓	-	-	-	-	-	-	[338]
periauricular	generic	wet	-	-	-	-	-	-	✓	[359]
periauricular	generic	wet	-	-	✓	-	-	-	-	[48]
concha	generic	dry	-	-	-	✓	-	-	-	[41]
concha	custom	wet	-	-	-	-	✓	✓	-	[47]
concha + ear canal	generic	dry	-	-	-	✓	-	-	✓	[163]
concha + ear canal	custom	dry	-	-	-	✓	✓	✓	✓	[197]
concha + ear canal	custom	dry	-	-	-	-	-	✓	-	[196]
concha + ear canal	custom	dry	-	✓	-	✓	-	✓	✓	[160]
concha + ear canal	custom	dry	-	-	-	✓	-	-	-	[168]
concha + ear canal	custom	dry	✗	-	-	✓	-	✓	✓	[158]
concha + ear canal	custom	dry	-	-	-	-	-	-	✓	[198]
concha + ear canal	custom	dry	-	-	-	✓	-	-	✓	[164]
concha + ear canal	custom	dry	-	-	-	✓	-	✓	-	[157]
concha + ear canal	custom	dry/wet	-	-	-	-	-	-	-	[156]
concha + ear canal	custom	wet	✓	-	-	✓	✓	✓	-	[170]
concha + ear canal	custom	wet	-	✓	-	✓	-	-	-	[229]
concha + ear canal	custom	dry/wet	-	-	-	-	-	-	-	[268]
concha + ear canal	custom	wet	✓	✓	-	-	-	-	-	[169]
concha + ear canal	custom	wet	-	-	-	-	-	✓	-	[353]
concha + ear canal	custom	wet	-	-	-	✓	-	-	-	[159]
concha + ear canal	custom	wet	-	-	-	✓	-	-	-	[155]
concha + ear canal	custom	wet	-	-	-	✓	-	-	-	[35]
concha + ear canal	custom	wet	✓	-	-	✓	-	-	-	[338]
ear canal	generic	dry	✓	-	-	-	-	✓	✓	[185]
ear canal	generic	dry	-	✓	-	✓	-	✓	✓	[160]
ear canal	generic	dry	✓	-	-	✓	-	✓	✓	[188]
ear canal	generic	dry	✓	-	-	-	-	-	✓	[154]
ear canal	generic	dry	-	-	-	✓	-	-	✓	[92]
ear canal	generic	wet	-	-	-	✓	-	✓	-	[245]
ear canal	generic	wet	-	-	-	✓	✓	✓	✓	[117]
ear canal	generic	wet	-	-	-	✓	✓	✓	-	[116]
ear canal	generic	wet	-	-	-	✓	-	-	-	[168]
ear canal	generic	wet	-	-	-	-	-	✓	-	[3]
ear canal	custom	dry	-	-	✓	-	-	-	-	[100]
ear canal	custom	dry	-	-	-	-	-	-	✓	[150]

F SLEEP

Sleep tracking based on earables sensing is summarised in subsubsection 4.2.2. In Table 11, tracking of different sleep parameters with earable sensors is summarised. It lists sensor positions and electrode styles. Additionally, the performance and number of study participants are described for every paper.

Table 11. Sleep tracking based on ear-worn brain activity sensing allows to predict different sleep stages from EEG data.

Parameter	**Sensor**	**Position**	**Style**	**Electrode**	**Performance**	**N**	**Ref.**
sleep stages	EEG	ear canal	generic	wet	74.1% accuracy	22	[239]
sleep stages	EEG	ear canal	generic	wet	95% accuracy	8	[245]
sleep stages	EEG	ear canal	generic	wet	show principle	4	[117]
sleep stages	EEG	concha + ear canal	custom	wet	$\approx$ 66% accuracy	9	[231]
sleep stages	EEG	concha + ear canal	custom	unspecified	85.7% accuracy	1	[317]
sleep stages	EEG	periauricular	generic	wet	show principle	1	[46]
sleep spindles	EEG	concha + ear canal	custom	dry	show principle	12	[228]
sleep spindles	EEG	ear canal	generic	dry / wet	show principle	1	[211]
sleep latency	EEG	ear canal	generic	wet	< 3 mins error for 84%	23	[8]
circadian rhythm	Infr. Ther.	ear canal	generic	-	show principle	1	[50]

G DROWSINESS

Drowsiness detection based on earables sensing is summarised in subsubsection 4.2.3. In Table 12, tracking of drowsiness with ear EEG is summarised. It lists sensor positions and electrode styles. Additionally, the performance and number of study participants are described.

Table 12. Drowsiness detection based on ear-worn brain activity sensing EEG data.

Parameter	**Sensor**	**Position**	**Style**	**Electrode**	**Performance**	**N**	**Ref.**
alpha power increase	EEG	periauricular	generic	wet	show principle	10	[46]
microsleep	EEG	periauricular	generic	wet	87% precision	19	[272]
drowsiness	EEG	ear canal	generic	wet	80% accuracy	23	[238]

H EMOTIONS

Emotion tracking with earables is described in subsubsection 4.4.1. Table 13 summarizes earable works that looked into tracking emotions of the wearer according to the applied scale (dimensional or categorical), the specific emotions predicted, the sensor used, the performance achieved, and the number of study participants recruited.

Table 13. Emotions were classified from the ear from audio data, brain activity and indirectly from body motion intensity.

Scale	Emotions	Sensor	Performance	N	Ref.
dimensional	valence (high vs. low)	in-ear EEG	71.07% accuracy	13	[29]
dimensional	valence (high vs. low)	in-ear EEG	94.1% accuracy	12	[190]
dimensional	valence (high vs. low)	accelerometer	show principle	3	[106]
dimensional	arousal (high vs. low)	in-ear EEG	72.89% accuracy	13	[29]
categorical	happiness, sadness, calmness, fear	in-ear EEG	53.72% accuracy	13	[29]
categorical	excited, relaxed, negative	in-ear EEG	58.8% accuracy	12	[190]
categorical	neutral, upset, happy, angry	microphone	91% F1-score	24	[161]

I GAIT

Gait tracking with earables is summarized in subsection 5.3. Commonly, gait parameters and related events are predicted by acceleration forces measured at the ear. Table 14 summarizes gait tracking earable works according to the gait-related parameter, performance, and number of study participants.

Table 14. Gait-related parameters have been explored heavily on earables through acceleration data. Timing of gait, detecting gait-related issues, and the relationship between standardized gait metrics were looked into.

Gait-Related Parameter	**Performance**	**N**	**Ref.**
timing of heel contact, and toe off events	35.38±3.22, 73.05±7.24 ms error	10	[146]
timing of swing, stance, and stride time	35.5±4.0, 36.9±3.8, 17.9±2.3 ms error	10	[148]
timing of step cycle and asymmetry	20±50, 10±70 ms mean difference	64	[27]
timing of step cycle	30 ms mean difference	43	[26]
detect steps (very slow, slow, normal, run)	95% accuracy	3	[280]
detect truncal impairment	> 97% accuracy	22	[19]
detect lower limb impairment	95% accuracy	20	[20]
detect freeze of gait	95.6% accuracy	16	[199]
detect simulated lower limb impairment	> 97% accuracy	10	[19]
Timed Up-and-Go (TUG) fall risk [223]	elderly at risk correctly identified	28	[173]
post-surgery gait pattern regularity	regluarity improves 24 weeks post-op	17	[22]
post-surgery asymmetry, stride and step time	metrics improve over a year post-op	16	[147]
Knee Injury & Osteoarthritis Outcome Score [294]	r = -0.68	12	[146]
Tinetti Gait and Balance Assessment (TGBA) [340]	360° turn, stand w/ eyes closed feasible	28	[173]
Parkinson's-related tremor noise removal	noise can be separated from gait	9	[264]

J EATING

In subsection 5.4 tracking of eating-related events with earables is summarized. In Table 15 below, earable works that have addressed tracking eating-related activities are summarized according to the parameter they aimed to predict, the study setup used (e.g., field, lab), the food ingested (e.g., free, N pre-defined foods), the sensor applied, the location where the sensor was placed, the achieved performance, and the number of study participants.

Table 15. Tracking of eating related events with earables. * = an additional sensor beside the sensor on the ear was used, ** = manual inter rater agreement (ICC)

Parameter	Setup	Ingest	Sensor	Location	Performance	N	Ref.
eating detection	field	free	bone microphone	mastoid	87.9% accuracy	14	[45]
eating detection	field	free	microphone	lateral	76.8% accuracy	4	[111]
eating detection	semi	33 foods	microphone	ear canal	88.0% accuracy	22	[260]
eating detection	lab	12 foods	microphone	lateral	95.5% accuracy	28	[111]
eating detection	lab	7 foods	2 × microphone	ear canal + lateral	88.5% accuracy	51	[266]
eating detection	lab	6 foods	bone microphone	mastoid	90.0% accuracy	20	[44]
eating detection	lab	5 foods	microphone	lateral	94.0% accuracy	5	[200]
eating detection	lab	7 foods	2 × microphone	ear canal + lateral	77.6% accuracy	40	[263]
eating detection	lab	5 foods	acc. + gyr.	lateral	95.0% accuracy	5	[200]
eating detection	lab	unknown	acc. + gyr.	lateral	84% accuracy	20	[181]
eating detection	field	free	acc. + gyr. + mag.*	posterior	93.0% accuracy	10	[37]
eating detection	lab	free	acc. + gyr. + mag.	posterior	86.0% accuracy	16	[37]
eating detection	lab	free	acc. + gyr. + mag. + prox.	posterior + canal	81.5% accuracy	16	[37]
eating detection	lab	5 foods	acc. + gyr. + microph.	lateral	97.0% accuracy	5	[200]
eating detection	field	free	proximity sensor	ear canal	82.3% accuracy	6	[38]
eating detection	lab	3 foods	proximity sensor	ear canal	90.4% accuracy	20	[38]
eating detection	lab	free	proximity sensor	ear canal	71.5% accuracy	16	[37]
eating detection	field	free	piezoelectric*	inferior	89.8% accuracy	12	[101]
eating detection	lab	5 foods	piezoelectric	inferior	81.0% accuracy	20	[303]
eating detection	semi	33 foods	PPG	ear canal	75.3% accuracy	22	[260]
eating detection	lab	6 foods	EMG	Mastoid	84.0% accuracy	20	[44]
eating detection	lab	6 foods	EMG + microphone	Mastoid	94.0% accuracy	20	[44]
bite events	lab	4 foods	piezoelectric + bone mic.	inferior + mastoid	ICC=0.935**	21	[302]
chew events	lab	free	2 × microphone	ear canal + lateral	72% precision	6	[225]
chew events	lab	5 foods	microphone	ear canal	98.07% accuracy	1	[249]
chew events	lab	3 foods	microphone	ear canal	>60% precision	8	[12]
chew events	lab	4 foods	piezoelectric + bone mic.	inferior + mastoid	ICC=0.928**	21	[302]
chew strength	lab	3 foods	pressure sensor	ear canal	show principle	15	[141]
chew strength	lab	3 foods	microphone	ear canal	>59.0% accuracy	8	[12]
swallow events	lab	4 foods	piezoelectric + bone mic.	inferior + mastoid	ICC=0.943**	21	[302]
drinking detection	lab	1 drink	microphone + bone mic.	ear canal + lateral	56.6% accuracy	5	[311]
drinking detection	lab	1 drink	2 × microphone	ear canal + lateral	30% recall	51	[266]
predict food type	lab	8 foods	2 × microphone	ear canal + lateral	79% accuracy	51	[266]
predict food type	lab	4 foods	microphone	ear canal	86.6% accuracy	2	[11]
predict food type	lab	3 foods	microphone	ear canal	94.0% accuracy	8	[12]
intake progress	field	1 meal	camera	lateral	show principle	1	[193]

K EAR AND EARABLE INPUT

Interaction on the ear and earable input is summarized in subsection 6.1. The Table 16 below summarizes how manipulation can be performed at varying locations based on different sensing principles.

Table 16. Summary of works that looked into manipulation of the ear and earable.

Manipulation	**Location**	**Sensor**	**Ref**
touch	earable	capacitive	[64]
touch	earable	capacitive	[192]
touch	earable	capacitive and resistive	[356]
touch	ear	camera	[184]
taps	earable	modified speaker	[209]
taps and sliding gestures	ear; cheek; temple; mandible	microphone	[361]
ear deformation	ear	proximity sensors	[171]
tensor tympani contraction	ear canal	pressure sensor	[290]
wearable state	earable	capacitive	[64]
wearable state	earable	proximity sensors	[219]
wearable state	earable	microphone + emitted ultrasound	[182]
3D position	earable	acoustic motion tracking	[66]

L HAND GESTURES AND LOCATION

Hand gestures and hand location tracking are described in subsection 6.2. The Table 17 below describes where the interaction takes place, how activation is performed, what sensing principle is used, the achieved performance, and the number of study participants.

Table 17. Hand tracking embedded inside earables enables interaction away from the ear.

Location	Activation	Sensor	Performance	N	Ref.
mid-air at mouth	obstruct mouth by hand	microphone + emitted sound	96.5% F1-score	12	[362]
mid-air at earable	swipe 1 to 4 fingers	proximity sensor	99% accuracy	2	[227]
mid-air at earable	42 sign language words	microphone + emitted sound	93.8% accuracy	8	[151]
mid-air	hand gestures	camera + mini-projector	show principle	1	[327]

M MOUTH-BASED INTERACTION

In subsection 6.4 mouth-based interaction is summarized. In the Table 18 below, mout-related gestures based on jaw, teeth, and tongue are introduced according to the type of gestures, sensors, achieved accuracy, and number of study participants.

Table 18. Movement of the jaw, tongue, and teeth was applied to offer subtle interaction to the user.

Mouth-Related Gesture	**Sensor**	**Accuracy**	**N**	**Ref.**
6 jaw movement gestures	pressure sensor	90.7%	12	[14]
4 open mouth levels	pressure sensor	87.5%	12	[14]
10 target points at teeth by tongue	EMG, EEG, capacitive sensing	88.61%	15	[247]
6 target points at teeth by tongue	microphone + emitted sound	94.8%	20	[67]
point tongue left, front, right	pressure sensor	66 - 96% (per user)	5	[205]
press tongue against roof of mouth	photo reflective	> 99%	5	[328]
click 5 different pairs of teeth	microphone	78%	20	[17]
6 tap and slide teeth gestures	modified speaker	> 90%	18	[281]
13 teeth tap gestures	passive microphone + gyro.	90.9%	11	[320]

N FACIAL EXPRESSIONS

In subsection 6.5 facial expression tracking with earables is described. In Table 19 facial expression tracking works with earables are summarized based on the types of facial expressions detected, sensors applied, performance achieved, and number of study participants recruited.

Table 19. Facial expressions were explored for discreet interaction with many works selecting the ideal subset of expressions for increased classification performance. * = final set selected from a bigger data collection

Facial Expressions	Sensor	Performance	N	Ref.
eye wink, head right, open mouth, say sh, smile*	EMG (EarFS)	90% precision	3	[221]
face up/down, tilt head left/right, jaw left/right*	mic. + emitted sound	90% F1-Score	11	[10]
smile, frown*	Acclerometer	85% F1-Score	9	[187]
15 facial expressions	Miniature Cameras	88.6% accuracy	9	[72]
32 facial expressions	Accel. + Gyro.	89.9% accuracy	12	[344]

O SHAPE-BASED AUTHENTICATION AND IDENTIFICATION

Authentication and identification based on the user's ear, skull or body with earables is described in subsection 7.1. In Table 20 different works are summarized based on the part of the body they target for authentication (e.g., complete ear vs. ear canal only). Additionally, the verification performance according to false rejection rate (FRR), false acceptance rate (FAR), and equal error rate (ERR) are presented. Equal error rate is the decision boundary at which FAR and FRR are equal. For identification, the rate of correct identifications is reported. The table also includes the number of participants from which the results have been derived.

Table 20. Perfomance of different earable verification and identification methods based on the characteristic shape of the ear and changes thereof. * indicates that no FAR/FRR combination was highlighted by the authors (FRR = FAR = EER).

		Verification			**Identificat.**		
Target	**Probe Signal**	*FRR*	FAR	*EER*	*Rate*	**N**	**Ref.**
ear	audible chirp (1.5 - 22 kHz)	*	*	0.8%	-	31	[7]
ear	audible seq. (6 Hz - 12 kHz)	*	*	14.9%	-	50	[87]
ear	audible chirp (100 Hz - 10 kHz)	*	*	≈ 5%	-	27	[87]
ear canal	audible chirp (20 Hz - 6 kHz)	2.6%	2.2%	-	-	20	[110]
ear canal	audible chirp (1.5 - 22 kHz)	*	*	1.0%	-	31	[7]
ear canal	audible chirp (1 Hz - 18 kHz)	*	*	0.28%	-	25	[206]
ear canal	audible seq. (200 Hz - 16 kHz)	*	*	0.97%	-	45	[16]
ear canal	inaudible chirp (18 - 48 kHz)	*	*	< 0.01%	-	25	[206]
ear canal change	inaudible chirp (16 - 23 kHz)	*	*	≈ 4%	-	24	[354]
cochlea response	audible click stimulus	1.55%	0.0%	0.02%	99.44%	54	[195]
skull	speaking-induced body sound	*	*	3.64%	-	23	[109]
skull	voice 'EMM' sound	*	*	1.28%	-	34	[194]
body (arm to ear)	laptop leakage current	< 8%	< 10%	-	93.6%	15	[89]