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Data Driven User Experience for Personalizing Hearing Health Care

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Abstract

What is good User Experience? How do we measure it? How do we quantify it? User Experience is not only about "getting the job done". User Experience is about guiding and supporting the user, leading them to a subjective end goal. It's about creating pleasant experiences and journeys. It's about creating emotional and affective bonds, while the user interacts with services or product. We need ways of implementing user experience in health care to address the challenges of a lack of clinical resources. Inspired by the 4Ps of medicine, this thesis tries to address the *participatory* and *personalized* perspective.

A UX framework, named data-driven UX is proposed to highlight how patient-generated data creates value in a clinical workflow. The framework highlights how UX methodology and tools can be applied to a health care domain, hearing health care. Hypotheses are validated early, frequently and iterative through rapid prototyping. Hearing aids are treated as contextual aware devices that collect data. The contextual data shows that individuals have unique behavioral patterns related to program and volume interactions. These individual nuances are not taken into account with the current hearing aid fitting paradigm. It is also shown that individual behavior can be modeled from contextual parameters, including acoustic environments, location, and motion. This data can be used to personalize hearing aids of the future.

Using the data actively in clinical sessions, to debrief patients, help with recall and to highlight behavioral traits, addressing participatory health care. To engage the patient, the interface to the medical device must be compelling. Thoughts on designing compelling interfaces, by addressing mental models, and using metaphors and microinteraction.

In the end, some considerations of the future of hearing health care are proposed.

Summary (Danish)

Hvad er god brugeroplevelse (user experience). Hvordan kvantificeres det? User experiece handler ikke kun om 'at udføre arbejdet'. User experience handler om at skabe mindeværdige oplevelser med teknologi, produkter og ydelser. Det handler om at skabe rare oplevelse og rejser. Det handler om at skabe følelsesmæssige bånd mens brugeren interagere med en ydelse eller et produkt.
Vi har behov for at implementere user experience i sundhedsteknologi for at addressere de nuværende og kommende udfordringer skabt af mangel på kliniske resourcer. Denne afhandling vil primært, inspiret af de *4P'er* indenfor medicin, forsøge at addresere perspektiver indendfor deltagende (participatory) og personaliseret (personalized) medicin.
Et user experience rammeværk kaldet datadreven user experience bliver beskrevet. Det forsøger at fremhæve hvordan patientgeneret data skaber værdi i kliniskpraksis. Rammen fremhæver hvordan UX metodik og værktøjer kan bruges i sundhedsvæsnet, specifikt for høretabs behandling.Hypoteser bliver valideret tidligt, ofte og iterativt ved brug af hurtig prototyping (rapid prototyping). Høreappareter bliver brugt som kontext bevidste (context aware) apparater som indsamler data. Den kontekstuelle data viser at folk har unikke individuelle adfærs mønstre relateret til program- og volumeinteraktioner. Disse individuelle nuancer bliver der ikke taget forbehold for i det nuværende høreapparats tilpasningsproces. Det vises også individuel adfærd kan moduleres fra kontekstuelle parameter, inkludering det akustiske miljø, lokation og bevægelse. Denne data kan bruges til at personalisere fremtidings høreapparater. " Klinkkere kan bruge data aktivt til at debriefe patienter, hjælper med at huske og til at fremhæve adfærsmønstre, alt for at skabe deltagende medicinering. For at engagere patienten må brugergrænsefladen på medicinskeapparatert være tiltalende. Tanker omkring design af medicinsek brugergrænseflader, bliver tiltalt ved brug af

mentale modeller, metaforer og ved at bruge mikrointeraktioner.
Til slut vil der bliver frembragt tanker om fretiden for personaliseret høretabs behandling.

Preface

This thesis is presented in fulfillment of the requirements for acquiring a Ph.D. in Engineering, and was prepared at the Cognitive Systems section of DTU Compute, under the supervision of Associate Professor Jakob Eg Larsen and Senior Scientist Michael Kai Petersen.
The thesis deals with aspects of how data driven user experience applied to hearing health care can improve the personalization of hearing aids, encourage user participation and create a better user experience for hearing aid users. The thesis includes 7 published papers, and 1 in submission.

Lyngby, March 31st-2019

Benjamin Johansen

Scientific Contributions

Conference Proceedings

A **Benjamin Johansen**, Michael Kai Petersen, Niels Henrik Pontoppidan, Per Sandholm and Jakob Eg Larsen. Rethinking hearing aid fitting by learning from behavioral patterns. (2017) *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems - CHI EA '17* (pp. 1733-1739). ACM, New York, NY, USA.

B **Benjamin Johansen**, Michael Kai Petersen, Maciej Jan Korzepa, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Hearables in hearing care. (2017). *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 39-49). Springer, Basel, Switezerland.

C Maciej Jan Korzepa, **Benjamin Johansen**, Michael Kai Petersen, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Modeling user intents as context in smartphone-connected hearing aids. (2018) *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization - UMAP '18* (pp. 151-155). ACM, New York, NY, USA.

D **Benjamin Johansen**, Maciej Jan Korzepa, Michael Kai Petersen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Inferring user intents from motion in hearing health care. (2018) *Proceedings of the 2018 ACM International Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers - UbiComp '18* (pp. 670-675). ACM, New York, NY, USA.

E (*) **Benjamin Johansen**, Michael Kai Petersen, and Jakob Eg Larsen. Obtaining data on hearing experience through self-tracking. (2018) *Proceedings of the 2016 ACM International Joint Conference and 2016 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers - UbiComp '16* (pp. 594-599). ACM, New York, NY, USA.

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F **Benjamin Johansen**, Michael Kai Petersen, Maciej Jan Korzepa, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. (2018). Personalizing the fitting of hearing aids by learning contextual preferences from internet of things data. *Computers, 7*(1), 1-21. 10.3390/computers7010001.

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Other Published Contributions

H **Benjamin Johansen**, Maciej Jan Korzepa, Michael Kai Petersen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Mapping auditory percepts into visual interfaces for hearing impaired users. (2018) *Workshop on Designing Interactions for an Ageing Population, CHI '18.*

I Maciej Jan Korzepa, **Benjamin Johansen**, Michael Kai Petersen, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Learning preferences and soundscapes for augmented hearing. (2018) *CEUR Workshop Proceedings, IUI '18.*

J **Benjamin Johansen**, Michael Kai Petersen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Modeling user utterances as intents in an audiological design space. (2019) *Workshop on Computational Modeling in Human-Computer Interaction, CHI '19.*

K (*) Niels Henrik Pontoppidan, Anida Memic, **Benjamin Johansen**, Yang Wang, Elisabet Sundewall Thorén, Michael Kai Petersen, et al. 2019. *Hearing Aid System.* European Patent No. EP3432606 (A1).

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Contents

Acronyms

ABR auditory brainstem response. 13

AI artificial intelligence. 22, 28

audiogram pure-tone audiogram. 10

BM basilar membrame. 14

CPU central processing unit. 51

DALY disability-adjusted life year. 12

DPOAE distortion product otoacoustic emission. 13

DSP digital signal processing. 85

EEG electroencephalography. 13

EMA ecological momentary assessment. 64, 65

GPU graphics processing unit. 51

HCI human-computer interaction. 4, 82

HCP hearing care professional. 5, 7, 17, 64, 83, 90, 96, 97

ICA independent component analysis. 67

IID interaural intensity difference. 48

IoT Internet of things. 51, 52, 59

ITD interaural time difference. 48

MDS multi dimensional scaling. 67

MVP minimum viable product. 32, 33, 35, 37

NFC near field communication. 52

NLP natural language processing. 93, 94

NLU natural language understanding. 93

OAE otoacoustic emission. 13

OHC outer hair cells. 10, 14

PCA principal component analysis. 67, 94

PoC proof of concept. 35, 36

PSAP personal sound amplification product. 13

PTA pure-tone audiometry threshold. 10, 11, 20, 64

RCT randomized controlled trial. 1, 2, 28

RNN recurrent neural network. 94

SFHA self-fitting hearing aid. 20

SNR signal-to-noise ratio. 22, 38, 68, 69, 71, 84, 89, 93

UX user experience. 4, 6, 7

VA Veteran Affairs. 13

WHO World Health Organization. 10–13

YLDs years lived with disability. 10

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Chapter 1

Introduction

Our everyday life has become digital with technological advancements within sensor development, increased computing power, connectivity and access to the world wide web, and deployment of mathematical and statistical models. We can monitor the world, and ourselves throughout the day, generating insights with a degree of detail unimaginable a few decades ago. We have changed our perspective, views and expectations to technology. Technology is expected to serve our every need, while being pervasive and ubiquitous. Technology have become a mean of convenience, which generate insights, and improve our life. Our relationship with technology have changed. We address technology in human form, exemplified by projecting human traits such as uttering *'Siri is so stupid, she doesn't understand me!'*. Technology have in large parts become ubiquitous, and when the user experience is dissatisfying, we see technology in a different light.
Personal technology is appearing within the health care domain. Technology enables patients to become an active part of their treatment, for better and for worse. Patients can now track the development of a skin rash, correlate minutes of strenuous activity with overall well-being, or track the progression of Parkinson's disease symptoms such as trembling. Doctors and other health care professionals struggle with using data generated by patients. The medical community has yet to develop strategies, where technology is part of treatment plans for patients. The gold standard within medical and pharmaceutical sciences is the randomized controlled trial (RCT). The RCT inherently ensures a

statistical significant result across population, attributed to the intervention or the drug. RCTs are long term investments and resource intense. This explains why a new pharmaceutical drug takes 5-10 years before being approved and cost millions of US dollars. The excellence of RCTs is the ability to generalize. In contrast, technology development, especially within personal computing, is considered retired after 10 years. The mismatch between clinical accepted studies, and the flexibility of technology development leaves health care workers in a dilemma. Technology within personal computing and big data opens up for possibilities of creating personalized medicine but is limited by the current paradigm of RCT studies. The question to ask is, how can technology be used, to demo and create value, enabling the medical sciences to leverage insights from data, without compromising treatment.

1.1 Technological Support in Health Care

Is there even a need for technology in health care? By 2035 the WHO [145] estimates a lack of 13 million health care workers globally, to provide the required services in the health care system. The current health care paradigm is not designed for a patient-led, and technology-driven, treatment. The lack of scalability, combined with a growing number of patients, and a health care workforce which grows slower, indicates that health care services are ripe for innovation. The challenge is to find demonstrations, which highlights the benefits of using technology within health care.

Successful attempts of supporting health care professionals through technology include automatic annotation of radiography[1], deep learning for screening lymph cancer [11] and detection of diabetic retinopathy [44], as a few examples. These studies stem from the machine learning and deep learning community and effectively demonstrates how algorithms can automate trivial tasks, such as annotating X-ray imaging, while leaving the final decision-making to health care professionals. The focus of these studies is to be as accurate as possible, with a low false positive or true negative rate as possible. However, this value proportion does not consider the effect on the clinical workflow, and the adaptation of health care professionals.

A different on the future of health care focuses on patient-led health care. Patients generate vasts amount of data and insights. The impact has still to be understood. There is a lack of tools highlighting how this data can better serve the patient and the health care professional to tailor the treatment for the patient, or what I call *personalized health care*.

[1] https://radiobotics.com/

The health care systems are under pressure due to an increase in expected life expectancy, a growing population where elders are in the majority, and health care systems struggling to make ends meet. While this may seem dystopian, there is hope. With the advent of pocketable computing power, big data, lean data processes, and improved user experience, the technology could enable a new era of health care. Hood et al. terms this as *the 4P's of medicine* [52]. The four P's in this context are: predictive, preventive, personalized and participatory. Hood [52], describes the impact of the 4P's as:

> As noted above, P4 medicine will lead to digitalization of medicine — with very broad implications (the creation of patient/consumer-driven social networks, the quantification of self, the information technology for healthcare which will capture data of individuals to create a database for the predictive medicine of the future). The quantification of wellness and the demystification of disease will create wealth for the institutions and organizations that are at the leading edge of this paradigm change.

The focus of this thesis is on how to personalize hearing health care using UX methodology. In the process I will propose a model of personalized hearing care, relying on a closed feedback loop, with user insights driven by data, adaptive interfaces, and how to leverage knowledge from other users, to provide a better fit of the hearing aids. The focus revolves around personalizing hearing aids and includes considerations for the rest of the personalized hearing health care paradigm. Hearing health care is build on the assumption of hearing loss is only a sensory loss. Enabling hearing aid users to be an active part of their treatment, I wish to demonstrate that other factors influences both the perception and usage of hearing aids. These insights can then be shared with clinicians, which can help the users personalizing their hearing aids. I will use UX methodology in combination with data driven insights, to explore how hearing aids can provide better user experiences. Considering both actively involving patients in a *participatory* treatment, and providing a *personalized* experience, without causing excessive burden for the health care professionals. The UX methodology provides a framework to view the problem of personalizing hearing health care holistically. Acknowledging that the problem can only be addressed by involving different research disciplines, stakeholders and perspectives on hearing health care.

1.2 The Research Objectives and Methods

The research objective behind this thesis is to generate a framework and recommendations for personalizing health care applications, with a focus on hearing health care. This is phrased as *personalizing hearing health care*, where the research methods stem from user experience, human-computer interaction and human-centered AI. The thesis draws on contextual aware systems including ubiquitous and pervasive computing, lean user experience (UX) methodology and interface design drawn from human-computer interaction. I call this *data-driven user experience*, or *data-driven UX*. There are several challenges related to personalizing health care using UX methods. My objective is to advance technology-driven health care research with respect to these challenges in the following ways:

1. Establishing UX methodologies to use data driven insights within health care.
2. Advance the empirical understanding of applying personalization and participation in health care settings.
3. Introducing a new point of view on hearing health care, considering technology part of the greater sum.

1.2.1 Experimental Methods

To advance our understanding of how users interact with a sound manipulating device, in a changing context, I have conducted a series of experimental studies. These include long-term studies, in the wild studies, and laboratory experiments. When choosing an empirical method, there is a trade off between criteria and desirable elements [89]: Generalizability, how well the results carry across the population of users; (2) precision of measurements, or how to control for factors not related to the study; and (3) realism of the situation or context in which the context is gathered. Based on these factors I have chosen my studies emphasizing on relevant factors which enriches the scientific community. *Laboratory studies* are commonly used in hearing sciences to investigate the performance of normal hearing listeners and hearing impaired listeners. *In-the-wild studies* and long term studies, are commonly used both within the human-computer interaction (HCI) and ubiquitous and pervasive computing fields. I have chosen to focus on these types of studies, as context aware computing resides here. This also means a compromise of control, versus a higher degree of a realistic situation. Where the laboratory experiments give a high degree of control, it is rarely applicable in real life environments. Observing the problem holistically, to improve the participation and personalization have been the focal point of this thesis. This also means that a small sample population have been chosen, as personalization may not generalize well. Choosing a longitudinal long term in the wild studies provides several challenges. It requires mature technology to involve the users. If the user experience is poorer than the current experience, users will drop out over time. Furthermore, to collect data, the systems needs to be robust, and to log data in unforeseen situations. On the other hand, working with real life experiments involves the users in ways a laboratory cannot. Using data driven imperial studies, and conducting follow-up interviews ensure that the users wish to continue. The experiment feels less clinical for the test subjects, and they are willing to participate further on. This brings the research closer to application and implementation, and general insights can be carried over to real life applications.

1.3 Motivation

Today health care is experiencing rapid change with outside pressure. IT systems are being rolled out, and patients want to be more included in their treatment. Hearing health care relies on personal items, notably hearing aids, which are expected to be worn throughout the day to provide the best conditions of living with a hearing loss. Modern digital hearing aids can be personalized to fit the individuals needs. However, in practice personalization falls short due to several factors. The personalization process heavily relies on manual fine-tuning combined with oral feedback. Users are asked to recall previous experiences, and the hearing care professional (HCP) have to translate the biased oral representation into hearing aid acoustical parameters. This process is time-consuming, and requires the user to come back, often for multiple fitting sessions. Hearing aid manufactures do provide simulations of acoustical environments, to reproduces acoustical experiences. However, either the clinics do not have the required physical environments to emulate the simulations, or time simply don't allow going in depth with personal preferences. Translating user needs into acoustical features prove challenging, and only experienced hearing care professionals can identify the relevant fitting parameters, and the actions to fit the hearing aids correctly. Additionally, there is a lack of a shared vocabulary between user and hearing care professional, meaning that only a minority of users can clearly describe an acoustical experience. Despite the wealth of opportunities, personalization rarely occurs in the fitting process. One barrier of hearing aid personalization stems from the lack of an established feedback system. Currently the clinical workflow is linear and based on calendar availability, rather than need based. The user is only providing feedback based on events that can be remembered, and may have a negative bias, even though their device performs well in most situations. The lack of established feedback mechanisms results in frustration, when the end user cannot adequately explain themselves. Hearing aid development today is driven by improving digital signal process, while limiting acoustical distortion, loss of audio quality, and having low power consumption. The focus of hearing aid development revolves around solving difficult listening scenarios, primarily situations characterized by speech in noise. However, the user experience extends beyond the difficult situations. As a hearing aid is a personal device, worn many hours a day, it should perform well in a variety of listening scenarios.

The hypothesis is that hearing care and hearing aid personalization can be improved significantly based on data-driven user experience. The implication is that hearing health care should be considered a systematic challenge, involving various stakeholders, different technologies, feedback patterns, and user interactions. The user is required to interact with devices, in order to collect data. The hearing care professionals must be willing to include data to provide better solutions for the end user. And hearing aid manufactures to see the value in scalable feedback systems, which may disrupt their current business models. Since the challenges revolve around systems, the need lies in building proof of concepts, which can support the various stakeholders, and through improved user experiences, improve the quality of hearing health care, while making hearing health care more accessible. Today, personalization fails because most people are not average. People may have needs that only they express, but may be considered noise or an outlier in an average data set. Personalization can help these people, by providing better user experience, and in turn, provide a better quality of life. The vision is to understand how to personalize a hearing aid such that the hearing aid becomes pervasive and ubiquitous. That the user only realizes that they wear a hearing aid when they need to recharge it. Wearing a hearing aid should restore the auditory ability to such that walking in the woods becomes as full of experiences for a hearing impaired, as for a normal hearing listener.

The aim of this thesis primarily revolves around improving the user experience for the end user and hearing care professionals. User experience provides the fundamental tools to investigate the personalization of hearing aids. Using the methodology of lean and rapid prototyping allows the designer to rapidly verify hypotheses. The lean and data-driven methodology supplements the current road-map-driven hearing aid development, by providing early insights into new types of offerings validated with the end user. UX provides value by highlighting areas of value, both commercially and for the user, which may not require new devices, but rather new mindsets. Rapid prototyping, using existing products and services, can generate insights, such as user behavior, with relatively few resources committed. Interweaving data in the UX process allows for both long term deployment studies, and to scalable studies, where data can be gathered.

This adds a complementary dimension to qualitative UX, where workshops, interviews, and observational studies, can be combined with in-the-wild, quantitative user studies. UX with a focus on hypothesis validation is the backbone of the thesis.

A shared vocabulary of acoustical experiences supports the interactions between HCP and user. By collecting contextual data, including acoustical context, time, activity and location, the user and HCP have visual landmarks to aid conversation in the fine-tuning process. Adding a layer of user interactions provides insights into the coping strategies of the user. Contextual data from physical environments and users context about user behavior and habits. Utilizing contextual data can be valuable in the fine-tuning process, and provides visual feedback mechanisms. However, privacy concern should be considered, meaning that the contextual data must provide more value, than negative consequences, without inferring privacy. Opt-out options should be a part of the system design. Not only does the user be willing to collect and share data with their HCP, but the HCP also needs to know the data is accessible and how to use it. The consequences of this is a change in the clinical workflow.

To gather information about user interactions new types of user interfaces are investigated. The current interface offerings are based on direct control on the hearing aid, a physical remote control, or a remote control app. Designing a new user interface that supports user interactions with sound augmentation is essential in motivating users to provide interaction data. Firstly, a common and accepted sound vocabulary does not exist, thus only basic descriptors such as loud, sharp, and dull can be used. This is then translated into actionable hearing aid parameters, which augment sound accordingly. Secondly, there's a challenge in translating an auditory experience into a visual interface, which in turn augment sound. Questions such as how does round sound look like, what is a sharp sound, what does focused sound visualize and so on. Conceptually I argue that visual metaphors may address these challenges. Specifically, a map metaphor may help guide the user in navigating in sound.

The final challenge of hearing aid personalization is extending the UX philosophy beyond the current offerings. Meaning, how can we build intelligent interfaces which can dynamically adapt to the changing context and the user intentions. I will briefly touch on the future of sound augmentation, and how novel interactions, driven by computational interactions, will create new user experiences, and change the way we interact with hearing aids.

1.4 Outline and Contributions

The thesis contributes to research into UX methodology for health care applications using a case study of personalizing hearing health care. The main outcomes of this work can be summarized with the following contribution statements:

Chapter 2 An introduction to hearing loss. Provides an overview and introduction to the case study of hearing health care. A short introduction Hearing loss, hearing loss prevalence, and how the human auditory system is provided. The chapter provides a theoretical model of personalized hearing health care, founded on the current state-of-the-art research within self-fitting hearing aids, user-driven algorithms, and context-aware hearing aids.

chapter 3 A primer to user experience in health care. This work provides the theoretical foundation for user experience. The work proposes a data-driven user experience model, used to collect data and generating value from insights. This is the methodological foundation this thesis provides.

chapter 4 Physical context. This dissertation contributes to building a framework investigating how hearing aids are used in rich contextual scenes, encountered in an everyday life setting. These insights demonstrate that the physical context of hearing aids include acoustical features, time, location and movement.

chapter 5 User context. This thesis provides a further understanding of different coping strategies from individuals. It shows the complexity of personalizing hearing aids, as each user have unique patterns. The proposal is to use several interaction patterns, combined with measurements, to profile the individuals. This data can be fed into a model, which can estimate a better first fit from *users like me.*

Chapter 6 Supporting user feedback. This thesis advances the understanding of coupling visual and auditory interfaces to support user interactions. Providing the user with metaphors to navigating an auditory landscape, in the form of a map. Creating user interfaces which supports user interactions are the foundation for collecting user data, which can be transmitted to the clinician or used to train algorithms.

chapter 7 Adaptive interfaces and future outlooks. The last contribution illustrates how physical context, user context, and user feedback can create adaptive interfaces for personalizing hearing health care. Considerations in how to build these interfaces are demonstrated.

chapter 8 Summarizes the main contributions presented in this dissertation.

Chapter 2

The status of hearing aids today

This chapter introduces the case of hearing loss and hearing health care. Hearing loss is highly prevalent, increasing with age caused by presbycusis, and also found increasingly in younger populations. Preventive care, through education and early screening, can reduce the need for hearing health interventions. Hearing and the auditory system is complex, the focus has been explaining how hearing works as a sensory system. Research shows that hearing is more complex, and also relies on perceptual brain processes. The technological interventions of hearing care today are hearing aids, which artificially amplify soft sounds while preserving good signal to noise ratios. However, hearing aids fail to solve the problem of hearing loss, which may explain why only one in seven [21] with a hearing loss uses hearing aids. And why 24% of hearing aids in a Danish population is used less than an hour per day [34]. At the end of the chapter, I present the motivation of this thesis, grounded in a personalized hearing care paradigm, with considerations to the current paradigm of hearing health care.

2.1 Prevalence of Hearing Loss

Hearing loss is one of the most prevalent diseases and handicaps. Studies show that hearing loss was the fourth leading cause of years lived with disability (YLDs) in 2015 [139]. Furthermore, hearing loss affects 1.3 billion people. In comparison, vision loss affects 661 million people [140], meaning between 15-20 percent of the world population suffers from hearing loss. A European review found at the age of 70, 30% of men and 20% of women have a pure-tone average loss of 30 dB or more [116]. For people above the age of 80, 55% of men and 45% are suffering from a hearing loss. The World Health Organization (WHO) [148] estimates that 466 million people live with a disabling hearing loss in 2018, and expect these numbers to grow to respectively 630 million in 2030, and more than 900 million in 2050. The majority of hearing loss have been attributed to age-related factors. However, hearing loss is not old (wo)mans disease. Shargodsky et al. [121] found a significant increase of hearing loss in US adolescents from 14.5% in 1988-1994, to 19.5% in 2005-2006, and found 20% of Americans aged 12 or older are suffering from a hearing loss. The WHO predicts that "some 1.1 billion teenagers and young adults are at risk of hearing loss due to the unsafe use of personal audio devices" [147]. These numbers indicate a trend where the prevalence of hearing loss increases across age groups, including adolescents and young adults. Meaning, the future hearing care solutions must cater to a broader audience with a more diverse demographic background. The prevalence of severe hearing loss is more frequent in lower income groups [121], and in low income and developing countries [148]. These groups may have limited access to hearing health care, and may not be exposed to preventive measures.

2.2 What is Hearing Loss

The accepted answer is a decreased sensitivity of the ear. Hearing loss occurs when weak sounds no longer elicit activity from the auditory nerve, and strong sounds elicit an attenuated response, compared to that of a healthy ear. Sensory hearing loss is often caused by dysfunction outer hair cells (OHC), for example, caused by mechanical damage or trauma, aging (presbycusis), heredity, medically as a side effect of chemotherapy and otoxicity [117], or a combination of these. The clinical screening of hearing loss identifies decreased sensory sensitivity. The clinical standard for hearing loss screening is a pure-tone audiometry threshold (PTA) test, which identifies reduced hearing threshold sensitivity. The patient is screened in each ear with a pure tone ranging from 250 to 8000 Hz and asked to click a button, indicating when a tone is heard, and in which ear [6]. The outcome of this screening is a pure-tone audiogram (audiogram), illustrated in Figure 2.1. The audiogram illustrated the auditory threshold for the right ear, marked in red, and the left ear, marked in blue. If the sensitivity in any band is greater 20 dB, it is considered a hearing loss. A PTA screening takes between 10-15 minutes. The WHO [144] differentiates between four levels of hearing impairment: *Slight/mild* 26-40dB hearing loss, *Moderate* 41-60dB hearing loss, *Severe* 61-80dB hearing loss and *Profound* over 81dB hearing loss. There are limitations to this method of hearing screening. It requires a quiet environment, preferably a sound-insulated room to reduce disturbance from outside. The method only accounts for pure tones, not for complex sound environments. Amplification is one among several parameters, discussed later, that affects a person hearing threshold. The test results are prone to false-positives and true-negatives, caused by unknown 'internal' noise. The method only accounts for pure tones, not for complex sound environments. Amplification is one among several parameters, as will be discussed later, that determines a person hearing threshold.

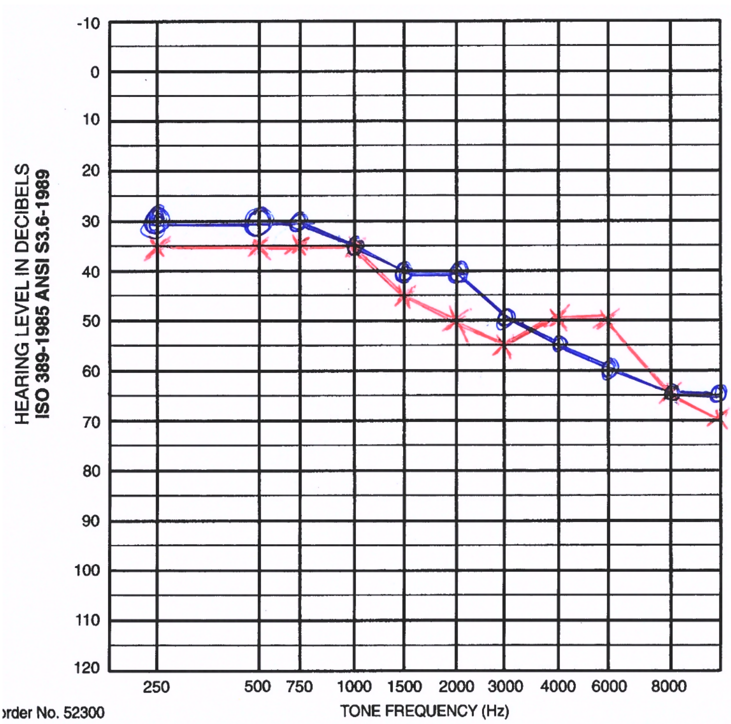


Figure 2.1: Example of an audiogram from a hearing-impaired person. The audiometric threshold for respectively right ear (red line), and left ear (blue line) is marked for pure tone thresholds between 250 Hz to 8000 Hz. The y-axis denote the hearing threshold in dB.

2.2.1 The consequences of hearing loss

The consequences of hearing loss can broadly be divided into three main topics of impact; functional, social and emotional, and economic. *Functional* impact relates to the degradation of the sensory organ of the ear, this includes a lower number of outer- and inner hair cells. Unaddressed hearing loss results in difficulties in the individual's ability to communicate with others. This includes degraded speech perception and comprehension. The functional impact also decreases sensitivity to external sound stimuli. The primary clinical management intervention is hearing aids. In cases of profound hearing loss, cochlear implants can be considered an intervention. The functional impact profoundly affects children, where untreated hearing loss results in degraded learning abilities, and language development [76, 102].
Social and emotional impact is caused by reduced communication skills. This can have a significant impact on the quality of life for hearing impaired. Hearing loss is directly related to increased rates of depression, social isolation, loneliness, altered self-esteem, and diminished functional status [5, 39, 128]. The recent finding suggests untreated hearing loss increases the risk for cognitive disorders. This includes an increased risk of dementia [81, 82], where lack of early prevention of hearing loss accounts for up to 10% of dementia cases.
Economic impact is mainly related to reduced quality of life and loss of productivity. Archbold et al. [4] estimate an annual cost in 2013 of £30 billion in the UK alone. The main contributors are related to reduced quality of life and lost earnings accounting for more than 98% of the costs, while both increased cost for general practitioners and social workers have a small impact. Associated costs in the US is estimated to billions of dollars in lost productivity [54]. disability-adjusted life year (DALY) is a measure for reduced quality of life. The WHO [96] describe DALY as "the DALY extends the concept of potential years of life lost due to premature death to include equivalent years of "healthy" life lost by virtue of being in states of poor health or disability". A DALY can be thought of as the loss of an imagined healthy year: a year without health issues, disability or death. The burden of disease can be thought of as a measure of the distance between the current health status and ideal health. In high-income countries hearing loss is the sixth leading cause of DALY, and is predicted to be among the top 10 diseases in 2030 [87].

2.2.2 Reducing impact through prevention and interventions

Hearing loss can be prevented by timely prevention, early hearing screenings, and education, and can significantly lower the associated societal cost of hearing loss. In high-income countries, hearing screening of newborns is used as preventive measures for hearing loss. The clinical assessment consists of either auditory brainstem response (ABR), measured using electroencephalography (EEG). The child is exposed to a short burst of acoustical clicks or pure tone burst and the ABR response is recorded [86]. Alternatively using otoacoustic emission (OAE), where a tone or click evokes a response in the outer hair cells, called a distortion product otoacoustic emission (DPOAE). DPOAE reflect frequency inactivity [69]. If the child fails the screenings, a hearing intervention is used to support language learning. Depending on the severity of the hearing loss either hearing aids or cochlear implants are used. Cochlear implants have the greatest impact on children less than 3.5 years old, and only minor benefits after the age of 7 [76, 122], due to brain plasticity.

If preventive measures fail, a hearing instrument like a hearing aid or cochlear implant can support the user. However, there are several barriers to acquiring an intervention. First, the high cost of entry leaves many in need without proper hearing care, add to this the long term cost of batteries. A hearing aid cost 1000 US dollars and upwards, the more expensive products costing 2500 US dollars or more. In some high-income countries, such as Denmark, and the United Kingdom, governments refund, or partially refund the cost of acquiring a hearing aid. In the USA the cost can be covered by insurance schemes, or for servicemen the Veteran Affairs (VA). The high cost limits the accessibility in low-income groups and low-income countries, where public funding schemes are not available. At a fraction of the cost of hearing aids, personal sound amplification product (PSAP) can be an alternative to hearing aids. However, these devices are neither medically approved, they only lower the price for entry, and they underperform in acoustical properties compared to hearing aids [114], making them less desirable. Hearables, such as Apple Airpods, Bragi Dash or Doppler Labs Here One, all feature microphone arrays, active noise cancellation, and a form factor similar to hearing aids, and may try to move into the hearing aid market. Secondly, there is a lack of clinical resources within hearing care. In Denmark, the public funding scheme has a waiting list of around a year [129] for receiving hearing care treatment. While private vendors are incentivized by selling products as efficiently as possible. This means a hearing aid fitting session may conclude within 30 minutes, including time for selecting a model, and training. In low-income countries, the lack of hearing care professionals limits access to hearing care. WHO [146] reports that low-income countries have less access to hearing health care, with less than one audiologist per million people. When looking at cochlear implants, the cost is exceedingly high due to the medical procedure involved. The gap between clinical resources and the increasing number of hearing-impaired people are growing. The third barrier is dissatisfaction with the technology. McCormack & Fortnum [88] list the performance related to hearing aid value and speech clarity as a primary point of dissatisfaction. This relates to the ability of the hearing aid to function in noisy situations, have perceived poor benefit, poor sound quality, does not suit the type of hearing loss, or is perceived to be broken. McCormack & Fortnum also indicated that using hearing aids are driven by attitude. Meaning, people perceive they hear well enough without a hearing aid, and they cannot identify situations where they would benefit from a hearing aid. These barriers may explain why in average it takes a person with hearing loss 10 years before using hearing aids [26], despite the negative consequences.

2.3 The Hearing as a Sensory Organ

The human ear is an extraordinary and finely calibrated sensory organ, closely coupled with our brains. The complex system translates and transmits weak airborne mechanical signals, sound, through complex electric and chemical reactions and impulses, to our brains. The highly non-linear auditory system can distinguish between tiny differences in air pressure change. The human hearing threshold is at 0 dB, while the pain threshold is at 10^{13} dB! The ear have a remarkable dynamic range, and through various organs can amplify fading sounds. This summarizes the hearing system as a sensory system that deals with amplification, compression and frequency analysis. The sound The system can be understood using a simplified situation of a pure tone. A human subject is affected by a pure tone of 1000 Hz, this is within the speech threshold. The sound wave travels through the ear canal, and excites the tympanic membrane. Vibrations of the tympanic membrane is amplified by the three tiny bone structure, the malleus, incus and stapes. The stapes is directly attached to the oval window, which itself is a thin membrame. The sound wave now enters the inner ear, also called the cochlear. The cochlear, a snail shaped organ forming part of the inner ear, transforms a mechanical signal into an electrical impulse. The excitement of the oval windows creates a pressure difference in the chamber called scala vestibuli, which in turn excites the basilar membrame. For intuition the cochlear is unrolled as a tube, this is illustrated in Figure 2.2. OHCs amplifies weak sounds, without amplifying loud sounds. This is known as compression of incoming sound. Using compression enables a highly dynamic range to be encoded in the auditory nerve. The basilar membrame (BM) is excited by the amplified signal from the OHCs. This creates a travelling wave, which peaks at certain frequencies. At the base, closest to the oval window, the BM is stiffer, and more sensitive to high frequencies. The end furthest away from the base, is called the apex. The apex is softer and more flexible, and is more sensitive to low frequencies [95]. As the BM moves the inner hair cells that are attached to it releases an electrical impulse to the auditory nerve. The inner and outer hair cells are transmitters of electromechanical and chemical signals. The auditory nerve amplifies the electrical signal send to the brain. When the OHC have sustained damage, the compressive features and amplification is reduced.

The auditory nerve sends the acoustical signal to the brain, this neurological pathway accounts for the other half of the audiotry system. There is still limited understanding of how the auditory cortex work. The auditory cortex is responsible for sound, speech and music perception [112]. However, the effects of hearing loss on the auditory cortex is not fully understood. It is known that brain plasticity degrades the auditory cortex. This thesis focus on how the ear works as a sensory organ.

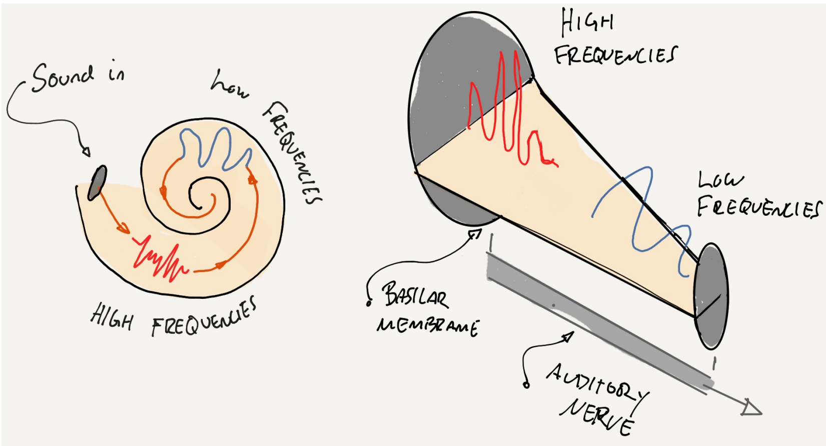


Figure 2.2: Simplified illustration of the inner ear. The figure on the left illustrates how sound travels from the oval window to the apex of the cochlear. The right illustrations show how the basilar membrane is excited by different sound waves, and the signal is transmitted to the auditory nerve.

Auditory scenes Auditory scenes are an analogy that explains how the auditory system works. Bregman [15] explains how the auditory system works by the following analogy:

> Imagine that you are on the edge of a lake and a friend challenges you to play a game. The game is this: Your friend digs two narrow channels up from the side of the lake. Each is a few feet long and a few inches wide, and they are spaced a few feet apart. Halfway up each one, your friend stretches a handkerchief and fastens it to the sides of the channel. As waves reach the side of the lake they travel up the channels and cause the two handkerchiefs to go into

> motion. You are allowed to look only at the handkerchiefs and from their motions to answer a series of questions ... The lake represents the lake of air that surrounds us. The two channels are our two ear canals, and the handkerchiefs are our eardrums. The only information that the auditory system has available to it, or ever will have, is the vibrations of these two eardrums.

The auditory scene is illustrated by Goldstein [41], with slight alterations shown in Figure 2.3. The highlighted oval illustrates the simplified view on how perceptual sensory hearing works, and how digital hearing aids addresses the issue by focusing only on parts of human perception, to explain an acoustical scene.

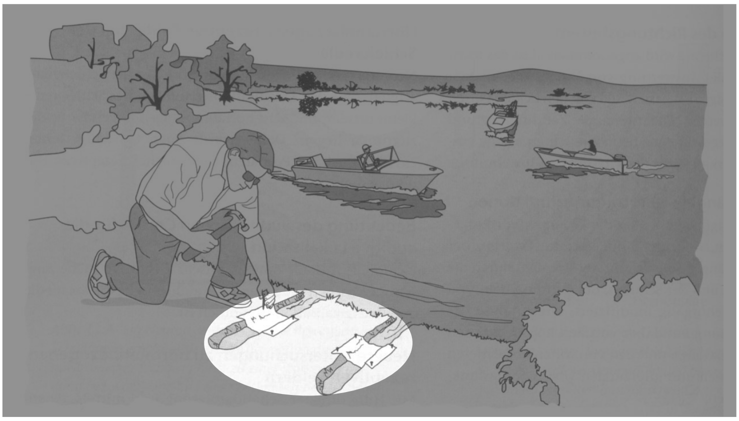


Figure 2.3: Adopted from Goldstein [41] illustrating Bregman's description of an auditory scene. The white oval highlights the information digital hearing aids use to recreate a contextual rich auditory scene.

2.3.1 How does hearing aids work

Today hearing aids work by restoring sensitivity that is no longer provided by the outer hair cells. The assumption is that hearing loss is primarily driven by a loss of sensitivity. This can be solved by amplifying weaker sounds. Early hearing aids and hearing horns relied primarily on amplifying soft sounds and did not have compression features. They worked well in quiet environments but had limited use in noisy environments. With the introduction of the digital hearing aid more, auditory features were introduced. Digital hearing aids use both slow acting compression, which preserves gain frequency and works well in low noise environments, and fast acting compression, which quickly adjusts gain level noisy environments. Fast compression systems are of high importance and can balance between, presenting a speech at comfortable loudness levels, protect the user from transient uncomfortably loud sounds and improve speech intelligibility by amplifying weak speech segments [83]. Adaptive directional microphones can change from an omnidirectional setting, where a 360° spatial acoustic scene is provided to the user, and narrow beamforming where the frontal focus is prioritized. The third feature relates to improving noise reduction systems. These systems assist the user by separating the target sound, from the noise floor. For hearing impaired listeners this can provide up to 6dB improvement, meaning the target signal is perceived double as loud, as the noise. However, digital hearing aids have been limited by acoustical processing artifact distorting the auditory scene or distorting the target signal. Feedback identified by a loud squealing noise is caused by the proximity of microphone array and speaker. Feedback distorts the sound signal and causes discomfort. Furthermore, the focus of hearing aid development has been on miniaturizing technology and form factor, while preserving a low power consumption. These constrain limits the processing power of a hearing aid, which usually has a few dedicated digital signal processors on an embedded system.

Lack of personalization of hearing aids The current clinical workflow is not optimized to personalize hearing aids and lacks a closed feedback loop. The fitting process is illustrated in Figure 2.4. The fitting process starts with a hearing screening. The screening determines the sensory hearing loss and is reflected in an audiogram. The HCP will then enter the audiogram data into a fitting proprietary fitting software, which converts the audiogram to hearing aid settings, primarily gain adjusted. The fitting is the starting point of the fitting process, where the HCP will choose a prescriptive formula such as NAL-NL1 [30], NAL-NL2 [68] or a proprietary fitting rational by the hearing aid manufacturer. These fitting rationals are based on average values from a population and do not guarantee satisfaction among all users. The user then receives the hearing aids and can use them. It is common only to provide the user with one program, which is based on average fitting settings acquired from clinical studies. Fine tuning is a common practice to find a more satisfactory setting for the program. The linear flow of fine-tuning is based on the availability of experienced HCPs. Personalizing by fine-tuning requires several visits to a hearing clinic. Fine tuning is a two-step process. Step one includes the user recalling and translating the issues they have with their hearing device. And step two involves the HCP translating the needs of the user, into adjustable hearing aid parameters. A lack of common vocabulary between HCP and hearing aid users may hinder the feedback process. Studies have shown that experienced HCPs workflow can be reduced into a linear workflow with the following steps utilized for troubleshooting: decreasing Low-Frequency gain, decreasing gain and output, increasing gain and output, reducing high-frequency gain, decreasing maximum output, removing or decreasing distortion, removing peak clipping, and increasing high-frequency gain [57, 134]. The lack of personalization in the clinical workflow may result in dissatisfied user. As mentioned earlier, the top reasons for not using hearing aids are poor performance of the device.

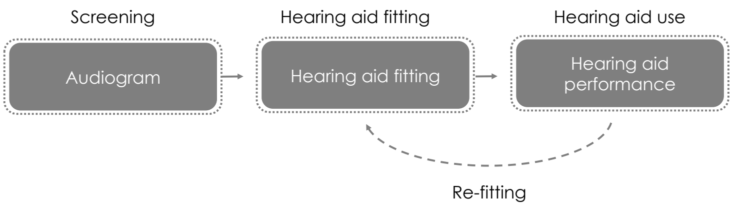


Figure 2.4: The current linear fitting paradigm starts with a hearing screening, then the hearing aid is fitted, and used. If needed and if resources are available, the user can come back and get the hearing aid re-fitted.

2.4 The Complexity of Hearing Loss

Hearing loss is a complex problem, which is solved by utilizing hearing aids. Unfortunately, there is still a mismatch between the expected outcomes and the actual outcomes of using hearing aids. Cognition and hearing is an alternative approach to describe how the human auditory system works. Research shows that hearing loss is more than a sensorial loss. Kral et al. [75] argues that hearing loss is a neurocognitive degradation, and have profound effects on executive function, sequential processing, and concept formation. Samar et al. [122] show that hearing loss is more than a perceptual loss. It is also a brain loss. They compared performance with children in various age groups and found that a cochlear implant has maximum effect before the age of 3.5 years. Meaning, hearing loss may also be attributed to a brain degeneration problem, due to the plasticity of the brain. Lesica [79] argues that hearing loss distorts the neural activity, and that hearing aids of the future must account for this distortion, and for hidden hearing loss, brain plasticity and central processing deficits. Brody [16] argues that hearing loss relates to cognitive impairment. Hearing impaired with similar audiograms may have a signal-to-noise ratio (SNR) difference of up to 15 dB [71]. Meaning, that they perceptually have more difficulties in understanding speech. Wendt [143] shows increased peak pupil dilation with decreasing speech intelligibility, which is attributed to listening effort. Ng et al. [98] shows that noise reduction has a positive effect on working memory for hearing-impaired listeners. And hearing-impaired listeners with adequate noise reduction schemes have a higher working memory capacity [83]. Rönnberg et al. [113] hypothesize that hearing loss directly affects both long and short term memory. The direction of these studies indicates that working memory and hearing loss are correlated, indicating that untreated hearing loss thus give rise to lower cognitive functions.

Hidden hearing loss is a new direction within hearing research. In mice experiments, damage to frequencies above 12000 Hz has had adverse effects. The experiments show that with a normal audiogram, degraded hearing occurs. Kujawa et al. [77] states "This primary neurodegeneration should add to difficulties hearing in noisy environments and could contribute to tinnitus, hyperacusis, and other perceptual anomalies commonly associated with inner ear damage". Later studies have found that the neurodegeneration may be caused by age, and have the same effect [120, 137]. The consequences of hidden hearing loss relate to speech discrimination and temporal processing, even with a normal audiogram [80, 107, 119].

These studies show the complexity of hearing and hearing loss. They also give insights to why hearing aid fails today. The field of hearing research is still evolving, and the bulk of research is still focused on sensorial hearing loss, the accepted gold standard. In order to address hearing loss, we may need to rethink how hearing aids work, and how they can perform better. We must accept that treating hearing loss is a complex problem, and needs to be better understood to address the issues. In this thesis, I primarily focus on current hearing aid technology. It is important to articulate, that hearing loss is complex and not fully understood.

2.5 Current and Future Trends in Hearing Health Care

Hearing loss and hearing care are complex and intertwined. To understand and address the problem, we have to address it as a systematic challenge, rather than a decomposed problem for digital signal processing, clinical research and technology development. The current state of the art within research addresses the problem for different angles. From the clinical perspective, several studies have addressed the shortcoming of hearing care. De Wet Swanepoel et al. [132] have worked on developing a smartphone-based screening method for developing countries and making hearing care more accessible and affordable. Early mobile screenings may reduce the cost of hearing health care long term. Ratanjee-Vanmali et al. [111] have worked on the concept of an online clinic. These studies address the issue of availability of hearing care professionals through technology. If these clinical approaches are scalable, they may support the growing markets of low-income countries, and high growth market like the Chinese market. Several of the major hearing aid manufacturers are working on remote care solutions, such as Starkey Remote Programming, Oticon RemoteCare, and GN eSound Assist[1].

To address the topic of personalizing hearing aids and clinical workflow, studies have proposed methods where the user themselves can tune and personalize their hearing aids. This includes a trainable hearing aid, also called self-fitting hearing aids (SFHAs) [22, 31, 33, 66, 67], where the user can perform a pure-tone audiometry threshold, and fit the hearing aids themselves. Others employ updates to the clinical workflow. Dahl and Hanssen[25] uses an interactive table-top to improve the fine-tuning process, allowing the user to simulate everyday situations and creating dialogues with clinicians. While Boothroyd and MacKersie [14] let users explore and find their optimal hearing aid settings related to overall gain, low-frequency cut, and high-frequency boosting while listening to speech. Aldaz et al. [1] use smartphones to register context, and based on user input trains a hearing aid based on user preferences and finds users prefer the personalized algorithms. Aldaz et al. [1] states the main shortcomings of modern hearing aids to learn about the user as:

> (a) a hearing aid has limited sensor inputs, relying entirely on two onboard microphones to collect information about incoming sounds; (b) a hearing aid has a restricted user interface, even if a remote control is available; (c) compared to other computing devices, a hearing aid has reduced processing power, which prevents the implementation of more advanced machine learning algorithms.

UbiEar by Sicong et al. [124] is the closest to a context-aware hearing aid that has been reported. They use a smartphone to label acoustic events and acoustic scenes. Other reported context-aware devices include work by Tessendorf et al. and Wang et al. [133, 141]. Jens Nielsen [100, 101] uses Gaussian processes to estimate a better fitting paradigm to personalize hearing aids.

In summary, several shortcomings of the current paradigm of optimizing hearing aid fitting have been identified. First, the complex problem of hearing loss and hearing care is boiled down to a sensory deficit. Secondly, the current practices of hearing aid fitting heavily relies on manual tuning and adjustment. Digital hearing aids are still relying on limited processing power and are fitted based on generalized fitting rationals like the NAL [30]. Thirdly, and possibly the

[1] Starkey Remote Programming `https://www.audiologyonline.com/ask-the-experts/starkey-livio-ai-hearing-care-24366`, Oticon RemoteCare `https://www.oticon.com/professionals/tools-and-support/remote-care`, ReSound Assist `https://www.resoundpro.com/en-US/assist`

main point is the missing feedback loop. There is not an established paradigm on using annotated contextual information to improve hearing aid fitting. The closest to a personalized hearing aid comes from using trainable hearing aids and algorithms to estimate user preferences. Despite the research efforts, a commercially context-aware and personalized hearing aid does not exist. The related work shows that hearing health care is a systematic challenge, and cannot be solved using only amplification. Despite several studies showing that people are dissatisfied with hearing aids, the issues still have to be solved. And an acoustical amplification may not be adequate. to the knowledge of the author, no studies have addressed hearing health care in the light of user experience.

2.6 Personalizing Hearing Care

An alternative approach to addressing personalized hearing care is through the lens of user experience. Building on established technological advancements, user experience methodology, including lean UX, can generate valuable insights, fast. There are several challenges that must be addressed to personalize hearing aids, and treat more people world wide. The main challenge is the lack of feedback. The focus is on optimizing the digital signal processing in hearing aids, and the feedback gathered from clinical trials does not reflect real life usage. There is little knowledge of how hearing aids are used. One way to break the glass ceiling is by closing the feedback loop. Building mechanisms which can support the user in their everyday lives, and tools which can support the clinicians when needed, would improve the user experience. There is a knowledge gap between laboratory studies and in the wild studies which must be addressed. Hearing aids have limited contextual awareness, and by improving the contextual awareness of both user and environment, the user experience can be improved. As a research community, we must also acknowledge that hearing loss is more than a sensory loss. It should be acknowledged that hearing loss affects other senses, the brain, and human behavior and that these parameters may be supplementing the sensory hearing loss in personalizing hearing care. To address this issue hearing aid technology must be viewed as an ecosystem of connected devices, and not only as a device which only observes contextual sound. Humans navigate the world with a wealth of information, and so should hearing aids. With the rise of wearables and smartphones, the sensing capacity exists and is waiting to be used. The user can actively be engaged in the fitting process through intuitive feedback interfaces. The fitting process and the everyday life of hearing impaired can be enriched by considerate feedback and data collection. In turn, this makes the fitting process participatory, generating insights for both user and clinician alike. Today the fitting process is linear and calendar based, which may rather reflect the needs of the clinician than the needs of the user. Improving the process, and shifting attention to care, rather than sales, could improve the clinical workflow.

Lastly, and out of the scope of this thesis, is a high barrier of entry, which requires an infrastructure that can support the process of hearing screening and acquiring technological intervention. Due to the lack of clinical resources, the screening and prevention paradigm must change. Remote screening, smartphone screening or home screening, should be considered for the future of hearing impairment treatment. Providing scalable technology which can provide insights allowing for the remote fitting of hearing aids could provide vast value. This is true for communities where access to hearing care is limited. I propose to view hearing care as a personalization challenge. Expanding the clinical workflow figure, Figure 2.4, to include more in-depth screening, and more tools to personalize hearing aids, while also learning from other users are presented in Figure 2.5. This figure illustrates that the screening should consist of an extended test battery including cognitive assessments and signal-to-noise ratio (SNR) assessments. The fitting also changes, and user-generated data is included. The hearing aid performance is updated and now have an additional three interconnected step. Context, relating to the physical context and the user context. User feedback and interaction, relating to interfacing supporting the user. And, adaptive interfaces, updating hearing aid settings and personalizing hearing aids based on user input and hearing aid performance. *Screening* now includes sensory hearing sensitivity assessment, cognitive assessment and signal-to-noise ratio assessment. The screening can be performed in a clinical setting, in a remote setting, or by the user themselves. The logged data is then anonymized and sent to a database, where it is compared against other users. The combined information of the users personal assessment, and with other users, helps reduce uncertainty for the first fitting. The goal should be two-fold. To enable a lower barrier entry for early screening, and to offer a more profound toolbox for hearing loss screening. *Hearing aid fitting* is the next step. Here the software can support the clinician in fitting the hearing aids, and provide relevant tips on counseling and training. Using data from other users *'user like me'*, including screening data and hearing aid usage, the software can propose settings estimated to the current user preferences. Supporting fitting based on 'users like me', addresses the needs of users who may other needs than an average setting can provide them. Alternatively, using remote care solutions, the clinician can fit the hearing aid remotely, or using an artificial intelligence engine, the system may automatically fit the hearing aids. The next step, *personalizing hearing aid usage* is radically different from the current offerings. It consists of four interconnected phases. The hearing aid performance is the fitting paradigm and similar to today's offerings. The *context* relates to data collected about the physical context, such as acoustical scenes, activity and time. The user context is related to how the user interacts with the hearing aid. To enable the contextual awareness, the systems need both an updated data management system, and user interfaces to support user interaction. The user is then asked to provide *feedback*, which is inferred from behavior and interactions, or through questions asked through dialogues. Alternative interfaces encourage users to actively partake in hearing aid treatment. The interfaces generate insights about the hearing aid performance, opening up the black box while providing educational value to the user and expanding their auditory vocabulary. The last step is *adaptive interfaces*, which dynamically update behavior based on hearing aid performance, context and user feedback. The data collected in the hearing aid usage is then relayed back to the fitting procedure, where clinicians can actively use the insights of context and user feedback for optimizing the hearing aid settings, either in a re-fitting session or remotely. The data is further anonymized and fed to a *users like me* model, which can help other users with similar patterns, to get a personalized hearing care solution. The model has several feedback loops, where feedback can be utilized by intelligent systems to improve the user experience, and it can be used for hearing care professionals as a decision support system. In the thesis I primarily focus on the *personalizing of hearing aids*, including contextual awareness, creating interfaces suited for interactions, and reflect on how to make adaptive interfaces. I will use UX methodology to motivate the investigation and insights.

UX methodology provides a toolbox considering existing, and emerging technology, to generate value. When considering personalized hearing care a top-down problem, also need a top-down mindset to create value. Providing tangible value that is easy to incorporate in the current workflow provides more value than improving speech intelligibility with 2% in the lab.

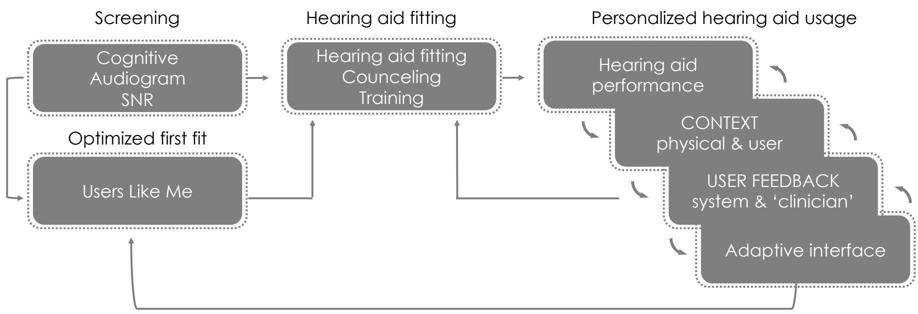


Figure 2.5: Personalizing hearing health care. The motivation for this thesis is within the personalized hearing aid usage and users like me.

2.7 Summary

Hearing loss is viewed as degradation of sensitivity, related to a loss of hearing sensitivity. Hearing loss is measured using a clinical procedure where hearing thresholds across varying frequency bands are investigated for both ears. Hearing loss is highly prevalent and may affect as many as one in five.

I propose a framework of *personalizing hearing health care.* This framework stems from hearing aids, and consider personalization of hearing aids a systematic challenge. The elements added to *personalizing hearing aid usage*, context, user feedback, and adaptive interfaces, will each be discussed in the thesis. Using technology and data as enablers, will shed light on how a different perspective can improve the clinical workflow, and in turn make hearing health care more participatory and personalized.UX methodology is applied to cast new light on personalizing hearing health care, while providing value to the hearing aid user and the hearing care professional.

Chapter 3

User Experience in Health Care

> This is the challenge designers and vendors of interactive products face: Experience or User Experience is not about good industrial design, multi-touch, or fancy interfaces. It is about transcending the material. It is about creating an experience through a device. [49, Mark Hassenzahl]

This chapter introduces the framework of UX within hearing health care, and how UX methodology can supplement the clinical workflow and research paradigm, by generating alternating views driven by hypotheses. The chapter revolves around validating or rejecting hypotheses using UX tools. First, an introduction to UX including the roots of UX is presented, and how it can be utilized within the health care domain. The introduction includes the principles of Lean UX, design thinking and how to design with data. Based on the paradigms of UX, lean UX, design thinking and designing with data, a theoretical framework for data-driven UX is presented. The framework consists of five overlapping steps, which all are driven by iterations, validation, and a feedback loop. Starting with observing and empathizing while defining the problem, then asking questions and formalizing hypotheses, leading to defining & describing user goals, which is the foundations of building data-driven systems that can be tested, and when ready are deployed and collect data, the final step is to validate or reject the hypotheses, and most importantly, ask why. The process is iterable, and may not proceed linearly. Further considerations about complexity, stakeholders and technology maturity are considered as underlying parameters in the model, which modulate the data-driven UX process.

User experience within health care receives little attention. Health care is a heavily regulated domain, and with good reason. As a consequence, the health care system is dominated by tangible and measurable outcomes. Within user experience, only usability caters for this need, where safety and functionality is the primary focus. Rather, have a safe and clunky user interface, than a pleasant one that will be used.

The EPIC system In late 2013, two regional hospital providers in Denmark, Region Hovedstaden and Region Sealand, signed a contract for a unified IT-hospital system. The service would include building a new digital IT platform with the management of patient data and a unified clinical workflow. Before the EPIC system, each hospital would use a custom build IT solutions, and different clinics would use different software suites. Several of the IT solutions had different providers, and the legacy systems lacked maintenance. The idea of a unified IT system was based on case studies from American hospitals. A unified IT-platform had improved efficiency and removed old legacy systems. The interfaces would be complimentary, and it would be easy to add extra features over time. However, 6 years later, and sundhedsplatformen is still struggling to gain traction. It is criticized from a host of stakeholders, including politicians, health care workers, and taxpayers. What went wrong?

The challenge with public IT systems is the management of stakeholders. The decision makers are rarely working with the systems, but are the ones managing the finance. Combining this with a health care system under pressure the idea is to relieve staff, and resources, by making the IT systems more efficient. The primary evaluation tool for such IT systems is whether the specification of requirements are fulfilled, or not, and does not evaluate quality. This creates a gap between the user of the system and the decision makers. What happened in the case of the EPIC system?

From the start, the EPIC system was heavily criticized by health care workers. To ensure consistency across medical entries, a requirement is using drop-down fields for journal entries. This ensures that only known entries are added to the system, which in theory should make the system more efficient and safe, by reducing human error. Doctors are notorious for writing journal entries shorthand, with several duplicates. However, it quickly turned out that especially doctors were frustrated with this solution, as it was not flexible. The drop-down fields can be checked off from the specification of requirements and usability is fine, reducing erroneous inputs. However, the user experience is not satisfying creating opponents of the system. The simple and relatively cheap fix to avoid this frustration, among others, is to utilize user experience. Including health care workers in the design and development process would have highlighted these issues earlier. Yes, the system itself might have had fewer features, but if these features created value, the system would be a joy to use.

To cater for the new needs in health care, and the future of personalized medicine, health care must move beyond usability, and towards user experience in health care. The functionalist mindset needs to change, and accommodate other means of creating value. Meaning, keeping safety and treatment as the primary focus, while improving and supplementing the treatment through non-measurable impacts and actions, which involves the patients, gives the health care professionals better decision-making tools, and improve the overall experience in the health care sector. Hood and Price [53] terms this aspect of medical care as

> *Participatory medicine* means that patients, researchers, physicians, and the entire health care community join forces to transform the practice of medicine to make it more proactive than reactive—and, in turn, less expensive and more effective.

Considering medical care as a participatory domain have both positive outlooks and face challenges. Hood and Auffray [51] predicts that each patient will gather billions of data points, which can be processed and distilled in simple models, enriching both the individual (N=1) and the general population by changing the medical paradigm. To succeed two major challenges must be addressed. First, technological challenges include big data management and a core IT infrastructure must be developed. Secondly, the societal implications, meaning ethical, regulatory, privacy and economic aspects. Defining who is included in 'participatory', including patients, doctors, and others. Changing education both for patients and health care workers. Providing social networks for patients, as seen in the quantified self movement. And finally, doctors, and other health care workers, need to be educated on how to handle the patient-generated data. User experience methodology can be an enabler, addressing the questions posed in participatory medicine. And as a result, optimizing wellness and minimizing disease in the individual patient.

3.1 Insights From User Generated Data

Patient-generated data is surfacing in health care. With widespread access to the internet, people are prepared when showing up at the general practitioner, or at the hospital. Some times with misinformation. The prevalence of mobile and wearable technologies enables collecting user-generated data, providing insights on activity, mobility, sleep and so on. However, using this data is currently not being utilized in a clinic, despite research providing insights on how to couple the quantified self paradigm and the health care paradigm [130, 131].
The clinical paradigm is not geared for these kind of interventions. The lack of agility within the domain of RCT and clinical guidelines, mean that digital interventions may be retired when approved for clinical practices. The rapid phase of technological development coupled with the lack of education, generates a gap, where clinicians retorts to known clinical practices. The consequence is a lack of clinical guidelines for digital and technological which the health care workers can use. Due to regulatory constraints, and established practices in research with human subjects, driven by the pharmaceutical and medical research areas, utilizing digital tools in care and treatment are currently facing a limited adaptation. Despite the promise of improved treatment, technology is not widely adopted. It faces limited adaptation, as the devices must be approved by clinical standards. The contradiction of lab approved equipment, where conditions can be controlled, versus equipment used out of the lab, have only been verified limited. The challenges may stem from the lack of collaboration between research fields, such as medical sciences and computer science.

New research fields are starting to rise, including mobile health (mHealth), telehealth, and using artificial intelligence (AI) and other digital interventions in health care. In the past 20 years several studies involving diverse cross-functional teams of designers, developers, clinicians, and other researchers have investigated digital tools in health care. In fields where counseling is part of the clinical workflow, there is a higher occurrence of technology usage. The monsenso studies present a framework, where bipolar disorder patients can track and log both passive data events, and qualitative data related to the mental state of the patient [9, 8, 36]. Other studies show that wearables and patient-generated data can support the treatment of dementia [135]. Rosenkilde et al. [115], shows that wearable devices can compliment gold standard clinical data to investigate habitual exercise in overweight patients. These studies demonstrate how patient-generated data provides value in the clinical workflow. To solve the challenge of participatory and personalized medicine a wider adaptation of technology should be encouraged. The current clinical verification standards are geared towards long-term medical interventions and lack the flexibility and agility of short-term technological interventions. The technological interventions may better address wellness aspects compared to medical interventions. Emphasizing that personalized medicine is both *wellness* and *disease*, and new insights should be generated for both. User experience is an enabler for creating system value and supports the participatory aspect of personalized medicine.

3.2 A Primer to User Experience

We encounter a variety of user experiences through our everyday life. Starting in the morning with our alarm going off, and we ask our phone 'how's the weather today', promptly receiving a weather forecast. To interacting with apps and wearables through the day, and, till we lay in bed turning off our phones. We are interconnected with technology, and with other humans. And woven in between all of this is user experience.

The term User Experience started to surface in the early 2000s. UX stems from human-computer interaction, usability, and interaction design. Hassenzahl and Tractinsky [48] highlights UX is "Beyond Instrumental", differentiating it from usability and interaction design. Nielsen and Norman [104] describes UX as ""User experience" encompasses all aspects of the end user's interaction with the company, its services, and its products." And Garret [38], points out that "every product that is used by someone has a user experience: newspapers, ketchup bottles, reclining armchairs, cardigan sweaters".

A primary goal of user experience is to move from the materialistic domain, toward the experiential domain, where *experiential* is emphasized. In recent years we have seen a shift from materialistic joy, towards experiential joy. Studies have shown that *experiential* investments (i.e., travels, event tickets, a dinner) make people happier than material purchases (i.e., electronic devices, clothing) of the same value, where the value is denoted as a momentary value [136, 20]. A *post-materialistic* culture have emerged since the 1990s as a contrasting view of the narcissistic culture developed through the 1980s. Interestingly, we rarely seem to recall the momentary experience, as humans, we are too preoccupied enjoying it at the moment. We do however recall experiences. Most married couples feast on the vivid recall of their wedding day, and parents emotionally describe the birth of their firstborn (and the next ones).

We arrive at a definition of UX consisting of both functional elements, such as task-specific fulfillment, and aspects considering design, hedonics (pleasantness and unpleasantness). I focus on the experience of encountering a meaningful event (in Danish: "Oplevelse"), and less on the experience gained in that event (in Danish: "Erfaring"). UX is a multidimensional model which links user needs and values, with outcomes reflected in an interaction pattern whether the medium being a service, a product, or an experience. Thus, UX seeks to enrich the human-computer interaction, by enriching the user, and by that create memorable user experiences.

The key takeaway is *user experiences are more than users, usability, and function. User experience is about experience and experiences.*

3.2.1 A Short Note on Usability.

Usability is a primer for user experience founded on functionality, thus the name usability, in contrast to user experience. The theories have overlapping elements. Usability and UX are co-existing. The aim of usability is narrowing and focusing, or generating tangible answers. Where UX is about being broad and holistic, looking at the user journey, and the user and system as a holistic interface. Preece, Rogers, and Sharp [108], addresses usability in the following domains:

- effective to use (effectiveness)
- efficient to use (efficiency)
- safe to use (safety)
- having good utility (utility)
- easy to learn (learnability)
- easy to remember how to use (memorability)

User experience and usability have different outlooks. Usability seeks to help the designer in answering specific questions. Examples of these are, "will this system support users in being more effective?", or "will the user be guided to avoid safety issues". User experience goals, on the other hand, encompasses a range of emotions and felt experiences. Both desirable and undesirable. Such goals include pleasantness, desirability, sociability and cognitive stimulation. Today UX in many cases goes beyond the interaction, and also encompasses what happens before, between and after interactions.

The following example illustrates the difference between usability and user experience. Asking Siri through voice commands, in general, good user experience, which is limited by usability, by asking: "Hey Siri, please enable flight mode", "Sorry, you'll have to unlock your iPhone first." This is frustrating for the user when you can ask for weather updates or other trivial tasks vocally, but you can't enable flight mode. This example shows how usability overrules user experience. The aspect of security is weighted higher by the developer, than the user experience. To address both the usability and user experience aspects, the developers and designers could us voice-detection algorithms, to determine the unique patterns of the talker, or a front facing camera could verify the user. This, in turn, would create a more pleasant user experience.

User Experience in Perspective. UX is human-centered design, resting between interaction design, visual communication, immersive experiences, and well-designed digital platforms. UX has evolved from being primarily focused on the visual experience, and today encompasses both the visual domain, the auditory domain, and the cognitive & psychological domain. It is important to acknowledge that UX is not only about the presentation of a media, but rather about the experience one has while interacting or being supported by a UX system. User experience stems largely from qualitative research and observations, including contextual observations, qualitative interviews, prototype testing, with the goal of verifying early concepts, through late stages product deliveries.

3.2.2 Lean UX

Lean UX, a term coined by Laura Klein, builds on the principles of user experience design and a lean paradigm. She states that Lean UX is composed of the following items, hypotheses validation, user-centered, agile, data-driven (measurable), Fast and Cheap (sometimes), and Iterative [72]. In essence, lean UX strives to validate ideas, or hypotheses, at a very early stage, limiting the commitment of sunk costs. Klein highlights three distinct phases. First, validation with a focus on validating whether users will buy your product or not. This including early validation by interviewing, using questionnaires, and finding pain points for the user. It is about finding the gap, and how to bridge the gap through a product. A tool for this is landing pages, easy, fast and cheap to produce, and can quickly verify if there is a user need. Secondly, *design* including considering how to verify and test design and designing the product. User stories and user story maps are tools that can support the design process. The goal is to sketch out a design, which should verify if it addresses the user needs. Wizard of Oz prototyping provide fast insights on features. Bootstrapping, and design paradigms such as Google Material Design[1] can accelerate the design process - there is no need to reinvent the deep plate. Sketches, wireframes, and

[1] Google Material Design `https://material.io/design/`

prototypes can help to get closer to actualizing a product. Third, the product, where a minimum viable product (MVP) is key to early success. The minimum viable product has to be both minimum, i.e., address the pain point with little complexity, and viable, i.e., feasible. The MVP tests the hypotheses while data is collected to verify if the product is viable. The product phase also includes working of requirements and building a cross-functional team that delivers. The Lean UX process is illustrated in Figur 3.1.

The lean UX framework requires a highly agile process supporting several iterations to ensure pain points are addressed and value is added. It reflects a process where designers and developers strives to build minimum viable products, in order to test and validate, rather than building perfect and beautiful products – not that an MVP cannot be either, or both. The iterative process of lean UX keeps looping through the three elements of designing, measuring and learning, build on the lean framework.

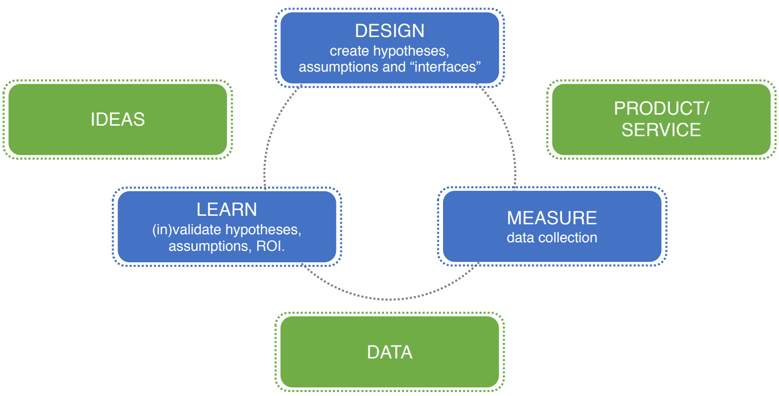


Figure 3.1: The lean loop, integrated with lean UX. The process is iterative, and providing continuous insights. Adopted from Klein [72].

The desired outcome from the lean UX process is a minimum variable product, which can validate hypotheses. This is in contrast to the maximum viable product, where feature after feature is added. An example of a maximum viable product is the recently re-launched taxing system EFI. Using a bottom-up approach the Danish ministry of tax managed to write a specification of requirements on several hundred pages. When the system was launched, it did not live up to expectations. It was scrapped and re-designed. A key value-adding feature was to collect old debts before they expired. However, rather than focusing on the top-level goal, the focus was to make sure the specification of requirements was fulfilled. A minimum viable product, on the other hand, would have focused on validating key value adding parts of the project and their dependencies. Collecting old debts would have been identified as a core issue, and the focus would have been to build a MVP which could rank, and collect old debts while minimizing loss. A visual representation is illustrated in Figure 3.2.

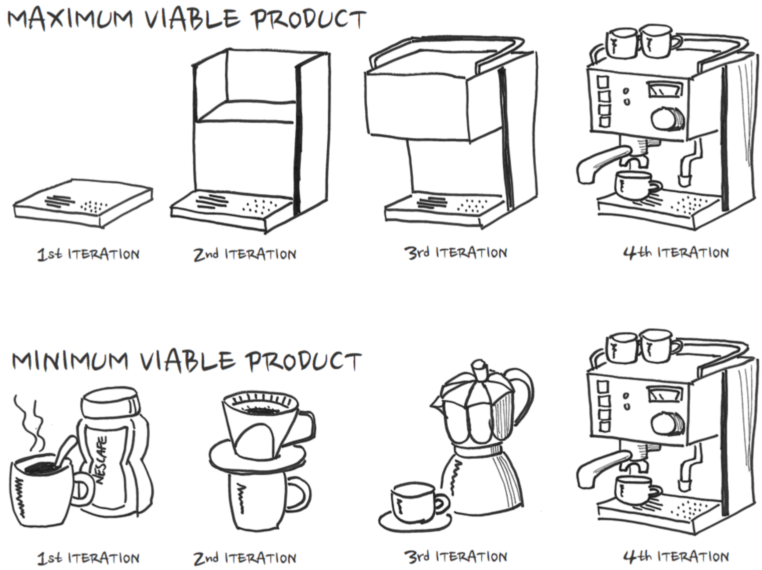


Figure 3.2: By focusing on outcomes, or high level goals, rather than features, experienced through tasks, design teams can build minimum viable products to validate hypotheses in an agile and iterative process. Courtesy Camilla Falk-Jensen [56].

Jeff Gothelf accurately states where UX is heading, and what the key principle of lean UX is:

> Features and services are outputs. The business goals they are meant to achieve are outcomes. Lean UX measures progress in terms of explicitly defined business outcomes... By managing to outcomes (and the progress made toward them), we gain insight into the efficacy of the features we are building [43].

3.2.3 Defining Value Through User Story Maps

User story maps, not to confuse with user journeys, is a key concept in user experience. A user story map is a tool which brings a hierarchical perspective into developing user experiences. User story maps serve as a platform for designing products and as a communication tool. First, as a communication tool, it creates a platform for shared understanding. Cross-functional teams lead to an ongoing discussion between engineers, developers, designers, and UX designers, and the user story map can help facilitate this discussion. User story maps allow different groups of designers to actively participate and communicate in a product or service development workflow. Second, user story maps functions as a tool to validate hypotheses and concepts and strive to identify a glsmvp. User story maps help scope user needs into activities while creating a hierarchy of prioritized tasks. Third, user story maps are a storytelling tool. It helps identify user goals and needs, and a storyline is build for different stakeholders. In the process of using user story maps, both engineers and developers are encouraged to actively partake in the shaping and development of the user story map. User story map helps the stakeholders to detach themselves from a 'feature' driven mindset to a value-adding mindset. This support the team in keeping the bigger perspective in mind, and balancing it with feature development. It can also be phrased as a top-down approach, which compliments the bottom-up driven feature development. User story maps addresses a problem through a top-down approach, driven by needs, goals, and pains, and fulfilled by features. After the iterating once, the user story map can be evaluated bottom up, ensuring technical feasibility.

User story maps consist of three distinct layers, goals, activities and tasks, that are both vertical and horizontal dependant. The vertical dependencies, means goals are dependent on activities, which in turn is dependent on activities. Using user story maps in health care is illustrated by an example, visualized in Figure 3.3. *Goals* are related to user intentions, needs, and goals. The example is drawn from a case study applying UX for heart failure patients [58]. In this example, the user story maps addresses to stakeholders, nurse and patient, and their interaction. The goal, indicated in blue, is *better understanding symptoms related to heart failure* and *A tailored treatment plan for the patient*. Where the first is primarily related to the patient and the latter to the nurse. Goals are often vague, to allow for flexibility in the design process. Typically, less than a handful of high-level goals are selected. Adding more increases the risk of either not formulating it as goals, and rather formulate it as activities and tasks, or, trying to build a product that becomes big and difficult to manage. *Activities* are formalized after the high-level goals, indicated in yellow. The activities relate to a series of actions that a user and system performs to address the high-level goal. Continuing with the previous example, to better understand symptom the user needs to *self-report systems*, get *information about the symptoms* and so forth. To tailoring the treatment plant, the nurse must *track weight* and receive fast *feedback* on a change in symptoms. The third layer is the tasks, marked in white. Tasks are what engineers are familiar with, as they often reflect a feature or a subset of features. Continuing with the previous example. The patient must report a range of symptoms such as breathlessness and sleeping. And to track the weight, the weight needs to be entered, edited and reviewed.

This example of providing an easy overview of the patient stems from a goal. This goal can either be hypothesized based on available information, or it can stem from observational studies, workshops, and interviews. When the high-level goals have been identified, they need to be sorted by how much value they generate for the user. The user can and should be involved in this process by providing input to the designer. After the goals have been prioritized, activities to these goals can be provided. These activities are related to user input and actions. These activities stem from the designers' perspective and hypothesize on how to provide value to the user. A goal usually has multiple activities assigned.

Horizontal dependencies mean that if *activity A* provides input or data to *activity B*, then *activity A* must occur before *activity B*. As an example, information about symptoms is only made available when the symptoms have been registered. The horizontal dependencies force the UX designer to evaluate the user story map. If a task has already been addressed, there is no reason to repeat it. These dependencies guard against unnecessary complexity and helps reduce visual clutter from the user story map.

An inherent property of user story maps is the use of slicing. User story maps can get out of hand, and grow with exponential speed. Actively using both horizontal and vertical slicing, different development paths can be articulated. Slicing appropriately helps define the minimum viable product, which may consist of only one or two high level goals, and a few activities. Slicing helps prioritize what is most important to build, in order to validate concepts or hypotheses. For example, does *activity A* provide value. Validation of slices provides fast and actionable insights in the development cycle. A minimum viable product is illustrated in Figure 3.3.

A short note on mock-ups, prototypes, proof of concepts (PoCs), and MVPs . The primary goals of these concepts are to have different levels of complexity through the development phases. In the early phases, a focus on defining both problem and value prompts the use of less complex solutions, to generate insights. Later in the development process, more complexity can be added, to closely resemble the final product or service. One concept is not mutually exclusive, and most if not all are encouraged to use in the development phase. I define the concepts as follows, in order to create a shared understanding.

In the perspective of UX, it is important to have a shared understanding of

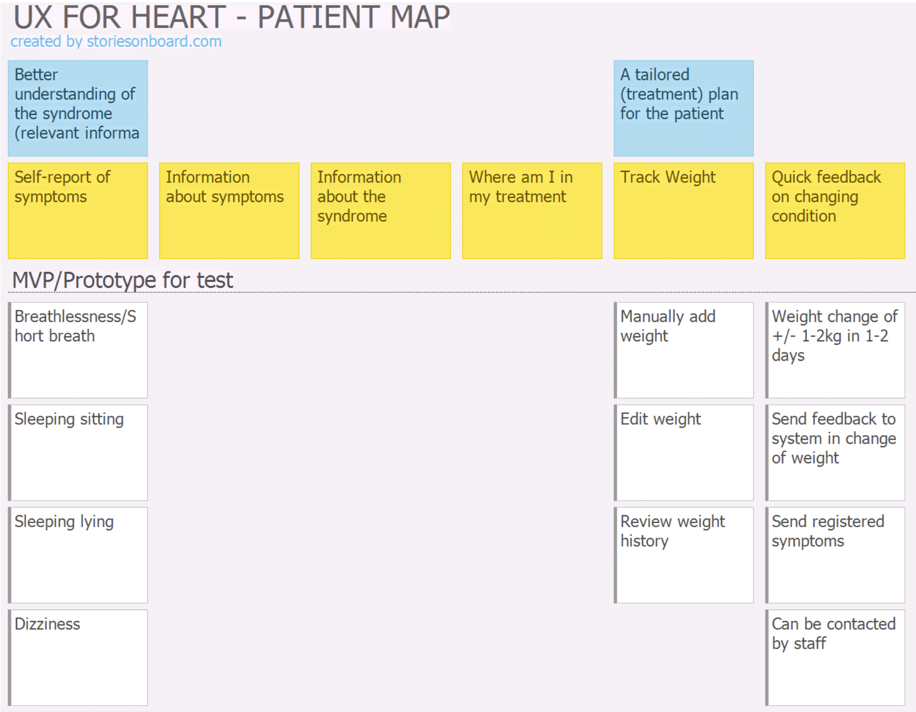


Figure 3.3: Example of a partial user story map highlighting the MVP for a heart failure patient. Credit, Benjamin Johansen [58].

the different concepts. Mock-ups are focused on illustrating conceptual ideas without being functional, a mock-up can be different ideas for screen elements, used to investigate what goals are important for the user. Paper prototypes are used similar early in the process of development and can provide insights fast. Between PoCs and prototypes is the concept of *wizard of Oz* solutions. A wizard of Oz solution is a semi-functional prototype, where a human is emulating actions performed by a system. As an example, you wish to create a calendar and location-based concept, to propose restaurants to visits while you are exploring a new neighborhood. To verify this, you find a handful of testers. Rather than developing a functional system, you use third-party services, such as access to the test subject calendar and a map with access to their location. You then add events to simulate how the system would do it. Wizard of Oz solutions can be effective as the test user may believe that the concept tested is working. The test user can then focus on providing input on the user experience, rather than the technical limitations. PoCs can act as a tool to validate concepts, as the name implies. PoCs may lack the technical feasibility, and is used primarily to validate concepts, ideas, and goals. They may be a bit further than mock-ups. Prototypes add the missing functionality after the PoC have been verified. Adding functionality leads towards a prototype. Prototypes do not necessarily have to be digital or fully functional. Sometimes paper prototypes give more insight into validation than a technical counterpart does. The last way of testing and validating hypotheses are building a MVP. Based on the earlier validations, and iterative updates of the user story map, it should now be clear what goals provide value. The next step is building a MVP which can be tested in real life settings. The MVP have to be technical feasible, but does not have to be the end product. Again, the importance is to validate hypotheses. If the designers, developers and customers are happy, work towards an alpha release can now start.

3.2.4 Microinteractions

Microinteractions are the small interactions which ensure a pleasant user experience. Saffer [118] describes microinteractions as

> Microinteractions differ from features in both their size and scope. Features tend to be complex (multiuse case), time-consuming, and cognitively engaging. Microinteractions, on the other hand, is simple, brief, and should be nearly effortless..

Microinteractions may not the essence of a product, but is what can make or break a user interaction. As an example, early in my Ph.D. studies, I was working prototyping chatbots for user interactions. The idea was to change setting on the hearing aids, by using third-party services. After a couple of months, we finally managed to build a prototype, where the user through text commands could control the hearing aids. The prototype was functional, we could change settings through text, we were thrilled, but had overlooked a seemingly minor detail. The delay in time between interaction and action. At best the users were annoyed and wouldn't use the system we developed, and at worse they were furious. We understood that the interaction paradigm was good, but it had one major flaw. It took 3-5 seconds before the user received auditory feedback, despite the visual feedback telling them the change had occurred. This mismatch between expectations and executions created a poor user experience. Microinteractions are not only about designing and executing interactions, but they are also about identifying when and how they provide value.

Microinteractions consist of four distinct parameters, Trigger, rules, feedback, and loops & modes, as illustrated in Figure 3.4. Triggers initiate the microinteraction, rules determine how the microinteraction works, feedback shows how the rules work, and loops and modes are metarules that affect the microinteraction. The trigger is initiated by the user. In the chatbot example, the user starts

Figure 3.4: Structure and flow of microinteractions. (Courtesy Dan Saffer [118])

a conversation with the chatbot, and ask for a setting update. Triggers can be both physical or non-physical and provide the starting point for a microinteraction. However, triggers do not need to be user initiated and is increasing system initiated. This is based on the device initiating a change when certain conditions are met. For a hearing aid, the noise reduction processor automatically adjusts the SNR to provide the user with more speech intelligibility. Rules define how the input, a trigger, performs an action to generate an output. For the hearing aids, the rule governs, that if the SNR is below a certain threshold, then increase settings that provide better SNR. For the chatbot case, when a user selects a certain set of actions, several rules came into action, one keeping an account of the answers provided, and a second one deciding which parameter to change. Rules are inherently invisible for the user, while feedback provides insights into how rules manipulate triggers. Feedback can take many forms, the most common are visual, auditory and haptic. In the case of a hearing aid, most of the feedback comes from acoustics. A hearing aid may provide a brief series of 'dings' to indicate the user that settings have changed. In the chatbot case, the feedback mismatch defeated the purpose of the microinteraction. The visual feedback told the user that a change had occurred, and the user might have put away their phone. And five seconds later loud acoustical feedback in the form of 'dings' would occur. The user would then have to match the acoustical feedback with the auditory feedback to confirm the right settings were selected. Lastly, loops and modes are meta-rules. These instances can happen over time or based on conditional changes. Loops are similar to a while statement in programming, and if nothing changes, then nothing happens. While modes reflect a fork in a microinteraction, and should be avoided if possible. Changing between physical button changes and an interactive display are an example of modes. Modes take you away to perform a subtask, before returning to the main task.

3.2.5 Elements of Value

Creating value have been mentioned several times, as a key element in (lean) user experience. Value is a cornerstone in user experience and goes hand in hand with good experiences. If there is a lack of value creation, the product becomes functional, but not valuable. Once the user doesn't believe a perceived value is fulfilled, there is a high likelihood of terminating the use of a product or service. The robotic seal PARO serve as an example. It is possible to provide elders with a teddy bear, which may create comfort. Adding a layer of intelligence and robotics creates value. Now the teddy bear is more than a functional item, it becomes animal-like. Meaning, the elders bond with the animal, cares for it, and look forward to interacting with it. Almquist, Senior and Bloch [3] describes four elements of assessing value, based on Marlows pyramid of needs, and appropriately named the value pyramid. These level are the functional, emotional, life-changing and social impact, and consist of 36 elements in total. Studying several big cooperation's and their offerings shows that the most successful companies provide several elements of value, across several levels. The elements of value are geared towards generating business value and also fit into the user experience domain. Actively using the elements of value in ideation sessions provides insight into which areas should be prioritized. Often it requires stakeholders to identify where value is created. Then, several concepts can be developed, deployed and tested by end users. As an example, the current solution from several hearing aid companies is a companion app to their hearing aids. The companion app is a remote control. Reviews on Google Play store and Apple app store reveals a big divide between the manufactures perceived value, and the perceived value from the end user.

3.2.6 Quantifying User Experience

User experience has been quantified through measuring a number of clicks on web pages, to tracing eye movements on screens, to quantify search patterns or areas of interest. But how do we quantify human behavior in a cohort of humans affected by impairments, such as hearing loss? However, with the recent increase in mobile computational power, accessibility to high performing intelligent systems build on machine learning and deep learning, the vast amount of data, including personal data being logged around the clock, and the formalization of the field of "data science" in the early 2010s, we are now in a new era of penalization and user experiences. We have to reconsider our view on user experience. To drive UX in the future we need to include and embrace the elements of scalability, agility, and data-driven insights from human-generated interactions. We cannot solely rely on the classic UX toolbox and need to build new toolboxes that can pool data from thousands, and even millions of users, that can generate insights from users, either on a group level or individual level, and which dynamically adapt to the user context and intents to create unique user experience. The technological maturity we have reached allows us to create new user experiences, we need only to embrace it, which is easier said than done. The future UX designer needs to extend the toolbox and will be able to work hand-in-hand with data scientist, machine- and deep learning specialist, and can translate the user needs into complex models, which can be translated into tangible AI models.

3.3 Data Driven User Experience for Health Care

Data-driven user experience is where data science meets user experience, and data science becomes human-centered, memorable, and enriched with humans in the loop. It is all about creating value for humans with the support of technology. Technology is a mean, not the goal. The starting point should be humans, their goals and values, and to identify how technology best support humans.

Data-driven user experience is about personalizing services to patients based on patient-generated data. Data-driven UX tries to address some challenges participatory medicine is facing. Data-driven UX about enhancing the communication between clinicians and patients. Making patients more involved in their treatment. Data is an enabler that can spark conversation and which supports the decision-making process of clinicians. Data-driven UX works as an enabler between clinicians and patients, and it provides a foundation for developing intelligent personalized systems to better support the clinical workflow in health care settings. The model is based on the experimental work and observations done in conjunctions with this Ph.D. thesis. The theoretical background and framework stem from elements of design thinking, human-centered product development, and lean UX. It is an iterative process with overlapping phases, and even though it is here projected as a linear process, in reality, the process is more circular, with breaks and jumps. The model is thought of a starting guideline to help developers and designers creating meaningful user experiences in health care settings while considering key stakeholders, such as patients and health care professionals. The model is not limited to hearing health care and can be used across health care domains. It does have a technological focus, and can also be applied to validate physical products and services. Based on this I propose the following elements, each described in detail.

Emphasize This element builds on observations and data collected. The goal of the *emphasize phase* is to identify pain points and challenges. Questions asked include, why does this matter, what is the impact, how is it done today. This is an observational part of the model, aimed at non-judgemental observations to help formalize hypotheses.

A wide variety of observational techniques can be used in the emphasize stage. Anthropological and ethnographic studies can help designers observe a new paradigm domain, through observational studies. Following a 'fly on the wall' approach, where the researchers tag along with a health care professional through a working routine. This approach may highlight pain points in the process for both health care professionals and the patient. Interview approaches can also be applied. Talk out loud sessions, which can both be used to explore or to validate designs, forces the interviewee to word their thoughts. This approach can be effective in revealing subconscious decision-making. Digital driven approaches including collecting data. This data may already be collected and available through existing devices. For example, activity and motion patterns, coupled with geolocation data, are useful reassures to evaluate the activity patterns of depressed patients. The data can help identify patterns. Both the dialogue based and data-based approaches can be combined, to highlight the pain points in the treatment process. The important thing of the emphasize phase is to better understand the context and problem investigated. It is not important which tool is used. The tools should be selected based on availability, and of the assumptions of the researcher on how to best create insights.

Define goals and values Based on the observations the designers and developers identify the goals and values of the various stakeholders. The result should be a better understanding of what drives and motivates the stakeholders, and how this can be used to create a great user experience.

From the observational studies, the researcher should have a better understanding of the context and underlying problems, challenges and pain points. The next step is to identify what the goals and values are of the various stakeholders. Different stakeholders may have different goals, a health care professional may strive to see as many patients as possible, while the patient wants the most accurate information. The stakeholders may also share common goals. Both health care professionals and patients may wish to reduce treatment time or reduce uncertainty. User story maps is a tool that can help identify and prioritize stakeholder goals. Explicitly mapping goals help researchers to formalize the goals. This creates a shared understanding, and serve as a communicative tool, which can facilitate communication in the research team and calibrate the team. This process is iterative. The team may agree at the first session, or it may take several sessions to agree. It can also be coupled with follow-up sessions between researchers and stakeholders, and thus work as a validation tool.

However, it should be highlighted that this is a starting point and that the next phases must not be forgotten.

Formalize hypotheses The next crucial step is defining hypotheses. This step is central to the model and cannot be neglected. Based on observations and collected data, new questions can be asked. The goal is to formulate less than a handful of hypotheses to be tested and to rank them in order of perceived importance. This steps also include articulating assumption and sharing them between the team members.

The research team must consider which hypotheses will be evaluated. It can range from simple to complex hypotheses. The hypotheses may appear easy to state and difficult to answer. If the hypothesis is 'Design suggestion a is more efficient than the existing interface', then the team must consider and define efficiency, is it reduction in clicks, is it having a higher patient throughput, or is it something completely different? The beauty of defining hypotheses is that they create insights, both to the problem space and the solution space. Through validation some hypotheses are scraped – think off: 'yes it works, but, I can't see myself using it'. The perceived value have to be higher than the perceived trade-off. Building hypotheses are the backbone of data-driven UX. Hypotheses should reflect value generating insights, in case they do not, they should be reformulated or removed.

Design, build and validate This step is about building interfaces that can validate hypotheses. Through the iterative process, this can range from paper-prototypes to minimum viable products. The importance here is to match the interface to hypotheses and to make sure questions are answered.

After clarifying what needs to be validated, through the formalization of hypotheses, building systems is the next step. Building interfaces which answers hypotheses can range from a wide variety of complexities. In the case of data-driven UX it is important to keep in mind, that it is highly iterative, and that the system build should reflect this. This means that in the beginning of a development product, paper-prototypes may be ideal to verify hypotheses. In the thesis, UX for heart failure, using paper based cards yielded more insights than the equivalent of a paper-prototype on a phone. The lessons learned, low fidelity prototypes is more powerful in the early design stages, where the hypotheses are more vague and build on many unknowns. In the later stages, high fidelity prototypes, and even working prototypes, can be used to identify value adding elements. For the researcher the point is to always focus on validating hypotheses, and doing so with the least investment. Adding value to the validation phase can also be done through data collection. Meaning, when technology allows for it, then use it to collect data. Tools like rapid prototyping, "which allows crucial design decisions as early as possible" ([91]), can effectively be used. The goal of rapid prototyping is to provide early insights, and may compromise on scalability.

Analyze The goal is to validate if the interface creates value by validating hypotheses. The goal is here to validate or invalidate hypotheses based on the insights. New questions may arise, that needs to be answered, and then thus this ties in with the observational nature of the emphasize step.

Analysis of insights can be done by evaluating the answers of a hypothesis. It frequently occurs more questions are raised than answered, and this guides the researcher to focal points.

To sum up, the focus of data-driven UX is to provide great user experiences and enable participatory medicine. Data-driven UX is an iterative process, with frequent validation, which seeks to reduce uncertainty. It has a user-centered perspective, where technology is a mean to the goal, and not the goal itself. Sometimes inferior technology creates the best user experiences. Apple exemplifies this through its product offerings, which is priced higher than competitors, and sold through branding and perceived luxury value, rather than functional value. If the functional value is what people buy, then Apple would have a limited market share.

The data-driven UX model is the underlying guiding principles of this thesis. Each step may not be explicitly stated. The reader may notice how various points of the project highlights different processes.

3.3.1 Consideration for Data Driven UX

Data-driven UX strives to reduce complexity to allow for fluency and flexibility in the validation stage. Complexity should be at an adequate level and is an important design factor. However, there may be simpler solutions to validating the problem. Take for example the case described later with using rapid prototyping. The hypothesis is people are different and interact differently with their hearing devices. The underlying assumption is that the difference in interaction patterns reflects the different personality and behavioral traits, and may also be an indicator of being exposed to different contextual sound environments. Let's investigate how two different development teams approach the task, denoted team a, and team b. Team a have a classic IT development perspective. They start out writing a specification of requirements, with a focus on features, also known as outputs. They then calculate the required amount of engineering, design, UX, etc., resources to develop the system. Engineering a system from scratch increases complexity, cost and resource allocation. Team b takes an alternative approach. They choose to focus on validating hypothesis, rather than building a fully functional system. Their choices include existing 3rd party frameworks. Using standard interfaces and offerings, team B reduce complexity, development costs and time. And they verify the hypotheses earlier than engineering team a. There are drawbacks of both approaches, team a have a longer lead time, and needs more stakeholder management. They do however get a more robust system, and if the framework is flexible enough, they have a foundation to build on later. If it turns out their assumptions were wrong, they may have to rebuild the system or build a new system. Team b quickly validates their hypotheses and want to scale up. They quickly realize that their solution is not scalable nor deployable. They then have to interact with team a to build a functioning system. The conclusion of complexity is, in the early design stages, to stay lean one should consider lower complexity to validate hypotheses. As the development stages progress, the complexity can increase. The foundation is laid by the lean data-driven process, and the agile development then supports the work carried out earlier. All projects should have varying levels of complexity, depending on the scope and the maturity of the design process. Too high complexity early limits flexibility, while little complexity late limits scalability and deployability.

Stakeholder management The last consideration in data-driven UX is stakeholder management. Stakeholder management plays a peripheral role in data-driven UX, though an important role. For a holistic view on data-driven management, one needs to consider, that it is rarely the designers, developers or users, that have the last say. This becomes evident in the health care case. Take the data-driven UX process within health care. Working with cross-functional teams means a big variety of stakeholders have to be involved. As earlier mentioned, in the scoping phase doctors, nurses, hospital management, even politicians may need to be involved. Despite the best intentions from the designers, the health care professionals may have a different outlook. Managing stakeholders means asking the right questions. For scoping it means asking, how does this creates value for you and your employees, does this make it more efficient, can we save time, etc. It also deals with the actions required in organizations, where middle- and top management controls resource allocation. If no resources are granted, no development happens. When validating yet other stakeholders have to be engaged. Here users play a central role. And yet again, health care professional should also be included, software developers, and whoever else is important. As one may guess, different stakeholders are important at different stages of the development. Stakeholder management is about valuing the variety of stakeholders, and utilizing stakeholders at the right time. As data-driven UX is an iterative process, so is stakeholder management. And hypotheses can be validated across various stakeholders, or can be used to rule in or out stakeholders.

3.4 Summary

This chapter highlights how UX can be used in health care to address the challenges posed in participatory medicine. Considerations to the history of UX and why UX can be an enabler, by providing fast insights and value. A few prominent UX tools have been mentioned, which can be used to build prototypes to verify the need for participatory medicine. This includes rapid prototyping, which will be used to validate hypotheses related to hearing aid users program and volume interactions. Iterative lean UX approaches to creating new hypotheses, and new ways to validate these. Learning from interviews with hearing aid users, on how they perceive using hearing aids and how they relate their behavior to the usage.

Data-driven user experience relies on the UX methodology, and include a foundation of data. In combination with intelligent systems, the data provides value to health care workers and users. Data-driven UX bridges the gap between clinical workflows and technology. The data will provide valuable insights, in collaboration with hearing aid users. It will provide stepping stones to the future of personalized hearing health care.

Chapter 4

Hearing in Context

This chapter introduces context and the three parts of context, physical, user and computing. The focus is on physical context and how contextual aware devices can enrich the user experience for hearing impaired users. The Meriam-Webster dictionary defines Context as “the interrelated conditions in which something exists or occurs”. Context is a central theme in understanding why hearing aids fail in everyday use. The physical context for hearing aid users are distorted, and hearing aids help with augmenting the distorted signal. This chapter illustrates how contextual aware devices provide input to users and hearing care professionals. A major challenge is the neglect of individual context. Resulting in an average setting for a non-average behavior. The chapter uses examples of physical context drawn from the three contributions: "Modeling User Intents as Context in Smartphone-connected Hearing Aids" Appendix C, "Learning preferences and soundscapes for augmented hearing" Appendix G and "Inferring User Intents from Motion in Hearing Healthcare" Appendix D. These studies highlight how time, location and activity affect the physical context, and supplements the acoustical knowledge.

Several experiments have shown that normal-hearing listeners have a signal-to-noise ratio, of up to 6 dB improvement, compared to hearing impaired. Killion [70], found that with a slight 30 dB hearing loss a 4 dB deficit in SNR can be expected, degrading with 1 dB per 10 dB frequency hearing loss. When hearing-impaired use a hearing aid with noise reduction, they have similar performance [12]. However, humans, also those who suffer from hearing loss, rarely navigate with sound alone. Several contextual cues are used to change the perception of sound. For example, the visual and auditory cortex interconnects in sound processing. Also, social context alters perception. At a children birthday a more comfortable noise reducing setting may be preferred, to attenuate the squeals of playing children. While at a jazz restaurant, with similar noise level and degraded SNR, the preference may be to enhance speech intelligibility by enhancing higher frequency, rather than improving SNR and degrading the ambiance experience.

4.1 Context Aware Computing

Every day, we are exposed to changing environments, social organization, culture, and different computing systems. Humans use the wealth of information available at the fingertips consciously and unconsciously. A human makes thousands of decision from dusk to dawn. The world is navigated based on both external and internal stimuli. The constant exposure to changes in both the environment, the social bonds and with technology, is what is defined as context. Context is ubiquitous and surrounds humans just like air does. It is not possible to navigate the world without relying on contextual information.
Hearing impaired listener misses out on contextual cues. This includes cues related to navigating the world, such as acoustical cues, which reduces the sensory experiences. At worst, it means missing out on warning signals such as squealing tires or sirens. Hearing impaired listeners have a decreased sensitivity negatively affecting speech intelligibility. This is caused by missing out on contextual cues, including temporal shifts, distorted interaural intensity difference (IID), and distorted interaural time difference (ITD). Where IID is caused by the shadowing effect of the head, and relates to high frequency distortion. ITD is caused by the frequency difference between high and low frequencies [95]. Degraded hearing results in difficulties with source location, caused by IID and ITD. On a personal level, missing out on contextual cues included in speech reduces quality of life and causes higher rates of social isolation and depression. Context affects humans, and lack of contextual cues affect hearing-impaired listeners to a higher extent. What is the definition of context in context aware computing?

Dey & Abowd, define context as computing environment, user environment, and physical environment. Dey, and Dey & Abowd draw a similar conclusion from previous work and describes context as

> Context is any information that can be used to characterize the sit-

> uation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and application themselves ([27, 28]).

A meta-study conducted by Bauer and Novotny [10] defines two higher levels of context, respectively generic and domain-specific context. Within the generic context, there are three sub-categories, social context, technology context, and physical context. I define context by merging the previous description and add the notion that if a piece of information characterizes a situation, then that is context. I use the three following descriptors:

Social context the user, their interests goals, background, demographics, sociographics etc. Also, includes the social and cultural environment, defined by norms, culture and organization. The social context carries information about the social relations and organizations. Most description of social context comes from the fields of anthropology and sociology, and is also used within ubiquitous and pervasive computing.

Physical context the *physical atmospheric environment*. This includes observable and measurable phenomena including sound, light and luminosity, pressure, and temperature, indoor & outdoor, and related semantic labels. *Time* measured in seconds, minutes, hours, days, and so on, and also time as categorical labels including weekdays & weekends, morning, noon, evening, events, among others. The context of *movement*, such as speed, velocity, orientation, rotation and categorical labels to motion, such as running, in vehicle and cycling. *Location* includes descriptors of geolocation, country, region, proximity.

Computing context the technology power, interface, connectivity, networking capabilities, security, efficiency, awareness etc. Some devices are ubiquitous such as servers, while others are present in our everyday such as smartphones.

For example, the social context of the user plays a key role in understanding how hearing impaired navigates in a contextual rich world. Different norms warrant different usage of the hearing aids. The changing context of a work environment, moving from a quiet office to a loud meeting, leads to a different use of the hearing aids. It is worth to consider that culture and norms may hinder the acceptance and usage of a hearing aid. The user plays a central role, which cannot merely be described through an audiogram. The user context is built on demographics, technology acceptance and usage, habits, and skill level, among others. User context can be reduced in dimensionality, and are unique for each individual, making it difficult to generalize, and average across all users.

Context is a central theme in personalizing hearing health care. Context for personalizing hearing health care primarily consist of *physical context* and *user context*, and to a smaller degree *computing context*. Hearing aids augment sound and affect the perception of context. Context on the other hand directly affects the hearing aid output. If the environment is noisy different settings are engaged compared to a quiet environment. The context can also be used to generate feedback when refitting the hearing aids. An overview of how physical context fit into personalizing hearing care is illustrated in Figure 4.1.

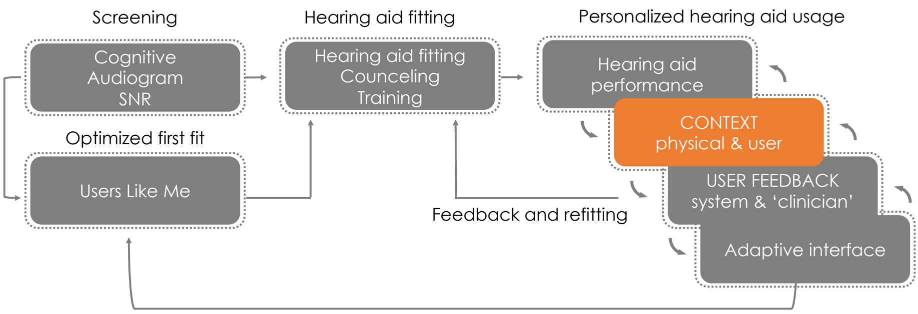


Figure 4.1: Contextual aware devices are a central theme in personalizing hearing health care, highlighted in orange. The context is affected by the output from the hearing aids, and can be used to give feedback to the hearing aid user and clinician.

4.2 Mobile and Pervasive Computing

In 1991, Mark Wieser [142] introduced a vision of intelligent environments, with systems aware of changing context, and with an observed change in behavior. The main takeaways from Weiser are: computers need to disappear and become an unconscious thought of interaction, computing devices need to be interconnected and to compliment interactions, and humans have to accept computers as an embedded part of their everyday life. There is still a long way to go to embrace Weiser's vision. Smartphones and wearables have become ubiquitous sensor devices providing a wealth of insights about the user. IoT devices are penetrating the production industry, providing timely and relevant information about machine performance. More and more data accumulates every day. Yet, we are still aware of and dependent on our devices. People are glued to the screen of smartphones, and treat it as a pocketable laptop computer, rather than a ubiquitous device. Quite the opposite of Weiser's vision. The future of computing systems needs to become embedded in everyday life. The devices of Weiser's vision should not be competing for our attention and act as distractions. Rather, they should augment humans, through context-awareness and with awareness of human intents.

For hearing aids, this may be a utopia, but being a ubiquitous device is the main driver for hearing aid acceptance. How do we get hearing aids to conform to a ubiquitous and pervasive environment? The question remains, how do hearing aid augment humans, and yet be ubiquitous and pervasive.

Mark Weiser ends his article by stating: "Machines that fit the human environment instead of forcing humans to enter theirs will make using a computer as refreshing as a walk in the woods" ([142]). And I hope that we can move towards this vision for hearing health care. Augmenting human hearing, while making the intervention desirable. To augmenting hearing aids relies on context-aware, interconnected, intent-aware devices.

4.3 Hearing Aids as Context-Aware Devices

The limitations of hearing aids as context-aware devices stem from historical form factor and hardware limitations. Today hearing aids consider only one contextual parameter, audio. Historically hearing aids did not have a supportive computing context to provide nuanced contextual information. That has changed, and today hearing aids work as Internet of things (IoT) devices, which can connect to third-party services and provide a wealth of contextual information. Including location, WiFi, or activity data from other connected IoT devices and wearables. Providing access to auditory features, hearing aids work as a sensor device. Intelligent systems can leverage the combined input to create better user experiences. An example of simple systems using multimodal data is weather apps. By providing location, weather services can provide local forecast fast and convenient. Using historical data collected across multiple sites, the service can forecast weather including wind condition, humidity, and chance of precipitation.

The computing context is rapidly changing. Smartphones have the computing power of personal computers. Smartphones host an array of sensors, including location, motion sensors such as gyroscopes and accelerometers, sound sensors through multiple microphones, images sensors, biometric sensors, ambient light sensors, are the most common sensors. Most come with multiple central processing units (CPUs) and the newer versions come with dedicated graphics processing units (GPUs) carrying out machine learning, deep learning, and artificial intelligence tasks. The smartphones are interconnected through various radio antennas, ensuring connectivity with local devices through Bluetooth and near field communication (NFC), streaming data through WiFi access points, and connecting remotely to the Internet through 4G and 5G technology. Context-aware systems consist of pairing smartphones and wearable devices, with temperature sensors, motion sensor, and environmental sensors. Or even independent Internet of things, with embedded intelligence, called the Internet of Things (IoT) devices. In summary, humans have adopted the computing context and are feeding it with contextual data. Context-aware devices are limited by limited battery life, and to some extent optimized user interactions. Adding a layer of intelligence brings these systems closer to becoming context-aware and better adapt to the user. The trends we have observed is increasingly sophisticated systems, termed "adaptive", "context-aware", "intelligent", etc. The intersection of these systems is context. They are further augmented with intelligence, from simple Boolean operations to modern systems build on massive data sets, using weeks of computation to train.

What composes augmentation of hearing through intelligent context-aware systems? There are several elements. First, hearing aids are seen as sound manipulators, which are aware of the sound environment. Secondly, in this setting context relates to human, device, and surroundings. Thirdly, intelligent context-aware systems relate to systems that are interconnected, can communicate between systems and humans and are context-aware, with a knowledge of where they are, what is happening, and how they can interact with the context.

A hearing aid is a context-aware device. Hearing aids rely solely on the contextual information provided from an acoustical signal. From a microphone array of two or more microphones, the hearing aids can estimate sound pressure level, directionality, and distinguish between noise and a signal. The primary research focus has been on optimizing sound input using various algorithms on embedded systems, and match a sound output to a degraded hearing. These systems have several assumptions build on physical models of human hearing and acoustical properties. Hearing aids are sophisticated head worn wearables with certain limitation. The form factor needs to be small. This limits the physical computing components in the device. The battery is the biggest physical component, and hearing aids are designed around batteries. The assumptions are that a smaller form factor and longer battery life are the most valued attributes of a hearing aid. A requirement is that the battery must last several days, preferably a week. This notion may stem from the high cost of dedicated batteries or from a usability requirement. Such requirements have limited the development of hearing aids, despite the vast amount of know-how within the industry. Hearing aids are considered independent, embedded systems, restricted to the current development paradigm. There is a need to reconsider the ecosystem around hearing aids and how to make the hearing aids' context aware. Drawing analogy to Henry Ford, who asked what people wanted, and the prompt answer was more horses. People could not imagine a technology that didn't require horses and would be more powerful than the existing technology. Hearing aids are facing the same glass ceiling, and are ripe for disruption.

One way to augment the computing context of hearing aids is to utilize connected devices. With the recent advancement of increased connectivity, hearing aids can connect to smartphones via Bluetooth of Bluetooth low energy. This enables a paradigm shift in the computational context for hearing care. Hearing aids can become an acoustical sensor, which streams audio to a pocketable computer, or smartphone. The computing device can analyze the signal, and provide feedback to the user and the hearing aid. Furthermore, moving away from embedded systems, to software ecosystems, would provide the foundations of context-aware hearing aids, which would use a multitude of sensory information to better understand context. This is a dream. Albeit, we will demonstrate examples of how hearing aids can be used as wearables, or hearables (Section 2.2.2) of the future.

4.3.1 Physical Context for Hearing Aid Users

Physical context relates to the surrounding conditions. This includes sound, lighting, environmental factors like sun and wind, atmosphere, and venue type. The main driver of hearing aids today is related to physical context. The sound is the primary factor. People suffering from hearing loss have a different sound perception than normal listeners. As sound perception is degraded, it has an effect on several levels. Signal to noise performance is dropping, reverberation is perceived differently, room acoustics changes, and even the perception of the atmosphere may change. For the past many years the focus has been on augmenting human hearing, to improve speech intelligibility. Measures of speech intelligibility are the gold standard within hearing research. This procedure is carried out in an anechoic chamber, where noise can be added artificially. However, most experience sound in a physical environment, where ambiance and social context have an influence on the performance. People end up with hearing aids that perform well for one auditory condition, such as speech in noise, or with reverberation. We argue that the physical context is more than the sound. Using a pair of hearing aids test subjects collect information related to acoustical features. The signal and data received has been pre-processed by the hearing aid algorithms, and is the hearing aid output. This feature vector contains information related to signal-to-noise ratio, noise levels, directionality, and a contextual flag related to the type of sound (including speech, noise and quiet). Using contextual data collected by hearing aid users, we investigate what an everyday look like for a hearing impaired listener.

We utilize the sensing capabilities of smartphones and hearing aids to generate information related to the physical context. The smartphone provides information related to location, based on GPS signal, on movement and activity type. The hearing aids provide information about the acoustical environment, including labels of the environment type. The hearing aids provide a contextual sound vector, with the following features:

Sound pressure level estimated loudness in dB

Noise floor the tracked sum of all sources not classified as speech.

Modulation envelope tracking the envelope of the acoustical signal. Corresponds to a line drawn from the top peaks of the signal.

Modulation index estimated difference between the modulation envelope and the noise floor.

Signal-to-noise ratio estimated as the difference between sound pressure level and noise floor.

The hearing aids capture this vector once a minute. Due to hardware limitations, the sound feature vector is used rather than a spectrogram. Limiting post sound processing and customization, and potentially the choice of learning algorithms applied later. However, it is memory light, low in power consumption, and privacy preserving. Based on the data we create four clusters, using k-means clustering algorithm [46]. We find four clusters respectively, C1: "quiet", C2: "speech in noise", C3: "clear speech" and C4: "normal speech". The clusters are compared with the soundscape labels provided by the hearing aids. The compositions is shown in Figure 4.2. It can be observed that the clusters we find contain a mixture of elements from the hearing aid label flags. Cluster 1 is primarily made up of the 'quiet' flag. Cluster 2 is a mixture of "speech in noise" and "noise". Cluster 3 primarily consist of "speech in quiet". And, cluster 4 has a smaller percentage of "speech in quiet", and a larger percentage of "quiet" and "noise".

We compare the clusters with the soundscape vector, by examining the centroid of the clusters. Cluster 1, "quiet", have low levels of sound pressure level and noise floor. Cluster 2, "speech in noise", captures higher levels of noise floor and modulation envelope, and the flags 'speech in the noise' and 'noise'. Cluster 3, "clear speech", captures high values of both sound pressure level and signal-to-noise ratio, Cluster 4, "normal speech", have similar attributes as cluster 3, with sound vector values closer to the mean.

It is hypothesized that humans encounter different contextual environments. And that these environments vary over time. To investigate this, two test subjects collected data over a period of six weeks. The percentage-wise distribution

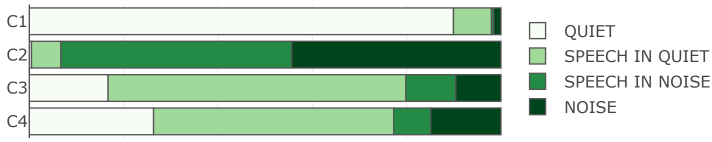


Figure 4.2: Four clusters, C1-C4 and their composition of the original hearing aid labels. C1: quiet, C2: speech in noise, C3: clear speech and C4: normal speech [73].

of average hourly usage is illustrated in Figure 4.3. The graph visually indicates a difference in exposure to acoustical environments for the two subjects. Subject 1 is primarily exposed to speech related content, both normal speech, and speech in noise. After 5 PM, the amount of speech in noise decreases, and the exposure of the quiet environment increases. Subject 2 has a balanced exposure to speech and quiet environments throughout the day. Between 4 PM and 19 PM, the subject have a higher exposure to speech compared to the rest of the day.

The soundscape vector provides insights into the everyday life of contextual auditory exposure. It gives a sense of what kind of life a person is living, which can help in personalizing the treatment for the person. In clinical settings, the clinician can explore what the different acoustical environments mean for the hearing aid user. Intelligent systems could potentially use soundscape data annotated with user labels and feedback, to optimize hearing aid settings. The two subjects experience a changing context over a day. The current medium setting may fit neither of these subjects. For subject 1, a personalized setting emphasizing speech, and a second setting reducing noise, may be a better fit. Whereas subject 2 may prefer a medium balanced setting, supplemented by either a setting providing ambiance or a speech focused setting. Data can potentially generate insights and contextual awareness. In turn, this can be used both clinically by an audiologist, or hearing care professional. Both for new and first-time users and for experienced users who return for adjustments. Alternatively, this can be used for long term optimization of hearing aid settings based on the changing needs, and context, of the end user. Giving access and insights to the contextual auditory environment allow users to compare their perceived auditory exposure with the hearing aid observed auditory features.

4.3.2 Time as a Contextual Parameter

Physical context is more than the auditory soundscape. Expanding the sensing capabilities of hearing aids with location, movement, activity and time, gives a

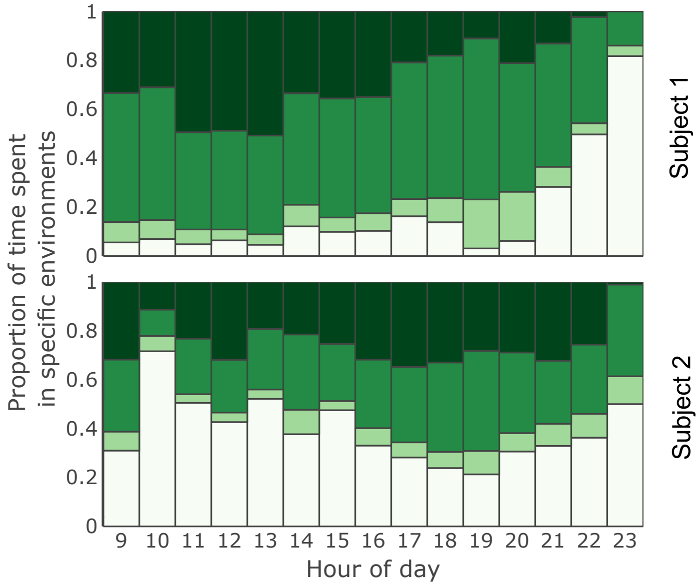


Figure 4.3: Contextual auditory environment for subject 1 (top) and subject 2 (bottom), averaged over six weeks of usage. Average percentage-wise exposure to the varying context on the y-axis. The color representation is; white for quiet, light green for clean speech, green for normal speech and dark green for speech in noise. The y-axis represents the hour of the day, averaged across six weeks [73].

detailed image of context. We will discuss each in turn, and how it affects the user interactions.

Time is an intuitive concept, with a shared understanding across populations. Humans use the time to measure the passing of events, the anticipation of future events as a reminder of past events. As clocks have become ubiquitous, ranging from middle age clock towers to the invention of the pocket watch, wristwatch from the quartz movement in the late 1970s, and today's use of digital clocks in smartphones and wearables. The passing of time provides a shared vocabulary, with a shared understanding. Time as a contextual parameter allows for putting things in new perspectives. I divide time into two major categories, inspired by statistics. Discrete-time (events) and continuous time (events). Hearing aids log time to some extent. To save power and reduce bit operations, time is stored as discrete events. Meaning, average hours of use can be extracted from hearing aids. It is a matter of bit operations, where updating and replacing an integer, or float value, is much cheaper, than appending values to a vector or matrix.

Several studies investigating self-reported usage with logged usage have been conducted [17, 18, 24, 55, 78, 85, 151]. This gives a good indication of the total and average usage of the hearing aids, which have a positive correlation with outcome-based measures. These studies show that hearing aid users overestimate the use of hearing aids, compared to objective measures. These studies have been limited to a discrete perspective on time. Only a few studies have been conducted for hearing aids, where continuous time logging is used. Aldaz et al. [1], uses a smartphone and time logging to optimize hearing aids. And to the knowledge of the author, no studies have been published on continuous usage logging for hearing impaired. Meaning, we only know what hearing impaired users experiences, through anecdotes and interviews.

We see time as an important factor in personalization. Time give cues about unique behavioral patterns. The example of hourly usage was mentioned in the previous section. Another example is used for the correlating program interactions with the time of day. This is illustrated in Figure 4.4. One can observe how the auditory context changes throughout the day, illustrated in 15-minute bins. Coupling auditory context on a timeline allows the user to investigate how they use their hearing aids. It allows the hearing care professional to ask relevant questions, such as: "how do weekends differ from weekdays", or "what would you need in an environment characterized by speech"? If a timeline is not desired, the average hourly usage can be used, as illustrated in Figure 4.3. This can be extended to illustrate the average daily use, or dividing the average use into weekends and weekdays.

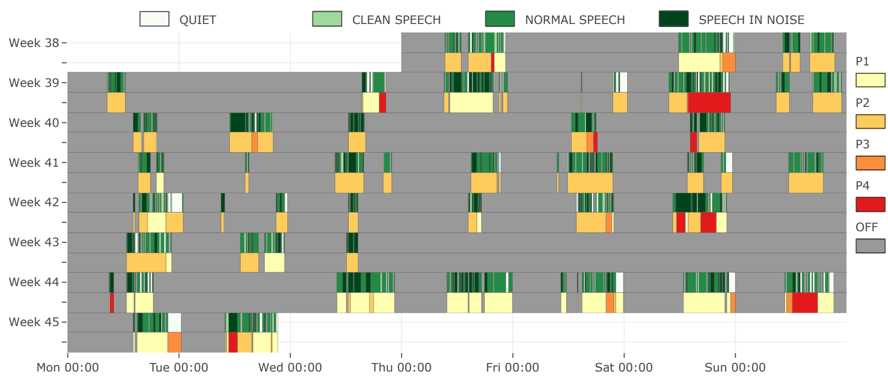


Figure 4.4: Example of coupling time with auditory context and program interactions. The green hues indicate the auditory context [73].

Time binds insights together in a format the users and clinicians can understand. It helps to tell stories of everyday life, and how things perceptually integrate.

Time is part of the analytical foundation.

4.3.3 Limited Implications from Location

Most, if not all, smartphones have built-in GPS sensing capabilities, and many apps taking advantage of this sensing. Geolocation, as acoustical sound, carries information about the context. It supplements user intents with a geotagged point. As an example, the home may have a different sound environment than work, the bus has a constant level of noise, and running in the woods may be quiet. Locations can provide general labels, associated with a stationary sound environment, or specific labels based on user intents and usage. As an example, a cinema will most of the time provide an acoustic scene with higher sound pressure levels. Alternatively, attending a lecture may provide an acoustic scene characterized by a clean speech signal, and lower sound pressure levels. One can use 3rd party services such as Google places API[1] or Foursquare places API [2]. These services are crowdsourced and contain labeled data from thousands of people tied to a geographical location. Both Google Places and Foursquare places have high-level categories, such as shopping, and sub-categories such as clothing or supermarket, which can be used to label data. An alternative approach is cluster geolocation based on density. Unsupervised clustering, such as HDBSCAN [90], can be an effective method for this. Using time as a marker of location change and alternatively, distance, are two other approaches [2] to HDBSCAN. In an unpublished study, we use HDBSCAN to find the top visited locations. We cluster geolocation labels, and then based on the density, we relabel each cluster denoted $location_N$. This approach pseudo-anonymize locations, while keeping a label. The user can be prompted or motivated to annotate their location with semantic meaning, such as *home, work, gym*, etc. Allesandri et al. show that humans visit around 25 locations [2]. Communicating that location is pseudo-anonymized have in our experiments led to a higher acceptance of using location. The promise of more convenience in exchange for sensitive information, such as location data, convenience some but not all. Anecdotally we experience that half of our test population actively asked to switch off location when applicable. Location is perceived as a severe compromise of privacy. Location cannot be relied on as a contextual feature, as some wish to avoid it, leading to missing data.

The limitation of using locations to determine the acoustical context is the variability in the two signals. The location signal is stationary. Meaning, a location may not change labels if the location, or building, is being re-purposed for a different use. A cinema may change into a supermarket. This may not change

[1] https://developers.google.com/places/web-service/intro
[2] https://developer.foursquare.com/places-api

the contextual location but would change the acoustical context. In contrast, an acoustical context is non-stationary. The acoustical signal changes over time, sometimes rapidly within a few minutes. A lecture hall is an example of a changing context over time. Early in the morning lectures may be conducted, later in the day students working in groups drastically change the scene, and in the evening the lecture hall may be used for movie screenings or receptions. The second drawback of locations is the granularity provided by GPS sensors. A GPS location consist, a longitudinal and latitudinal coordinate, and height can be estimated. This works for outdoor locations, which in many cases are two-dimensional. Buildings, in contrast, can have several floors, and building materials can distort or block GPS signal. GPS may not be able to identify whether the location is a lecture hall is located on the first floor, a lab in the basement, and meeting rooms and offices floors above the lecture hall. What would then be the most correct label? Several attempts on indoor locations have been investigated such as the *Active Bat* system [45], or using wifi [7]. None of these approaches for the indoor location have been widely adopted yet.

4.3.4 Movement and Activity as Significant Event Identificators

The last type of contextual information gathered relates to motion and activity. Using dedicated motion sensors and third party activity recognition API libraries [3], enables the extraction of time-stamped motion data. Motion is an indicator of the physical activity of a user. It highlights when a user moves from one activity state to another, such as stationary to walking to driving. Motion is used as a state indicator and indicates a state change. Meaning, motion enables insights into how states changes, and can supplement the geolocation. For example, a user reports that they work on the fourth floor. The contextual sound is relatively stable, reporting a quiet environment. The user moves for a few minutes, and the contextual sound changes. It is reported by the user that a meeting has started. Around noon 10-minute walking segment occurs, followed by a noisy environment with high sound pressure levels. After half an hour, 10 minutes motion occur, and the contextual sound is logged as quiet. The user reports the previous segment as lunch. The geolocation has been stationary in the three scenarios, while the contextual sound has changed drastically. Here motion and activity highlight stories, geolocation could not.

Layering more contextual information tells a story with more details, than relying on solely one contextual parameter. Smartphones, wearables, and IoT

[3] Activity Recognition API `https://developers.google.com/location-context/activity-recognition/`, Core Motion `https://developer.apple.com/documentation/coremotion`

devices come with vast sensing capabilities. Interconnecting the devices enables sensor sharing, in essences enabling context-awareness across devices. Getting closer to Weiser vision of the computer for the 21st Century. Figure 4.5 illustrates how multiple devices can enhance the contextual understanding. The hearing aids collect contextual information related to the acoustical environment. The smartphone collects movement from embedded motion sensors and geolocation from a GPS antenna. This information is then processed, locally or remotely, to add semantic labels. The contextual awareness can be fed into intelligent systems, and ultimately create a good user experience.

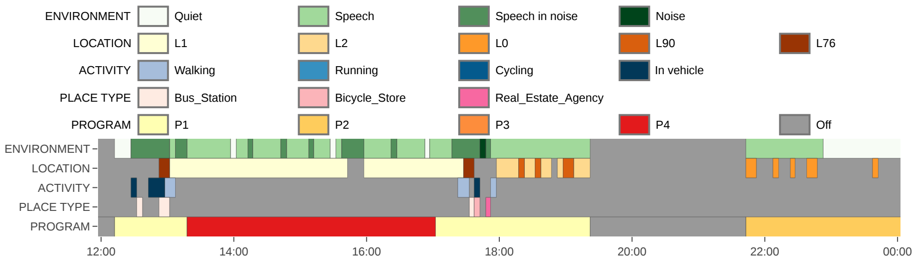


Figure 4.5: Four types of contextual information. The acoustical context called environment, Location relates to both the geolocation and the labeled place type, activity is based on motion and labeled accordingly. Program is the user interactions with the hearing aid [74].

4.3.5 Verifying Auditory Context from Hearing Aid Users

To verify the type of physical context, we rely on user input, to label the context. This also encourages users to share their intents in a given context. In clinics, the increased awareness of hearing aid performance in annotated context can support the fitting process. From a series of experiments, we utilize program and volume interactions as pseudo-labels for user intents. A program or volume interaction, initiate a discrete event, reflecting a mismatch between the user perceptual model, and the augmented sound signal from the hearing aid. The hypothesis is that context influences user interactions, and the research question is how user interactions are affected by context. We assume the user interactions are the labels and use these labels for training a naïve Bayes model. Initially, the model is trained with a week of observations, updating the prior of the model. The prior is updated and the model re-trained on a rolling basis over time. In Figure 4.6 we illustrate the effect of various environmental contextual parameter to predict user intents. We use the training data to predict the posterior, or the inteded label. We can then calculate the posterior value for each of our test set, while continously updating the prior or likelihood. We use a naïve Bayes model for this. Defined as:

$$Pr(p \mid w) = \frac{Pr(w \mid p)Pr(p)}{Pr(w)}$$

or in words

$$Posterior = \frac{Likelihood \times Prior}{Average\ Likelihood}$$

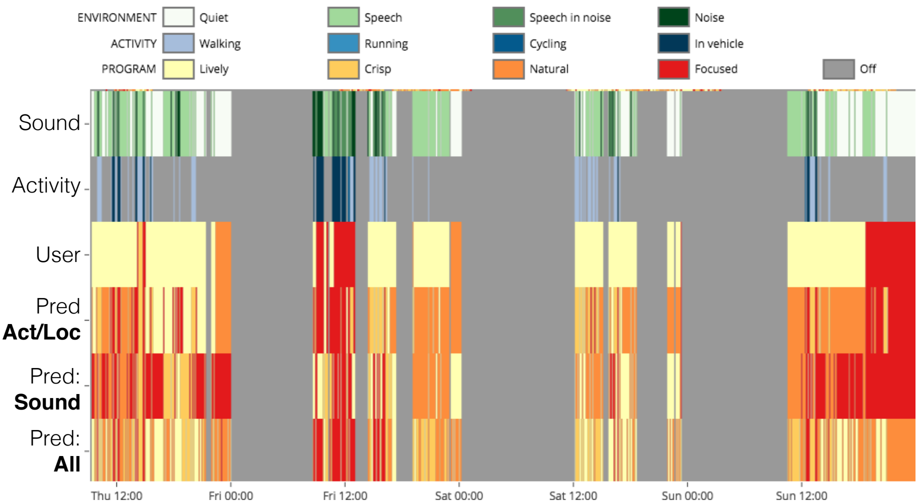


Figure 4.6: Naïve Bayes prediction of contextual program preferences for one subject over four days. The upper three tracks (green, blue and yellow gradients), represent the soundscape environment, motion activity, and user selected programs, respectively. The following three tracks of color bars (yellow gradients) show conditional probabilities for user preferred programs, based on a) motion activity and location alone (*Act/Loc*), b) soundscape environment alone (*Sound*), c) motion activity, location, soundscape and time combined (*All*) [60].

The model predicts the most likely program based on previous observation based on activity and motion, location and acoustical features. The best performance is achieved when combining several modalities. Using only one, such as soundscapes, location, or motion, results in poorer predictions. There are still challenges related to these models. First, more data is needed and more features are needed to improve the predictions of the model. The sampling frequency is relatively low, with one update per minute, or when user interaction is instantiated. Access to raw data, such as spectrograms, would enable the possibility of using deep learning frameworks to relabel the acoustical features. Secondly, this model accounts for physical context, and not the user context. No prior knowledge exists on how the user is feeling, what desires the user have or the level of fatigue. The program labels are assumed to reflect these features, and in reality, it is only a limited reflection. To better understand the physical context, and how it affects hearing aid usage, we need to understand the user.

4.4 Summary

The advent of sensor-packed devices, ranging from smartphones, through personal wearables, to IoT devices, are candidates for creating intelligent context-aware systems. Petabytes of data are collected on a daily basis, yet still much of rest in a server center. The foundation for making context-aware devices exist, sensor-packed personal hardware, inter-connectivity, and advanced artificial intelligence systems. Hearing aids are part of this system, and still need to find the killer app, to break the glass ceiling.

In this chapter, we examined what computing context and physical context. We illustrated that hearing aids are context-aware devices with limited computing context. Despite the lack of resources hearing aids can be part of bigger ecosystem. Understanding context is one of the keys to solve the challenge of the use and non-use of hearing aids. The challenge cannot be solved by relying only on the acoustical signal. We observe that two subjects experience different acoustical context. This can help in personalizing hearing aids, and to distinguish between a person mainly in quiet settings, or with a more dynamic sound environment. The device of the future must include context awareness. We have shown that time, location, and activity all contributes to certain behaviors. And, statistical modeling, such as a Naïve Bayes model, may be able to predict human goals based on contextual information.

Chapter 5

Personalization of the User Contextt

This chapter focuses on providing insight on designing for the user context, within hearing health care. To design for better user experiences we need to understand the user. This chapter highlights a two-fold description of users. One is from the user experience paradigm and the other stem from contextual aware devices. The first part of the chapter describes the view on personalization from the UX perspectives, including defining personas and highlight individual differences. While the second part of the chapter investigates how using rapid prototyping quickly provides insights on user context for hearing aid users. The hypothesis is: to personalize hearing health care both the physical context of a user, and the user context must be understood. The topic covers how to collect quantitative data, how to collect qualitative data, and how to use this data to better understand the user. The chapter uses examples of user context and user behavior drawn from the contributions: "Hearables in Hearing Care: Rethinking Hearing Aid Fitting by Learning From Behavioral Patterns" Appendix A, Discovering Usage Patterns Through IoT Device" Appendix B, and "Personalizing the Fitting of Hearing Aids by Learning Contextual Preferences From Internet of Things Data" Appendix E.

People are unique and have different behavioral patterns. Behavioral psychology has spent decades on profiling different behavioral characteristics, and we know for sure, that people have different behaviors. The challenge with hearing

impairment is that everyone is treated equally. The fitting rationale does not compensate for individual differences and is fitted based on physical measurements. The PTA and neglects both how people behave, and the kind of everyday life they lead. In the clinical workflow HCPs can ask the hearing impaired how they intend to use the hearing aids. Questions related to age, if they live with a spouse, and how active the lifestyle is, all provide input on which situations the hearing aid can be expected to perform in. However, clinical resources are limited, and it may take as little as 15 minutes for a customer to exit a hearing clinic with a pair of hearing aids. The visit includes a hearing assessment, which takes 5-15 minutes, selecting a product, and having the hearing aid fitted. In the case where time is limited, the user is often left with a medium setting, where the HCP relies on the build in settings of the fitting software.
An alternative approach is to support the user and clinician by using quantitative measures. These measures provide insights into the everyday life of the hearing aid user. In the previous chapter, contextual information was used to provide insight into the environment hearing aids are used in. Here the focus will be on how to use quantitative data to investigate the user context. This fits into the personalized hearing care model, as illustrated in Figure 4.1. The user context and physical context provides a foundation for scalable hearing care solutions, generating insights for both clinicians and hearing aid users, and potentially input for intelligent systems.

5.0.1 Quantitative Tools for Describing Behavior

User experience is known for using qualitative methods to investigate behavior. The toolbox consist of *interviews*, *observational studies*, and *questionnaires*, followed up by a session of coding. These tools work well for a small group of participants, but may not generalize well. Just imagine trying to code and identifying themes from interviews conducted on 100s of people! At the other end of the scale is questionnaires with lickert scales. *Questionnaires* are often a one-shot method, and gives insights quickly which can be compared across subjects. Example questions could be: "How often do you have problems understanding speech?", or "On a scale from 1-10 how much does loud noises bother you?". *Ecological momentary assessments (EMAs)* is a collection of methods which assess the everyday life of a person. Shiffman, Stone, and Hufford [123] define EMA as “Ecological momentary assessment (EMA) involves repeated sampling of subjects’ current behaviors and experiences in real time, in subjects’ natural environments.”. EMAs allows the user to rapidly attach meaning to a current context, and works well over shorter periods, in experiments or when they are not perceived as disturbances. The frequency of questions asked for an EMA typically range from once every 30 minutes in the span of a few days, or daily for a year. EMAs are limited to a subset of questions, which may be specific for a certain domain. EMAs have been successfully carried out within audiological research. However, most studies are from 2014 or earlier, and the findings are biased by focusing on difficulties [37, 47, 50, 150]. Despite these findings, EMAs are not clinically accepted within hearing aid fitting. A different take is using *quantitative* observations. This is a quantitative *fly on the wall* approach, where the researcher potentially collects big amounts of data, and try to generate insights from these data sets. The idea is to investigate behavioral traits over many users, many trials, long time periods or a combination of the aforementioned. As an example, what can we learn from millions of keystrokes? Dhakal et al. [29] shows how keyboard typing can be used to create a cluster of users based on features related to typing, such as word per minute or error rates. While arguing that the same features can be used as a security measure. Netflix group people based on their interaction patterns with the service and uses key metrics such as engagement and retention [42]. Interviews provide many insights, but are not scalable. At the other end of the scale is EMAs, which are both scalable and provide a high level of insights. The different approaches have a varying scale of scalability, insight, and effort required. An overview is illustrated in Figure 5.1.

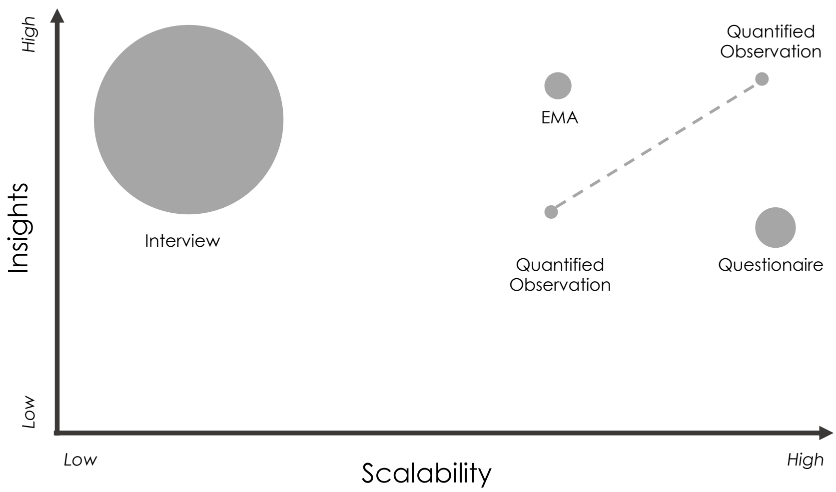


Figure 5.1: An illustration of insight and scalability of different observational methods. The size of the bubble indicates a simplified notion of time, effort and awareness put into collecting the data. Based on [106].

In the case of personalized hearing health care the technology should be ubiquitous and pervasive, and not interfere with the user's everyday life. We want to contribute with a framework, which is scalable and can be deployed to thousands of hearing-impaired listeners. Using program and volume interactions as a starting point to highlight individual differences and behaviors. To personalize hearing health care, the individual must be considered, while learning from other users' behavior.

5.0.2 Personas, archetypes and clusters

Personas can help articulate certain characteristics for a hearing aid user. In the realm of personalized hearing health care, it can help to identify archetypes, which can guide the clinical workflow and potentially intelligent systems. A persona describes characteristics of a real user, or users. Allan Cooper et al. [23] describes personas as:

> Although personas are depicted as specific individuals, because they function as archetypes, they *represent* a class or type of user of a *specific* interactive product. A persona encapsulates a distinct set of **behavior patterns** regarding the use of a particular product (or analogs activities if a product does not yet exist), which are identified through the analysis of interview data, and supported by supplemental quantitative data as appropriate. These patterns, along with specific motivations or goals, define our personas. Personas are also sometimes referred to as **composite user archetypes** because personas are in a sense composites assembled by grouping related usage patterns observed across individuals similar roles during the Research phase.

Why do personas play such a central role in UX and interaction design? Personas help address different needs, values, goals, and motivations. Personas in UX are heuristically derived or from field study observations. As an example, when designing an app for travel booking several personas emerge, the businesswoman with a focus on efficiency and working while traveling, the young female solo traveler looking for experiences or the family of four. These archetypes have different needs, values, and goals, and guides the UX process in different directions. If for example, we wanted to serve everyone needs, we'd end up with a product that satisfies no one. Imagine being a family and always getting recommend the most efficient, and expensive tickets. Personas can be used in tandem with user story mapping.

Archetypes showcase generic traits representing a group. These traits can be derived from individuals as a representation of a bigger group, or an individual can be placed within a representative archetype group. The former is common within a UX process, based on field studies, observations and interviews, one or several people create an archetype or persona. The later is based on large studies, where groups of people are analyzed and then clustered into representative groups. This practice is common in statistics and demographic research, where age, sex, income level, marital status, level of education, and occupation can generate archetype groups. A related approach from psychology groups people based on personality traits, as popularized by psychologists such as Carl Jung [65] on psychological types, or the Big Five Personality Traits popularized by Lewis Goldberg [40]. An algorithmic approach cluster people based on features. Clustering techniques cluster across high dimensional vector spaces, based on feature vectors of $features_N$. Three common approaches to reduces the feature space are principal component analysis (PCA), independent component analysis (ICA) and multi dimensional scaling (MDS). Afterward, based on the clustering pattern, techniques such as k-means [46, 127] clustering relying on centroid radius and the number of clusters, the nearest neighbor approaches such as kd-tree search [94], or density based scan such as DBSCAN [35] using an epsilon parameter to determine cluster based on density. An algorithmic approach reduces bias from the researcher and relies on quantitative measures.

5.0.3 Archetypes From Audiogram Data

The audiogram is the de facto standard of hearing aid fitting. What can we learn from it? The test subjects in the various pilot studies have been fitted individually based on their audiogram. An audiogram is visualized in Figure 2.1. In our studies, the audiogram is compromised of 11 frequency bands from 125 Hz to 8000 Hz. Based on WHO guidelines hearing impairment can be categorized as slight, mild, moderate and moderate-severe [144]. This grouping only accounts for the severity of the hearing loss, not the shape. Bisgaard et al. [13] propose 10 audiogram classes based on shape of the hearing loss curve and the severity of the hearing loss. From our studies [59, 61, 64], we do not observe correlation between WHO classified hearing loss and user behavior. We apply a dimensionality reduction method to investigate if behavior can be described from the audiogram. PCA is used to reduce the 11 band audiogram into a lower dimensional space. The two first components of the PCA account for respectively the slope and the severity of the hearing loss. The severity, the first component explains 52,4 % of the variance, while the second component, the slope, explains 32,6 % of the variance. The two first components explains 84,4 % of the variance within an audiogram. PCA can visualize these two dimensions of hearing loss, while still preserving privacy. This is illustrated in Figure 5.2.

The axis of the figure is respectively principal component 1 and principal component 2. The colors indicate different subjects, while L and R denote either left

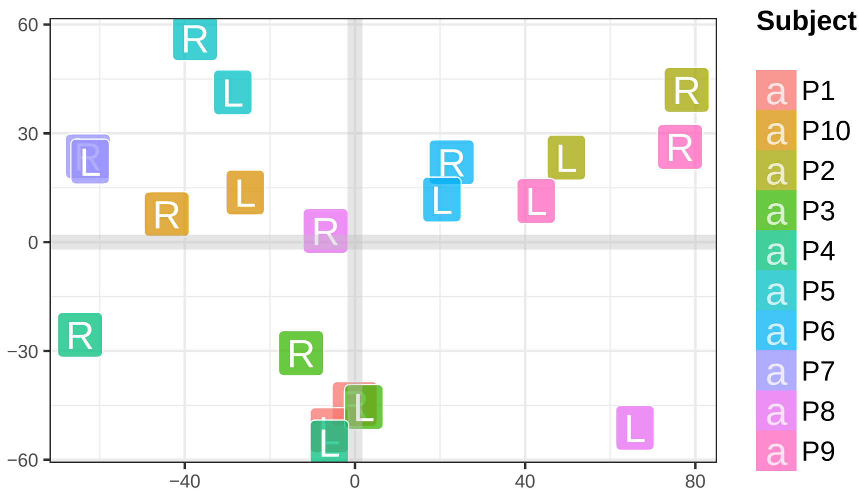


Figure 5.2: An example of using PCA on audiograms from 10 test subjects. The PCA scales the 11 frequency bands into 2 dimensions, visualized as component 1 and component 2.

or right ear. It can be observed that most subjects have symmetrical hearing loss for both ears, while some subjects such as P8 and P4 have different hearing loss across the ears. From visual inspection, three major clusters can be identified. Cluster 1 occurs in the upper left corner, Cluster 2 in the lower left corner and Cluster 3 in the top right corner. Two ears appear to be outliers. We then couple the clustered audiograms with interview insights. The audiogram may be a good start to estimate potential hearing aid usage. At least we see that the severity and the slope both promote different behavioral patterns. Archetypes based on audiogram data are described as:

Perceptual SNR The subjects located in Cluster 2 have a preference for programs with a distinct sharpness and crispness attributed to amplified mid- and high frequencies. These people prefer to perceptually and cognitively improve SNR, rather than relying on the hearing aids noise reduction algorithms. This archetype prefers to have spatial awareness and to be able to orient within the acoustical scene. The hearing loss for this archetype is characterized by a ski-slope shape and a moderate hearing loss.

I don't really need a hearing aid This archetype is characterized by using the hearing aid on-off. The archetype is aware of when help is needed. Consider their hearing loss annoying, and knows when to use hearing aids to correct it. Cluster 1 is characterized by a mild hearing loss, mostly in mid-frequencies.

Comfort and high SNR Prefers to attenuate noise more and to use the hearing aids beamforming focus. Characterized by using programs that work well in noisy environments. Cluster 3 is characterized by a moderate hearing loss and with a cookie-bite or flat shape.

People in the upper right corner have a preference for neutral sounding programs, and to use more noise reduction. In contrast, users in the lower left corner tend to prefer brighter sounding programs. The raw audiogram data shows that these users have a steep fall off in high frequency. Compensating by adding brightness, gives a better sound experience for these users. Interestingly, a user notes, “I prefer the brighter sounding programs because they help me more understanding speech, especially in noisy environments. However, the sound is not as pleasant as programs with more flat sounds.”

5.1 Finding Similarities for Hearing Aid Users

The audiogram only tells the story of the physical measurable part of the hearing loss and does not acknowledge the individual differences and behavioral traits. And this may be a reason why the current personalization of hearing aids are sub-satisfactory.
A question raised is, how can we supplement the audiogram. Leading to, what happens over time, if people change habits, work, or the context is affected in other ways? We start the discussion by investigating what alternatives can be used to personalize the hearing aids. Using lean prototyping we investigate what stories volume and program changes can tell about user behavior. We use a framework of rapid prototyping, to quickly deploy prototypes and collect hearing aid data. This interaction data form the bases for comparing users from quantitative interaction patterns.

We hypothesize that internal motivation and perceptual exposure is as important as the actual sound environment. We look at this through hearing aid manipulations. Interaction patterns exhibit behavioral traits, which can be used as a foundation for personalization of hearing aids. What effect do weekends vs weekdays have, what about the time of day, and if we provide test subjects with the same devices, same program, and volume settings, do they then exhibit different interaction patterns. If the answer is yes, then what interaction patterns do they exhibit, and how can we use this when personalizing hearing care?

5.1.1 Investigating User Context With Rapid Prototyping

To address some previously asked questions, we recorded how hearing aid users use their hearing aid over several weeks. We hypothesized that people are more than an audiogram and that we can tease different behavioral patterns apart, based on volume and program interactions. We provided test subjects with a commercially available hearing aid, and created 10 IFTTT recipes, to log the interactions with the hearing aid. Rapid prototyping was used as a research tool to move the research from a laboratory to 'the wild'. Research within hearing is primarily focused on clinical studies, or observatory studies with conclusion questionnaires, not *in-the-wild* studies. The rapid prototyping process allows the researcher to circumvent the technological limitations of the hearing aid, by augmenting it with 3rd party services. During early workshops, this technique was used to simulate what would happen when a user interacted with their hearing device. To establish data-driven personas, interviews and passive data collection was used. Through interviews, it was discovered, that the design of the product mustn't drastically slow down the interaction. This was discovered when testing alternative interfaces, where audio feedback slower than 500 ms were unacceptable. To discover individual interaction patterns, we fitted the test subjects with hearing aids, containing four distinct acoustically different programs. Perceptually the difference is described as contrasts. Each program alters the following settings, *volume gain* in mid- and high frequencies, *beamforming directionality*, noise reduction and attenuation. We keep the prescribed dynamic compression settings, which balances the hearing aid output with acoustical input level, to fit the dynamic gain range for the user. The fitting parameters are the same across the following studies.

Volume gain in mid- and high frequencies Contrast was obtained by altering the high-frequency gain, either increasing high-frequency gain resulting in a perceptive *sharper, brighter and distinct* sound which emphasizes hissing sounds, such as *z and s.* In contrast, lowering high-frequency gain, and flattening the gain prescription results in a *flatter and muted* sound experience. This can be perceived as more comfortable, as high frequencies sound muffled. The general shape is preserved, and perceptually be experienced similar across sound environments.

Beamforming directionality A metaphor for altering the beamforming directionality is a pair of horse blinders. With a high level of directionality, sound from the back and sides are reduced. Perceptually sound from the front is enhanced. At the other end of the spectrum is no blinders. By simulating the shape of the human pinna, the outer ear, sound from the back is attenuated, while sound from the sides and front are preserved. If no natural attenuation is provided, a 360 degree sound field is provided. The directional sound is similar to a narrow torchlight beam, while the broad directionality is closer to the light cast from a lamp near a wall. This effect is accomplished by utilizing a microphone array pair to determine the shape of the sound field. The setting was set at either a minimum, allowing for immersive sounds, and at maximum to accomplish a frontal focus. By default, the directionality becomes pinna like in quiet environments.

Signal-to-noise ratio (SNR) Noise reduction aims at balancing the signal between the target signal, speech, and noise. The noise reduction system of hearing aids can improve the SNR with 6dB. Perceptually a 6 dB SNR improvement should increase the target signal to double strength. The signal to noise ratio can be estimated using the noise floor and the target signal. In one end of the spectrum, a 6 dB signal improvement can be applied, while in the other end 0 dB improvement is applied. In the field studies, noise reduction is only engaged when noisy environments are detected and disengages in quiet environments.

Four programs are uploaded to the hearing aid. This is the maximum number of programs, due to the software constraints of the hearing aids. Programs here denotes a change in the volume gain shape, the directionality and the noise reduction parameter. The volume gain setting ranges from -4 to 8. The users can interact with volume and program independently. Volume is reset to 0 when a program change occurs.

5.1.2 Different Volume and Program Interaction Patterns

Based on related work we picked various metrics to measure and compare different types of users. Solheim & Hickson [125] and Laplante-Lévesque et al. [78] measures the average daily usage of hearing aids. Both studies conclude that users tend to overestimate the usage of their device. Laplante-Lévesque used clustering analysis to show to archetypes of users: " *'Regular'*, where hearing aids are typically switched on for between 12 and 20 hr before their user powers them off (57% of the sample), and *'On-off'*, where hearing aids are typically switched on for shorter periods of time before being powered off (43% of the sample)" ([78]).

To collect data related to hearing aid program and volume interactions, a rapid prototype architecture was designed. The Oticon Opn released in 2016 combined with the web-based service IFTTT. User-initiated volume and program interactions are logged in a Google sheet, owned by the test subjects. Data access rights were granted to researchers by test subjects and could be revoked at any time. All data point contains a timestamp, an action, either volume, program or connection. The data is extrapolated, and used as follows:

Time & date One of the main contributions from these papers are the minute by minute logging of hearing aid usage. The data is timestamped, and the timestamps are used to analyze recurring daily, weekly or monthly events. The time is further used to analyze the difference between weekends and weekdays. Finally, it is used to compare how behavior change over time, where we hypothesize different stages of adaptation occurs. The time stamps are a convenient format to use for data analysis, as it's actively used to separate data.

Average daily usage Number of hours the device is used. This number is an approximation from the data, as this data could not be collected. The approximation is based on an assumption, that if no interactions occur between 10 PM and 6 AM and if a *disconnected* event occurs, the device is set to off. If no event occurs within 30 minutes of a disconnected event, we treat it as an off event.

Program usage Two measures of program usage is used. Daily usage in hours, and daily percentage usage split between programs. The connection event is used to divide the programs.

Volume usage Similar to program usage. We log a given program with a given volume setting. The volume is reset to 0 when a program change is initiated. If no volume change is observed, we assume the volume is 0.

Within this smaller pilot study, the test subjects exhibitA unique behavioral patterns. The average daily usage for five subjects ranges between 3.54 hours to 8.08 hours (mean = 6.58 h, SD = 1.78), these findings are similar to Solheim & Hickson (mean = 6.12, SD = 4.94). Through post-study interviews we confirm the two groups of *regular* and *On-off* users, where the test subjects with the lowest average time, confirmed that the hearing aid was frequently switched off.

It gets more interesting when comparing program usage patterns between subjects. A comparison of how subjects use programs are illustrated in Figure 5.3. The figure shows that subject 3 prefers the default program, subject 2 prefers two programs and subject 1, 4 and 5 uses, or at least tryout, all programs.

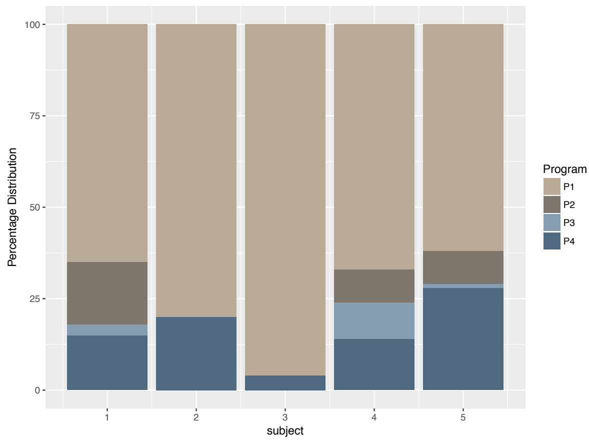


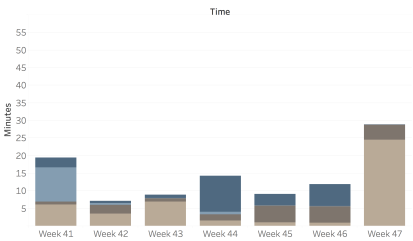
Figure 5.3: Program usage distribution for five subjects, based on data from [64]. The subjects are along the x-axis, and the y-axis shows the percentage wise distribution of programs. The programs are P1 (tan), P2 (brown), P3 (light blue), and P4 (dark blue).

5.1.3 Weekdays and weekends

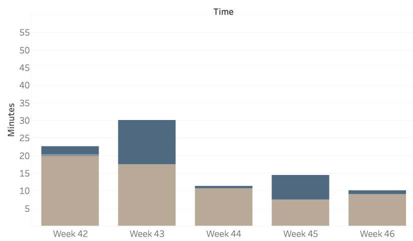
The data shows that the regular and on-off user may not cover all aspects of hearing aid usage. The five subjects program interactions over weekdays compared to weekends seems to differ. All subjects use their hearing aids less on the weekends than weekdays. We report an average usage of 7.8 hours per day during weekdays and 5.4 hours during weekdays. For this small sample size, the difference between weekdays and weekends are significant ($F_{1,4} = 17.0, p < 0.2$). We define additional archetypes from this data, *the conscious user*, using hearing aids primarily during weekdays in working hours, and limited use on weekends. *The weekend warrior*, living an active lifestyle and don't need or want to use hearing aids in the weekends.

5.1.4 Adaptation Over Time

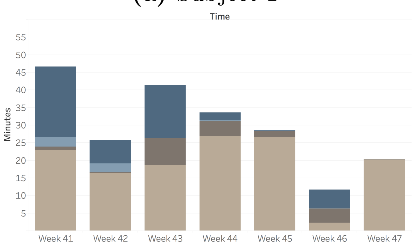
How does the program and volume interactions change over time? This question relates to how the subjects cope with multiple programs. Without personalization, the subjects would receive one program. We wish to highlight, that one program may not be enough to satisfy the needs of the user. Over the course of several weeks, we observe the program interaction changes. Most subjects experiment at the beginning of the experiment, using several programs. However, with time the subjects become more familiar with the capabilities of their device. We denote the first weeks as an exploration phase, where the subjects have a higher number of program interactions, and generally explore more programs. After a few weeks, the participants find their favorite programs, and most settle for two programs. This is a consideration when deploying new technologies within health care, as a period of adaptation occurs. The trade-off between exploration and exploitation is a unique trait. Some people like to explore more. Through interviews, we found people with a more tech-savvy mindset to prolong the exploration phase, and smooth into the exploitation phase. Other subjects would explore for a short time, before resorting to exploitation, when they found their favorite settings for a given context.



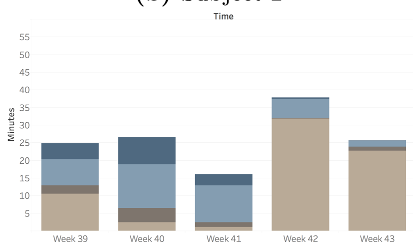
(a) Subject 1



(b) Subject 2



(c) Subject 5



(d) Subject 7

Figure 5.4: Four subject displaying different periods of exploration and exploitation. The x-axis denotes the number of weeks, and the y-axis is the number of minutes per hour usage. The programs are P1 (tan), P2 (brown), P3 (light blue), and P4 (dark blue) [59].

5.1.5 Micro adjustments through volume interactions

Volume is gain control. This indicates a satisfactory program has been selected, but the gain settings are not adequate. How can we actively use volume? When correlating program usage with volume settings, it becomes evident if some programs are too loud, too soft, or if they work as intended. We observe that the volume is not an either-or state, meaning, the volume can be increased and decreased in the same program, depending on time. We attribute this behavior to a changing context, where different intents occur. For some users, the gain prescription is too loud, or too intense, while others do not need to adjust volume. The users will adjust the volume in several increments while exploring. From the data, we observe that users over- or undershoots, seen through several interactions in a short time span, before settling on the desired volume. Over time, this over-/undershoot effect diminishes, when the mental model matches the gain output from the hearing aid.

5.1.6 Balancing between different interactions

In the included studies the test subject can only interact with the program and volume. We were interested in investigating what the interaction effects between program and volume were. We looked at the percentage-wise distribution of program and volume interaction for the sum of interactions, using data to illustrated different interaction patterns. If the users could only change programs, all interactions would be program changes. Alternatively, If the users can only change gain, volume gain would account for 100 % of all interactions. The standard in a hearing aid fitting is one to two programs. An average user would then primarily use volume interactions, if any, as this would be the only enabled interaction domain.
Interestingly, most subjects have a balance between program and volume interactions. This is illustrated in Figure 5.5. If there are more program changes than volume changes, it indicates that the gain level is acceptable, while the program illustrates adaptation to various contexts. One or two volume adjustments are needed to personalize the device to the current context. Fewer program interactions than volume interactions indicate that the desired program setting is found, and several gain adjustments are used. The subject population we investigated have a balanced usage, with a preference for changing programs. This illustrates that these users, despite having four programs, actively uses the volume gain to adjust their devices to a changing context. It also illustrates, that given the possibility, no user relies only on the default program. The users actively use the program control and volume control, to update and customize their devices.

We then ask "how does interaction between program and volume behave over time"? The average volume with respect to the program, and with respect to time, is illustrated in Figure 5.6. This figure illustrates that the interaction between the program and volume tells an additional story. It shows how test subjects gain preferences depends on the usage time of a given program. Meaning, is the gain preferences stable, i.e., no gain change, and in case not, how do these gain changes look like. This adds an additional input to the interac-

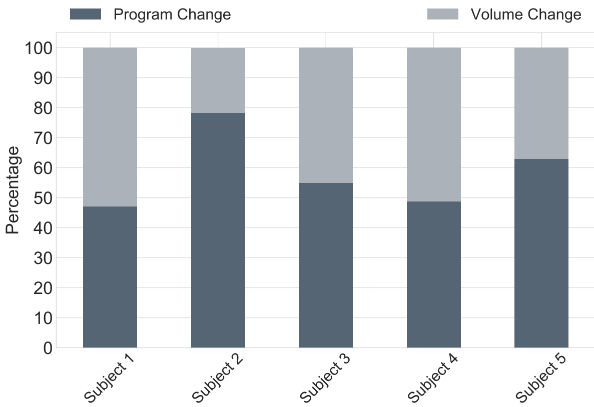
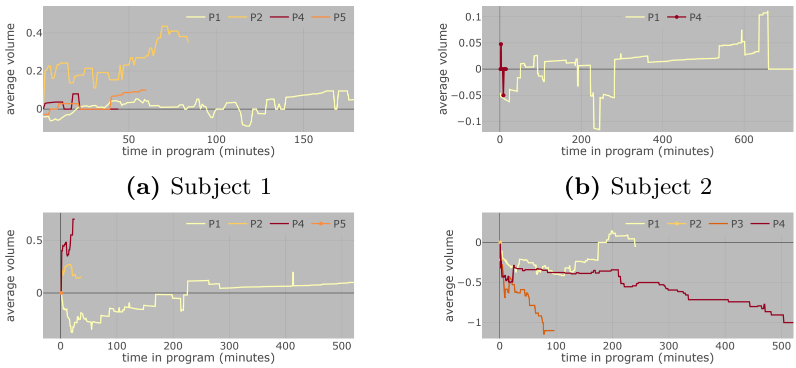


Figure 5.5: Percentage-wise distribution of total interactions between program and volume interactions. Program changes illustrated in dark blue, and volume changes indicated in light gray. With a 50/50 split, a program interaction is followed by a volume interaction, caused by the volume being reset from a program interaction [61].

tion between program and volume and how the program interacts with volume across users. Program P1 is used as an example. This program is characterized by a natural sound mimicking the pinna omni shadowing effect and with no noise reduction. The perceived 'natural' sound of P1 is firstly intense, showed in a decrease of volume gain. Over time the test subjects adapt and manually increase the perceived intensity through volume gain. Other programs such as P4, seems to need an increase in volume gain, as this setting flattens the overall gain while increasing noise reduction. Interestingly, one subject prefers to decrease volume across all programs, indicating a too loud gain prescription. Using the program and volume interactions with respect to each other, gives a tool for debriefing patients. The insights also illustrates that the preferences for each program are unique.

5.1.7 Visualizing behavior as a conversation tool

The collected data is treated as time series data. It is visualized using program duration over a week. This is illustrated in Figure 5.7 for one subject. Timestamps enable building visualizations which can encompass long time series. It is more informative illustrating hourly usage, rather than per minute usage. The clinician can actively use the data while debriefing a patient in a clinical setting. From the illustrated example the clinician can ask why the preference in pro-



(a) Subject 1 **(b)** Subject 2

(c) Subject 5 **(d)** Subject 7

Figure 5.6: Volume with respect to the program. Programs with less than 20 interactions have been excluded. The colors denote programs, the x-axis is time, and the y-axis is the average volume at at a given time, t [61].

gram changes over time, why some weeks are dominated by yellow and others by orange, and so on. Such tools provide new insights for the clinical workflow. The clinician can use such visualization to analyze trends over long time periods. And can act as a feedback tool, highlighting what instructions or changing of hearing aid settings affect the usage pattern. Enabling user and clinician to discuss events. Providing a quick overview of preferences and behaviors. And supporting memory recall.

5.2 Personas From Interaction and Interview Data

From program and volume interaction, and from the audiogram data, we define personas. The personas reflect data collected from interviews, where the test subjects were debriefed using their data as a communication tool. A user was debriefed and asked why the subject preferred the noise attenuating programs, the response was, "I work in noisy environments throughout the day. When I get home I just want peace and quiet. This program is really comfortable and sounds nice... But I don't really think it helps me." The personas are summarized as:

The tech savvy The tech-savvy user loves technology. This user has several devices and actively seeks out ways to make life more convenient through

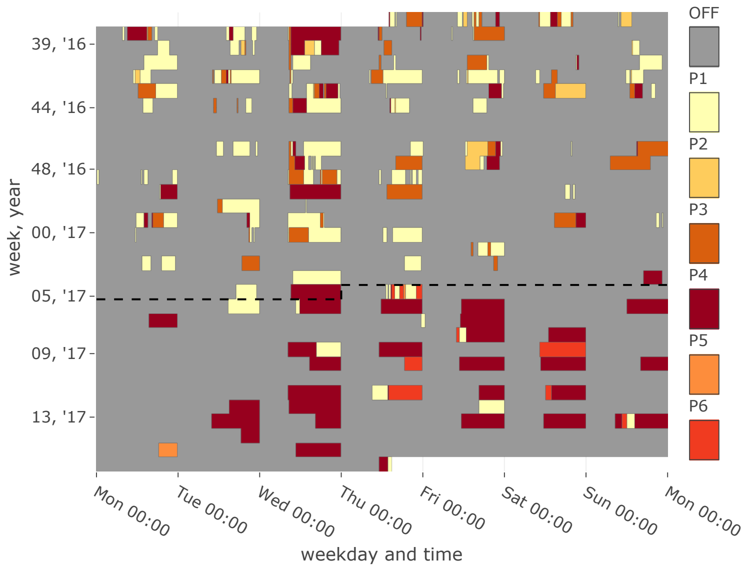


Figure 5.7: Subject 4s program interactions over 7 weeks. The x-axis is weekdays, y-axis weeks, and the programs are colored from yellow to red [61].

technology. This user is curious when it comes to technology and is willing to try several settings out in varying context to tune the hearing aids. The tech-savvy is characterized by frequent program changes, and to test the hearing aids out in challenging situations.

The active The active user have an active lifestyle. This user has a dynamic life where new events and contextual sound data creates experiences. This user needs contrasting programs to cater to changing needs. This is reflected in using the open pinna omni program to create immersive sound experiences. Supplemented by using a noise reducing program in evenings. The user can also be physically active and needs a device which can withstand physical abuse.

The 'I use it when I need it' This persona is characterized by low average usage, and infrequent interactions. This user mostly relies on one or two programs, and may not enjoy fiddling around with the hearing aid. Based on the user interactions, this persona likes to have an everyday program and a program that can help when it gets noisy. This person uses hearing aids when they feel there is a need. Most of the time they spend in quiet surroundings, such as an office, and shut off the hearing aids and the data stream. This person will stay in the default program more than 80% of the usage time. This persona is usually aware of the surroundings and only use the hearing aid when needed. The persona is similar to the 'on-off' type described by Laplante-Levesque et al.

The observant The observant likes to explore. The observant will usually be curious in the beginning, trying to match a setting to a context. Over time the observant accurately can describe challenging listening scenarios. The observant benefits from visualizations to emphasize the experiences.

The complient This persona reflects the 'average' 70+ years old women which are usually used to model hearing aid settings after. This person needs one program, doesn't like technology, and needs the hearing aid to be out of the way.

Most of the personas do not fit the average persona and archetype used in the hearing aid industry. The compliant may be the most prevalent persona in reality, but the other personas are neglected and end up with the same settings as the compliant. Data-driven personas provide insights on non-typical users. Using these personas can help the clinician in personalizing hearing aids.

5.3 Data as a Communication Tool in the UX Process

From the three papers, we hypothesize that data can be an enabler within health care. Most subjects overestimate the usage of an assistive device, in this case, hearing aid. Several studies show this behavior. We focus on using data actively through a fitting process, in contrast to using only descriptive statistics. This makes the usage transparent for the user, clinicians and researchers alike. Using data actively can be an enabler within healthcare. When the process becomes transparent, the user can actively engage in their data, explaining why so-and-so happened. Combining data with timestamps enables focus communication. The drawbacks and challenges include involving users to share data, optimizing a clinical workflow based on debriefings rather than 'guess and remember games', and active participation from both users and clinicians. Data acts as an enabler for the user. The user can actively participate in their treatment, using data as a discussion starter. As the data per se is objective, the user can then decide how and what to change. This ties into the participatory P of the four Ps of medicine mentioned earlier. These examples illustrated how data actively can be used to personalize hearing aids based on behavioral traits. Such data have yet to be actively used when personalizing hearing aids. We do however see potential in using behavioral data, with contextual data, to personalize hearing aids.

5.4 Summary

The recently developed hearing aids with IoT capabilities open for alternative approaches for personalization. Using minute-by-minute data generated by users supports hearing care professionals when personalizing hearing aids. With a relatively small amount of data, based on volume and program interactions, the clinician has access to data as a conversation starter. The data can be used for persona and archetype generation, dealing with the cold start problem of hearing care and health care. These tools assist the clinicians in personalizing hearing health care, using off-the-shelve products.
The data benefit the end user in becoming more aware of their needs and how to address these using technology. Making data available and visually appealing encouraging the user to actively participate in their treatment. Inclusive health care is one element in the future of health care, and act as an enabler for users to be involved in their own treatment and to provide the users with timely and relevant feedback.

This chapter illustrated how to use off-the-shelve hearing aids, coupled with third-party services to enable an internet connected device. This works as a technology enabler, providing the technical foundations for a personalized hearing treatment. To build the user experience, we need to understand the users. Combining qualitative data through interviews and observations, quantitative behavioral data, and data related to the complications enables nuanced personas. In theory scalable, allowing the UX process to include big data sets.

Chapter 6

Hearing Aid Interfaces for Feedback

Collecting user feedback generates value for the hearing aid user, the clinician and potentially also for intelligent systems. Personalizing hearing aid usage relates to collecting user feedback. This chapter introduces how to collect passive user feedback through optimized interfaces. Providing an interface to support these interactions gives a more accurate interaction surface. It also supports the user experience by matching the user mental model and intents, to a visual interface. A more accurate interface improves the efficiency of hearing aid interactions and provides a pleasant experience. The chapter will highlight how known metaphors can support the mental model of the hearing aid user. The map provided, helps the user navigating and matching an auditory context, to augmented sound output. This is done by modulating the acoustical signal through a visual modality of a smartphone app. Providing users with compelling interfaces can facilitate usage while solving underlying problems. The chapter is based on the contribution: 'Mapping auditory percepts into visual interfaces for hearing impaired users' Appendix F. The user feedback collected through interactive interfaces can be used to provide insights to the user and clinician. For the user, an appropriate interface allows for fast and accurate interaction with the context. The clinician can receive annotated contextual data. This feedback can be used to improve adaptive interface. This is illustrated in Figure 6.1.

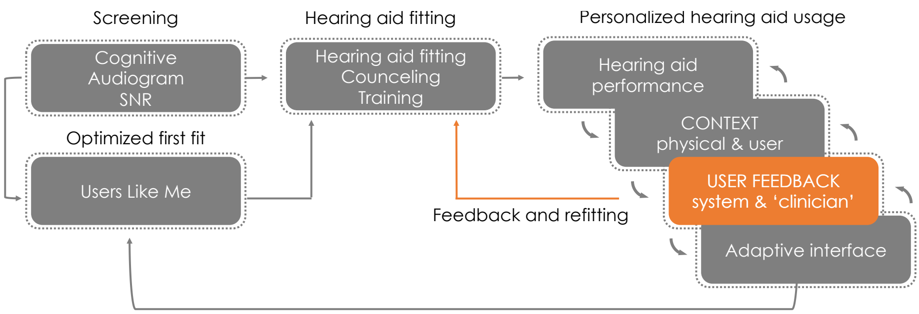


Figure 6.1: User feedback is provided through interactive interfaces. This feedback is based on contextual data and can be used both in clinical settings and as input for intelligent systems.

6.1 Improving Interactions with Hearing Aids

The offers from most hearing aid providers today is either a haptic interface on the hearing aid, remote control or a remote control app. These interfaces fulfill the same goal of changing program and volume of the device. However, they do only provide limited feedback on the device. Hearing aid users rely on button presses. Anecdotal, a user pointed out that using the buttons are more discrete than using either a remote or a smartphone. Hearing aid user perceives it inappropriate to modulate the hearing aids from an external device, rather than manipulating the hearing aid directly.

Why does the current user interaction fail? From an interaction point of view, it is about a mismatch between control and display. MacKenzie [84, p. 73-79] describe this as “Control-display relationships are some- times called mappings since the relationships attribute how a controller property maps to a display property”. For hearing aids the mismatch between control and display can be limited, simply by omitting controls. This can be done with fitting only one program on a hearing aid. Now the control is one-dimensional, namely volume gain increase or decreases, modulated through a display. In the case where multiple programs are available, the control and display do not match. The degrees of freedom within a hearing aid program is vast, including attenuation, compression, directionality, noise reduction and spatial awareness. This is then coupled with volume gain, increasing the complexity of the control. The display remains almost unchanged, now the user can select between program 1 and program 2, and can change volume gain in these programs.

The challenge is that an established framework for navigating in high dimensional acoustical spaces, neither exist in HCI nor within hearing research. It is similar to driving a car without experience. How does the gas pedal work, and the brakes? What about the gears? Add the cognitive load of navigating the roads, avoiding crashing, and keeping the speed limit. It takes months, if not years to become a good driver. Even with explicit controls and displays, such as the speedometer and the haptic feedback from the speeder, it requires training to ride a car. For hearing aids, you are expected to walk out of a clinic, with limited training, and being able to steer your hearing aid. It will take years before we see self-driving cars or self-driving hearing aids.

6.1.1 Using Metaphors to Enrich the Auditory Interface

Articulating audio is difficult. This is probably caused by the lack of a shared vocabulary. Trained musicians, audiologist, and others that work or have a deep interest with sound are exceptions. Metaphors and cognitive models can address the discrepancy between the visual and auditory domain. The usage of metaphors to understand an interface can accelerate adaption and creates more satisfaction. Metaphors in this context is both for *naive* and *experienced* users. A known metaphor within physics and engineering is the pipeline and liquid metaphor. This metaphor explains how electricity flows through circuits. Students without prior knowledge of electrical systems and circuits can understand this metaphor. For human communication, metaphors can provide a common language. This can help a HCP in the fitting of hearing aids. Caroll and Thomas [19] explains how metaphors are used to transfer learning in computing systems as "People develop new cognitive structures by using metaphors to cognitive structures they have already learned.". Meaning, using experiences can support the development of new cognitive structures, which can support the user. Metaphors are powerful in conveying information. We actively use metaphors as an integral part of the language. Metaphors are used to transform abstract concepts into an understandable, or relatable, abstraction, which helps share a common understanding between individuals.

The metaphor must be congruent with the way the system really works. Hearing aid manufactures creates narrow metaphors for hearing aid settings. When the hearing aid is fitted the user may get instructed that they have a restaurant program and a regular program. But what does it mean to have a restaurant program? And what does the user do if the program does not work well in restaurants? The lack of concurrency between a "restaurant" program and the auditory output, provides a displeasing user experience. Metaphors should be used concisely to improve the user experience.

In the case of mapping auditory sound to visual sound, we use the metaphor of navigating a map. The challenge with communicating auditory features is the lack of shared vocabulary. As an example, for some test subjects amplifying mid- and high frequencies become too sharp and distort the auditory scene. For others, this amplification improves the perceptual SNR and helps them navigate the auditory scene. Matching the auditory features with the perceptual information is individual, and challenges the designer. The power of metaphors is to detach from the actual auditory features, and rather rely on similarities from other domains and past experiences.

We use the metaphor of a map to guide the user interactions. A map is an abstraction of the real world. Maps convey information about multidimensional data, such as relational and relative distance, height differences, and visual orientation of shapes and colors. Within cognitive science, this is called imaginary and percept [112, p.339-372]. Human has a strong notion of creating mental images, and to accurately recall these, or imagine a distance from one object to another.

When navigating we use markers for orientation. This can be landmarks, signs, or abstractly, items orientation on a map. The map is always visible for the user and resembles a static map from an atlas. In contrast, using the haptic interface of a hearing aid relies on the user's ability to have a mental map of the settings. The user can use acoustical cues from *bips*, to navigate. Using *acoustical bips* temporarily uses the available auditory memory, and the user can miss out on speech and contextual cues. We propose to preserve the auditory working memory resources, by using relevant visual information. This would engage the visual working memory. We propose an alternative interface, build on a map metaphor. The interface is illustrated in Figure 6.2. Labels, colors, and space as markers. In this space, the positioning of the ball, contrasting colors, and labels helps the user navigate. Using two audiological parameters, namely brightness and attenuation, as symbolic markers. The users are encouraged to explore the auditory map. A ball is utilized as a pointer. The inspiration comes from map applications, where the user's position is indicated by a pointer. Google Maps uses a blue ball, with a light blue halo, illustrating uncertainty in location precision. The user can tap or drag the ball around, to select the desired position. Think of it as a mental route planer, where a line can be drawn between the starting point and the desired endpoint. Colors and shapes divide the map into distinct areas. This is similar to how continents are visualized on a map. Country borders are here illustrated by gray lines. Using colors and shapes gives the user a visual cue on what to expect. For example, moving from the west towards the east, the user perceptually may be aware of brightness alterations. While moving from north to south, perceptually correspond to modulating attenuation.

The second part of utilizing metaphors in auditory interfaces is denoted "learning to navigate the map". Firstly, the interface changes the current interaction pattern. The user can now change both program and volume in one interaction, whereas the conventional interface requires the user to first change program, then volume. In current hearing aid solution, the general practice is to update one fitting parameter at a time, whether this being gain settings, volume, or it is the SNR, directionality, and rationals, reflected in program changes. This essentially shortens the path between the beginning and end point, by translating a *Manhattan distance*: $d(x, y) =\mid x_1 - x_2 \mid + \mid y_1 - y_2 \mid$ into an *Euclidean distance*: $d(x, y) = \sqrt{((x_1 - x_2))^2 + ((y_1 - y_2)^2)}$. These interactions are often provided with auditory feedback, either as a tone, indicating the current status, by announcing the change in speech, or by listening to the change in acoustic scene provided by the digital signal processing (DSP). The alternative approach we utilize is a two-dimensional tweaking of the acoustic scene. The user is instructed that the colored fields correspond to contrasting changes in sound perception. While manipulating the dot outwards or inwards, respectively increases or decreases the volume gain. They are then told they can perform both actions simultaneously. The user is given more control, or freedom, to operate their device. At the same time, they are given visual feedback, on where their favorite settings are, with respect to gain and auditory features. In practice, this means the users can use the visual interface like a map which they can explore. The interface supports the user in matching a given context, both auditory, social and activity-driven, with a certain point in the map. The interface further supports interactions through distance. The user learns over time, that the neighboring fields correspond to a smaller change in acoustical manipulation than jumping from one corner to the other. This supports a mental model and an imaginary model of a map. Objects in proximity are equally manipulated by the relative proximity.

Thirdly, microinteractions support the map metaphor. With the proposed interface the user receives appropriate visual feedback, coupled with auditory feedback. The trigger of moving the ball engages with the rule of program and volume change. The user gets instantaneous feedback and can repeat the same interaction over and over with the same result. Visualizing both volume and program control in the interface helps to match the user expectation with the system output. This improves the microinteraction flow, and ultimately the user experience.

Considerate design decisions like the map metaphor illustrate how to improve the user experience, by updating interface changes, and making a minor adjustment to the interaction patterns. Considering what brings value, or thinking about outcomes, supports the user experience. In contrast, focusing on output, such as volume change or program change, works for feature development, and may not support the user experience. Considerate choices grounded in psychology and cognitive sciences, support the perceptual value of interfaces. And in turn, opens up for the possibility of engaging users.

6.1.2 Gestalt Principles in Hearing Aid Interfaces

The Gestalt principles stem from a group of German psychologist in the 1920s. The key principle is that the perceptual whole is different from the sum of its parts. In other words, focus on the organization of the entire shape, not just on the shape's parts. These principles can be applied to the auditory domain. Bregman [15, p. 9-36] extensively discus how to apply the Gestalt principles for auditory scene analysis. We use the Gestalt principles to fuse an auditory display, provided by the hearing aid output, and the visual display on a smartphone. We abstract the auditory features the hearing aids output, to visual shapes and colors. Some gestalt principles are used to help the user when mapping from the visual to the auditory domain. 1) Proximity relates to how close different objects are together, this principle is used when visually grouping objects, as illustrated in Figure 5.2. Proximity relates to *spatial* distance. We use proximity to illustrate that neighboring programs are more similar, then programs on the diagonal. 2) Similarity, are similar to proximity, and no clear distinction exists. Similarity also relates to color gradients, shapes, etc. We use color similarity to abstractly illustrate similar programs. 3) Continuation and Completion relate to the phenomena of being able to mentally continue broken lines. We use circular diagrams to guide the user's eye. This supports the user when moving the ball inwards or outwards. 4) Organization, relates to how objects appear spatially. The red ball seems to be closer to the user, as it overlays the other shapes in the app interface. This helps the user identify the ball as an interactive element. 5) Context relates to perceiving the value in relation to the greater picture. In our example, the combination of the placement of the ball, and the auditory output provides the context for moving the ball around.

The test subjects reported that this interface was much more intuitive than the current remote control interface. We attribute it to using descriptive labels, such as crisp or lively while providing the user visual guidance on where they are located. This organization of interface better match the display-control expectations earlier mentioned.

Mental Models for Hearing Aid Interfaces Mental models are the users' representation of how something works Norman [103, p. 26] states: "Mental models, as the name implies, are the conceptual models in people's minds that represent their understanding of how things work. Different people may hold different mental models of the same item". Mental models are described as any thought process in which there are defined inputs and outputs to a believable process which operates on the inputs to produce outputs [105, 126]. Conceptual models are simplifications of how a system or technology work. A manual, a

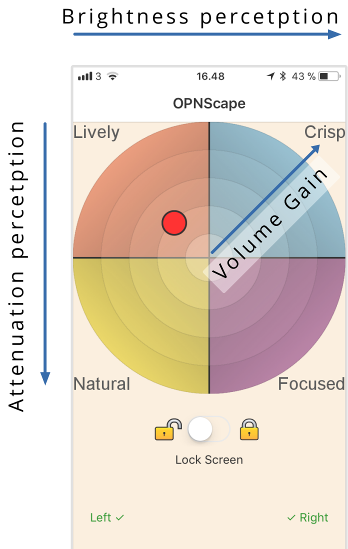


Figure 6.2: The app consists of four distinct programs and volume interaction in one. By moving the red ball, users may increase the brightness perception (x-axis), attenuate ambient sounds (y-axis) and adjust the perceived loudness (from center to edge). [62]

speedometer, or an onboarding screen are all embeddings of conceptual models. I define a mental model as the abstract representation on how technology, can transform an input, to an expected output. For example, hearing aids volume reflects the mental model. The thought of more 'loudness' is easily translated into volume gain. The high level of abstraction of hearing aid program settings does not have an equivalent matching model, i.e., if the user change from program 1 to program 2, the input, the user change, results in several outputs, which is black-boxed for the user. These two scenarios is illustrated in Figure 6.3. The hearing aid program consists of several features being updated when changed. We focus on matching the user intent with a meaningful output. The associated labels, *Lively*, *Crips*, *Natural* and *Focused*, reflects an abstracted output of the hearing aids. This, in turn, creates a better user experience for the hearing aid user.

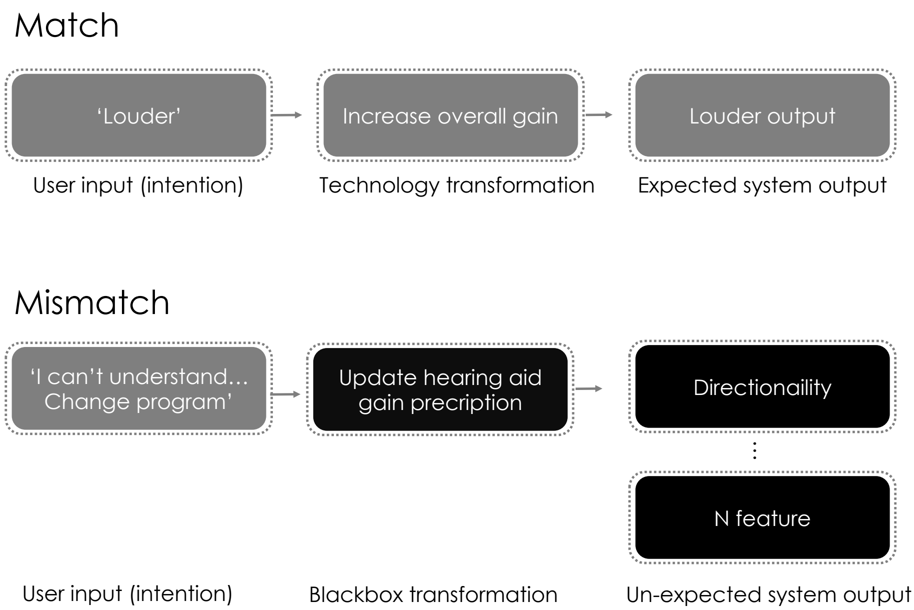


Figure 6.3: Two examples of mental models. The upper illustration shows a match between user intentions and the system output with regard to volume changes. The lower illustration shows a mismatch between the user intentions and the system output for hearing aid program change.

6.1.3 Using Feedback to Understand Hearing Aid Usage

We asked the test subjects to provide feedback through a questionnaire. We asked questions related to audiological parameters, including how easy or difficult it is to change brightness, reduce ambient sounds, etc. Annotating questions with audiological features gives insights into how the user mental model, matches the designers mental model. These questions provide a direct link between audiological settings and user intents, helping clinicians in fitting hearing aids. The responses from the questionnaire indicate that the test subjects understand the difference between attenuation and brightness, where more than 90% indicates it is very easy to change using the proposed interface. 70% found it easy to modulate program and volume simultaneously. The main concern related to volume is the reduction in increments, meaning the volume is changed with ± 2 in contrast to the regular ± 1. We ask for the program the test subject use the most. This is the perceptual recall of program usage, which we know can be positively biased. The default program *Lively* is the preferred program. A test subject states: "Lively is most suitable in general, and works better when I need to focus on one person". Interestingly 9 out of 10 test subjects neglects the *Neutral* program, attributing it with too little received value. Either the program does not provide enough attenuation and noise reduction, or it is not bright enough to improve SNR. The Neutral program is the default medium program. The most interesting finding is illustrated in Figure 6.4. The test subjects were asked to rate which program performs respectively best to attenuate noise and increase speech focus. The subjects could answer more than once. These findings show that lively works well at increasing speech focus, whereas focus works better at attenuating noise. Such findings help the clinician matching both the user intents and percepts when updating hearing aid settings.

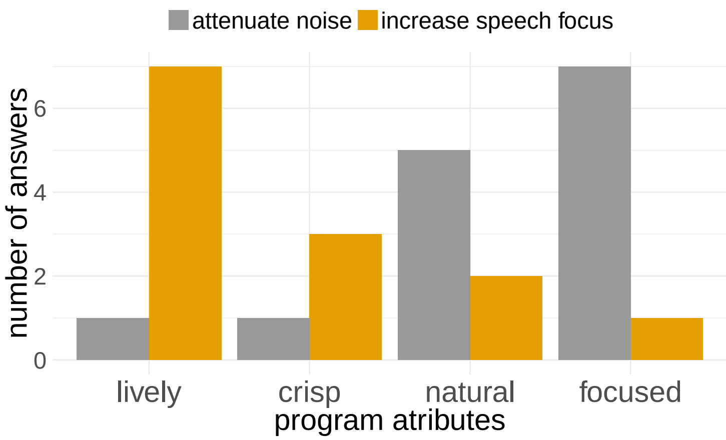


Figure 6.4: Perceptual benefits from the four programs. Lively is preferred to increase speech focus, and Focus is preferred to attenuate noise. Based on data from [62].

6.1.4 Conclusion

When designing interfaces to gather feedback from the user, the interaction patterns must be considered. This includes metaphors, which effectively conveys information, and creates a shared understanding. Being able to translate a system output using metaphors, can support a shared understanding of a topic. We actively used metaphors of space, labels, and colors to support the user in navigating the map. Mental models of the user should also be expected. Experts, users and designers may have different mental models. To succeed in designing health care application, there needs to be a match between the different mental models. We propose to work with outputs that matches inputs. High-level labels can provide the context needed for the user to understand what the system does. When a user is exposed to a new interface an associated learning curve follows. The designer should strive to reduce this learning curve, to reduce frustrations, and negligence. Using microinteractions and gestalt principles can help the user understand the interface, create trust and ultimately better user experience. If the user finds the interface pleasant to use, the user interface can be designed to collect feedback data from the user and, create a closed feedback loop. Transparency of how the system work, what data is collected, and how the user react, all create support for the clinical workflow. In this case, a hearing care professional can use the data and feedback to improve the performance of the hearing aid. Ultimately, creating personalized hearing care through participatory interactions.

Chapter 7

Perspectives and Future Outlook

This thesis have covered several perspectives on personalizing hearing health care. First, the causes and prevalence of hearing loss was presented. This also gave a brief introduction to how hearing aids work. It also opened up for some perspective of the future trends of hearing aid development. The scope of this thesis lie within using hearing aids as an enabling technology, to address how to personalize hearing health care.

Understanding the context how hearing aids are used in is the first step to personalize hearing aids. Considering hearing aids as part of a context aware ecosystem, enables hearing aids to become a provider of valuable contextual insights. This showcases what kind of acoustical environments users are exposed to, and the corresponding coping strategies. To investigate coping strategies, program and volume interactions was logged. These two parameters provides insights on how hearing aid users, augment acoustical features to match intents. In the clinical workflow, this data can be used to generate insights and optimize the fitting. This includes how users perceptually evaluate auditory scenes, and how they mentally map an intent to an expected outcome. To better support the users within this interaction paradigm, the interface to the hearing aids were optimized. Engaging interfaces not only help the user in matching a mental model with a context, it also provide valuable feedback. Building interfaces on metaphors and gestalt principles, which support the user interactions, encourages the user to actively participate in their treatment. This thesis have focused on how to use technology as an enabler participatory hearing health care. With the future outlooks, I briefly discuss how to address the personalization of hearing health care. And, I look into how to address the challenge of providing hearing health care to more in need. This chapter uses ideas from the contribution 'Modeling User Utterances as Intents in an Audiological Design Space' H to describe scenarios of personalized hearing health care. This last chapter will summarize the contributions of this thesis, including how to use user generated data to create insights and train AI models, discuss the implications, and how we move on from here.

7.1 Adaptive Interfaces

The last component of personalization of hearing aids is adaptive interfaces. Hearing aids have an interface limited by hardware and memory constraints. This limits the hearing aids to a few program slots. These programs, or settings, can only be updated at a clinical visit. If the user wishes to change the auditory settings on their devices, or are dissatisfied with the performance of the devices, they need to visit a clinic.

A challenge is to serve people with limited access to clinics. This can be caused by poor health, low mobility, or geographical limitations, etc. Several of the big hearing aid manufacturers have opened up for remote fitting. This means the fitting can be done via a remote video connection, and the clinician can push new settings to the device. This is known as telehealth [32], meaning, consultation over the phone. Telehealth addresses the challenge of providing access to clinics. However, telehealth cannot solve the problem of scalability, which may be a greater problem. Firstly, as mention in Chapter 2, there is a lack of health care workers. A remote care solution relies on a health care worker conducting a clinical consultation. The remote care solution solves the problem of *accessibility*, but not the problem of scalability. Second, if the user cannot describe their situation or challenges, a remote solution will not solve this problem. Education, or supportive technology, which can help the user in uttering their needs, are needed to optimize the fitting. Thirdly, the remote care solution does not utilize contextual information, as sketched out in this thesis. The clinician still has to guess the optimal setting to match the user's need.

Conversational interfaces are rapidly becoming popular. Many people have greeted a chatbot, which can sustain dialogues. The most advanced conversational interfaces emulate human speech and even sound human. Notably, the Google Duplex AI which carries out natural phone conversation to reserve a table at a restaurant, or making an appointment at the hairdresser. If the boundaries are too strict, the interface act as question-answer machines, and do not consider context. On the other hand, without design boundaries, the conversational agents may act unexpectedly. Tay, a twitter bot launched by Microsoft, turned into a racist within hours of deployment [97, 138].

We propose a different approach to adaptive interfaces. The adaptive interface meets the following criteria: it accounts for contextual parameters, including sound, activity, and user demographics. User feedback is an integral part of the system, meaning the system over time adapts to user behavior. The adaptive system is part of an ecosystem, utilizing a pool of training data. This feedback system uses information from other users and their context, to improve the model. The adaptive interfaces in personalized hearing care are illustrated in Figure 7.1. This part of the model interacts with user feedback. The interface propose a program pair, and the use provides feedback by selecting the most appropriate. The program pairs are selected based on contextual information. The model can then update the program setting, and remembers the context, user intent and user interaction. This information is fed to a training pool of *users like me*, to help train the model for other users. The output of the model can also be used in a clinical workflow, supporting a clinician in fitting hearing aids based on user behavior.

We propose an interactive conversational agent. The conversational agent mimics human memory and has a short term memory component, called *attention*, and a *long term memory.* The input to the conversational agent is a context vector. This context vector consists of physical context parameters, notably auditory parameters related to SNR, noise floor, modulation, and soundscape flags. It also receive input from the user. This is called *a bag of utterances.* The two inputs are then processed in an intent extractor. And the output of the intent extractor is fed through a parameter tuning block. The parameter tuning block estimates two program settings with the highest probability match. These programs are then returned to the user, which picks one of the two as a preference. An overview of the model is illustrated in Figure 7.2. The agent can either be accessed through a written interface or an oral dialogue interface. For this prototype, we have worked on a speech interface, which will be as the interface in the chapter.

7.1.1 Modelling Utterances as Intents

Natural language processing (NLP) is used to extract the meaning of the user utterances. We use a third party speech-to-text engine, and end up with sentences or sequences of words. to extract meaning from the utterances we use word embeddings. Word embeddings is an effective procedure in natural language

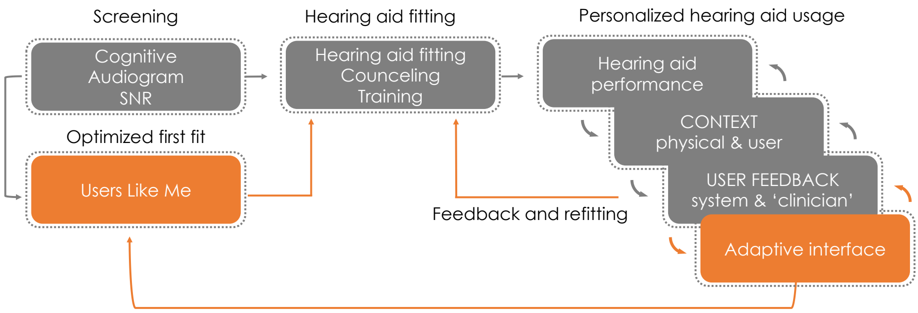


Figure 7.1: Adaptive interfaces use contextual information and user feedback to improve the user experience.

understanding (NLU) and NLP, as demonstrated by Mikolov et al. [92, 93]. A sentence is tokenized, and the individual words get encoded using a *1-of-K encoding*. We utilize the concept of skip-grams on longer sequences such as sentences, or on documents, to create sequence embeddings [109]. Instead of using a pre-trained vocabulary, such as an English dictionary, Wikipedia or Google news, we create a dictionary from user utterances. Meaning, the model keeps updating the dictionary based on user input. Pooling user input from several users creates a larger vocabulary. We estimate the similarity between different utterances based on a cosine similarity between the word and sentence embeddings. For example, *'There is too much noise'* and *'I can't hear because there are too many people'* have short cosine similarity than *'Turn down volume'* or *'It's quite'*. Using the same embedding approach, we estimate the intents similarity of sentences. For example, the hearing aid settings related to the utterance *'I cannot hear the professor lecturing'*, maybe, more frontal focus, more noise reduction or more volume amplification. The intent extract uses a RASA embedding model [99, 110], which cast the intents and utterance embeddings into a shared low dimensional space using supervised learning inspired by StarSpace [149].

7.1.2 From Intents to Fitting Parameters

To find the optimal fitting parameters, we use work from the audiological domain. Jenstadt et al. and Thielemans et al. [57, 134] identifies 7 components, from a PCA, which the audiologist can fit a hearing aid from. These include gain for soft, normal and loud inputs, maximum power output, compression and unwanted sounds. We use a recurrent neural network (RNN) to create a sequential embedding of perceived intent and corresponding fitting actions. The model compares known dialogues with new dialogues, to estimate program settings.

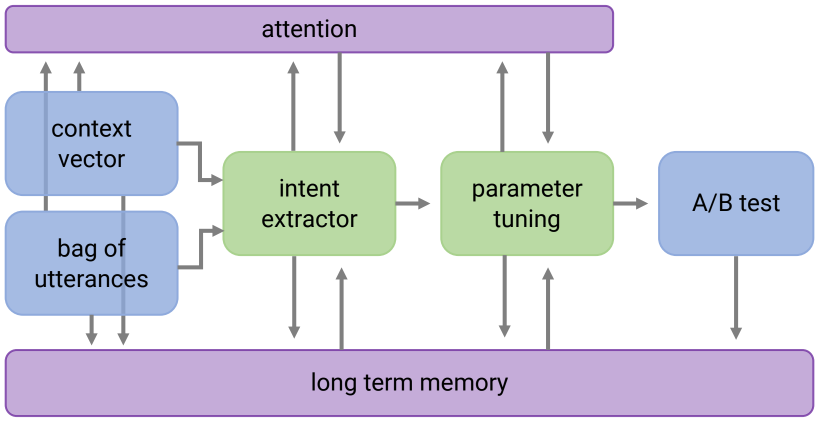


Figure 7.2: Proposal for a conversational agent. The agent uses both contextual information and user input. Probabilistic it proposes A/B program pairs. The user chooses one of the two, and the model is updated. [63]

The model predicts the highest likelihood for the four program settings in the hearing aid. The two highest ranked settings are presented to the user, as an A/B test. This extends the model to include user feedback, which is stored in the long term memory of the system. Exemplified below is a conversation with our conversational agent:
utterance: “can’t understand what is being said”
intent: enhance speech
action: increase B high frequency and soft gain
reply: “maybe try setting B ?”
utterance: “what does B do ?”
intent: explain B
reply: “it adds brightness to better separate sounds, do you prefer setting B ?”
utterance: “its very noisy in here”
intent: noise reduction
action: adjust B beamformer, attenuation and noise reduction thresholds.
reply: “try setting B, do you prefer B ?”
utterance: “its better”
intent: confirm
reply: “great I’ll remember you like setting B in this listening environment”

7.1.3 Considerations for Adaptive Interfaces in Hearing Health Care

Adaptive interfaces are the last piece of personalized hearing care, from a technological perspective. However, it does not fully address the full system of hearing health care. More work must be put into how adaptive interfaces improves the user experience, both for clinicians and for hearing aid users. The implications of using conversational agents and artificial intelligence must be further investigated. The conversational agent automates several human tasks normally carried out by a clinician. One challenge is whether it will be accepted by the clinician. HCPs may fear they will lose their jobs, even though the conversational agent can automate trivial tasks. Also, as the end user is interacting with a machine, it will also have profound effects on the hearing aid user. The user experience will be personalized to the user, based on user behavior and interaction, creating great user experiences. The conversational agent may even be perceived as a human! The question is whether we are ready for these interactions, and are willing to provide the necessary data. These ethical concerns must be addressed, before deploying and launching such systems. On the other hand, such systems may break the glass ceiling of hearing health care today, providing scalability and reaching many in need.

7.2 Integrating UX Design Principles in Health Care

The data-driven UX model described in Chapter 3 sketches out a framework that can accelerate insights within the health care domain. Using the five elements provides value from the early discovery phases to product delivery. The power of data-driven UX lies within the cross-section of lean UX and data science. Rapidly iterating with a focus on hypothesis validation can provide fast answers. And rather than being limited to the current technology, one should investigate whether alternative solutions exist, such as third-party services. The approach should be to validate hypotheses, and it should not be either driven or limited with the current technological offerings.
UX methods use a top-down approach when addressing the challenge of personalizing hearing health care. The focus on addressing systematic challenges provides different insights, compared to a bottom-up approach.

7.2.1 Making Hearing Aids Contextual Aware

One of the main contributions of this thesis is considering hearing aids as contextual aware devices. Hearing aids are small, discrete head-worn devices, which can provide acoustical information. When coupled with other sensors, including smartphone and wearables, a wealth of contextual information becomes available. When translated, this sensor data creates insights for the user and the user behavior, and it provides insights for health care workers. It is important to present the data as valuable information. Context awareness within hearing care works as a communication tool. Data is not dangerous, it is informative. It provides hearing care professionals (HCPs) a tool which highlights scenarios which may need hearing aid adjustment.
The hearing aid of the future may look very different from what we have today. With the advancement of low-cost hearables, such as Apple Airpods, head-worn hearing devices might be more accessible. These devices could address the need for early care, or may even provide preventive and predictive insights on noise exposure. This could be scaled up, where millions of people provide insights into noisy environments and could generate information on noise pollution. Connected head-worn devices could have positive implications reaching far outside of hearing health care!

7.2.2 Conducting Trials With N=1

Conducting trials with one or few subjects can provide valuable insights, that can supplement clinical trials. In the case of hearing health care, the longitudinal studies allow clinician and researcher to better understand the coping strategies of a hearing aid user. These strategies can already be implemented in the clinical workflow. We imagine using dashboards or creating reports, which can help clinicians in the fitting process. Letting people explore and exploits, motivates the user to engage with the technology. In the wild studies are accepted within the human-computer interaction and ubiquitous and pervasive computing communities. Cross collaboration with health care professionals is needed if the research should make an impact. As research communities, we need to embrace each other and respect each other's differences. I believe this thesis can be a starting point in integrating HCI principles, such as UX methodology, within hearing health care.

The last consideration is related to the use of adaptive and autonomous systems. If adopted, hearing health care could reach the ones in dire need. Most cases of severe hearing loss occur in low-income countries, which lack the infrastructure to provide hearing health care. A mobile or online accessible technology could be changing the lifes of million of people.

Chapter 8

Conclusion

The objectives of this thesis were to investigate how data driven user experience can provide value in a health care setting. I found that UX for health care enables participatory data driven insights. When clinicians and patients come together around informative data, new insights on the treatment is highlighted. I defined a data-driven UX framework which can be used in health care. The contribution provides insight in how different UX tools can be used to validate relevant hypotheses. Using tools such as rapid prototyping and 3rd party services, health care products can generate insights into the treatment of chronic diseases. UX is driven by top-down processes. This enables a holistic view of a problem, and how technology can address this. In the case of hearing health care, improving hearing aids does not fix the problem. Talking about hearing aids are used, creates new clinical insights. Contextual aware devices and hearing aids provide insights into hearing aid usage. Using rapid prototyping approaches, it is illustrated how little data can create big insights.

Involving the user in their treatment, also when it comes to early UX investigations, may guide the development of future products, services, and clinical workflows. Feedback is an integral part of the flow. Data can help paraphrase questions, to better match clinical parameters with user perception. I showed that using considerate interfaces encourages user interaction. Even when there is a lack of clear guidelines on mapping between two domains, a rapid prototype approach can quickly validate whether the designer intentions are valid.

I hope this thesis has provided tools to rethink health care research, and to propel health care research into personalized medicine.

Appendix A

Rethinking hearing aid fitting by learning from behavioral patterns

Benjamin Johansen, Michael Kai Petersen, Niels Henrik Pontoppidan, Per Sandholm and Jakob Eg Larsen. Rethinking hearing aid fitting by learning from behavioral patterns. (2017) *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems - CHI EA '17* (pp. 1733-1739). ACM, New York, NY, USA.

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Abstract
The recent introduction of Internet connected hearing instruments offers a paradigm shift in hearing instrument fitting. Potentially this makes it possible for devices to adapt their settings to a changing context, inferred from user interactions. In a pilot study we enabled hearing instrument users to remotely enhance auditory focus and attenuate background noise to improve speech intelligibility. N=5, participants changed program settings and adjusted volume on their hearing instruments using their smartphones. We found that individual behavioral patterns affected the usage of the devices. A significant difference between program usage, and weekdays versus weekends, were found. Users not only changed programs to modify aspects of directionality and noise reduction, but also continuously adjusted the volume. Rethinking hearing instruments as devices that adaptively learn behavioral patterns based on user interaction, might provide a degree of personalization that has not been feasible due to lack of audiological resources.

Author Keywords
Hearing impairment; user behavior; health; aging; augmented audio

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction

The current practice of fitting a hearing instrument relies on a trained audiologist, and it takes on average two months, with 2-3 visits, to fit the hearing instruments [6]. Hearing instruments are rarely fitted optimally at the first consultation, as the amplification of specific frequency bands only explains part of the problems encountered when aiming to understand speech in noise. Postponing the first visit for a decade [3] from first experiencing hearing problems until acquiring a hearing instrument provides other challenges. During this period the brain may have started to rewire due to its inherent plasticity and consequently the ability to comprehend speech may have begun to degenerate [7, 9]. As a result it may be difficult for the wearer to separate voices in challenging listening environments. In many cases there may be a lack of audiological resources for optimally adjusting the device. A perceived bad user experience may result in the user giving up on adapting the settings or simply returning the hearing instrument to the clinic. Kjeldsen and Matthews [5] identifies two types of tests in the hearing instrument fitting: as a minimum identify the needs for amplification in the frequency bands affected by the hearing loss based on an audiogram and subsequently assess the user's ability to separate sounds in noisy environments in sessions with trained audiologists. It may be difficult for users to describe how they perceive sounds in words in order for the audiologist to adjust the settings. Furthermore, the listening experience is only simulated based on audio samples in the clinic, which may differ from the problems the user actually encounters in real life. Other papers within the HCI literature have addressed the issue of retrieving and describing a situation. Dahl and Hanssen [2], build a tabletop prototype, where the user could choose between predefined soundscapes, but such participatory approaches may require that an audiologist is present to be useful.

In this paper we investigate how a hearing instrument is used throughout the day. Meaning, rather than simulating listening scenarios in a clinic, we aim to infer the optimal settings based on how the user adjusts programs and/or volume as the context changes in real life situations. In the present study we focus on the temporal dimension of interaction patterns observed over hours and days within a 10 week period. To our knowledge, no other studies have investigated in situ temporal interaction patterns of hearing instrument users at this level of detail. Traditionally hearing instruments have been perceived as independent devices limited by memory size and processing power, and only recently been able to wireless connect with smartphones. Utilising the power of an Internet connected hearing instrument, we investigate how a snapshot in time, represents a situation where the hearing instrument performs suboptimal. In this scope, the hearing instrument is perceived as a device that augment a soundscape. Previous studies within HCI have described similar devices augmenting hearing, usually involving a pair of binaural microphones and a pair of head worn speakers[8] [10], however, they have not investigated adaptation patterns or user fitted hearing experiences.

We propose a different way of hearing instrument fitting, connecting hearing instruments with smartphones and the Internet, making them cloud connected devices. Based on data and user engagement, we generate new types of personalization of hearing instruments. We propose a paradigm shift where audiological best practice and interventions includes decisions making from user generated data reflecting everyday usage.

Figure 1: The interface of the Oticon ON iPhone app available from the App Store (iOS) to control the hearing instruments. To increase volume the user swipes up, and to reduce, swipes down. To change program the user taps the black circle and taps on a program to select it. The app then communicates directly with the hearing instruments via Bluetooth, and data is send via the iOS IFTTT app.

Method

Participants
6 participants volunteered for the study (6 men), from a database provided by Eriksholm Research Centre. The median age was *61.8 years (std. 11.1 years)*. All participants have more than a year experience using hearing instrument. The participants suffers from a symmetrical hearing loss, ranging from mild-moderate to moderate-severe as described by the WHO[12]. All have an iPhone 4S or newer. One participant was excluded due to missing data.

Apparatus
Each subject were equipped with two Oticon Opn™ hearing instruments, stereo Bluetooth low energy (BLE) 2.4 GHz. All subject used personal iPhone 4S or newer iPhone models with Bluetooth 4.0. The logged data consist of any user initiated program change or volume change through the Oticon ON iPhone app (see Figure 1), formatted as time series data, transferred using IFTTT (If-This-Then-That), stored in the cloud and shared via Google Drive. The hearing instruments were fitted with four programmes. The subjects were provided with a test user Google account prior to the experiment. The account was used for data collection, and the subjects had full ownership of the account and data.

Procedure

Subjects were fitted with OPN hearing instruments by an audiologist. The hearing instruments were fitted based on a unique frequency dependent volume amplification for each subject. Each subject was fitted with four programmes, through the Genie 2.0™ fitting software. The programs emulates different types of auditory focus, by increasing amounts of signal processing to enhance voices and reduce background noise when encountering challenging listening scenarios. These are trade offs between speech intelligibility, and background sound amplification. The four programs are:

- *P1*: Resembling an omnidirectional perception with a frontal focus. Sounds from the sides and behind the listener are slightly suppressed to resemble the dampening effect of the pinna.
- *P2*: similar to P1 but gently increasing balance and noise removal when encountering complex listening environments.
- *P3*: similar to P1 but increasing balance and noise removal even in simple listening environments.
- *P4*: similar to P3 with high sensitivity to noise increasing balance and noise removal in all listening environments.

Results and Discussion

In this section we first analyse the collected data to explore what differentiates the program usage based on the time of the day. Next we probe whether demands related to specific activities influence the behavioral patterns, by comparing program usage on weekdays (Mon-Fri) against weekends (Sat-Sun). Subsequently we discuss to what degree such learned behavioral patterns could sufficiently provide a foundation for adapting the device settings based on temporal aspects alone. For the analysis, only data collected between 8AM and 12AM is used, under the assumption that the hearing instruments would be switched off during the night. Data was collected between 12AM and 8AM, as the participants not always switched off the hearing instruments, introducing noise in the data set.

The difference between programs
Each subject shows unique interaction patterns when it comes to program usage. It should first of all be noted that the usage time for each participant varies between 3.5 to 8

	Average daily usage
S1	3.54 h
S2	7.21 h
S3	7.41 h
S4	6.66 h
S5	8.08 h

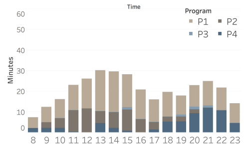
Table 1: Average hours of usage of the hearing instrument for each subject (S1-S5).

	P1	P2	P3	P4
S1	65%	17%	3%	15%
S2	80%	0%	0%	20%
S3	96%	0%	0%	4%
S4	67%	9%	10%	15%
S5	62%	9%	1%	28%

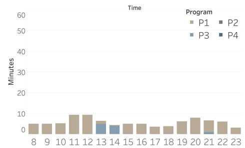
Table 2: Average usage of hearing instrument per subject. P1-P4 are programs, and S1-S5 are subjects. The average usage is in percentage of total usage of the device from 8AM to 12PM.

hours per day. The total usage can be observed in Table 1. To determine if there is a significant difference between the usage of the four programs an analysis of variance was performed. The mean usage of the four programs are: P1 18.4 minutes per hour (mph), P2 1.5 mph, P3 0.6 mph and P4 4.1 mph. Meaning, the difference in usage time related to the four programs was significant (F(3,4) = 23.1, p < .0001). The subjects have a preference for using P1, while P4 is second. The preference for P1, may reflect that it provides a frontal focus with a slight dampening of sounds from the back. This is similar to the acoustical characteristics provided by the natural shape of the ears and head. This suggest that P1 may provide adequate compensation in most of the listening scenarios encountered during the day. The three other programs offer increasing degrees of frontal focus and noise removal, where on average program P4 is preferred. However, from Table 2, subject 1 seems to prefer P2 which offers increased brightness facilitating speech intelligibility to P4. Based on the program changes alone it seems that at least two different auditory focus settings are needed. One program for less demanding listening scenarios allowing the user to shift the attention between several sound sources, and another program for challenging environments with multiple voices and background noise requiring more attenuation of ambient sounds.
Table 2 shows the average usage of the four programs, P1-P4. Interestingly, we found that program P1 was preferred 74% of the time. This is significantly different from previous findings of respectively 33% [1] and 37% [11]. This could be due to manufacturer-specific noise reduction and gain reduction algorithms[4]. An interesting observation along the temporal dimension is illustrated in Figure 2. As an illustrative example, subject 4 uses P1 over the course of the day. However, the more supportive program P4 is primarily used between 11AM and 4PM and again between 7PM and 10PM. In Figure 2c patterns for the same two programs are shown for Subject 2. A notable difference appears for the usage of P4, who uses P4 from 9Am to 5PM, and then barely uses this program for the rest of the time period. The patterns thus seem highly individual and any design of algorithms for automatically adapting device settings would need to incorporate temporal aspects in regards to the individual preferences.

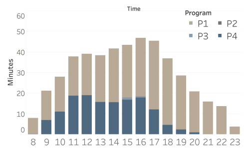
The different usage in weekdays compared to weekends
The next question to investigate is whether specific activities in weekdays and weekends change the behavioral pattern. The average use on weekdays are 7.8 hours per day, and 5.4 hours per day for the weekends. The difference between the aforementioned is significant ($F1, 4$ = 17.0, p < .02). To understand how the usage patterns varies between the weekdays and the weekend, a statistical analysis was performed on the four programs across participants. The different usage of the four programs was significant ($F_{3,12}$ = 23.1, p < .0001). However, the interaction between program and day was not significant ($F_{3,12}$ = 1.4, p > .5).
This indicates that the behavioral patterns vary over the course of a week. From Monday through Friday P1 is on average used 71% (of 7.8 hours) versus 80% (of 5.4 hours) Saturday to Sunday. Both the overall usage time and reduced selection of the P2-P4 programs, indicate that the user activities during weekends may represent fewer auditory challenges. In the light of this, we argue that any algorithms aiming to adapt the device settings according to behavioral patterns should also take these weekly patterns into consideration.
Using Subject 2 and 4 as contrasting examples in Figure 2d and 2h notice how the P4 usage pattern changes between weekdays and weekends. Subject 2 uses P4 more throughout the day (Mon - Fri), and only uses the program sparingly during evenings in the weekend. Subject 4 prefers P4 primarily during afternoons in the weekends, whereas



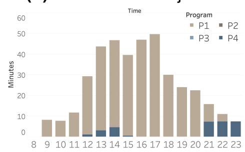
(a) Mon-Fri for subject 1



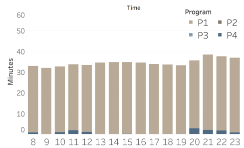
(b) Sat-Sun for subject 1



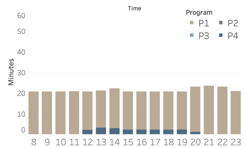
(c) Mon-Fri for subject 2



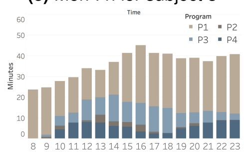
(d) Sat-Sun for subject 2



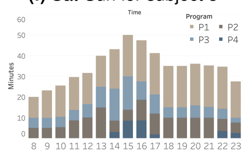
(e) Mon-Fri for subject 3



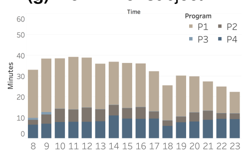
(f) Sat-Sun for subject 3



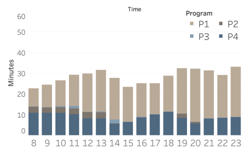
(g) Mon-Fri for subject 4



(h) Sat-Sun for subject 4



(i) Mon-Fri for subject 5



(j) Sat-Sun for subject 5

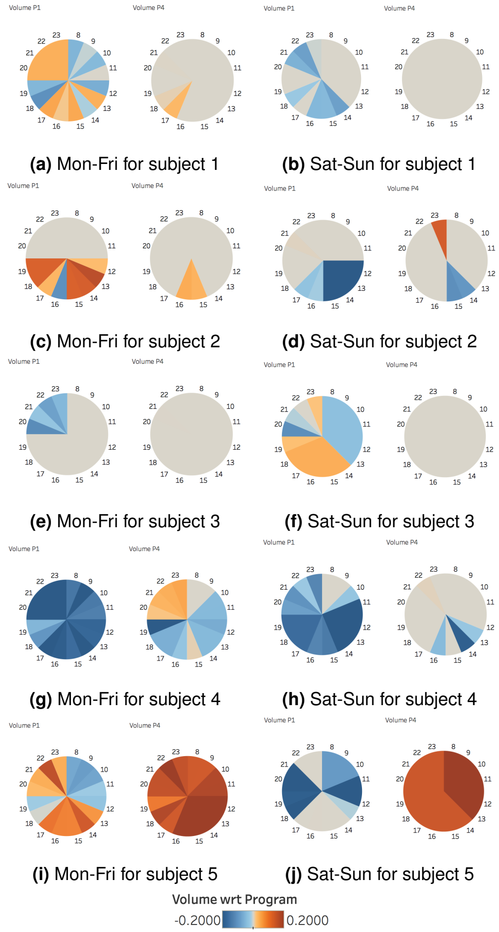
Figure 2: Program usage over time, from 8AM to 12AM. P1 is beige, P2 is brown, P3 is light blue and P4 is dark blue. The left hand columns represents usage over weekdays, and the right ones represents usages in weekends.

this usage patterns is not found during weekdays.

Volume and program interactions

An additional parameter to investigate when modeling the behavioral patterns are the volume change interactions. The volume interaction can be interpreted as a fine tuning of the desired auditory scene, by increasing or decreasing the intensity, thus zooming in or out of an auditory scene. In Figure 3 a comparison of the 5 test subjects and their usage of volume with respect to program can be observed. The light to dark blue colors reflect decreasing volume, while the yellow to orange gradients reflect an increase in gain. It can be observed that most subjects decrease the volume in P1 during the weekend. Subject 4 prefers to primarily reduce the volume, in contrast with Subject 5 which prefers to mostly increase the volume. In these cases we hypothesize that the gain settings of the devices might need to be adjusted. Subject 1 adjusts the volume both up and down from Monday through Friday, whereas the volume is only decreased during weekends.

While the above user interaction over a 10 week period can be inferred directly from the program change and volume adjustment, we subsequently in follow-up audiological sessions with the subjects found that the behavioral patterns were aligned with the aggregated program usage history data continuously collected over 4 months by the devices. Subsequently we interviewed the test subjects to determine what defined their program and volume preferences. The P1 program was preferred in most listening scenarios because it allows the users to selectively shift their attention omnidirectionally to any sound sources. However, when encountering more challenging acoustical environments, the three alternative program settings were selected, whether the aim was to enhance speech intelligibility, attenuate ambient sounds or remove background noise. Additionally



(a) Mon-Fri for subject 1 **(b)** Sat-Sun for subject 1

(c) Mon-Fri for subject 2 **(d)** Sat-Sun for subject 2

(e) Mon-Fri for subject 3 **(f)** Sat-Sun for subject 3

(g) Mon-Fri for subject 4 **(h)** Sat-Sun for subject 4

(i) Mon-Fri for subject 5 **(j)** Sat-Sun for subject 5

Figure 3: Program usage with respect to volume gain, from 8AM to 12AM. For each column the left figure is P1 and right figure is P4. Left hand columns represents usage over weekdays, and the right are usages in weekends.

users increased or reduced the perceived loudness of these settings by continuously adjusting the volume.

Perspectives

These results indicate that the users predominantly preferred to combine volume adjustments with settings providing an open frontal focus coupled with a natural attenuation of ambient sounds in 74% of the usage time. This differ from earlier studies reporting that an omnidirectional focus was only chosen in respectively 37% [11] and 33% [1] of listening scenarios. In contrast to earlier studies using simulated sound environments [2] our findings are based on the actual acoustic environments encountered by users over several weeks of usage. It is difficult to compare these studies, as the data generated in our study represent snapshots of user intents triggered by the changing auditory context throughout daily life. When compared to earlier studies, the quality of sound enabled by recent advances in digital signal processing provided by the state of the art devices used here is also likely altering how the auditory focus is perceived subjectively. The method of continuous data collection may facilitate long term personalization of auditory interfaces not limited to hearing instruments but encompassing next generation hearables in a wider sense. We propose that our data driven approach could potentially be used to individualize settings based on continuous interaction with Internet of things connected devices. In turn providing a dynamically optimized personalization, inferred from learned behavioral patterns.

Acknowledgements

This work is supported by the Technical University of Denmark, Copenhagen Center for Health Technology (CACHET) and the Oticon Foundation. We would like to thank Eriksholm Research Centre and Oticon A/S for providing resources.

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Appendix B

Hearables in hearing hare

Benjamin Johansen, Michael Kai Petersen, Maciej Jan Korzepa, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Hearables in hearing care. (2017). *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 39-49). Springer, Basel, Switezerland.

Hearables in Hearing Care: Discovering Usage Patterns Through IoT Devices

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Abstract. Hearables are on the rise as next generation wearables, capable of streaming audio, modifying soundscapes or functioning as biometric sensors. The recent introduction of IoT (Internet of things) connected hearing instruments offer new opportunities for hearables to collect behavioral data that capture device usage and user intents and thereby provide insights to adjust the settings of the device. In our study 6 participants shared their volume and interaction data capturing when they remotely changed their device settings over eight weeks. The data confirms that the participants preferred to actively change programs rather than use a single default setting provided by an audiologist. Furthermore, their unique usage patterns indicate a need for designing hearing instruments, which as hearables adapt their settings dynamically to individual preferences during the day.

Keywords: Hearables, quantified self, usage patterns, behavioral data

1 Introduction

Hearables may be the wearable of the future. They fit on or in the ear, providing audio playback, soundscape argumentation, and integrate biometric sensors[6]. More than $28 million have been raised from crowdfunding for hearables since 2014[5] showing an increased interest in hearables. However, many start-ups have struggled to deliver, and have been forced out of the market in the process. Nick Hunn projects that the market for hearables within 2 years will increase to more than 230 million units, with a market revenue of more than $30 billion[5].

Hearing instruments are a medical device subcategory of hearables, which offer advanced capabilities for augmenting listening scenarios, including amplification, noise reduction and speech enhancement. The latest generation of hearing instruments connects to smartphones through Bluetooth, enabling them to communicate with other apps or cloud services supporting the IFTTT standard, effectively making them IoT connected devices.

Hearing instruments primarily support enhanced speech intelligibility in challenging listening scenarios characterized by speech in noise or multiple talkers. However, only a small fraction of the 360 million people suffering from severe hearing loss[12], including 48 million Americans (20% of the populatioon)[9] suffering from hearing loss, use hearing instruments.

In a previous study, Laplante-Levesque et al.,[7] investigated the usage of hearing instruments, and compared self-reported use, and historical summarized use from the hearing instrument (average on/off time). It was found that there are two distinct types of behaviors associated with hearing instrument usage. Users wearing the device from morning to bed, and users using the hearing instruments when needed. The hypothesis of this study is that each participant have a unique behavior, and that there may be more than one usage pattern. They furthermore concluded that the average wear of a hearing instrument averaged 10.5 hours. This is well beyond the battery capacity of current hearables, with Apple AirPods claiming up to 5 hours play on a charge [1] and technologies with binaural microphones, such as the Doppler Labs Here One and the Bragi Dash claims 3 hours of use on a battery charge[4, 3]. In comparison, current hearing instruments batteries can sustain a week of use, or more, before the need for changing batteries.

This paper investigates the usage patterns of hearing instrument users based on user initiated program and volume changes through a pilot study of 7 weeks. These adjustments are converted into time series data saved in the cloud using IFTTT to transfer data. Previous studies have primarily used summarized historical data retrieved from the hearing instrument software, whereas IoT devices may potentially learn from usage data, such as volume and program interactions, to dynamically adapt the hearing instruments to behavioral patterns. In this article hearing instruments will also be referred to as hearables.

2 Method

6 participants (median age 61.8) with more than 5 years experience of hearables were recruited for the study. Half of the participants were retired, while the other half are still working. Participants were equipped with two Oticon Opn™ hearing instruments connected personal iPhones using Bluetooth. All user initiated program selection or volume changes were recorded as time series data stored over a 7-week period. All participants were provided with a Google Drive account used for data collection, allowing them to retain full ownership of the data. The hearing instruments were fitted based on audiograms by an audiologist to provide individualized frequency dependent amplification for each subject. Rather than a single optimized setting the hearables were fitted with four alternative programs from the Oticon OpenSound Navigator™

These programs are trade-offs between speech and noise balance, i.e., speech intelligibility, and of background sound amplification. The OpenSound Navigator works with three modules to analyze the sound, these are described by Le Goff et al,.[8] as: Analyze, analyzes the sound environment both omnidirectional, and backward, estimating where a noise sources are placed. This simulates how sound normally are perceived by the human ear, with more sound attenuation from the back and the sides of the listener. Balance, which determines speech sources and attenuate noise sources between speech sources. This balances the signal-to-noise ratio (SNR). And, noise removal, which attenuate noise sources and amplifies speech above the hearing threshold.

Each of the programs gives various support depending on the context, from simple environments such as speech in quiet to more complex environments with multiple talkers and ambient background noise, such as an outdoor cafe.

The four programs are:

- *P1*: Resembling an omnidirectional perception with a frontal focus. Sounds from the sides and behind the listener are slightly suppressed to resemble the dampening effect of the pinna.
- *P2*: similar to P1 but gently increasing balance and noise removal when encountering complex listening environments.
- *P3*: similar to P1 but increasing balance and noise removal even in simple listening environments.
- *P4*: similar to P3 with high sensitivity to noise increasing balance and noise removal in all listening environments.

2.1 Participants

6 participants were recruited for the study (6 men). The median age was *61.8 years (std. 11.1 years)*. All participants have used hearables for more than 5 years. All have an iPhone 4S or newer. Half of the participants are retired, and the other half are working. The hearing loss ranges from mild (26-40dB), moderate (41-60dB) and severe (61-80) as described by the WHO[11]. Two participants were not included in the study due to lack of data or missing data. A short summary of each subject is provided in Table 1.

Subject	Age group	Hearing loss	Experience with OPN	Occupation
1	50-59	Moderate-severe	No	Working
2	70-79	Moderate	No	Working
5	50-59	Mild	Yes	Working
7	70-79	Mild-moderate	No	Retired

Table 1: Demographic information related to 4 subjects

The study was carried out in Denmark in the autumn of 2016, and follow up in January and February 2017. Participants were instructed at Eriksholm Research Centre.

2.2 Apparatus

Each participant were equipped with two Oticon Opn^{TM} hearing instruments, stereo Bluetooth low energy (BLE) 2.4 GHz, Near-Field Magnetic Induction (NFMI). All participants used (personal) iPhone 4S or newer models, Bluetooth 4.0 (or newer). The data streamed by the hearables consist of any user initiated program change or volume changes (-4 to 8) accompanied with a time-stamp of the interaction, stored in the cloud on a test subject owned Google spreadsheet and shared via Google Drive. The hearing aids were fitted with four audio profiles P1, P2, P3 and P4, described earlier.

The participants were provided with a private test user Google account prior to the experiment. The account was used for data collection, and the participants have full ownership of the account and data. Data was collected over a 7-week period.

2.3 Procedure

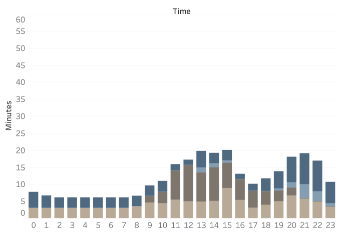
Participants were fitted with OPN hearing instruments. The hearing instruments were fitted based on a unique frequency dependent volume amplification for each subject, by an audiologist. User initiated program and volume changes are collected trough the ON app, which in combination with the IFTTT app collects and store usage patterns as time series data. Each user initiated action is stored as a row on a private Google drive spreadsheet. 10 IFTTT recipes[1] were installed on the participants smartphone. The participants were encouraged to explore the hearables and their functionality with no further instruction provided in which scenarios the programs would be best suited. Participants could then test the device, while the researcher and an audiologist were present. The participants were informed that data would be continuously streamed for the duration of the experiment. Each participant was fitted with four programs, through the Genie 2.0^{TM} fitting software using the OpenSound Navigator. Follow up consultations with an audiologist was planned for the end of the study. These consultations included an interview about the use of the hearables along with: Usage history collected by the device compared with the collected cloud data. Secondly, inquiring into the usage of specific programs to further understand the users preferences and intents in various scenarios. Leading to defining new program settings for a follow up study. The aim would be to tease apart the need for increasing attenuation of ambient sound sources, noise removal and improving speech intelligibility associated with different scenarios.

3 Weekday program usage over 24 hours

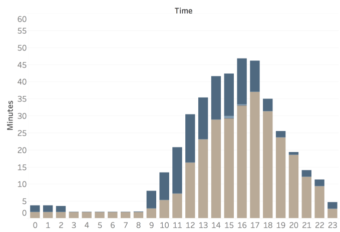
The program patterns in Fig. 1 & 2 ranging from P1 (beige), P2 (brown), P3 high (light blue), to P4 (dark blue), illustrate the large differences between users, their contrasting needs throughout the day, as well as their changing preferences

[1] accessible online: https://ifttt.com/p/benjaminjohansenphd/shared

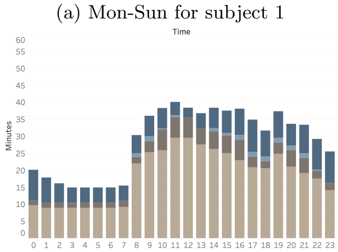
for weekday vs weekend activities. General trends towards increased support during the day can be seen for users 1,5 and 7. Conversely, less need of support in the evening is reflected in the behavior of user 2. In addition, the bright sound represented by the P2 (brown) versus the full sound of P3 (light blue) may indicate how preferences for the P2 increases speech intelligibility, whereas P3 provides a less intense listening experience. Likewise, the program usage on weekdays could be driven by the demands of work related activities, while the preferences on weekends might to a larger degree reflect individual baselines defining their cognitive processing needs[2, 10].



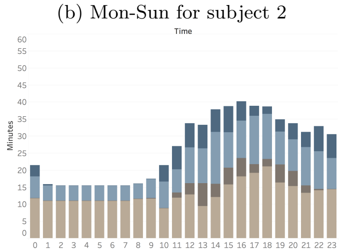
(a) Mon-Sun for subject 1



(b) Mon-Sun for subject 2



(c) Mon-Sun for subject 5



(d) Mon-Sun for subject 7

Fig. 1: Aggregated average program time. The time is displayed in minutes for each hour, and is aggregated for the full data collection period. The use of P1 (beige), P2 (brown), P3 (light blue), and P4 (dark blue), varies for each test subject as well as over the course of the day.

4 Changing preferences in the weekends

4.1 Weekends as a baseline

In Fig. 2 a comparison between weekday usage (left side of the figure) and weekends (right side of the figure) is illustrated for subject 2 and 5. It can immediately be noticed that the behavior pattern varies from weekdays compared to weekends. A clear trend of preferring P1 in the weekend is evident. The preference for a more natural sound in the weekend can be due to a less challenging context, compared to weekdays (and working days). It can also be observed that the weekends have a later onset of the day.

From these observations it seems as the weekend reflects a baseline state where the user prefers natural sound and does not need the enhanced speech intelligibility and noise reduction associated with the P4 program.

4.2 Varying context creates different needs

An interesting observation from Fig. 2.a and 2.b for subject two, is the distinct pattern of removing background noise from morning to late afternoon. In a follow up interview, this subject indicated that he works in the transportation industry, and indeed works between 8AM and 4PM. The choice of this program is to reduce noise. This subject along others, indicated that the weekends have the least troublesome scenarios, and a more natural sound, such as the one provided by P1, is preferable in these contexts.

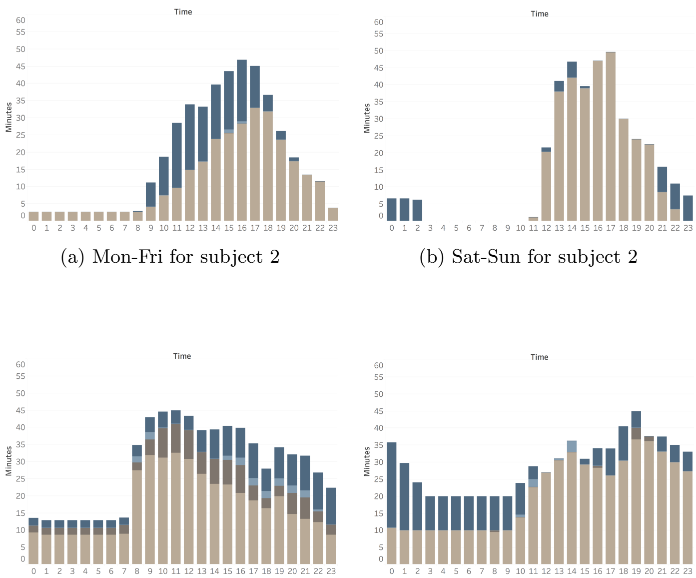
Subject 7 have a distinct pattern using the automatic and supportive programs, especially P3. These programs increase speech intelligibility and have a higher sensitivity to background noise. This subject play cards 2-3 times a week for several hours. Due to the nature of the card game and a room with poor acoustics, the P2 and P3 program increases speech inteligibility.

Both of these subjects mentioned that the weekends contains less challenging scenarios. Anecdotal, the reason for wearing the hearables later in the day is caused by reading the newspaper in the morning. The newspaper creates an uncomfortable sound environment containing rattling and sharp noises, where a quiet environment is preferred.

5 Program use over several weeks of use

From Fig. 3 the preferences for program use over several weeks can be observed. Due to some weeks without data, caused by a lack of Internet connection (e.g, in outdoor environments), some subjects have fewer weeks represented than others. It can be observed that the majority of the subjects uses two or more programs the first 3 weeks. While at the end of the pilot study they seem to prefer two programs, typically P1 and a program that assist in challenging listening environments. This indicates that over time the participants become aware of the capabilities of the hearables, in which scenarios it can support them as needed, and at which times it performs the best. From the figure it is visible that a preference for the more open and natural sounding P1 is used most frequently. This indicates that the participants prefers a natural sound, and when a challenging scenario occurs, they change to a supportive program.

A second observation indicates that the preference between the changes in many cases includes two contrasting programs. Over time a preferred supportive program for the subject emerges.



(a) Mon-Fri for subject 2

(b) Sat-Sun for subject 2

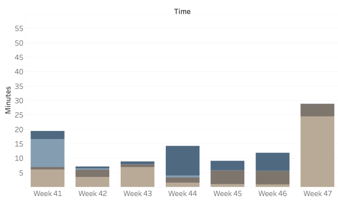
(c) Mon-Fri for subject 5

(d) Sat-Sun for subject 5

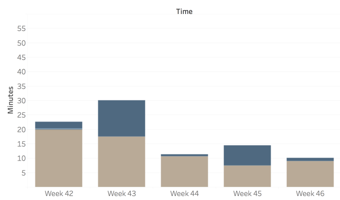
Fig. 2: Comparison of weekday and weekend patterns for subject 2 and 5. The data is aggregated over the full study period, and is displayed as an average minute per hour. Notice the distinct pattern of less support in the weekends (brown and teal colors are preferred). P1 (beige), P2 (brown), P3 (light blue), and P4 (dark blue).

5.1 Perceived sound quality

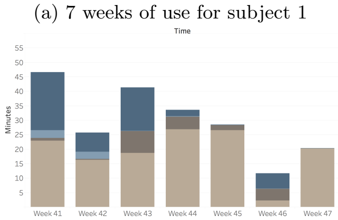
The perceived sound quality is a motivator for behavioral use of hearables. The primary focus from the established hearing aid industry have been on increased speech intelligibility and dealing with challenging listening scenarios. However, from interviews of the subjects in this study, the majority of the wear time is not spent in challenging environment. The natural open characteristics of P1 seems to provide a natural sound environment, which provide sufficient amplification in most listening scenarios, involving only few speakers and less background noise. As confirmed by accumulated usage history, the P1 is used to reproduce a natural sound up to 75% of the time.



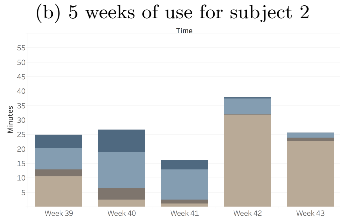
(a) 7 weeks of use for subject 1



(b) 5 weeks of use for subject 2



(c) 7 weeks of use for subject 5



(d) 5 weeks of use for subject 7

Fig. 3: Preference of using the hearing aid over time. The data is aggregated and averaged per week of collected data. Notice how the first weeks include use of more programs, while this decline towards the end of the data collection period. This indicates that the user finds a "preferred" setting over time. Some subjects have missing data due to lack of Internet connection (outdoor environments).

6 Program duration and volume changes

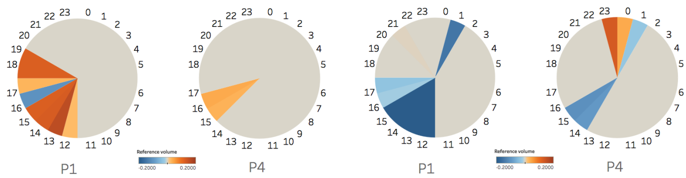
The program changes can explain part of the behavioral patterns of each of the subjects. The programs can be observed as macro settings modifying a soundscape by adjusting the noise removal and attenuation of ambient sound sources. As earlier mentioned, P1 has the least effect on the soundscape, with a frontal focused omnidirectional producing a natural sound, while P4 has increased noise removal and attenuation of ambient sound sources. The interaction between programs and volume can be interpreted as user intents.

The volume control on the other hand works as a micro adjustment. By controlling the volume gain the user can zoom in or out of a soundscape, alternating how present in the current context they wish to be. This does not affect the reproduced sound from the programs, only the gain and intensity of the reproduced sound.

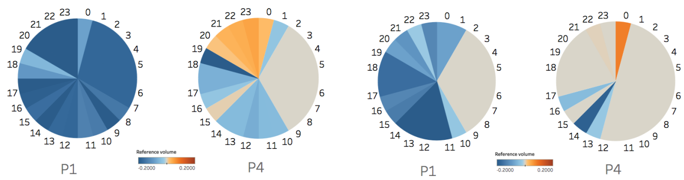
6.1 Fine-tuning using the volume control

To illustrate the use of the volume control for fine-tuning, the usage patterns for subject 2 and subject 7 can be observed in Fig. 4. In Fig. 4 the average change in volume gain is displayed, with respect to the two contrasting programs of P1 and P4, blue for decreasing and orange for increasing gain.

Fig. 4a indicates a unique pattern for subject 2 of a need for an increase in volume, around meal times. In the weekend, shown in Fig. 4b the volume is primarily decreased, and only increased in the late evenings on weekends. This pattern is contrasting with subject 7s pattern, seen in Fig. 4c where the volume is always decreased in P1. In P4 there is a contrasting volume change from evening meal time, and just after this meal time.



(a) Mon-Fri for subject 2 (b) Sat-Sun for subject 2



(c) Mon-Fri for subject 7 (d) Sat-Sun for subject 7

Fig. 4: Comparison of volume interactions with respect to weekdays (left figures) and weekends (right figures) for subject 2 (top) and subject 7 (bottom). Notice the distinct difference in volume patterns between the two subjects. Observe the contrasting volume changes for weekdays versus weekends.

Comparing just these two programs for two subjects with respect to volume shows how the subject intentionally uses a combination of a program and a volume to adjust the auditory experience. Furthermore, it highlights the difference between usage pattern between two subjects. One prefers to primarily increase volume, while the other prefers to decrease volume. These changes also occurs at different time intervals, indicating a need for personalized hearables.

7 Conclusion

These results show how user generated volume and program interaction data may capture preferences for personalizing the listening experience to the changing context. The usage patterns highlight individual needs for selecting contrasting programs rather than a medium one size fits all setting often provided by default. The shared user generated data might potentially be used to learn behavioral patterns enabling the devices to automatically adapt their settings and thus optimize the user experience of hearables.

It seems that at least two programs are needed to optimize the hearing experience. Test subjects prefer to change settings of the hearables in the course of a day. This is visible in the emerging patterns, where each user has unique usage patterns. These patterns are influenced by the changing context.

At least two programs are needed to satisfy the needs of the users of hearables. It can be observed that most users tend to have an early onset of testing the various modification of the soundscape observed by changing programs. Later in the period they find a preferred program that works in most situations. For all subjects this is program P1, the one that reproduces sound most naturally.

These observations could be the foundation for the future design of hearables. The findings in this paper can be used to optimize, not only the listening experience, but also how the devices can learn from human behavior to adapt to the user. This could lead to a "I forgot I'm wearing an in-ear device", which reproduces sound naturally. At the same time, the device could be used to enhance a social interaction, when needed, by enhancing speech intelligibility.

We suggest a need for better control, or smarter devices, that learns and adapts to the users individual patterns are needed in the future. These devices can be used in any hearable augmenting sound, to create an enhanced user experience.

8 Acknowledgment

This work is supported by the Technical University of Denmark, Copenhagen Center for Health Technology (cachet) and the Oticon Foundation. We would like to thank Eriksholm Research Centre and Oticon A/S for providing resources and access to test subjects, devices, clinicians, developers and researchers.

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Appendix C

Modeling user intents as context in smartphone-connected hearing aids

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Maciej Jan Korzepa, **Benjamin Johansen**, Michael Kai Petersen, Jan Larsen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Modeling user intents as context in smartphone-connected hearing aids. (2018) *Adjunct Publication of the 26th Conference on User Modeling, Adaptation and Personalization - UMAP '18* (pp. 151-155). ACM, New York, NY, USA.

Modeling User Intents as Context in Smartphone-connected Hearing Aids

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ABSTRACT

Despite the technological advancement of modern hearing aids, many users leave their devices unused due to little perceived benefit. This problem arises from the limitations of the current fitting procedure that rarely takes into account 1) the perceptual differences between users not explained by measurable hearing loss characteristics and 2) the variation in context-specific preferences within individuals. However, the recent emergence of smartphone-connected hearings aids opens the door to a new level of context awareness that can facilitate dynamic adaptation of settings to users' changing needs. In this position paper, we discuss how user auditory intents could be modeled as context collected via mobile devices and suggest what kinds of contextual information are relevant when learning situation-specific intents and the corresponding preferences of hearing impaired users. Finally, we illustrate our ideas with several examples of real-life situations experienced by subjects from our study.

KEYWORDS

context awareness; user adaptation; augmented hearing

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1 INTRODUCTION

In recent years, hearings aids (HA) have undergone great technological advancements transforming these once bulky, analog devices into powerful, yet discrete wearables. However, despite this substantial change, a considerable fraction of the hearing impaired population fitted with HA does not wear them [20]. One of the most commonly reported reasons for non-use of HA is that they bring users little benefit. However, as at the same time, numerous studies prove the effectiveness of modern HA [8], we rather seek the source of the problem in the limitations of the current fitting procedure.

The current audiological approach bases on prescriptive formulas that determine the frequency-gain curve for a user with specific audiogram i.e. hearing loss characteristics measured as audible hearing thresholds at different frequencies. There are, however, several issues with this approach which lead to suboptimal settings that often do not provide satisfactory level of help to users. First of all, it is well established that hearing loss is not just weakening of neural activity, but also its serious distortion [18] and thus hearing impairment cannot be fully characterized by an audiogram. Killion et al. [15] demonstrated that the ability to understand speech may differ by up to 15-20dB difference in signal-to-noise ratio for subjects with nearly identical audiogram. Similarly, the perceived loudness of soft sounds can vary greatly as shown by LeGoff et al. [17]. Even though modern HA are equipped with advanced signal processing algorithms that go beyond simple amplification, they are rarely taken into account and, without proper control, may even work against wearers. For instance, noise reduction can introduce distortions of spatial cues that might be crucial for some users to distinguish between different auditory streams [18]. All these variations in users' cognitive processing capabilities help to explain why the standard 'one size fits all' approach fails, and indicate that more personalization is needed when fitting HA.

Yet, it has been also established that there are large variations in setting preferences not only between different users, but also within individuals. Keidser et al. [14] demonstrated that the preferred frequency gain characteristics are highly dependent on the auditory environment the user is in. Likewise, Johansen et al. [13] showed that individual users, when given a set of settings varying in terms of omnidirectionality, brightness and noise reduction and freedom to change between them in real, non-clinical environments, exhibit consistent usage patterns of multiple, often very contrasting, settings. These results indicate that user preferences are dependent not only on users' cognition but also on the environments and situations they experience every day. As a result, it is not even 'one size

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fits one' approach that should be aimed for, but rather continuous adaptation to individual users' perception in dynamically changing contexts.

Contextual personalization of HA has been researched for many years. Over a decade ago, Dillon et al. [6] presented a concept of HA with trainable frequency-gain curve based on acoustic measurements of environment and ecological momentary assessment, and discussed the potential benefits of such solution. In the following years, the introduction of body-worn gateway devices made it possible to connect the HA with smartphones and prototype intelligent HA systems. Aldaz et al. [4] developed a prototype that used reinforcement learning to discover user preferences based on auditory and geospatial context by prompting users to perform momentary A/B listening tests. However, only with the emergence of the current state-of-the art HA such as Oticon Opn [21], it has become possible to go beyond ecological momentary assessment by continuously tracking both users' interactions with their HA together with auditory context perceived by these devices. For more than a month, Korzepa et al. [16] continuously observed how users switch between different HA settings in different auditory contexts, discussed possibilities and challenges of learning contextual preferences directly from continuous data and suggested the application of conversational AI interfaces and collaborative filtering in this process.

The advancements in the connectivity of hearings aids, accessibility to various sources of contextual data as well as rapidly increasing adoption of smartphones among the elderly open up new possibilities for building context-aware and user-adapted solutions for hearing healthcare. To that end, one of the key elements is the ability to distinguish between different situations hearing-impaired users experience in their daily lives and understand the difficulties they face and the intentions they have in these situations. The purpose of this position paper is to present our views on how to facilitate such context awareness in HA. In Section 2, we explain how user auditory intents can be modeled as context and propose different types of contextual information that are relevant to hearing impaired users. In Section 3, we demonstrate how context can represent the underlying intents based on a few examples of real-life situations experienced by the subjects of our study.

2 USER AUDITORY INTENTS AND CONTEXT

User intent is a common term used in web search domain and refers to the information a user is looking for with a specific goal such as learning/doing something or going somewhere. Web browser and its search engine constitute an interface that attempts to identify what a specific user intent is and provides the user with the most relevant information. Analogically, we define user auditory intent as what a hearing impaired user expects with respect to a specific listening situation. Some examples of auditory intents can be understanding a specific person in a noisy environment, enjoying quiet sounds of nature or zoning out from distracting noises. We will refer to them also simply as user intents in this paper. Likewise, HA constitute an interface that is capable of filtering and processing the content, in this case, different auditory streams.

Even though modern HA have highly advanced signal processing capabilities, they make no attempt whatsoever to identify user intents. In the light of the evidence that users exhibit very contrasting preferences in different situations [13, 16], it is clear that the lack of adaptation leads to wasting the great potential offered by modern HA. Without understanding user intents, these devices will not be able to offer the optimal settings at the right time. However, learning the actual user intents is challenging as it would require getting users' explicit feedback and giving it an actionable form. To address this problem, we assume that we could instead use context, i.e. the state of the user and the situation the user is in, as a representation of user intents. This can be greatly facilitated by the emergence of smartphone-connected hearings aids which bring completely new opportunities for collection and processing of contextual information.

Nonetheless, context awareness is certainly not enough to offer users the optimal settings. HA also need to know user's contextual preferences, or in other words, what settings user prefers or benefits from most in a given situation. User preferences can be inferred by continuously observing user's adjustments of settings and the corresponding context in a non-invasive manner [16] or by asking user to perform ecological momentary assessment, e.g. in the form of A/B tests [4, 23]. Given enough data, multiple streams of contextual information and the corresponding preferences can be also potentially modeled through recurrent neural networks similar to how Rajkomar et al. [22] used multiple layers of healthcare data such as medications or test results as sequential events to predict patient hospitalization outcomes. However, inferring contextual user preferences itself is beyond the scope of this paper as we focus here on discussing the potential of different context sources that might facilitate accurate modelling of user intents. We present them in the following sections.

2.1 Auditory context

Acoustic scene might be the richest source of information that can help to determine user intents. Numerous auditory streams mix together and form so-called soundscape - sound understood as environment that is perceived by humans. Soundscape can consist of e.g. nature sounds, human speech, music or appliance noise. They all might provide useful insights into what users do and what their auditory intent is, and can be represented in a number of ways. Basic information about the soundscape can be extracted from HA as they measure various sound characteristics in different frequency bands and use them as control parameters for signal processing algorithms. [16] represented the auditory context by clustering records based on sound pressure level, noise level, signal-to-noise ratio and modulation characteristics. The authors also used HA' in-built sound classification that labeled soundscapes as quiet, noise, speech in quiet or speech in noise. These characteristics allowed the authors to identify primary patterns related to soundscape.

Another information that can be learned from soundscape is its higher level representation that is connected to a physical location or specific sources of sound. This can be achieved by means of acoustic scene classification (ASC) which has been widely researched for the past two decades. The methods of ASC primarily use probabilistic models (e.g. Hidden Markov Model [7]) or neural networks (e.g. convolutional neural networks [24]) usually with the input in the form of Mel-frequency cepstral coefficients (MFCC) calculated from short audio frames. ASC has the potential to distinguish between various environments users spend their time at every day such as supermarket, street, bus, restaurant, party, forest or seashore. Such acoustic environment awareness allows to infer much more about user intent. For example, it is very likely that in a restaurant or at a party, the user wants to understand speech despite the surrounding noise while in a forest or at a seashore, the user might rather want to focus on the sounds of nature.

Yet another highly informative component of soundscape is connected with what HA are primarily optimized for - enhancing human voices. The characteristics of human speech such as pitch, timbre or pace vary greatly between speakers dependent on their gender, age, language, possible disorders and many other factors. Additionally, signal processing in HA influences speech differently due to its varied characteristics and, as a result, users' perception of different speakers is challenged [9]. Voice- and speaker-awareness in HA would allow to learn user preferences and personalize settings with respect to voice characteristics. Simple distinction between male and female combined with basic hand-crafted features representing pitch and timbre would be already very informative but one could go even further. Speaker embeddings have been recently widely used for tasks such as speaker recognition or diarization with state-of-the-art results achieved by deep learning methods (e.g. [11, 19]). Speaker embeddings are real vector representations of different speakers that encode distinctive characteristics of their voices. Using such embeddings, HA could not only learn which types of voices need what processing to optimize user's perception without being constrained to a set of arbitrary features that might miss some important characteristics, but also they could help to selectively amplify specific, for example familiar, voices in order to solve the cocktail party problem [10].

2.2 Location

Similar to how acoustic scene analysis gives insight into the user's location, geolocation data can provide information about the acoustic environment and the corresponding user intents. In this way, these two context sources can complement each other by providing information if one is lacking. When both are available, they can be used as labeled data to adapt and optimize ASC model to user-specific environments. Location plays also another important role - it might be mapped to an activity which in turn could be interpreted as specific intents.

The type of location may often be obtained via a public API such as Google Places API [3] or Foursquare Places API [1] based on geographic coordinates. We see particularly big potential in the latter one which, in many countries, has very detailed venue maps and supports adding new, private or public, places. Additionally, venue category structure is very fine and hierarchical (e.g. Arts & Entertainment → Performing Arts Venue → Theater) which can facilitate learning user preferences on different levels of granularity.

Most commonly visited locations can be also learned based on clustering of geospatial coordinates (e.g. by HDBSCAN [12]). This approach might prove helpful especially when there is no access to venue type information. However, as locations expressed as a cluster of coordinates do not carry any semantic information, it is not possible to benefit from learned preferences without knowing to what degree the new locations resemble the familiar ones.

2.3 Time and motion

Some user intents might be related to the way users move. For example, when biking, the user might want to keep maximum omnidirectionality faithfully preserving spatial cues to be aware of the location of other traffic participants and potential dangers, while when in a car, the user might prefer to reduce traffic noise to focus on driving. Motion or activity can be easily predicted using one of many public APIs such as Google's Activity Recognition API [2]. Moreover, motion can be used to track location changes more robustly.

Time is another factor that can support modelling user intents as it often carries information about repeating activities that user is involved in. As shown by Johansen et al.[13], user preferences can greatly change throughout the day and week (especially weekdays vs weekends). Naturally, time context carries lots of uncertainty as what a user does at a specific time may vary greatly, but it might often prove very informative when coupled with other context sources. Time can be also potentially considered as a measure of mental fatigue. Listening in challenging environments requires higher listening effort and increases mental fatigue, especially for hearing-impaired people [5]. Tracking time of day and time spent in challenging listening conditions could conceivably allow to adjust HA settings (e.g. increase noise reduction) according to the estimated level of mental fatigue of a user.

3 DISCUSSION

Relating user intents to a single source of context is naturally prone to errors that might arise not only from limited accuracy of context classification but also from excessive generality. For instance, in a noisy environment with speech, the user might want to understand a specific speaker or zone out from the noisy surroundings. To model user intents, different context sources need to be used in a complementary way. An example from a not yet published study, where we collected data over 2 months capturing user's interactions with the HA and the corresponding context from 10 users, may illustrate both the different components defining the context as well as how they relate to the actual user intents which we learned through interviews with the test persons.

Figure 1 shows how a subject changed his HA program preference and the corresponding context classification for acoustic environment, location, type of location and activity over a period of 12 hours. Between 1pm and 5pm, the subject attended a bridge card game competition. In order to focus on the game, he aimed to attenuate the ambience and chose the program reducing noise ('P4'). Interestingly, the HA does not detect much noise, but mainly speech. In this case, the environment classification alone would not be sufficient to capture user intents and the corresponding program preference. Nor would it explain the preference for a brighter, more intense sound later in the evening, caused by a wish to enhance a TV soundtrack. However, adding the location and time might here generate recognizable patterns.

Another subject reported the benefit of a program offering maximum brightness and amplification of soft sounds during walking

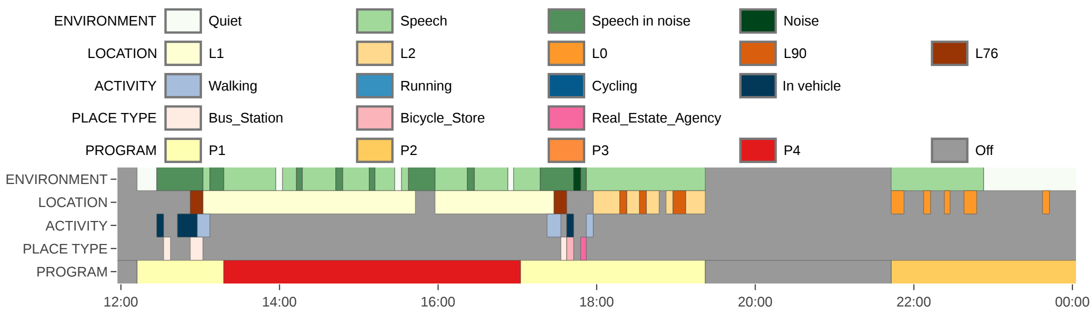

Figure 1: Example of user setting preferences (four programs - P1-P4) juxtaposed with different types of context captured in a continuous manner for a period of 12 hours. Environment is obtained through HA' in-built environment classification, location is represented as cluster membership based on HDBSCAN clustering, activity was estimated by Google's Activity Recognition API and place type was queried using Google Places API.

his dog in the evening when his intention is to enjoy the subtle sounds of nature. In this case, motion combined with acoustic scene and possibly time would be needed to capture and act upon this user's preference. Yet another subject indicated the benefits of using a highly omnidirectional program with some added brightness when his intention is to understand other speakers during lunch in a noisy corporate canteen. In this case, location, acoustic scene and time could be combined to define the user intent. The last example is a subject who generally prefers an omnidirectional, bright setting enhancing the gain in mid and high frequencies, but complains that some female voices get too shrill in that program. Tracking the speakers' voice characteristics might facilitate adjusting the brightness to optimize the user's listening comfort.

The quoted examples serve as yet another proof that hearing impaired users have greatly varying intents and setting preferences that go beyond the need for speech understanding. Understanding intents and personalizing settings with respect to them requires redefining the concept of context awareness in hearing aids. Basic distinction between quiet/noisy and speech/non-speech environments is simply not sufficient to discern between many situations in which user auditory intents differ. However, the new generation of smartphone-connected hearing aids opens the door to infer behavioral patterns from multiple kinds of context that can be obtained through ubiquitous mobile sensors, powerful deep learning techniques and widely available cloud APIs. Combining various soundscape characteristics, location, motion, time and potentially other contextual features not considered in this paper would be a major step towards a whole new level of user-adaption that could unlock the full potential of modern hearing aids.

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Appendix D

Inferring user intents from motion in hearing health care

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Abstract
Sensors in our phones and wearables, leave digital traces of our activities. With active user participation, these devices serve as personal sensing devices, giving insights to human behavior, thoughts, intents and personalities. We discuss how acoustical environment data from hearing aids, coupled with motion and location data from smartphones, may provide new insights to physical and mental health. We outline an approach to model soundscape and context data to learn preferences for personalized hearing healthcare. Using Bayesian statistical inference we investigate how physical motion and acoustical features may interact to capture behavioral patterns. Finally, we discuss how such insights may offer a foundation for designing new types of participatory healthcare solutions, as preventive measures against cognitive decline, and physical health.

Author Keywords
Hearing impairment; user behavior; health; aging; augmented audio; activity; motion; mental health

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction

In the past century humans have gone through a cultural evolution, drastically transforming dietary patterns and manual labor, leading to mostly sedentary work and spending hours in front of computer screens. The resultant lack of physical activity has contributed to a dramatic rise in lifestyle inflicted type 2 diabetes, heart disease and dementia [9]. There is an urgent need for conceptualizing new preventive approaches, where awareness of motion will be fundamental in order to deliver personalized participatory healthcare solutions [14]. To target the comorbidity of chronic diseases we need to integrate both physical, mental and social aspects of health.

Several studies have linked lack of physical activity to mental health issues, including dementia, cognitive decline [8] and depression [16]. Even small measures of physical activity has a preventive effect on mental health [4], and for some disorders are positively correlated with higher self rated quality of life [1]. Likewise, hearing loss is correlated with lack of physical activity [2, 3]. Additionally, a connection between hearing loss and cognitive decline has been established [11]. One of the major risk factors for dementia is caused by untreated hearing loss [10]. Recent research indicates that physical exercise may alleviate hearing loss in mice [5]. This may indicate a direct relation between hearing health and physical activity in humans.

The introduction of Internet connected hearing aids offers new insights into the life's of hearing aid users. Contextual features, such as motion and activity data combined with GPS location gives an objective measure of the level of physical activity. Combining this with the corresponding acoustical sound environment may potentially offer a more personalized treatment of hearing loss.

Capturing contextual user preferences

A longitudinal study, aiming to learn preferences for hearing aid settings dependent on the context, were carried out in the winter 2017-2018 at Eriksholm Research Centre, Denmark. 10 participants volunteered for the study (9 males, 1 female). The median age was *62.9 years (std. 11.5 years)*. All participants are regular smartphone users, and have used hearing aids for a year or more. All subjects used either an Android or iOS compatible phone. Data was logged for eight weeks, or more. One subject dropped out after four weeks, and was excluded.

Location data consists of clustered GPS positions, while motion activity is estimated by the smartphone accelerometer sensors. User interactions include changes between four acoustically contrasting program settings, and volume adjustments, either initiated on the hearing aid, or via the accompanying smartphone app. Soundscapes are modeled as a vector representing aspects of sound pressure level and modulation characteristics processed by the hearing aids. All data is time stamped. An example of subject 3's time line for a week is shown in Figure 1, where the top three bars show contextual sound environment, motion activity and user preferences related to selection of contrasting hearing aid programs. We then process the motion data using a Bayesian probabilistic approach. Subsequently, we combine the probabilities with additional contextual parameters including GPS location, inferred activity, time and day of week.

Modeling human behavior

We combine three modalities to model human behavior:1) Motion activity patterns captured by the smartphone, sampled as categorical events. 2) Locations derived from clustered GPS coordinates sampled as categorical events. 3)User initiated program changes combined with the corresponding soundscape context, segmented according to time, as discrete categorical events. Based on a naive Bayes prediction we investigate the influence of the aforementioned modalities. These predictions are shown in Figure 1, for subject 3 for four days. The top green bar illustrate changing sound environments, the blue bars shows motion activity, while the yellow-red bars shows, user initiated program changes in response to motion and soundscape, and three predicted scenarios based on activity and location, soundscape, and the activity, location, and soundscape combined.

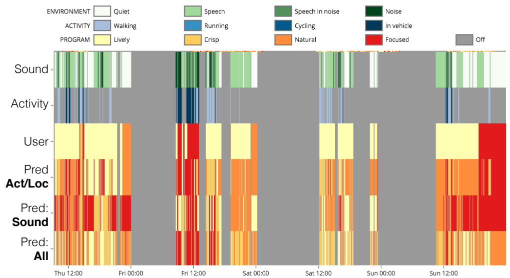

Figure 1: Naive Bayes prediction of contextual program preferences for subject 3 over four days. The upper three tracks (green, blue and yellow gradients), represent the soundscape environment, motion activity and user selected programs, respectively. The following three tracks of color bars (yellow gradients) show conditional probabilities for user preferred programs, based on a) motion activity and location alone (*Act/Loc*), b) soundscape environment alone (*Sound*), c) motion activity, location, soundscape and time combined (*All*).

Changes in motion and location generate discrete events in time series data, providing a visual segmentation of soundscape data. Motion can also be interpreted as contextual information, when location is not available. As an example, a subject walks to lunch around 12. The location is not updated, but the inferred motion, walking, indicates a change of environment. This is confirmed by the soundscape data, reflecting that the environment changes from a quiet office to a noisy canteen. Motion in our study not only defines a specific state, but may also mark the beginning or end of a segment in the acoustical soundscape. From Figure 1 we see that changes in motion may trigger user intents related to program changes, which might not seem evident when considering the acoustical soundscape alone. Thus, motion plays and integral part in predicting user intents and behavior. Additionally, the amount of motion also characterizes the overall level of activity or physical exercise reflecting the lifestyle of the user. We speculate such features related to fitness might potentially correlate with other healthcare metrics e.g. a lower resting heart rate. Further analyses of variability in motion patterns could indicate declining trends in physical activity. This could potentially be used in personalized preventive healthcare solutions, to proactively monitor the onset of diseases before symptoms are observed [14]. We enrich the data by using GPS location. Using clustering algorithms, we determine various places visited by the user. This can then be used to further segment the data, and helps predict user intents. We also categorize the places using Google places API.

Individual behavioral patterns are reflected in the coverage of data related to contextual sound environments, motion activity and user initiated interactions. While the sound data is sampled once per minute $f_{sound} = \frac{1}{minute}$, both motion activity (including location) and user interactions are discrete events $f_{motion} = [0 : n]$, and $f_{interaction} = [0 : n]$. We interpret these discrete events as conscious actions by the user, which can be used in a probabilistic model. The data is treated as time series data, segmented into hourly and daily bins, along with a bin for the full experiment.

Combining knowledge of motion, time, activity and location, with individual preferences, facilitates participatory hearing healthcare solutions. Such user preferences continuously change dependent on the contextual environment, activity, time or cognitive state of the user [6]. It is essential as Korzepa et al. [7] has argued to incorporate user intents for predictive modeling. Here, physical motion and activity is a central component. Our Naive Bayesian approach illustrates the impact when including or omitting contextual parameters related to soundscape, motion, and location, in order to predict user intents over time, see Figure 1.

We wish to further investigate how contextual data form sequential patterns. An alternative could be to interpret GPS locations as clusters forming spatial trajectories. The current position in a motion sequence would be predicted based on the preceding and subsequent locations. GPS coordinates are thus treated as a vocabulary similar to word2vec embeddings [12]. Such sequences have been shown to capture demographic patterns that may be used to classify gender, age or marital status of the users [15]. Likewise deep learning neural networks may be trained to predict patient outcomes, by combining embeddings from multiple modalities e.g. interventions, test results or prescribed medicine in electronic healthcare records, as shown by Rajkomar et al. [13].

Discussion

The prohibitive costs of healthcare will cause a shift from reactive treatment towards data driven personalized, predictive and preventive approaches. Based on our pilot study we suggest: *First*, in order to infer personalized hearing healthcare insights, complementary motion, location and soundscape environmental parameters need to be combined. *Second*, analyzing large amounts of longitudinal data gathered through internet connected devices, we may provide predictive hearing healthcare suggestions of contextual coping strategies learned from multiple users. *Third* applying a data driven approach to model user intents, patterns may be extracted as a basis for developing next generation preventive healthcare tailored to the needs of each individual. However, to provide personalized, predictive, and preventive hearing healthcare, the user needs to be an integral part of a continuous feedback loop involving context-aware devices and health care professionals.

Acknowledgements

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Appendix E

Personalizing the fitting of hearing aid by learning contextual preferences from internet of things data

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Article

Personalizing the Fitting of Hearing Aids by Learning Contextual Preferences From Internet of Things Data

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Abstract: The lack of individualized fitting of hearing aids results in many patients never getting the intended benefits, in turn causing the devices to be left unused in a drawer. However, living with an untreated hearing loss has been found to be one of the leading lifestyle related causes of dementia and cognitive decline. Taking a radically different approach to personalize the fitting process of hearing aids, by learning contextual preferences from user-generated data, we in this paper outline the results obtained through a 9-month pilot study. Empowering the user to select between several settings using Internet of things (IoT) connected hearing aids allows for modeling individual preferences and thereby identifying distinct coping strategies. These behavioral patterns indicate that users prefer to switch between highly contrasting aspects of omnidirectionality and noise reduction dependent on the context, rather than relying on the medium “one size fits all” program frequently provided by default in hearing health care. We argue that an IoT approach facilitated by the usage of smartphones may constitute a paradigm shift, enabling continuous personalization of settings dependent on the changing context. Furthermore, making the user an active part of the fitting solution based on self-tracking may increase engagement and awareness and thus improve the quality of life for hearing impaired users.

Keywords: quantified self; hearables; sound augmentation; behavior patterns

1. Introduction

1.1. The Growing Societal and Personal Costs of Hearing Loss

There are enormous societal implications related to hearing loss that are estimated to top £25 billion a year in the United Kingdom alone, including reduced productivity, which decreases the economic output [1]. However, the personal costs are even more severe: hearing loss is considered one of the biggest risk factors for dementia. Livingston et al. estimate that a third of the lifestyle-related causes of dementia can be explained by untreated hearing loss in midlife, partially due to a decline in cognitive functions. Meanwhile, multiple studies have shown that “hearing aids can prevent or delay the onset of dementia” [2] and may attenuate cognitive decline [3], by both reducing cognitive load and improving working memory [4–6]. Despite the availability of devices, often fully covered by health insurance or through public health care, less than 5% of people suffering from a hearing loss address this by using a hearing aid [7]. Even after acknowledging the need, on average it takes hearing-impaired persons a decade before they acquire the devices [7]. Furthermore, less than 25% of those who have a hearing aid use them [8]. In a scoping study by McCormack and Fortnum, the top reasons for not using a hearing aid were that the devices did not provide sufficient benefits in noisy situations and there was a perceived poor quality of sound [9].

One may ask, why is it that people do not choose to use hearing aids, given the evidence of a high risk of incident dementia, and knowing that these could potentially alleviate cognitive decline? Studies analyzing outcome measures capturing the user satisfaction indicate that this is largely determined by two factors: (1) whether the user perceives an improved quality of life through use of the devices, and (2) to what degree they help overcome limitations when interacting with others around the user. The degree to which the user feels involved in the traditional clinical fitting process highly impacts the overall satisfaction [10]. Alternative models for selling hearing aids over the counter based on do-it-yourself audiometry tests may technically provide the same fitting as provided in a clinical setting [11]. However, the lack of dialogue and hearing care counseling has been shown to result in lower satisfaction. Actively involving the user in shaping the listening experience when adapting to the devices appears to be crucial.

1.2. The Lack of Personalization in Hearing Health Care

Currently, hearing aids are by default, fitted solely by relying on a pure-tone audiogram measurement. The audiogram defines the thresholds at which a sine wave tone can be perceived, in order to determine which frequencies should be amplified to compensate for the hearing loss. A mild hearing loss may involve a 20–40 dB decline across frequency bands, typically spanning from mid range (2–4 kHz) to high range (5–10 kHz). However, this test measures only the sensitivity to an artificially produced tone, rather than the sounds that characterize a normal listening experience. Killion points out that individuals with similar audiograms may have up to a 15 dB difference in their ability to understand speech in noisy environments [12]. Wendt et al. have further shown that individuals benefit from noise-reduction algorithms [13]. Likewise, Marozeau and Le Goff show that the concept of loudness is highly individual, which in turn may determine whether soft sounds should be amplified to provide added intensity or are merely perceived as unwanted moderately loud noise [14,15]. This highlights some challenges, even in clinical settings, to optimize the hearing experience. Today's solution uses discrete steps, varying the thresholds in regard to noise reduction and attenuation [16]. In order to simulate real-life listening scenarios, clinicians are often limited to playing back a few audio clips, capturing situations such as attending to several talkers in a crowded cafe or a conversation in a car masked by background noise. More advanced solutions for simulating true listening scenarios, such as Oticon Sound Studio, enable the hearing care professional (HCP) to compose auditory scenes consisting of all sorts of environmental sounds, such as a drill hammer, a bird chirping or a crying child. In a lab setting, such simulations can optimize the fitting process, as found by Dahl and Hansen (2016) [17,18], as these make it easier to determine true user needs in simulated listening scenarios, potentially decreasing the number of follow-up visits to the clinic for follow-up fitting. However, a major challenge in hearing health care worldwide is the lack of audiological resources. Few, if any, HCPs have the option of extending the fitting procedure further to personalize settings, as the time allocated is highly constrained. Hence, the need for fundamentally different solutions is of high demand.

1.3. Learning Preferences From User Behavior

In a previous study, Laplante-Levesque et al. [19] investigated the usage of hearing aids and found two distinct types of behaviors: Users wearing the device from waking up until going to bed, in contrast to those using the hearing aids only when needed, possibly driven by external demands and context. However, all users have unique behavioral patterns. Aggregated data averaged over longer periods does not convey the fine structures of hearing aid usage. Without somehow establishing a dialogue between HCPs and users, it has up to now, not been possible to identify and learn preferences from these fine structures.

Instead, aiming to infer preferences by connecting directly to users through their smartphones, Aldaz et al. investigated the feasibility of using machine learning to predict the optimal settings, on the basis of the signal-to-noise ratio (SNR) and attenuation for the hearing aids. They found that half of the test subjects preferred the personalized settings [20]. Other attempts at using machine learning to optimize hearing aids have shown similar findings [21,22].

1.4. Making User-Generated Data an Essential Part of Hearing Health Care

Quantified self (QS) and personal informatics (PI) have increased in interest in the past decade. With the prevalent usage of smartphones and wearables, personal, quantifiable, and accurate data on everyday phenomena has become broadly available. Such data has been applied for health tracking within QS and covers a vast range of phenomena, including menstrual tracking [23], mental health in students [24,25], Post-traumatic stress disorder (PTSD) effects [26], sleep patterns [27] and diabetes management [28], to mention only a few. The examples illustrate that such data can lead to new personal discoveries, insights and improved health in terms of quality of life.

The Oticon Opn is the first hearing aid that is connected to the Internet and is able to interact with other Internet of things (IoT) devices, such as cars, smart light bulbs, music streaming or learning from cloud-based artificial intelligence (AI) services provided through the "if-this-then-that" (IFTTT) standard [29]. Essentially, hearing aids can, as U.S Food and Drug Administration (FDA) approved medical hearables, be considered state-of-the-art wearables capable of providing augmented hearing. From a technical point of view, a hearing aid is a miniature size IoT connected smart speaker, equipped with an omnidirectional microphone array. Combined with embedded advanced signal processing or neural networks, hearing aids may continuously adapt to learned user preferences or the features characterizing the changing soundscapes. Coupling the hearing aids with other sensor data, such as heart rate, motion and location, will add further insights to the context of soundscapes experienced throughout a day. Because of the unobtrusive placement behind the ear, this type of wearable can be worn during the majority of the waking hours. Investigating how the user adapts to the volume or changes program settings can provide additional information about individual sensitivity to noise, motivation to interact and the changing cognitive state. Not only the external context but also the user's state, cognitive capabilities or sense of fatigue may affect how preferences are altered in order to cope with the changing listening scenarios during the day. This changing context may be stable over time, forming patterns repeated at specific hours of the day, on weekdays versus weekends, and varying over weeks, months or years. Thus, applying tracking methods from QS and PI can lead to insights into user preferences inferred from behavioral patterns and soundscape data.

This paper explores how to infer user preferences solely on the basis of user-initiated program and volume changes throughout a 9 month pilot study, without taking the corresponding soundscape data into account. These adjustments are converted into time-series data saved in the cloud, using IFTTT to transfer data. Previous studies have primarily used summarized historical data retrieved from the hearing aid software, whereas IoT devices may potentially learn from usage data, such as volume and program interactions, to dynamically adapt the hearing aids to behavioral patterns. In this study, we look at the long-term behaviors and patterns displayed for five test subjects over at least 9 months. This study investigates both daily, weekly and monthly interaction patterns, in order to highlight differences between weekdays and weekends, and changes in behavioral patterns when modifying device settings, as well as more general usage patterns, when aiming to personalize augmented hearing by learning from user-generated data. The hypotheses to investigate include the following: Do users wish to actively select alternative programs to individualize their listening experience? Do these preferences constitute unique behavioral patterns? Is it possible to identify specific coping strategies displayed in program and volume interactions over time?

2. Materials and Method

2.1. Participants

$N = 6$ participants volunteered for the study (six men), from a screened population provided by Eriksholm Research Centre. Age ranged from 49 to 76 (median age of 62.8 years). All participants had more than a year of experience using hearing aids. The participants suffered from a symmetrical hearing loss, ranging from mild–moderate to moderate–severe as described by the World Health Organization (WHO) [30]. All had an iPhone 4S or a newer model. Subject 6 was excluded because of missing data. The test subjects received financial compensation for transportation only. All test subjects had signed an informed consent before the beginning of the experiment. An overview of the subjects can be seen in Table 1.

Table 1. Demographic information related to six subjects.

Subject	Age Group	Hearing Loss	Experience with OPN	Occupation
1	58	Moderate–severe	No	Working
2	76	Moderate	No	Part-time work
3	65	Moderate	No	Working
4	75	Mild–moderate	No	Retired
5	54	Mild	Yes	Working
6	49	Mild–moderate	No	Working

Subject 1 worked in construction. This subject had a dynamic work environment including noisy construction sites, quiet meeting rooms and driving in between.

Subject 2 worked in the transportation sector as a bus driver. This subject was exposed to a constant noise level while at work. The subject retired half-way through the experiment. The subject returned to work in the last month of the experiment, only part-time.

Subject 3 worked in an office environment. This subject attended many meetings, including teleconferences. The subject reported that the acoustics in the canteen at work were poor. This subject had many international travels, spending time primarily on flights.

Subject 4 was retired. The subject spent several days a week playing cards, with a high noise level and several competing talkers. The subject lived an active life, including activities such as sailing, and was exposed to various sound environments.

Subject 5 worked in an office environment. The subject had many meetings in or out of the office, experiencing multiple auditory environments during weekdays.

Subject 6 worked in the naval industry, restoring boats and supervising team-building events on sailboats. This subject was subjected to heavy noise exposure from power tools, as well as engine and wind noise. The subject tended to wear the hearing aids when the noise was acceptable or otherwise was not obscured by hearing protection.

2.2. Apparatus

Each subject was equipped with two Oticon Opn hearing aids, stereo Bluetooth low-energy (BLE), 2.4 GHz (Oticon A/S, Smørum Denmark). All subjects used a personal iPhone 4S or newer iPhone models with Bluetooth 4.0. The logged data consisted of any user-initiated program change or volume change through the Oticon ON iPhone app, formatted as time-series data, transferred using IFTTT, stored in the cloud and shared via Google Drive. The hearing aids were fitted with four programs. The subjects were provided with a test user Google account prior to the experiment. This account was used for data collection, and the subjects had full ownership of the account and data and could terminate access, and thus the experiment, at any given time.

2.3. Procedure

The subjects were fitted with two Opn hearing aids by an audiologist. The hearing aids were fitted on the basis of a unique frequency-dependent volume amplification based on a pure tone audiogram for each subject. Each subject was fitted with four programs, through the Oticon Genie 2.0 release 17.1 Opn fitting software (Oticon A/S, Smørum, Denmark) on a PC with Windows 7, via a Sonic Innovations EXPRESS*Link*[3] (Sonic AG, Bern, Switzerland). The programs were changed after 3–4 months of use, half-way through the experiment.

Whereas hearing aids traditionally apply a beam-forming algorithm to make the auditory focus more narrow in noisy environments, the Opn devices instead omnidirectionally preserve all signals resembling voices while filtering out ambient noise. In the present experimental design, all four programs preserve any sounds with voice-like modulation characteristics, but to varying degrees for attenuated directional and diffuse background noise [16]. Rather than providing a default medium setting offering a compromise in terms of directionality and noise reduction, the four programs represent contrasting aspects of omnidirectionality, brightness and noise reduction. Assessing which programs are preferred, making it possible to assess how users apply aspects of omnidirectionality or noise removal, to spatially differentiate auditory streams, which is essential in order to cognitively separate and selectively attend to competing voices or interfering sounds [31]. There were three dimensions altered in this experiment: brightness and noise reduction, coupled with attenuation.

Brightness perception of sound is directly related to volume gain, primarily in high frequencies. Increasing brightness may contribute to *interaural level difference* (ILD), which may give up to a 20 dB difference in sound perception. Even without directly affecting the speech frequency spectrum, added brightness helps with separating streams by improving sound localization in the 10 kHz range related to the shape of the pinna. The experimental setup thus highlights whether the program usage provides sufficient spatial cues for separating the auditory sources in a given context. That is, the program usage reflects whether the users rely on binaural differences in loudness and head shadow to attenuate ambient noise and enhance the amplification of high frequencies, which improves sound localization [32,33], or actively reduce directional and diffuse noise [13] in order to cope with the changing auditory environments. An increased brightness results in further amplification of mid-frequency sounds, typically consonants, which improves speech intelligibility. However, added brightness may in some situations be perceived as too harsh, as other sounds with similarly high frequency characteristics will likewise be amplified and seem shrill.

The noise reduction includes both attenuation of interfering sounds not resembling voices coming from a specific direction, for example, a dog barking or a passing car. Additionally, it removes the amount of diffuse noise removal, such as background noise from an air-conditioning system. A low attenuation of directional sources without noise reduction preserves ambient sounds, resembling the natural dampening provided by the shape of the head and the ears, whereas a high attenuation of interfering sounds with non-voice characteristics coupled with noise reduction, artificially creates a better SNR.

In the experimental setup, P1 was always the default startup setting, which in each experiment was compared against the alternative programs listed below, and which is illustrated in Figure 1:

- **P1** Resembling an omnidirectional perception with a frontal focus. Sounds from the sides and behind the listener are slightly suppressed to resemble the dampening effect due to the shape of the head and the pinna.
- **P2** Similar to P1 but gently attenuating directional noise and removal of diffuse noise when encountering complex listening environments.
- **P3** Similar to P1 but increasingly attenuates directional noise even in simple listening environments. Has less amplification in mid and high frequencies, producing a "rounder" or "softer" sound. Provides the highest amount of diffuse noise reduction.
- **P4** Similar to P3 with even lower thresholds for attenuation of directional noise and diffuse noise removal in all listening environments.

P5 Identical to P3 with regard to high attenuation and high noise reduction. Has added amplification in mid and high frequencies to provide a brighter sound.

P6 Similar to P4 with high attenuation. However, no noise reduction is applied. Has an increased amplification in mid to high frequencies, producing a brighter sound.

P1 constituted the default program throughout the experiment. The choice of using P1 as a baseline was based on the acoustical characteristics of this program, which mimic the natural dampening of sounds due to the shape of the ears and the binaural shadowing effect of the head. The result is an omnidirectional focus with only a slight attenuation of sounds coming from behind and from the sides. Using P1 as a default program thus highlights when users actively select any other program, offering additional attenuation of noise or increased brightness, improving the spatial separation of sounds.

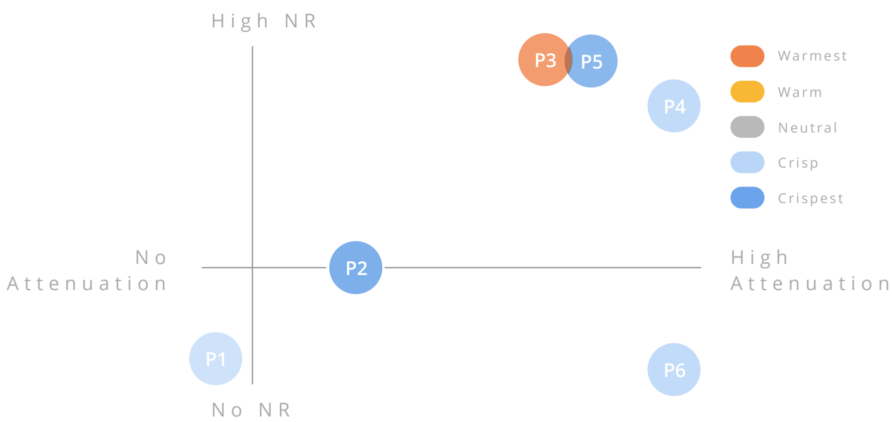


Figure 1. Six programs were used over the period of 9 months. The horizontal represents the amount of attenuation applied, from natural dampening only based on the shape of the head on the left side, to maximum attenuation of ambient sounds on the right-hand side. The vertical represents the amount of noise reduction, ranging from no noise reduction at the bottom, to maximum removal of diffuse noise at the top. The colors represent the brightness of the sound, from dark blue hues, indicating crisp and bright sound produced by greater amplification in high frequencies, to orange hues, indicating a soft and round sound, caused by less amplification in the mid and high frequencies.

The experiment consisted of two periods. The first period ran from September 2016 to January 2017, and the second period, from February to June 2017. An intervention occurred in the middle of the experiment, to further investigate whether a change in programs also generated a corresponding change in user behavior. Programs 1 and 4 were available in both periods of the experiment. For the first half of the experiment, programs 1, 2, 3 and 4 were used. After the intervention, programs 1, 4, 5 and 6 were used, as illustrated in Figure 2.

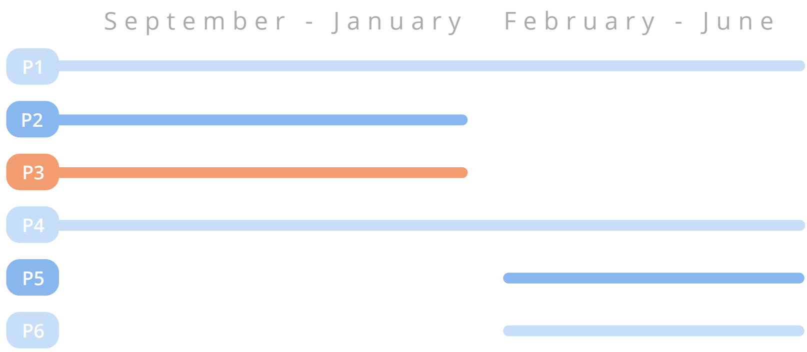


Figure 2. Graphic illustration of the two test periods, run in the fall of 2016 and spring of 2017. The programs used from September to January were P1–P4, while from February to June, the programs used were P1 and P4–P6.

For the first visit, the participants were instructed to "use the program that fits the situation the best" and "to use the hearing aids as you would normally, but primarily controlling it from the iPhone app", in order to explore the programs and natural behavior. The test subjects were not informed about what the four programs represented. The test subjects were further encouraged to adjust the volume gain if needed.

The volume control does not reflect decibel values. It ranges from -8 to 4 and gives visual feedback to the user when interacting with the iPhone app.

3. Results

Even on the basis of the limited data collected in this pilot study, analyzing only the aspects of time and user interaction, while not considering cognitive capabilities, the individual differences between users are evident. These differences lead to different coping strategies, which highlights the need for personalyzing settings individually. However, the clinical resources in hearing health care are already overburdened, meaning that any further individualization would require that such preferences are automatically learned from user-generated data.

The behavioral patterns inferred from data in this pilot study indicate that users prefer to switch between highly contrasting aspects of omnidirectionality and noise reduction depending on the context. This is very different from the prescribed medium "one-size-fits-all" program, frequently provided by default in hearing health care. The key takeaway is that a single prescribed audiological setting did not fulfill the needs of the test subjects in this study. Rather than selecting one program offering a balance between omnidirectionality and noise reduction, the test subjects typically changed between programs that appeared highly contrasting in terms of attenuation or brightness.

3.1. Behavioral Patterns Inferred from User-Initiated Program and Volume Changes

The observed program and volume changes alter the perceived soundscape along several dimensions, attenuation, noise reduction and brightness, as described in the Methods section. Overall, the subjects of the experiment described in this paper primarily altered the settings along these three dimensions. For an overview of the programs, see Figure 1.

The selected programs thus reflect when a user prefers to increase the brightness to enhance spatial separation of sounds, which improves the ability to selectively attend to any sound, or remove diffuse noise and sounds that do not resemble voices, in order to increase the SNR and thereby improve speech intelligibility. With only five test subjects, we see different behavioral patterns in relation to usage time; see Table 2. This indicates that some users comply by wearing their hearing devices from when they wake up until when they reach bedtime, while others may selectively decide to wear their hearing devices only when they see a perceived benefit, depending on the context.

Table 2. Total usage time for all six programs in hours, for five test subjects.

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5
Total usage time (h)	486.25	1189.90	255.78	373.32	551.62

A more detailed percentage-wise split of the program distribution for each program is illustrated in Figure 3. The color for P1 is yellow, for P2 is dark yellow, for P3 is brown, for P4 is orange, for P5 is red and for P6 is maroon. The same color scheme is used throughout the paper.

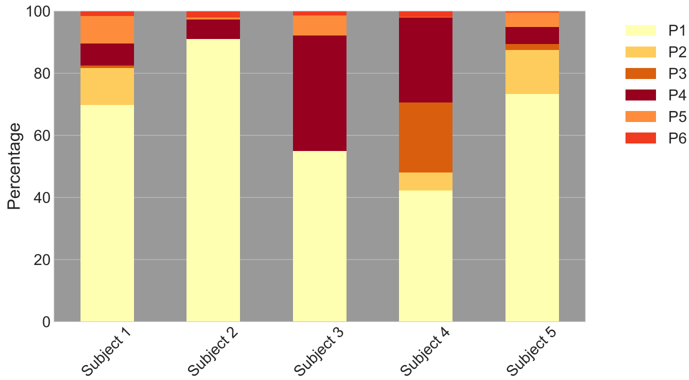


Figure 3. Percentage-wise distribution of programs throughout the entire experimental period. P1 is yellow, P2 is dark yellow, P3 is brown, P4 is orange, P5 is red and P6 is maroon. We note that a user such as subject 2 relies primarily on one program, in contrast to the more diversified program usage of subject 4.

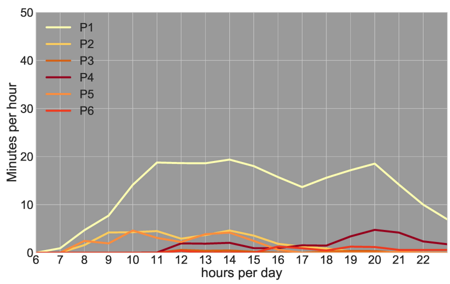
This figure shows that three of the subjects preferred the default omnidirectional focus with added brightness more than 70% of the time. They alternated using programs providing more attenuation and directionality, such as P3–P6, when needed. Subjects 3 and 4 actively chose one or more programs with more attenuation and directionality (P4–P6), whereas subjects 1 and 5 used brighter sounding programs (P2 and P5) to cope with a changing context. We found that program P1 was preferred on average 66% of the time. This was significantly different from previous findings of respectively 33% [20] and 37% [34]. This could be due to this being the default program, or more likely, that it fulfilled the needs in most contexts by providing an omnidirectional frontal focus mimicking the natural dampening of sounds from behind and from the sides, caused by the shape of the ears and the shadowing effect of the head.

The usage patterns indicate that one program may rarely be adequate, as most users have a need for more than one program to cope with the changing context. Even in a small test population, it becomes evident that the majority actively selects contrasting settings depending on the context. The next sections display these individual preferences in more detail.

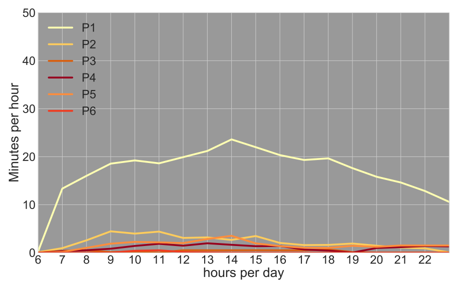
3.2. Unique Patterns Characterized by Program Changes

The user preferences are characterized by attenuation, noise reduction and brightness perception. Various coping strategies are observed in the program interactions. The following figures contain the average daily usage per hour, from 06:00 to 24:00; the average daily usage per hour in weekends, from 06:00 to 24:00; and an overview of the full experimental period, for one or more subjects.

The first observed coping strategy is based on alternating the brightness perception. By increasing the gain of mid to high frequencies, the perceptual brightness is increased. Subjects 1 and 5 both actively chose a more bright sounding program, either P2 (dark yellow) or P5 (red) to compensate for their hearing loss. They wished to increase speech intelligibility by perceptually adding more detail, both to speech and source localization. Both of these subjects used P2 and P5 20% of the total time, as observed in Figure 3. In Figure 4a,b, the average program usage in minutes per hour between 6:00 AM and 12:00 PM, is illustrated, for subjects 1 and 2. For both subjects, it seems that the brighter programs (P2 and P5) were used to complement P1 more often in the morning than in the rest of the day. Subject 1 furthermore used the directional program P4 in the evenings to complement P1. Interestingly, the need for added brightness depended on the day and time. This can be observed in Figure 4e,f, where a full overview of the programs over the test period is illustrated. The vertical axis represents weeks, the horizontal axis represents the time of weekdays, and the dashed line marks the intervention when programs were adjusted during the experiment. From these illustrationm it becomes visible that both subjects 1 and 5 actively chose P2 and P5 programs on weekdays, while the selection of these programs, as well as the overall usage of hearing aids, was reduced during the weekend. Both test subjects reported that programs P2 and P5 sounded either more "harsh, bright, or crisp", depending on the context, but enhanced speech intelligibility and the overall intensity of the auditory environment.



(**a**)



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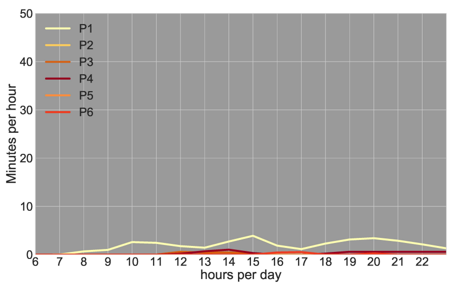

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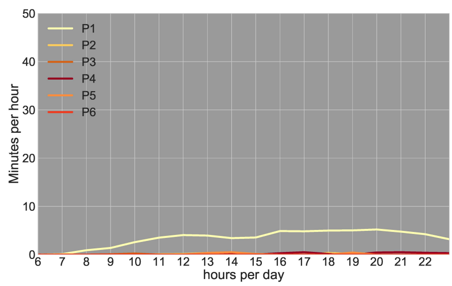

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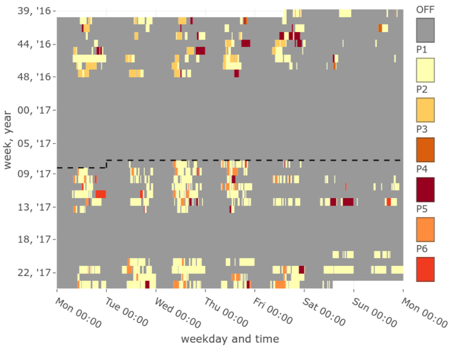
Figure 4. *Cont.*



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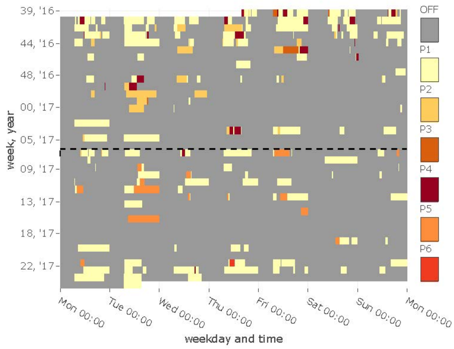


(f)

Figure 4. Behavior characterized by preference for switching between omnidirectionality without noise reduction and using more gain in high frequencies, termed **brightness**. Subjects 1 and 5 appeared to actively use brightness to improve speech intelligibility in challenging listening situations. This is seen in the active choice of selecting the programs, marked as dark yellow above the dashed line in the first half of the experiment, and marked as orange below the dashed line in second experiment. (**a**) **Subject 1**, average daily program usage; (**b**) **subject 5**, average daily program usage; (**c**) **subject 1**, average daily program usage in weekends; (**d**) **subject 5**, average daily program usage in weekends; (**e**) **subject 1**, detailed program usage; (**f**) **subject 5**, detailed program usage.

Test subject 1 described the usage of the brighter sounding programs as follows:

"When I attend meetings, which I do a lot, I like to shift my attention between the participants in order to hear everyone in the room. Thus combining omnidirectionality with a more bright timbre. It may not sound as nice, or pleasant compared to my default preferences. However, it helps me understand what is being said. When the meeting ends, I usually change to another program."

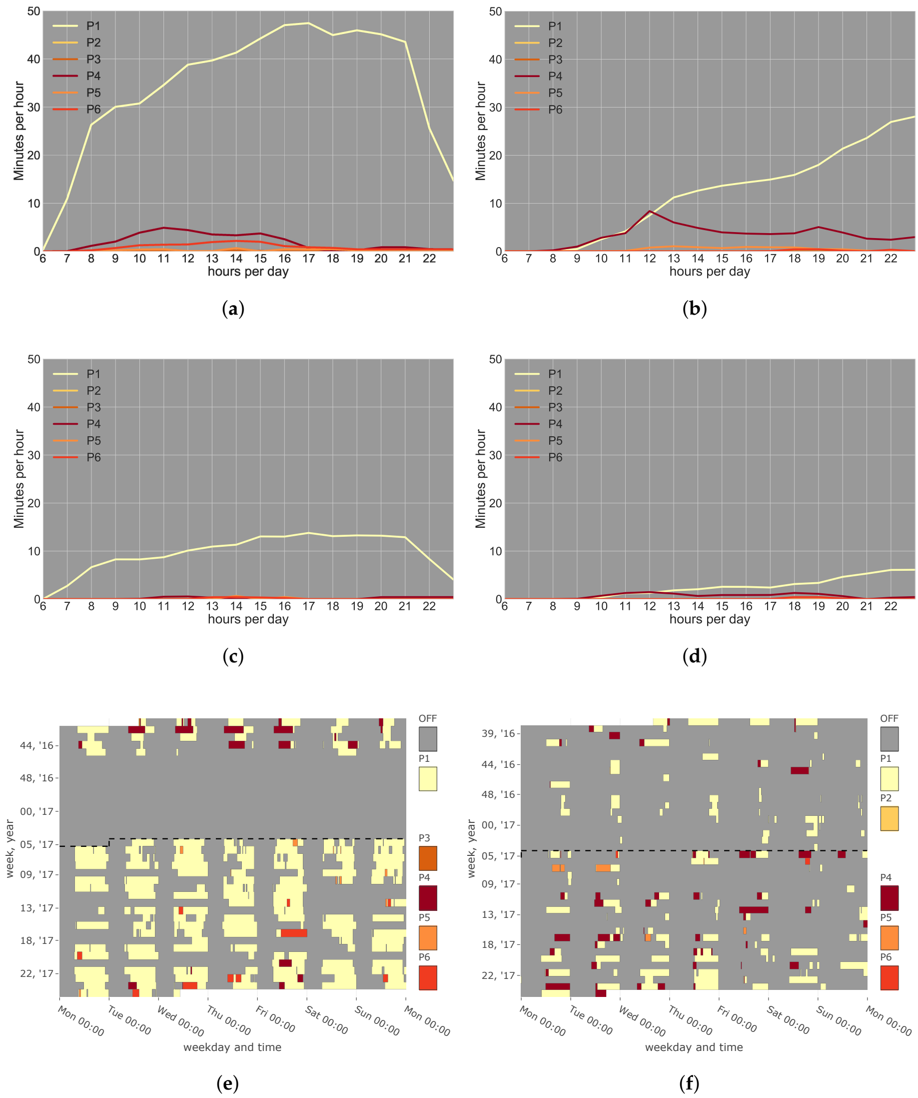
After an intervention, during which the programs were changed, both subjects 1 and 5 actively chose a brighter sounding program. The intervention added attenuation and noise reduction to a brighter sounding program (P5), while retaining the increased high-frequency gain. Despite this, the subjects preferred the brighter sound, indicating that brightness was what supported these subjects.

3.3. Alternating Between Omnidirectional and Frontal Focus

An alternative coping strategy is characterized by changing between an omnidirectional natural sound without noise removal, towards a frontal focused sound with increased noise reduction. This strategy was evident for subjects 2 and 3, as illustrated in Figure 5. Looking at the average usage per hour for subject 2 (Figure 5a) and subject 3 (Figure 5b), it can be seen that P1 was preferred, and the frontal directional program P4 was used to compliment P1 when the context changed. For subject 2, this was more evident between 7:00 AM and 8:00 AM, whereas subject 3 seemed to increasingly use the program from 8:00 AM, with a peak at midday, and then decreased the usage during the day, whereas P1 was increased throughout the day.

Test subject 2 used a coping strategy, with a directional program P2 between 7:00 AM and 4:00 PM in the first of the experiment before the intervention when the programs were adjusted. Coincidentally, at the same time, subject 2 retired from his job, which is reflected in the change of preferences defined by the frontal directional focus (dark red) on weekdays in the first half of the experiment. Subsequently, this behavioral pattern reappeared when he began working again part-time, resulting in sporadic usage of the same program towards the end of the experiment. Subject 2 described the behavioral pattern as follows: "When I drive I do not like the road noise, and noise in the bus. I prefer a program that attenuates these noises." A similar pattern appeared for subject 3 after the interventions towards the end of the experiment, when the frontal focus with noise reduction was preferred on Mondays and

Tuesdays. This augmentation of sound was displayed on some Fridays and Saturdays, suggesting a need for increased speech intelligibility. Subject 3 reported that the directional program "helps in noisy environment, such as a restaurant or a bar".



(**a**) (**b**) (**c**) (**d**) (**e**) (**f**)

Figure 5. Behavior characterized by preference for switching between omnidirectionality without noise reduction versus frontal focus with noise reduction. Subjects 2 and 3 appeared to actively attenuate noise to improve speech intelligibility in challenging listening situations. This is seen in the active choice of selecting the programs, marked as dark red (P4) above the dashed line, and bright red (P5) below the line in second experiment. (**a**) **Subject 2**, average daily program usage; (**b**) **subject 3**, average daily program usage; (**c**) **subject 2**, average daily program usage in weekends; (**d**) **subject 3**, average daily program usage in weekends; (**e**) **subject 2** detailed program usage; (**f**) **subject 3** detailed program usage.

3.4. Active and Habitual Users

Laplant-Levesque describes two types of users, which either wear the hearing aids from waking up until bedtime or on a more casual basis, only using the hearing aids driven by external demands [19]. Subject 1 had a unique behavioral pattern characterized by many interactions, constituted by both program changes, and on/off events. This test subject was working in different environments throughout the day, which was reflected in preferences for changing between brightness, attenuation, noise reduction or even "silence", depending on the changing context. The subject reported back that "I wear the hearing aids when I have a need. For example, when I'm in a quiet office, I prefer not to wear them". This pattern can be observed in Figure 4e and supports the findings from Laplante-Levesque. The user had a relatively low hourly usage of 13.74 min, as shown in Table 3. However, the detailed and fragmented illustration gives a level of detail not previously seen. Interestingly, both subjects 3 and 5 had a usage time per hour that was less than 20 min. These subjects did however seem to switch off the hearing aids for periods. In contrast, when turning on the devices, they used them for hours, without any off events.

Table 3. Average usage in minutes per hour, for five test subjects.

	P1	P2	P3	P4	P5	P6	Average Per Hour
Subject 1	9.71	1.41	0.11	1.14	1.07	0.31	13.74
Subject 2	25.48	0.00	0.01	1.38	0.14	0.66	27.67
Subject 3	9.28	0.00	0.00	2.46	0.30	0.06	12.10
Subject 4	6.70	0.69	2.86	8.98	0.15	0.84	20.23
Subject 5	12.65	1.64	0.21	0.78	1.18	0.05	16.51

Test subject 2 had a visually different coping strategy, remaining in the default omnidirectional program for extended periods and changing to a frontal noise reducing program when needed. It is interesting to see the adjustments being related to the dynamically changing context of work scenarios. Furthermore, subject 2 had the highest average usage time, with 27.7 minutes of use per hour. The amount of detail displays the need for assessing when and why a hearing aid is used as it is. The authors are not aware of similar findings in the literature, other than anecdotal findings from hearing care clinicians. This subject would be classified as a "habitual user", without concern for the fine structures of program changes motivated by a changing context. This information is lost when averaging and aggregating data.

3.5. Alternating and Unique Patterns

The previous sections highlight the similarities and differences in various coping strategies. However, for several subjects, the coping strategy changed over time, for some, even radically. Subject 4 displayed an evident detour from the original behavioral pattern, as illustrated in Figure 6. Initially, subject 4 used both brightness and attenuation of noise to improve speech intelligibility in challenging listening situations. This subject primarily remained in the omnidirectional program for the first part of the experiment. After the intervention, this subject actively changed to using the frontal focused program as the default program. Only a few program changes to a similar program without noise reduction and the default omnidirectional program occurred. This suggests there is a need for continuous personalization, as user preferences might change over time. Furthermore, it indicates how a change in lifestyle, or context, may radically alter the needs of the user. Such changes in user needs are rarely addressed today because of the limited resources in hearing health care.

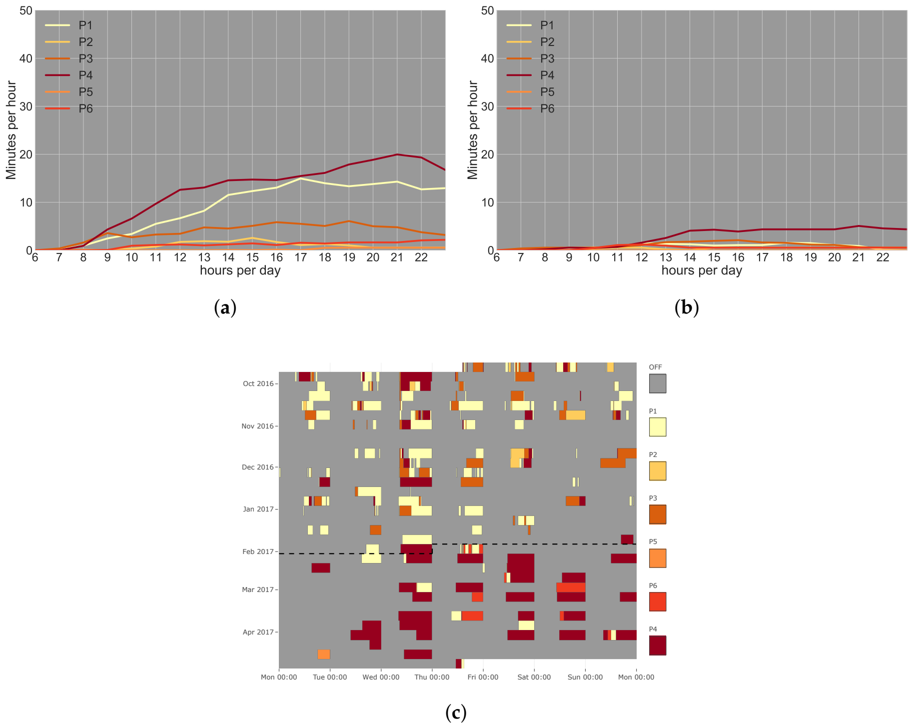


Figure 6. Behavior characterized by switching between omnidirectionality, brightness and frontal focus with noise reduction. Subject 4 initially actively used both brightness and attenuation of noise to improve speech intelligibility in challenging listening situations, while later primarily preferring a frontal focus combined with noise reduction. This is seen in the active choice of selecting the programs, marked as yellow and brown above the line in first experiment and bright red and dark red below the line in second experiment. (**a**) **Subject 4**, average daily program usage; (**b**) **subject 4**, average daily program usage in weekends; (**c**) **subject 4**, detailed program usage.

3.6. Weekdays versus Weekends

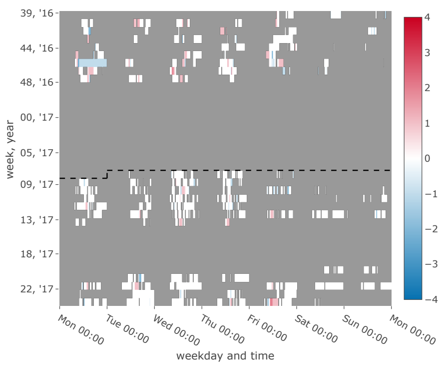
A significantly different behavioral pattern, for all subjects, can be observed in the difference between weekdays (Monday through Friday) and weekends (Saturday and Sunday). The average minutes of usage per hour for weekends is illustrated in the previous Figures 4c,d, 5c,d and 6b. The usage of the hearing aids was overall lower during weekends. All test subjects confirmed that lower usage in the weekend was due to a less demanding context. Several highlighted that "weekends are usually less challenging, both in regard to context and to mental work load". This indicates that the environmental context in weekends provides, in general, fewer challenges than in weekdays. Furthermore, as a result of changes in activities, the need for increased support is lower in the weekends. Subjects 1, 3 and 5 all mentioned that they did not benefit as much from the hearing aids in weekends because of less demanding activities, the exception being when they attended a social event with competing speakers, and noisy environments with poor acoustics. This behavioral pattern was consistent over several months, indicating a reduced need for hearing devices during weekends. If the listening scenarios were perceived as less challenging during weekends, the resulting usage patterns could be interpreted as a baseline characterizing the minimum needs of the user. In contrast, weekdays were likely to represent more dynamic and challenging sound environments, causing the users to actively change programs dependent on the changing context.

In current hearing health care, these unique behavioral patterns cannot be addressed because of limited clinical resources. From the previous findings, we see the majority of the five test subjects actively used more than one program. They did this to increase the dynamical width of the experienced sound environment. At least two contrasting programs, such as P1 and P4, were needed to cover the needs of these test subjects.

3.7. Unique Behavioral Patterns over Weeks, and within Weeks

Subject 3 increased the volume of the omnidirectional program in the last third of the experiment, which may indicate an adaptation to the volume gain. Both subjects actively adjusted the volume gain in the omnidirectional program to increase speech intelligibility, as shown in Figure 7c. Subject 5 chose a different strategy on weekdays. This can be observed in Figure 4f, where additional selection of brightness, marked in two shades of orange, appears on Tuesdays. However, the volume was increased more in the omnidirectional program. Lastly, Subject 3 tended to use the frontal focused program on Monday and Tuesdays, while actively increasing the volume. This was in contrast to weekends, on which the default program was used with only few volume adjustments, as shown in Figures 5f and 7c. This indicates two coping strategies: either choosing a program with more directional focus, or combining omnidirectional characteristics with a volume increase.

These behavioral patterns may indicate that some user actions are driven by recurring events, while others change dynamically over time.



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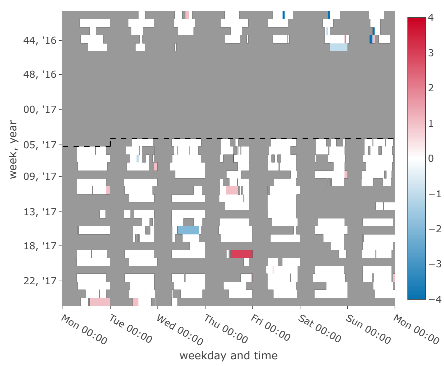

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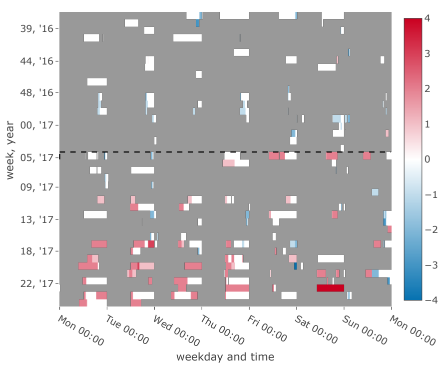

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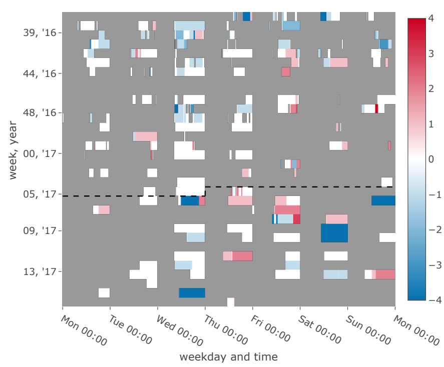
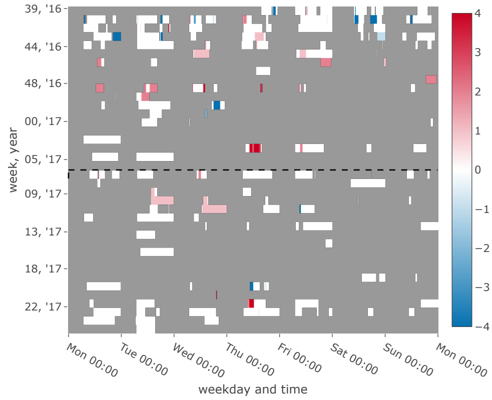


(**d**)

Figure 7. *Cont.*



(**e**)

Figure 7. Volume interactions over the full experimental period. The red colors are volume increase up to +4, and blue colors are volume decrease down to −4. (**a**) **Subject 1**; (**b**) **subject 2**; (**c**) **subject 3**; (**d**) **subject 4**; (**e**) **subject 5**.

3.8. Unique Patterns Characterized by Volume Change

Another interactive parameter is volume gain. Essentially, a non-linear amplification of soft sounds is applied across all frequency bands, rooted in a fitting rationale based on the user's audiogram [15]. Adjusting the volume gain additionally provides the user with the opportunity to either zoom in or out, while keeping the desired noise attenuation or brightness preferences associated with the selected program parameters. Figure 7 displays the individual differences of volume interactions for the five test subjects. This figure illustrates the individual preferences for actively using the volume to complement or tune the current program used. Subject 1 (Figure 7a) and subject 2 (Figure 7b) had a limited use of the volume, indicating that the brightness and attenuation was sufficient. Both these subjects primarily used P1, where subject 1 used brighter programs around 20% of the time. In contrast, subject 3 (Figure 7c) subject 4 (Figure 7d) and subject 5 (Figure 7e) actively used the gain to adjust the current program. Subject 3 primarily used P1 and P4 and began increasing the volume after the intervention. Subject 4 primarily relied on P1 and P4. This subject actively used the volume in either program.

3.9. Number of Program and Volume Interactions

The number of interactions between the program and volume indicates whether a user prefers controlling the attenuation, noise reduction and brightness, or the overall gain of the device, where the volume ranges from −8 to 4. It should be noted that the devices reset the volume to 0 after a program change. The volume interactions can thus be interpreted as an indication of moving away from the default settings. If the program changes for a user account for the majority of interactions, there are few deviations from the default volume, and vice versa.

In Figure 8, the percentage of usage split between the number of program and volume changes is illustrated. This does not indicate the amount of volume steps, but instead, a discrete count of volume changes.

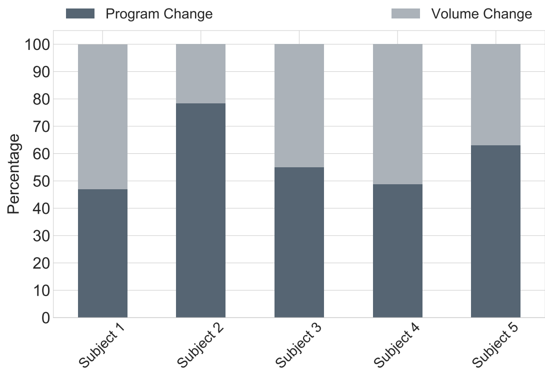


Figure 8. Percentage-wise distribution of total interactions between program and volume interactions. Subjects 1, 3 and 4 had close to an even split between volume and program. This indicates that both volume and programs were used to augment the sound environment. Subject 2 had a significantly lower number of volume interactions, compared to the rest of the subjects. This however, indicates a preference for using the programs, rather than volume, to augment sound.

Three out of five subjects had a balanced split between program and volume interactions. This indicates that such adjustments are needed in order to augment the sound and thereby achieve the desired outcomes. For two subjects, there was a preference for using the program changes more frequently than the volume interactions. This was evident for subject 2, who had significantly fewer volume interactions.

Looking only at the aggregated and split number of interactions, it is evident that each user interacted with their hearing aids in unique ways. Some users perceptually benefitted from changing the attenuation, noise reduction and brightness, while others utilized the volume to further customize the default programs provided.

3.10. Volume Interactions With Respect to Programs

Volume interactions with respect to programs indicate how the hearing aids are used. Figure 9 illustrates volume changes over time, with respect to a program, before changing to another program. It is observed that volume interactions varied considerably across the test subjects. Subject 4 seemed to primarily decrease volume, and subject 3 seemed to primarily increase volume. These nuances would disappear if simply averaging volume over a longer period.

Interestingly, it is observed that all subjects lowered the volume of the default omnidirectional program (light yellow) from the beginning. However, if the subjects remained in the program, the volume was increased. For all subjects, the omnidirectiona focus of program P1, which amplifies any sounds within a 360° radius, may be perceived as louder. These illustrations show how users adapt to the increased gain, or intensity within minutes. As one subject phrases it: "P4 sounds round and nice. However, when you speak I'm not sure how much I benefit from this program. On the other hand, if I use P2 or another bright program, I understand more, but I need some time to adjust to the sound. Actually, I like the sound of P2". This illustrates that programs with a rounder sound, P4–P6, with added attenuation, sound nice and round. However, the lack of added high frequency gain limits the ability to separate sources and lowers the contrast in consonant utterances. Today's hearing aids modify only the overall gain, without taking such short-term adaptation of the perceived loudness into consideration.

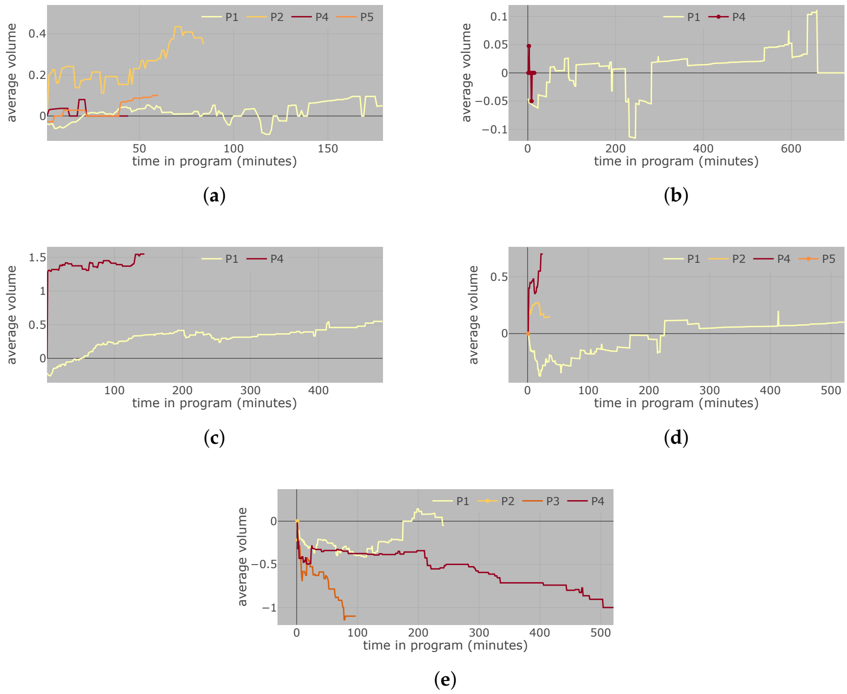


Figure 9. Volume with respect to program. Programs with less than 20 interactions have been excluded. On average, the volume gain for P1 (light yellow) was initially reduced and over time increased across all test subjects. This suggests that the omnidirectional characteristics and lack of noise reduction were initially perceived as being too intense, in turn triggering that the subjects decrease the volume. As the subjects adapted to the perceived loudness over time, the general trend was to increase the volume again. (**a**) **Subject 1** coped by increasing volume in the brightest program (P2, yellow). This may indicate a need for more presence, and more amplification in high frequencies, in order to improve speech intelligibility; (**b**) **Subject 2** coped by actively using volume to zoom in and out. This subject primarily used the default program P1; (**c**) **Subject 3** coped by initially lowering the volume in P1 and over time increasing the volume again, when adapting to the intensity. The increase in volume gain seen in programs with noise reduction may suggest a need to zoom in to compensate for a perceived lack of intensity; (**d**) **Subject 5** actively used programs and reduces the intensity of sound by lowering the volume in P1; (**e**) **Subject 4** preferred to reduce volume in the selected programs to reduce the presence. This preference seems also reflected in the actively chosen programs, which provide more attenuation of non-voice directional sources and removal of diffuse noise.

4. Discussion

4.1. The Opportunity for Personalizing Hearing Health Care as hearing aids Become Internet of Things Devices

There is an urgent need to rethink how users can be empowered to become an active part of an individualized fitting process; WHO has warned that more than 1 billion young adults are at risk of hearing loss when listening to music at too high a level [35] and predicts that hearing loss will be the seventh highest cause of chronic diseases in 2030 [36]. Hearing loss is one of the most common sensory deficits and is more common than vision impairment [37], as it is estimated that one in four adults aged 45 years and older have hearing loss [36], out of which, a third have a disabling hearing loss (40 dB or more) [38]. These numbers stress the necessity for alternative approaches providing large-scale personalization of devices currently not feasible because of a lack of audiological resources. On an anecdotal note, an audiologist shared the following story regarding the challenge of personalizing hearing instruments:

> "The hearing aid user comes in for a refitting in the middle of the week. I ask, 'Recall a situation where the hearing aids did not perform as you wanted it to'. The patient thinks, and comes up with, 'Well, yeah, I don't remember that much, but Monday I had an episode.'
>
> I then have to guess what is the essence of this episode, and try to refit the hearing aids to better accommodate similar situations in the future. However, I face several challenges. One is that the users rarely recall episodes, unless they are significant. If it's a compliant user, they may be writing notes. The second happens only in rare cases. Furthermore, I have to guess what's needed to be tuned to give a better experience. All of this is based on memory recall and heuristics".

Establishing sufficiently accurate information about the situation and context, in this case to reconfigure the hearing aid, is not a unique problem in health care. Larsen et al. highlighted a similar problem when treating PTSD patients [26].

4.2. One Size Does Not Fit All

When enabling users to change between multiple settings as outlined in the present study, a first research question would be whether test subjects are willing to interact with their devices. From a limited set of users, we observe over several months that there appears to be an urge to actively change not only programs but also modify them by adjusting the volume. A caveat here is that the users in the present study were hearing impaired individuals who were highly motivated as test persons to improve their listening experience. Future studies would need to address to what extent broader segments of hearing-aid users would similarly wish to actively improve their listening experience.

From the pilot study presented in this paper, it is evident that users are not one-size-fits-all. The data indicates not just one but several unique behavioral patterns, defining "arch-typical" approaches to dynamically modify settings. We outline these as different strategies for coping in a changing context depending on cognitive state and effort related to multiple listening scenarios. The diversity of these interaction patterns are affected by the changing context. From only time, program and volume interactions, it becomes clear that various factors stimulate users to adjust, and thus personalize, their hearing aids to adapt to a given context. Here, the context may be summed up in behaviors related to the difference between weekdays, for which in many cases work-related activities represent external demands, in contrast to weekends, which might be characterized by leisure activities, defining a baseline in the general needs for augmenting listening scenarios. However, we also observe user interactions that might rather be related to the cognitive load experienced during the day, when selecting programs in the evening, offering attenuation of noise in order to rest the ears and brain. The diversity illustrated in the user interactions highlights the need for a personalized fitting process. Our findings indicate that there are multiple coping strategies involving not only noise reduction and volume, but also changing the timbre of the sound, when aiming to optimize the listening experience for each user.

Whether this results in improved speech intelligibility for the users or an overall better listening experience remains to be validated. Solely looking into the unique behavioral patterns, we observe individual coping strategies that seem to be preserved over days, weeks or even months.

4.3. Involvement and Engagement May Lead to a Higher Satisfaction

Empowering users to change settings related to both attenuation of noise and the timbre in terms of brightness, we observe consistent behavioral patterns suggesting that engaging with the hearing device creates an awareness about how to best cope in different sound environments. Future studies involving more users need to assess to what extent the ability to modify settings and volume translates into a significant improvement in hearing aid outcome measures defining the perceived user satisfaction.

Several of the users in the present study have hinted at this. One of our test participants said the following: "When I'm part of such an experiment, where I have to pay attention to when and how I can benefit the most from my hearing aids, it does affect how I use them. Even when a program which enhances brightness sounds harsher in some context, on the other hand it helps me understand speech. I wouldn't have chosen such a program before the experiment, but would rather have stayed in a program which by default attenuates noise. Now I can better see the benefits of the different programs, in order to assess when one, or the other, would be most beneficial for me." For the program with automatic noise reduction and attenuation engaged on the basis of acoustical characteristics, the test subjects reported that they had difficulties in hearing the perceptual difference, unless they chose the extremes of the spectrum.

4.4. The Next Steps to Create Better Hearing Experiences

While considered out of scope in the present study, we plan future experiments investigating how the observed user-initiated program and volume changes relate to the changing auditory context. That is, whether the sound pressure level, modulation characteristics and SNR describing how the devices perceive the changing sound environments correlate with user-initiated program or volume change. Alternatively, if the auditory context remains constant whereas the user interacts by changing the program or volume, it may rather reflect the user's cognitive state related to the time of the day or fatigue; or, if apparently similar soundscapes do not always trigger the same user preferences in terms of program or volume changes, it may indicate that the activities are different: a similarly noisy environment occurring in a workout session or during an important meeting may trigger very different user interactions. Additional contextual parameters retrieved from smartphone motion data, calendar events or biometric sensors such as heart rate may need to be combined in order to describe both the sound environment and the corresponding user preferences.

Essentially, our aim is to investigate how to optimally learn intents from user-generated data and thereby predict contextual preferences on the basis of behavioral interaction patterns.

Overall, we wish to explore how active participation can improve the outcome measures constituting user satisfaction. Empowering the user to become an active part of the treatment is not limited to audiology but constitutes a central component when rethinking health care by involving patients, supported by IoT technologies and the ability to learn from user-generated data.

Optimizing the clinical workflow of hearing aid fitting by making the user an active part of the solution will have an impact for the clinicians, the next of kin and policymakers. What we see in the data of this pilot study, where users to a much higher extent than reported previously were able to cope by remaining in an omnidirectional setting without noise reduction, may reflect their ability to actively shift their attention, resulting in a corresponding attenuation of unwanted sounds in the auditory cortex. We listen with our ears, but understand using our brains. Empowering hearing impaired users to actively define their preferences could trigger a paradigm shift allowing for context-aware augmented hearing solutions, which dynamically adapt devices to the changing context by continuously learning from the user generated data.

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Author Contributions: Benjamin Johansen and Michael Kai Petersen conceived the experimental setup and performed the experiments with subsequent follow-ups; Benjamin Johansen and Maciej Jan Korzepa performed the data analysis and visualizations; Benjamin Johansen wrote the paper. Michael Kai Petersen contributed to writing the paper. Jan Larsen, Niels Henrik Pontoppidan, Jakob Eg Larsen contributed in proof reading, giving input and supervision.

Conflicts of Interest: The authors have no conflict of interest related to funding; however, clinical resources and access to test subjects and hardware was provided by Oticon A/S.

Appendix A. Study data

The study data is available at https://drive.google.com/file/d/0B9s0-FJfzzL8bmNtUXZtMmdDQ2M/view?usp=sharing.

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Appendix F

Mapping auditory percepts into visual interfaces for hearing impaired users

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Mapping auditory percepts into visual interfaces for hearing impaired users

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Abstract
Auditory-visual interfaces for hearing aid users have received limited attention in HCI research.We explore how to personalize audiological parameters by transforming auditory percepts into visual interfaces. In a pilot study (N = 10) we investigate the interaction patterns of smartphone connected hearing aids. We sketch out a visual interface based on two audiological parameters, brightness and directionality. We discuss how text labels and contrasting colors help users navigate in an auditory interface. And, how users by exploring an auditory interface may enhance the user experience of hearing aids. This study indicates that contextual preferences seemingly reflect cognitive differences in auditory processing. Based on the findings we propose four items, to be considered when designing auditory interfaces: 1) using a map to visualize audiological parameters, 2) applying visual metaphors, turning auditory preferences into actionable interface parameters, 3) supporting the user navigation by using visual markers, 4) capturing user intents when learning contextual preferences.

Author Keywords
Hearing impairment; health; aging; augmented audio.

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous

Introduction

Designing interfaces for the changing demographics of an increasingly aging population should not be limited to haptics or visual impairment, but include auditory paradigms, as a third of 65+ years old have a disabling hearing loss.

It is estimated that 20% of the American population have a hearing loss [10], and one in 3 adults aged 65 or older is suffering from a disabling hearing loss (40 dB or more) [14]. The World Health Organization (WHO) further estimates that 1.1 billion young people are at risk due to loud music exposure [15]. Yet, only limited research within the HCI community has been addressing how to improve the current haptic interfaces of hearing aids. The focus has typically been on visual interfaces, as exemplified by the WCAG 2.0 guidelines making web sites accessible for the visually impaired [4]. How to map auditory percepts have previously been related to visual shapes and size as in Köhlers Gestalt principles, reflecting how sounds like "bouba/kiki" are associated with round or edged forms [8, 11]. Conversely, how to map visual icons into auditory sounds [2, 6, 13]. However, the challenge of visually representing and interacting within auditory scenes has rarely been addressed. Nor the potential in designing interfaces enabling hearing impaired users to manipulate how sounds are perceived based on audiological parameters.

Recent advances in user experience (UX) have been driven by speech interfaces, including speech recognition and speech synthesis, combined with the uptake of smart-speakers and digital assistants such as Alexa, Siri and Google Assistant. Gartner predicts a third of all search will by 2020 be non-screen based on voice [5]. However, for a large part of the aging population voice interaction involves enhancement of speech intelligibility or ambient noise reduction.

Pilot study

Using smartphone connected hearing aids, we explore how to map such auditory preferences into actionable parameters in a visual interface. Based on a pilot study (N = 10), we asses how high dimensional auditory percepts may be conceptualized as simple color contrasts and spatial metaphors.

N = 10 participants volunteered for the study (one female, nine males), from a screened population provided by Eriksholm Research Centre. Age ranged from 39 to 76 (median age of 65 years). All participants had more than a year of experience using hearing aids. The participants suffered from a symmetrical hearing loss, ranging from mild-moderate to moderate-severe. The study has two goals: 1) to investigate the ability to modify audiological parameters using a visual interface, and 2) to investigate the individual behavioral patterns, inferred from continuous contextual data collected by hearing aid and smartphone sensors, coupled with the users interactions as illustrated by Johansen et al. [7] and Korzepa et al. [9]. In this paper we focus on the first goal. In particular, we wish to address the following issues: 1) How do we design 'intuitive' interfaces, using map and navigation as metaphors? 2) how do we map characteristics of brightness or noise reduction to colors, shapes or other markers? 3) Could such interfaces enable users to successfully navigate and adapt the settings of their hearing aids?

Extending the haptic interface of hearing aids

Hearing aids have been engineered as small behind-the-ears devices with built-in microphones. Thin cables connects to the speaker units positioned inside the ear canal. The most prevalent interface for hearing aids are physical buttons, used to increase or decrease volume gain. Users may press buttons on either device. The same buttons may

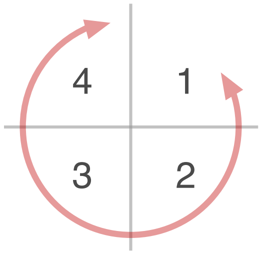

Figure 1: Haptic button press interfaces enable users to sequentially move within a cycle of programs. Perceptually the user moves clockwise or anti-clockwise, but can only move in steps to the nearest neighbor, but not jump from e.g., 1 to 3.

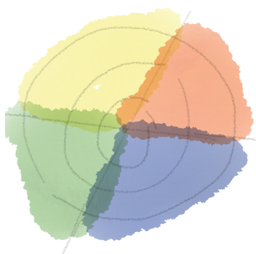

Figure 2: Four distinct programs illustrated as four different colors.

enable the user to change between alternative programs, by sustained button presses. The devices provide auditory feedback through series of ’beeps’, depending on the interaction. Volume changes happen within a second, while program changes may take several seconds before being fully engaged. The haptic interface is essentially a sequence of steps, which enables the user to move through alternative programs in a cycle as illustrated in Figure 1. Volume adjustments moves up or down. The haptic interfaces allow for rapid interaction. However, the user may struggle to keep track of what constitutes the current program or volume setting.

Bluetooth connected hearing aids can enrich the interaction by visualizing settings on a smartphone app. One approach enables users to select between program settings associated with symbolic icons related to locations such as "restaurant", or activities like going for a walk in "nature" [12], thus mapping one context to one setting. This helps to inform the user of the current state of the hearing aid. Both haptic button presses and symbolic icons are limited to sequential steps, and do not support parallel interaction patterns.

Mapping from auditory to visual metaphors

Bregman [3] describes auditory scene analysis metaphorically, as similar to making out the numbers and size of boats at sea, as well as the characteristics of the wind, based only on two handkerchiefs being excited by the waves. We similarly face the challenge of transposing the sense of moving within a high dimensional auditory space into a two dimensional visual interface.

Initially we investigated whether symbolic icon buttons would reflect the actual usage scenarios. Hearing care professionals (HCP) often simplify the usage of alternative settings by labeling programs to a specific location, activity, or with a generic "program"-name. However, our findings indicate that such contextual labeling may introduce a limiting bias, obscuring the highly individual preferences related to different usage scenarios. This means that one program translates into many scenarios, unlike the current approach where a program maps to one scenario.

Labels, colors and space as markers

Our metaphor can abstractly be interpreted as a spherical ’space’, where the user can move around. In this space we use both positioning of the ball, contrasting colors and labels, to help the user navigate.

We used two audiological parameters, brightness and attenuation, to create a map, rather than symbolic icons. Essentially empowering users to modify their listening experience, and to explore the auditory map. Increasing the perceived brightness enhances spatial cues, enabling the user to selectively allocate attention to separate voices. Or, conversely attenuate ambient sounds to increase the signal-to-noise ratio (SNR), making it easier to separate competing voices. The enhanced brightness perception is visualized as two color segments in the top half of the circle, combined with associative labels naming them "lively" and "crisp". The two remaining parts were assigned noise attenuating programs, accordingly labeled "natural" and "focused". Discrete program selection is illustrated in Figure 2. with four distinct programs.

A colored ball is used as a visual pointer, reminding the user of their current location. The ball can be moved accordingly, and augment the sound while updating the settings. To help the user navigating we use text labels, rather than icons. Four labels characterizing the sound are, "lively", "crisp", "focused" and "natural". As an example, "crisp"

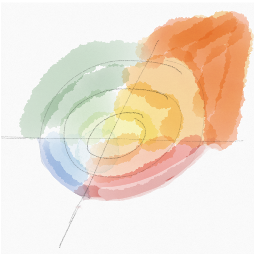

Figure 3: An abstract visualization of the interface based on color contrasts and saturation, without associative textual labels .

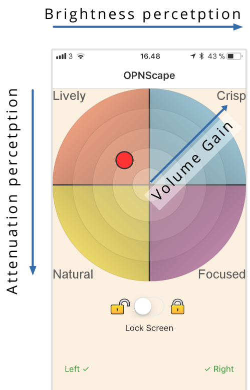

Figure 4: Proposed app interface. By moving the red ball, users may increase the brightness perception (x-axis , attenuate ambient sounds (y-axis) and adjust the perceived loudness (from center to edge).

might be associated with the sensation of auditory cue localization, while "focused" might reinforce aspects of directionality. Assessing the spatial metaphor, all users in the pilot study, spanning the age of 39 to 76 years old, find it easy to adjust both the brightness, and the attenuation. Additionally, most users prefer a visual interface to the current haptic interfaces of hearing aids. The subjects find the moving ball responsive and visually intuitive in navigating the auditory space, irrespective of age.

However, attaching labels, may bias the end user. An alternative view of navigating the auditory scene is presented in Figure 3. The labels have been removed, and colors, saturation, depth, contrasts, and shapes alone define the auditory space visualized as a sphere. This may support the user in exploring the room, rather than moving through a discrete space.

Learning to navigate the map

To build up auditory awareness one would assume that training is needed to navigate spatially, just as it is when learning to ride a bike. When first learning to ride a bike one may start pedaling, and can thus get from A to B. This is the stages where one starts to use a hearing aid. Later, one experiences the gears of the bike. This is similar to changing between four discrete programs. Later, brakes are discovered to regulate speed. This corresponds to adjusting the volume. Wearing the devices combined with a contextual selection of programs and volume, allows one to steer the bike. However, navigating a bike, or an auditory space requires practice. The perceptual difference when adding brightness, or adding attenuation, impacts the loudness. The brighter sounding programs may perceptually exceed or fill the sphere, compared with the lower bottom attenuated programs.

Our interface depicted in Figure 4. allows for parallel modification of both sound perception and volume intensity. The ball can move horizontally, to alter brightness perception and soft gain, i.e., the frequency response in mid- and high frequencies. Navigating vertically allows the user to attenuate ambient sounds, i.e., removing noise while still preserving sounds with voice-like characteristics. Moving the ball from the center towards the periphery increases or decreases the volume intensity. Several users found it difficult to simultaneously modify both the gain and program. This may be due to the mapping from higher granularity of the haptic interface, to the more coarsely controlled volume gain in the visual interface. Only 6 out of 10 found the visual volume adjustment easy or very easy.

Translating auditory scenes into intents

An added outcome when observing user preferences in real life listening situations, is to learn the preferences in a given context. Established hearing aid paradigms, e.g., as proposed by Stuart Gatehouse [1], would assume that noise reduction should be increased as the signal-to-noise ratio deteriorates, to enhance speech intelligibility. However, given the ability to explore an auditory space, our pilot study indicates that most of the subjects rather prefer the omnidirectional "lively" program without attenuation of ambient sounds, to improve speech intelligibility. All of the 10 subjects indicated they prefer the "lively" (7) or "crisp" (3), illustrated in Figure 5. These programs offer little or no noise reduction in order to enhance speech intelligibility. Whereas they select programs like "focused" or "natural" to attenuate ambient sounds in noisy environments. Our visual interface, thus seem to spatially reflect the user intents for either increasing brightness along the horizontal plane, or vertically to reduce background noise.

The subjects also showcase the importance of considering

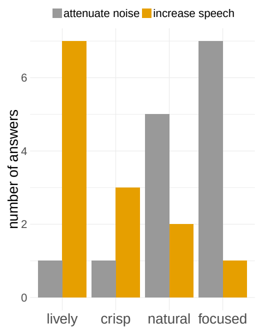

Figure 5: User preferences for attenuation (grey) and speech intelligibility (orange). Sum of program as "most preferred" and "preferred" for each condition.

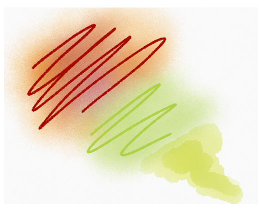

Figure 6: An acoustical environment (red). The hearing aid signal processing compensates for the hearing loss based on the program and volume interaction (green). The modified auditory percept should contextually reflect the desired outcome supporting the user intents (neon).

intents in relation to preferences. One says: 'When I'm in meetings with 4-5 people I prefer to use the "lively" program to better understand speech. When I'm attending a presentation in a larger hall with more people, I prefer to attenuate noise, especially behind me. I also use the "focused" program in the cinema to minimize annoying background noise'. Several subjects reported: 'The program I select to enhance speech intelligibility depends on the people I'm focusing on. Female voices or small kids have higher pitched voices, and the "bright" program becomes too shrill'. The translation from auditory scene to user intents is illustrated in Figure 6. The user is subjected to the demands of an acoustic scene marked in red. Through interaction with the hearing aid, marked in green, the user changes the settings to modify the perception of the auditory scene. The modified auditory percept should contextually reflect the desired outcome of the user intents, marked in pointy neon green.

Future work

Designing next generation interfaces, reflecting the changing demographics of an aging population, may provide novel opportunities for the HCI community to redefine voice interaction in a broader sense as augmented hearing. However, the interaction models would need to be redefined, in order to facilitate personalized hearing care by empowering users to adapt settings along audiological parameters.

We found the usage of visual metaphors and spatial exploration empowers hearing aid users. The users intuitively understood the two-dimensional mapping of audiology parameters. Providing markers such as color, labels, and a ball to indicate current position, helps the user navigate in an auditory space. However, compensating for the perceived loudness of contrasting settings requires further work. We furthermore see a potential in empowering users to become an active part in compensating their hearing loss at any age, in order to explore the potential of augmenting hearing. In our pilot study the users were equally capable of modifying hearing aid settings regardless of their biological age. Their preferences might rather reflect how they cognitively process auditory percepts differently. It is therefor crucial to provide added means of personalization, rather than providing "one size fits all" settings based on age. It might not be feasible for all elderly users to engage with their hearing aids to the extent outlined above. Although even if only some users would engage actively, it might still facilitate a crowdsourcing of user generated data, making it possible to learn behavioral patterns as a foundation for designing next generation augmented hearing interfaces that adapt to "users like me in soundscapes like this" as outlined by Korzepa et al. [9].

We propose the following points to consider when designing such auditory interfaces: 1) using a map as a metaphor to visualize audiological parameters such as brightness perception and attenuation, 2) applying visual metaphors together with associative text labels may help turn auditory preferences into actionable interface parameters, 3) suppor the user navigation by using markers, based on contrasting colors, spatial layout and position, 4) incorporating the perceived intents of the user whenever aiming to learn contextual preferences.

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Appendix G

Learning preferences and soundscapes for augmented hearing

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Learning preferences and soundscapes for augmented hearing

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ABSTRACT
Despite the technological advancement of modern hearing aids (HA), many users abandon their devices due to lack of personalization. This is caused by the limited hearing health care resources resulting in users getting only a default 'one size fits all' setting. However, the emergence of smartphone-connected HA enables the devices to learn behavioral patterns inferred from user interactions and corresponding soundscape. Such data could enable adaptation of settings to individual user needs dependent on the acoustic environments. In our pilot study, we look into how two test subjects adjust their HA settings, and identify main behavioral patterns that help to explain their needs and preferences in different auditory conditions. Subsequently, we sketch out possibilities and challenges of learning contextual preferences of HA users. Finally, we consider how to encompass these aspects in the design of intelligent interfaces enabling smartphone-connected HA to continuously adapt their settings to context-dependent user needs.

ACM Classification Keywords
H.5.2 Information Interfaces and Presentation (e.g. HCI): User Interfaces—User-centered design; K.8.m Personal Computing: Miscellaneous

Author Keywords
personalization; augmented hearing; intelligent interfaces

INTRODUCTION
Even though hearing loss is one of the leading lifestyle causes of dementia [11], up to one quarter of users fitted with hearing aids (HA) have been reported not to use them [5]. One of the reasons behind the prevalence of non-use of fitted HA is identified by McCormack et al. [12] as users feeling that they do not get sufficient benefits of HA. However, in the light of technological advancement of HA as well as the abundance of research indicating clear benefits of HA usage, we rather seek the source of the problem in the lack of personalization in the current clinical approach. The increasing number of hearing-impaired people [6] and lack of hearing health care resources often results in users getting a 'one size fits all' setting and thus not exploiting the full potential of modern HA.

Furthermore, the current clinical approach to measure hearing loss is based on pure tone audiogram (PTA). PTA captures the audible hearing thresholds in frequency bands usually from 250 Hz to 10 kHz. However, PTA does not fully explain a hearing loss. Killion et al. showed that the ability to understand speech in noise may vary by up to 15 dB difference in Signal-to-Noise ratio (SNR) for users with a similar hearing loss [8]. Likewise, users differ in terms of how they perceive loudness. Le Goff showed that speech at 50dB can be interpreted either as moderately soft or slightly loud [9]. This means that some users may perceive soft sounds as noise which they would rather attenuate than amplify. These aspects are rarely taken into account in current clinical workflows.

Earlier research by Dillon et al. [3] indicated potential benefits of customization both within and outside the clinic including fewer visits to clinics, a greater choice of acoustic features for fitting and end users' feeling of ownership. Previous studies that focused on customizing the settings of devices based on perceptual user feedback [13] or using interactive tabletops in the fitting session [2] indicate that users prefer such customization. Aldaz et al. [1] used reinforcement learning to personalize HA settings based on auditory and geospatial context by prompting users to perform momentary A/B listening tests. However, only with the recent introduction of smartphone connected HA like the Oticon Opn [15], it has become possible to go beyond ecological momentary assessment by continuously tracking the users' interactions with the HA and thereby learn individual coping strategies from data [7]. Such inferred behavioral patterns may provide a foundation for

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correlating user preferences with the corresponding auditory environment and potentially enable continuous adaptation of HA settings to the context.

When interpreting user preferences, one needs to consider how the brain interprets speech. Auditory streams are bottom-up processes fused into auditory objects, based on spatial cues related to binaural intensity and time difference [4, 10, 14, 16]. However, separating competing voices is a top-down process, applying selective attention to amplify one talker and attenuate others. HA may mimic this top-down process by either 1) increasing the brightness to enhance spatial cues facilitating focusing on specific sounds or 2) improve the signal to noise ratio by attenuating ambient sounds to facilitate better separation of voices. Incorporating these aspects into our experimental design, we hypothesize we could learn top-down preferences for brightness or noise reduction based on HA program and volume adjustments combined with bottom-up sampling of how HA perceive the auditory environment in terms of sound pressure level, modulation and signal to noise ratio. This allows us to assess in which listening scenarios the user relies on enhanced spatial cues provided by omnidirectionality with more high frequency gain to separate sounds and in which environments the user instead reduces background noise to selectively allocate attention to specific sounds.

In our pilot study, we give two subjects HA programmed with four contrasting programs in terms of brightness and noise reduction, and register how they interact with programs and volume over a period of 6-7 weeks. The purpose of this work is to:

- show how the subjects interact with HA settings in real environments without any intervention,
- discover basic contextual preferences for the subjects,
- identify possibilities and challenges of learning contextual preferences of HA users,
- suggest application of intelligent user interfaces that would continuously support users in optimizing their HA not only by learning and adjusting to individual preferences but also exploiting crowd-sourced patterns.

METHOD

Participants

Two male participants (from a screened population provided by Eriksholm Research Centre) volunteered for the study (Table 1). The participants suffer from a symmetrical hearing loss, ranging from moderate to moderate-severe as described by the WHO[17]. All test subject signed an informed consent before the beginning of the experiment.

Subject	Age group	Hearing loss	Experience with Opn	Occupation
1	65	Moderate	Yes	Retired
2	76	Moderate-severe	No	Working

Table 1: Demographic information related to the subjects.

Apparatus

The subjects were fitted with a pair of research prototype HA EVOTION extending Oticon Opn. The subjects used Android 6.0 or iOS 10, connected via Bluetooth. Data was logged using the nRF connect app and shared via Google Drive.

Subject	Program	Mode	Brightness	Soft Gain
1	P1	omnidirectional	+1	0
	P2	omnidirectional	0	0
	P3	low noise reduction	+2	+2
	P4	high noise reduction	-2	-2
2	P1	omnidirectional	+2	+2
	P2	low noise reduction	+1	+1
	P3	medium noise reduction	0	0
	P4	high noise reduction	-2	-2

Table 2: Program settings for subject 1 and 2, with modified brightness $\{-2\ldots2\}$ and soft gain for low sounds $\{-2\ldots2\}$ where 0 corresponds to the default level.

Procedure

Based on the individual hearing loss, the subjects were fitted with 4 programs as shown in Table 2. For all programs, HA volume could be adjusted to one of the levels from $-8\cdots+4$, where 0 is the default volume. The subjects were instructed to explore different settings using HA buttons over a period of 6-7 weeks. In the experimental setup, the HA always start up in the default program and volume. The default program for subject 1 was P2 in the first five weeks which was then switched to P1 for the last two weeks at the subject's request. Subject 2 used P2 as the default program.

Soundscape data

To create an interpretable representation of the auditory features defining the context, we applied k-means clustering to the acoustic context data collected from HA. The values comprise auditory features defining how the HA perceive the acoustic environment:

sound pressure level measure of estimated loudness,

noise floor tracking the lower bound of the signal,

modulation envelope tracking the peaks in the signal,

modulation index estimated as difference between modulation envelope and noise floor,

signal to noise ratio estimated as difference between sound pressure level and noise floor.

The above parameters are captured as a snapshot across multiple frequency bands once per minute. Additionally, the HA perform a rough classification of the auditory environment and represent it as a categorical variable with one of the following values: 'quiet', 'noise', 'speech in quiet', and 'speech in noise'. These labels are used as ground truth for evaluating the performance of the clustering by means of normalized mutual information (*NMI*) score. The optimal number of clusters K was estimated to be 4 with $NMI = 0.35$.

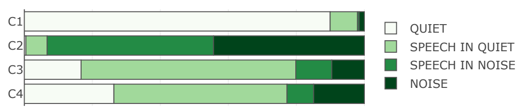

Figure 1: Applying k-means algorithm to the soundscape data captured from the HA results in four clusters which estimate the acoustic context as C1 'quiet', C2 'speech in noise', C3 'clear speech' or C4 'normal speech'.

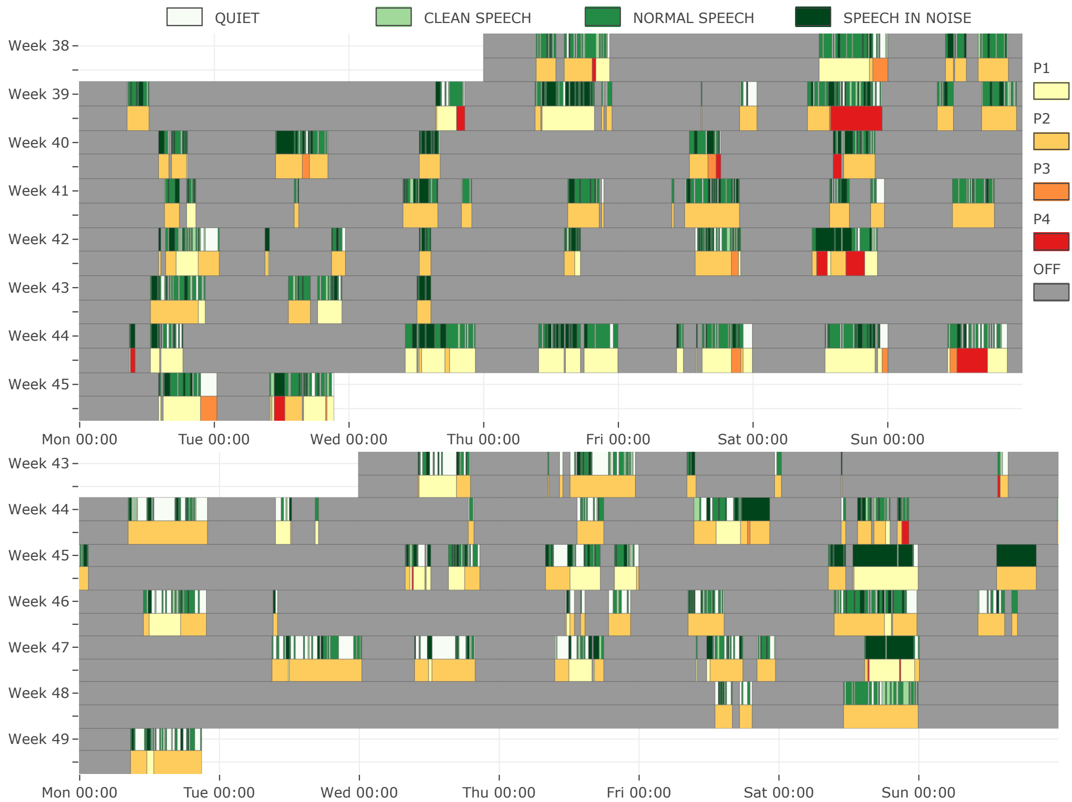

Figure 2: Time series data combining the contextual soundscape data captured from the HA (green gradient) with the corresponding interactions related to the user selected programs (yellow-red gradient) for subject 1 (top) and 2 (bottom).

The resulting four soundscape clusters were labeled according to the proportion of samples with different ground-truth labels within each cluster (Figure 1) while ambiguities were solved by examination of the cluster centroids. The first cluster mainly captured the 'quiet' class which is also validated by the cluster centroid having very low values of sound pressure level and noise floor. Thus, the environments assigned to this cluster will be represented as 'quiet'. The second cluster captured both 'speech in noise' and 'noise' classes which suggests that the numerical representations of these environments are similar. For simplicity, we label them as 'speech in noise'. The third and fourth cluster both captured mainly 'speech in quiet' with a small addition of other classes. As the third cluster captured samples with much higher sound pressure level and signal to noise ratio, it will be labeled as 'clear speech', while the fourth cluster with attributes of the samples closer to mean will be represented as 'normal speech'.

RESULTS

We refer to the user's selected volume and program choice as user preferences, and to the corresponding auditory environment as the context. Juxtaposing user preferences and the context allows us to learn which HA settings are selected in specific listening scenarios. To facilitate interpretation we assign each cluster a color from white to green gradient, in which increasing darkness correspond to increased noise in the context (quiet $\rightarrow$ clean speech $\rightarrow$ normal speech $\rightarrow$ speech in noise). Likewise, we assign each program a color from yellow to red gradient. Lighter colors define programs with an omnidirectional focus and added brightness. Darker colors indicate increasing attenuation of noise. This coloring scheme will apply throughout the paper.

Contextual user preferences

Figure 2 shows the user preference and context changes for both subjects, plotted across the hours of the day over the weeks constituting the full experimental period. Subject 1 most frequently selects programs which provide an omnidi-

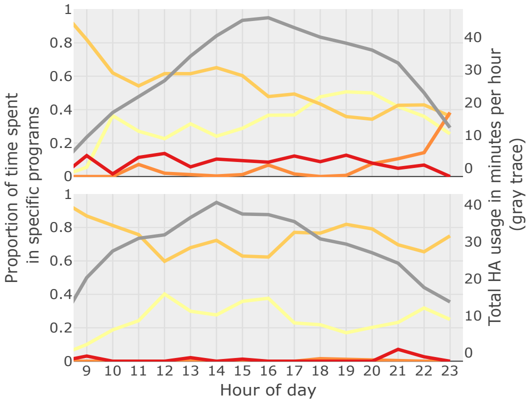

Figure 3: Average HA usage time per hour (grey trace, right axis) and relative program usage over day (left axis) for subject 1 (top) and 2 (bottom).

rectional focus with added brightness (the default program was changed from P2 to P1 after week 43). However, the default program is occasionally complemented with programs suppressing noise. This suggests that the user benefits from changing programs dependent on the context.

Subject 2 mainly selects two programs; P1 offering an omnidirectional focus with added soft gain and brightness, and P2 (default) providing slight attenuation of ambient sounds. Compared to subject 1, this user spends more time in 'quiet' context. Comparing weekdays to weekends, the latter seem to contain a larger contribution of 'normal speech' and 'speech in noise' auditory environments.

Figure 3, illustrates subjects' average usage of their HA and which programs are used most throughout the day. Days without any HA usage are excluded from the average. The HA usage for subject 1 steadily increases in the morning and early afternoon and peaks at around 4pm. P1 and P2 are the most used programs throughout the day. Interestingly, in the evening, P3 is used more frequently reaching similar usage level as P1 and P2 between 11pm and midnight. P4 is used very rarely yet consistently throughout the day. The HA usage of test subject 2 is shifted towards the morning with peak activity around 2pm. The default P2 is the most commonly used program throughout the whole day. However, during afternoon, P1 seems to be chosen more often.

Figure 4 shows which contexts the subjects use their HA at different times of the day. The HA usage for subject 1 is dominated by speech-related contexts most of the day. Only after 5pm, the context has more 'quiet' and 'clear speech' and less 'speech in noise' contribution. From 9pm, the 'quiet' context rapidly overtakes context containing speech. Subject 2 appears to be exposed to different contextual patterns. Normal and noisy speech contexts seem to be dominated by 'quiet' soundscapes in the morning. Subsequently, their contributions increase and peak around 7pm. Afterwards, the 'quiet'

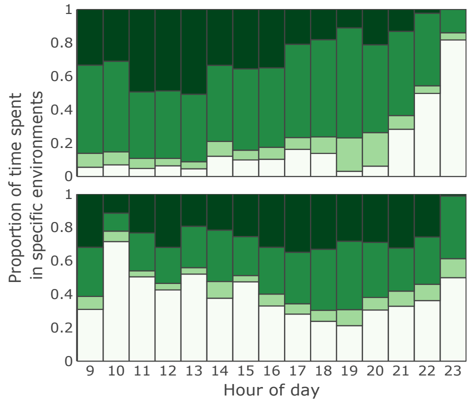

Figure 4: Relative time spent in different contexts over day for subject 1 (top) and 2 (bottom).

		Subject 1				Subject 2			
		P1	P2	P3	P4	P1	P2	P3	P4
Context	QUIET	1	1	3	0	3	3	0	0
	CLEAN SPEECH	3	2	1	0	1	0	0	1
	NORMAL SPEECH	10	3	3	3	5	6	0	2
	SPEECH IN NOISE	6	5	4	7	17	5	1	2

Table 3: Counts of changes to a given program in different contexts for both subjects.

context gradually increases. Both subjects seem exposed to more 'speech in noise' around midday which is likely due to lunchtime activities.

Behavioral patterns

We quantify the relationship between program/volume interaction and context by assuming that the settings are preferred in the corresponding context only at the time when they are being selected. Under this assumption, we count how often programs are selected in different contexts. Table 3 shows the counts of program changes for both subjects. The total number of changes was 52 and 46 for subject 1 and 2 respectively. Considering the small number of changes, we outline only the most apparent behavioral patterns.

Subject 1 switches to P4 mainly in 'speech in noise' context (twice as often as in 'normal speech'). The fact that 'speech in noise' is a less common environment than 'normal speech' strengthens this behavioral pattern. This suggests that subject 1 seems to cope by suppressing noise in challenging listening scenarios. Examples of this behavioral pattern are illustrated in Figure 5. Likewise, a clear behavioral pattern can be seen for subject 2. P1 is the preferred program in 'speech in noise' environments. Considering that P1 offers maximum brightness and omnidirectionality with reduced attenuation and noise reduction, this behavioral pattern suggests the user compensates by enhancing high frequency gain as a coping strategy in complex auditory environments (examples in Figure 6).

Table 4 shows the number of volume changes for subject 2 (subject 1 rarely changes volume). All increases beyond

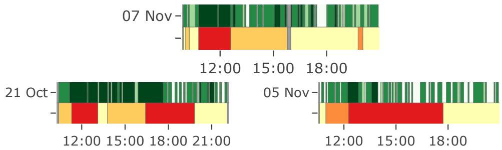

Figure 5: Details of behavioral patterns for subject 1, indicating preferences for reduced gain and suppression of unwanted background noise (P4) in challenging 'speech in noise' environments (dark green).

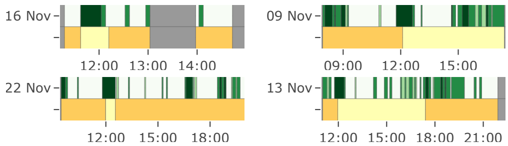

Figure 6: Details of behavioral patterns for subject 2, indicating how omnidirectionality coupled with additional high frequency gain (P1) may enhance spatial cues to separate sounds in challenging 'speech in noise' listening scenarios (dark green).

the default volume level (0) were made in 'speech in noise' context. On the other hand, changes to the default volume were evenly distributed across all contexts. This suggests that increasing the volume is another coping strategy for subject 2 in more challenging listening scenarios.

		Subject 2		
		0	+1	+2
Context	QUIET	2	0	0
	CLEAN SPEECH	2	0	0
	NORMAL SPEECH	2	0	0
	SPEECH IN NOISE	2	12	1

Table 4: Counts of changes to a given volume in different contexts for Subject 2.

Figure 7 shows a behavioral pattern that might be more difficult to interpret based on the auditory context alone. Occasionally, subject 1 selects P3 in a 'quiet' environment late in the evening. The test subject subsequently reported that these situations occur when going out for a walk and wanting to be immersed in subtle sounds such as rustling leaves or the surf of the ocean. The preference for P3 thus implies both increasing the intensity of soft sounds as well as the perceived brightness.

DISCUSSION

Inferring user needs from interaction data

Empowering users to switch between alternative settings on internet connected HA's, while simultaneously capturing their auditory context allows us to infer how users cope in real life listening scenarios. To the best of our knowledge, this has not been reported before.

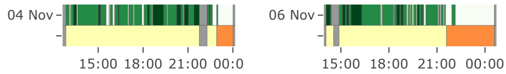

Figure 7: Details of behavioral patterns for subject 1, indicating preferences for additional soft gain and brightness (P3) in 'silent' (white) environments, in order to enhance the perceived intensity of the auditory scene.

Learning the mapping between preferences and context is a non-trivial task, as the chosen settings might not be the optimal ones in the context they appear in. For example, looking into the soundscape data, it is clear that the environment soundscape frequently changes without the user responding with an adjustment of the settings. Conversely, the auditory environment may remain stable whereas the user changes settings. We need to take into consideration not only the auditory environment but also the user's cognitive state due to fatigue or intents related to a specific task. Essentially, the user cannot be expected to exhibit clear preferences or consistent coping strategies at all times. We hypothesize that many reasons could explain why the user does not select an alternative program although the context changes:

- being too busy to search for the optimal settings,
- too high effort is required to change programs manually,
- accepting the current program as sufficient for the task at hand,
- cognitive fatigue caused by constantly adapting to different programs.

Similarly, we observe situations in which user changes settings even though the auditory environment remain stable, which could be caused by:

- the user trying out the benefits of different settings,
- cognitive fatigue due to prolonged exposure to challenging soundscapes
- the auditory environment not being classified correctly

In our pilot study, the context classification was limited to the auditory features which are used for HA signal processing. However, smartphone connectivity offers almost unlimited possibilities of acquisition of contextual data. Applying machine learning methods such as deep learning might facilitate higher level classification of auditory environments. Different types of listening scenarios might be classified as 'speech in noise' when limited to parameters such as signal to noise ratio or modulation index. In fact, these could encompass very different listening scenarios such as an office or a party where the user's intents would presumably not be the same. Here the acoustic scene classification could be supported by motion data, geotagging or activities inferred from the user's calendar to provide a more accurate understanding of needs and intents.

Nevertheless, in some situations as illustrated in Figure 6, the behavioral patterns seem very consistent; the user preferences appear to change simultaneously with the context, remain unchanged as long as the context remains stable, and change back when the context changes again. Identifying such behaviors could allow to reliably detect user preferences with limited amount of user interaction data. Furthermore, time as a parameter also highlights patterns as illustrated in Figure 6 related to activities around lunch time, or late in the evening (Figure 7), as well as the contrasting behavior in weekends versus specific weekdays.

Even though our study was limited to only two users, we identified evident differences in the HA usage patterns. Subject 1 tends to use the HA mostly in environments involving speech, whereas subject 2 spends substantial amount of time in quiet non-speech environments. This might translate into different expectations among HA users. Furthermore, our analysis suggests that users apply unique coping strategies in different listening scenarios, particularly for complex 'speech in noise' environments. Subject 1 relies on suppression of background noise to increase the signal to noise ratio in challenging scenarios. Subject 2 responds to speech in noise in a completely different way - he chooses maximum omnidirectionality with added brightness and increased volume to enhance spatial cues to separate sounds. These preferences are not limited to challenging environments but extends to the ambience and overall quality of sound, as subject 1 reported that he enhances brightness and amplification of quiet sounds to feel immersed in the subtle sounds of nature. We find this of particular importance as it indicates that users expect their HA not only to improve speech intelligibility, but in a broader sense to provide aspects of augmented hearing which might even go beyond what is experienced by normal hearing people.

Translating user needs into augmented hearing interfaces

We propose that learning and addressing user needs could be conceptualized as an adaptive augmented hearing interface that incorporates a simplified model reflecting the bottom-up and top-down processes in the auditory system. We believe that such an intelligent auditory interface should:

- continuously learn and adapt to user preferences,
- relieve users of manually adjusting the settings by taking over control whenever possible,
- recommend coping strategies inferred from the preferences of other users,
- actively assist users in finding the optimal settings based on crowdsourced data,
- engage the user to be an active part in their hearing care.

Such an interface would infer top-down preferences based on the bottom-up defined context and continuously adapt the HA settings accordingly. This would offer immense value to users by providing the optimal settings at the right time, dependent on the dynamically changing context. However, the system should not be limited to passively inferring intents, but rather incorporate a feedback loop providing user input. We see a tremendous potential in conversational audio interfaces as HAs resemble miniature wearable smartspeakers which would allow the user to directly interact with the device, e.g. by means of a chatbot or voice AI. First of all, such an interface might resolve ambiguities in order to interpret behavioral patterns. In a situation when user manually changes the settings in a way that is not recognized by the learned model, the system could ask for a reason in order to update its beliefs. Ideally, questions would be formulated in a way allowing the system to directly learn and update the underlying parameters. This could be accomplished by validating specific hypotheses that refer to the momentary context as well as the characteristics captured in the HA user model, incorporating needs, behavior and intents; e.g.'Did you choose this program because the environment got noisy / you are tired / you are in a train?

Secondly, a voice interface could recommend new settings based on collaborative filtering methods. Users typically stick to their preferences and may be reluctant to explore available alternatives although they might provide additional value. Similarly, in the case of HA users, preferred settings might not necessarily be the optimal ones. Applying clustering analysis based on behavioral patterns, we could encourage users to explore the available settings space by proposing preferences inferred on the basis of 'users like me, in soundscapes like this'. For instance, the inteface could say: 'Many users which share your preferences seem to benefit from these settings in a similar context - would you like to try them out?' This would encourage users to continuously exploit the potential of their HA to the fullest. Additionally, behavioral patterns shared among users, related to demographics (e.g. age, gender) and audiology (e.g. audiogram) data, could alleviate the cold start problem in this recommender system, thus enabling personalisation to kick in earlier even when little or even no HA usage data is available.

Lastly, users should be able to communicate their intents, as the preferences inferred by the system might differ from the actual ones. In such scenarios, users could express their intents along certain rules easily interpreted by the system (e.g. 'I need more brightness.') or indicate the problem in the given situation (e.g. 'The wind noise bothers me.'). Naturally, translating the user's descriptive feedback into new settings is more challenging, but could potentially offer huge value by relieving users of the need to understand how multiple underlying audiological parameters influence the perceived outcome.

Combining learned preferences and soundscapes into intelligent augmented hearing interfaces would be a radical paradigm shift in hearing health care. Instead of a single default setting, users may navigate a multidimensional continuum of settings. The system could be optimized in real-time by combining learned preferences with crowdsourced behavioral patterns. With growing numbers of people suffering from hearing loss we need to make users an active part of hearing health care. Conversational augmented hearing interfaces may not only provide a scalable sustainable solution but also actively engage users and thereby improve their quality of life.

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Appendix H

Modelling user utterances as intents in an audiological design space

Benjamin Johansen, Michael Kai Petersen, Niels Henrik Pontoppidan, and Jakob Eg Larsen. Modeling user utterances as intents in an audiological design space. (2019) *Workshop on Computational Modeling in Human-Computer Interaction, CHI '19.*

Modelling User Utterances as Intents in an Audiological Design Space

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ABSTRACT

The global number of people living with hearing loss continues to grow, while the clinical resources are limited. To address this we describe a scalable goal oriented system. We outline a method on creating an audiological vocabulary, which can be mapped to intents. We create a shared audiological parameter space, with inspiration from clinical workflows. Matching of the intents and the audiological space, results in hearing aid fitting parameters, which then receive feedback from the user. We discuss how to train embedding and recurrent neural network models implementing attention mechanisms, to predict the optimal settings based on learned sequences of dialogue states and device fitting outcomes.

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; • **HCI theory, concepts and models**;

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INTRODUCTION

Computational interaction is an emerging research field spanning from optimizing input and interaction techniques using control theory and Hidden Markov Models. An emerging field within computational interaction is goal oriented interaction. An example of this is conversational interfaces. Notably the Google Duplex AI system capable of carrying out natural phone conversation to reserve a table at a restaurant, or make an appointment with a hairdresser [5]. The primary challenges of conversational interfaces are; the interface lacks understandable boundaries, the interaction mimics human behavior and is expected to act accordingly, the interface needs to have a robust speech-to-text engine, and the interfaces needs attention or memory to stay focused on the dialogue. Often, one or more of these challenges are not addressed, and triggers a mismatch between user expectations and interface performance. State of the art conversational systems overcome these challenges by thoroughly mapping out design boundaries, rather than attempting to encompass a full conversational dialogue. As an example, humans are capable of adapting dynamically to a changing context, and still revert back to the initial topic. We are able to do this through memory and attention mechanisms, and we understand the unvoiced boundaries of the conversation.
In the present paper we discuss how to enable interactions in an audiological design space, by embedding and training recurrent neural network models with simple attention and memory components. The goal is to predict the optimal hearing aid settings in real life listening scenarios.

AUDIOLOGICAL DESIGN SPACE

We focus on the use case of conversational agents within hearing health care, and on hearing aid fitting and optimization. The current clinical work flow is sequential, relies on calendars, and experienced hearing care professionals. The main challenge is lack of scalability. This is evident in emerging markets such as China and in low income countries, where the later has less than 1 audiologist per million citizen [13]. General health and medical care are facing similar challenges, where the number of patients are growing faster than the number of health care practitioners. Combining mobile internet connectivity with conversational interfaces may enable us to provide scalable healthcare solutions.

Voice enabled digital assistants, implementing artificial intelligence, are rapidly changing how we interact with internet of things devices including car dashboards and smartphone connected hearing aids. The most successful goal-oriented dialogue systems, model conversations as partially observable Markov decision process (POMPDS) [15]. However, these goal-oriented application requires a lot of domain-specific handcrafting of features, which restrict their usage to specific domains. This hinders scalability and transfer learning to new domains [1]. The lack of annotated vocabulary for the audiological design space limits the use of POMPDS. It requires extensive effort to collect and annotate dialogues related to audiological trouble shooting. However, know-how of clinical practices can help establish a framework and context for dialogues. We draw inspiration from several studies where hearing care professionals map utterances into hearing aid fitting parameters [2, 11]. These parameters are related to frequency specific gain, loudness perception, and thresholds for attenuation and noise reduction. Based on the clinical practices, we outline an audiological design space.

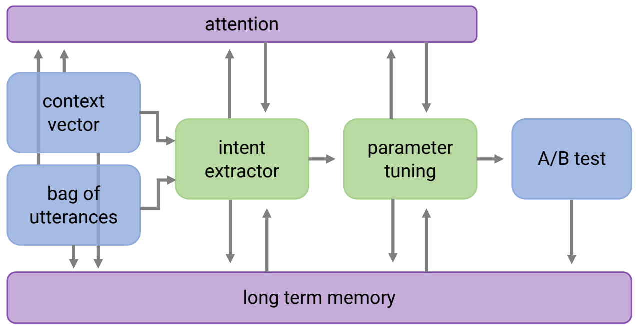

Figure 1: The proposed conversational agent uses both contextual and user input. It then probabilistic proposes a A/B program pair. The user picks a preference, and the memory network is updated.

We propose an interactive conversational agent, based on attention mechanisms mimicking human memory. The agent uses a context matrix and a utterance matrix as input, which is then fed through an intent extractor. The model includes both an attention unit for short term memory, using the current inputs to update parameters, and an attention network utilizing previous learned weights. Intents are not only inferred from semantics but also include comparison of four contrasting programs representing audiological parameters. The user is presented with an A/B program pair to select the preferred hearing aid setting. The memory is continuously updated based on a recurrent neural network model. An overview of the conversational agent is presented in Figure 1

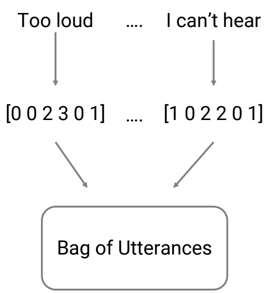

Figure 2: Using utterances to create a bag of utterances, a vocalbury. Our model use cosine similarity between utterances. The similarity is later used for audiological parameters.

MODELING UTTERANCES AS INTENTS

Word embeddings have been demonstrated to be an effective procedure in natural language understanding, as demonstrated by Mikolov et al.[6, 7]. The concept of skip-grams can be applied to longer sequences such as sentencens, or on documents, to create sequence embeddings [9].
We use the same principles of word embeddings to train a natural language understanding part of our model. We start by creating a vocabulary based on user utterances. Due to the model flexibility, we can create a new vocabulary from scratch. As an example, *'There is too much noise'* and *'I can't hear because there are too many people'*, have embedding vectors more similar than either *'Turn down the volume'* or *'It's too quiet'*, this is illustrated in Figure 2.

The model infers the most likely labels of new utterances, based on their cosine similarity to previously learned word vector representations. The feature and intents vectors have the same dimensionality, allowing the model to be trained by simply maximizing the cosine similarity between utterances and fitting label embeddings. A cosine similarity matrix of a selection of utterances are illustrated in Figure 3

We use a similar approach to embed intents from utterances. For example, *'I cannot hear the speaker in front of me'*, can relate to intents of focusing on the person, reducing surrounding noise, increasing volume output, or a combination of these. We cast the embeddings of utterances and intents into a shared low dimensional space using a supervised learning approach similar to StarSpace [14], implemented as a TensorFlow embedding model in Rasa [8, 10].

FROM INTENTS TO FITTING PARAMETERS

The first part of our model infers intents based on utterances from the user. The second part of the model search for optimal fitting parameters. The model fitting is based on empirical evidence on troubleshooting work-flows from hearing care professionals. A challenge within hearing care is the lack of *one to one* mapping between utterances and audiological solutions [2]. Meaning, a hearing care professional has to deduct a suitable hearing aid setting, by interpreting the challenges associated with the listening scenario the user has experienced. The fitting parameter labels thus resemble a flow chart of potential interventions [11].This requires the audiologist to interpretate utterances like *"it is very noisy"* which dependents on the listening scenario, the hearing loss compensation, and the cognitive state of the user. The audiologist has to estimate what the optimal audiological solution would be in a specific context. These solutions could involve highly different fitting parameters related to beamforming, noise reduction, loudness sensitivity or gain adjustments

To model such a clinical workflow, our goal oriented dialogue system needs to learn sequences of perceived intents, fitting actions and estimate the updated settings. Similar to the previous mapping of utterance to intents, we apply a supervised learning approach to train an embedding model. We

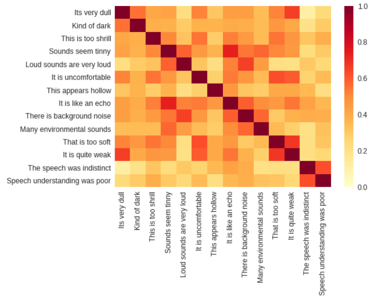

Figure 3: Confusion matrix of user descriptions of challenging listening scenarios based on semantic similarity generated by Universal Sentence Encoder; pairwise groups along the diagonal reflect how utterances are often mapped by audiologists to parameters of frequency specific gain, beamforming, occlusion and loudness.

then use a Recurrent Neural Network (RNN) to create sequential embeddings of perceived intents and fitting actions. This generates a memory state from previous dialogues and outcomes. Embedding dialogue states and fitting actions in the same vector space allows for comparing a new dialogue input against the system long term memory. Subsequently predicting the most likely audiological solution based on its cosine similarity to previously learned outcomes. Target labels or fitting actions can be represented as a bag of multiple features. Attention mechanisms enables the model to infer which intents and system actions contributed the most to previous outcomes, as shown by Vlasov et al. [12]. That is, separate user and system attention probabilities are inferred from the embeddings of past user inputs and fitting actions in order to adjust the weights determining the next hearing aid adjustment.

SIMULATING FITTING OUTCOMES BASED ON DIALOGUE STATES

Rather than relying solely on utterances for intent classification, we are able to generate contrasting hearing aid settings, which similar to AB testing enables the user to compare fitting parameters in real life listening scenarios [3]. Configuring four contrasting hearing aid settings, reflecting the fitting parameters that hearing care professionals commonly associate with utterances, enables users to indirectly accept or decline the suggested fitting parameters in a given context. Thus extending the underlying supervised learning of the goal oriented dialogue system with an additional reinforcement learning framework, to facilitate prediction of the preferred hearing aid settings. Defining the design space, according to the hearing aid adjustment parameters identified in previous studies [1, 11], we train an embedding model, in order to map utterances into intents related to adjustment of: maximum power output, frequency specific gain, beamforming, noise reduction thresholds, and loudness recruitment. We train the model based on multiple sequences of utterances, intents, hearing aid adjustments and final outcome. As exemplified in this simulated fitting dialogue we simply sequentially map utterances to intents:

utterance: "can't understand what is being said"
intent: enhance speech
action: increase B high frequency and soft gain
reply: "maybe try setting B ?"
utterance: "what does B do ?"
intent: explain B
reply: "it adds brightness to better separate sounds, do you prefer setting B ?"
utterance: "its very noisy in here"
intent: noise reduction
action: adjust B beamformer, attenuation and noise reduction thresholds
reply: "try setting B, do you prefer B ?"

utterance: "its better"
intent: confirm
reply: "great i'll remember you like setting B in this listening environment"

The embedding model is trained with multiple utterances for each of the intents to infer the most likely fitting parameters. These are used as dialogue flow inputs to train a RNN model, in order to predict fitting outcomes. As can be seen in the above simulated dialogue, utterances like *"can't understand what is being said"* might initially be mapped to the intent of enhancing speech based on gain fitting parameters. The subsequent utterance *"its very noisy in here"* shifts the intent towards adjusting beamformer, attenuation and and noise reduction thresholds.

Training on multiple dialogues, the TensorFlow RNN model applies attention mechanisms to learn which intents in a sequence contributed the most in order to predict to the final fitting outcome. These fitting parameters can furthermore be contextualized as the goal oriented dialogue system has access to continuous time series data describing the corresponding listening environment data [4]. Meaning, that the reinforcement learning of intents based on dialogues and fitting outcome, can be complemented with soundscape data, in order to automatically adjust hearing aid settings in real life listening scenarios.

FUTURE OUTLOOK

We suggest the following to be considered when designing flexible computational interfaces based on natural language understanding. 1) embeddings are useful for both understanding language, and for projecting other parameters into embeddings. This creates a shared embedding space, where different entities can be compared. 2) using attention mechanisms facilitates limiting the solution space. Learning from previous dialogue states and actions, helps the model to generate repsonses and predict the most likely next action. 3) our approach shows how to translate observed clinical workflows into parameter settings. This could be extended to general healthcare while supporting healthcare staff in the decision making process. 4) utilizing flexible and dynamic frameworks, such as the one we propose, continuously learn from interactions. This type of model can initially be trained on a small labeled data set, and continue to learn in a semi-supervised manner through user interactions.

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