Computational Audiology: New Approaches to Advance Hearing Health Care in the Digital Age

Jan-Willem A. Wasmann,[1] Cris P. Lanting,[1] Wendy J. Huinck,[1] Emmanuel A.M. Mylanus,[1] Jeroen W. M. van der Laak,[2,3] Paul J. Govaerts,[4] De Wet Swanepoel,[5] David R. Moore,[6,7,8] and Dennis L. Barbour[9]

The global digital transformation enables computational audiology for advanced clinical applications that can reduce the global burden of hearing loss. In this article, we describe emerging hearing-related artificial intelligence applications and argue for their potential to improve access, precision, and efficiency of hearing health care services. Also, we raise awareness of risks that must be addressed to enable a safe digital transformation in audiology. We envision a future where computational audiology is implemented via interoperable systems using shared data and where health care providers adopt expanded roles within a network of distributed expertise. This effort should take place in a health care system where privacy, responsibility of each stakeholder, and patients' safety and autonomy are all guarded by design.

Key words: Artificial intelligence, Big data, Computational audiology, Computational infrastructure, Digital hearing health care, Hearing loss, Machine learning

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INTRODUCTION

The estimated number of individuals suffering from disabling hearing loss has been growing ever since global reporting began (Vos et al. 2016; World Health Organization 2019), with WHO projections reaching 900 million by 2050 (World Health Organization 2019). Besides effects on interpersonal communication, psychosocial well-being, and quality of life, hearing loss has a substantial socioeconomic impact (Olusanya et al. 2014; World Health Organization 2017). Conservative estimates suggest that the overall global annual cost of unaddressed hearing loss is 750 to 790 billion US dollars (World Health Organization 2017). In children, hearing loss restricts language development, often resulting in a lasting effect on social and cultural engagement and unfulfilled educational potential. In adults, hearing loss leads to higher unemployment, missed workdays, and social isolation (Kramer et al. 2006). Hearing loss is further associated with more rapid cognitive decline and increased occurrence of dementia-like symptoms (Livingston et al. 2017). Evidence is growing that timely intervention, including hearing aids, can reduce many of these consequences (Maharani et al. 2018).

[1]Department of Otorhinolaryngology, Donders Institute for Brain, Cognition and Behaviour, Radboud University Medical Center Nijmegen, the Netherlands; [2]Department of Pathology, Radboud University Medical Center Nijmegen, the Netherlands; [3]Center for Medical Image Science and Visualization, Linköping University, Sweden; [4]The Eargroup, Antwerp, Belgium; [5]Department of Speech-Language Pathology and Audiology, University of Pretoria, South Africa; [6]Communication Sciences Research Center, Cincinnati Children's Hospital Medical Center, Cincinnati, Ohio, USA; [7]Department of Otolaryngology, University of Cincinnati, Cincinnati, Ohio, USA; [8]Manchester Centre for Audiology and Deafness, University of Manchester, Manchester, United Kingdom; and [9]Department of Biomedical Engineering. Washington University in St. Louis, St. Louis, Missouri, USA.

The actual problem could be even greater, stressing the need for the computational approaches we introduce below. Mild hearing loss (20 to 34 dB HL), which is two to three times more prevalent than moderate or more severe loss (>35 dB HL), has recently been recognized as an adverse factor in daily life (according to the new GBD 2010 classification on grades of hearing loss; Wilson et al. 2017; Shield 2019). Hearing loss is arguably the most prevalent of all impairments in years lived with disability (Vos et al. 2016) if we include all known pathologies that currently have no clinical consequences for rehabilitation. Examples include slight or minimal hearing loss (15 to 20 dB HL; Moore et al. 2020), extended high-frequency loss (8 to 20 kHz; Motlagh Zadeh et al. 2019), and suprathreshold deficits related to understanding speech in noisy situations (Kollmeier & Kiessling 2018).

Existing audiological services cannot address the global burden of hearing loss due to inherent barriers, including a dearth of trained professionals, equipment costs, and required expertise (Swanepoel & Clark 2019). New approaches that transcend current models of practice are essential to overcome global access challenges. Computational augmentation, enhancing and complementing human capabilities by digital tools (Wilson & Daugherty 2018), is an essential strategy given the lack of enough qualified human experts in ear and hearing care worldwide (World Health Organization 2013), the large number of people suffering from hearing loss that is currently underserved, and the growing complexity of high-quality diagnostics and therapeutics.

Computational approaches are enabled by significant global developments, including growing computational power, data storage, and artificial intelligence; a paradigm shift referred to as the fourth industrial revolution (Schwab 2016). An essential enabler for this digital transformation is the exponential growth in internet connectivity in almost every country, exemplified by the broadband subscription penetration in Africa (currently 81%; Jonsson et al. 2019). Continued growth is expected worldwide as 4G and 5G mobile networks become increasingly available. Another catalyst is the tech companies entering the medical market, applying expertise from algorithms and big data to health problems. There is also a trend towards the "quantified self," which encourages the continuous use of personal tracking devices and stimulates the development of future generations of personal (in-ear) electronics that monitor stress, mental effort, and mental well-being (Crum 2019).

Other clinical disciplines have implemented computational approaches to parts of the clinical care pathway, but this has not yet resulted in a paradigm shift in health care (Rajkomar et al. 2019). To give a few examples, the field of ophthalmology has adopted the use of automated diagnostic data collection hardware (Bizios et al. 2011). Radiology has begun adopting computational image segmentation for automated diagnoses (Hosny et al. 2018). Genotype information is standardized to evaluate patient health and effective cancer treatment (Benson et al. 2012). Also, mobile phones are becoming standard tools in many disciplines, including diabetes management (Thabit & Hovorka 2016) and dermatologic diagnoses (Ashique et al. 2015), among many other applications. These are examples of computational approaches for diagnosis, self-evaluation, and treatment. Unfortunately, all the different components identified have developed across different fields—there is no clear indication that all have been applied to a single field. Therefore, if clinical audiology adopts most of the principles defining computational audiology, it can generally become a standard-bearer for modern clinical care delivery. In this perspective paper, we sketch out how computational approaches may further develop audiology and illustrate fundamental advances in diagnosis, therapy, and rehabilitation that could become essential elements in a comprehensive digital transformation of clinical audiology.

DEFINITION AND EXAMPLES OF COMPUTATIONAL AUDIOLOGY THAT MAY IMPROVE PRECISION

Audiology is an exceptionally strong candidate for computational augmentation and may benefit from the current and novel power of computational science because of its strong mechanistic theory, numerical nature, measurement-driven procedures, and the multitude of clinical decisions to be made. Here, we introduce the term *computational audiology*, which we define as:

COMPUTATIONAL AUDIOLOGY

Computational audiology: the approach to diagnosis, treatment, and rehabilitation in audiology that:

- uses algorithms and data-driven modeling techniques, including machine learning and data mining, to generate diagnostic and therapeutic inferences and to increase knowledge of the auditory system;
- leverages current biological, clinical and behavioral theory and evidence;
- provides or augments actionable expertise for patients and care providers.

The readily quantifiable nature of audiological procedures makes audiology well suited for modern machine learning and data collection techniques. Translational reasons to apply computational techniques in audiology include (i) improved accuracy, increased speed, wider application of (diagnostic) tests and evaluation (applied to, e.g., audiometry; Schlittenlacher et al. 2018b); (ii) objective and consistent interventions, outcomes, and decisions across clinicians and clinics (applied to, e.g., CI fitting; Meeuws et al. 2017). Over time, algorithms can become more sophisticated and take over tasks now performed by humans or take on tasks that are currently not performed due to a lack of resources, time, or clinical consequences, including screening for milder forms of hearing impairment. Computational audiology can improve care by dealing with multifactorial data, including indices of psychosocial well-being, quality of life, comorbidity, and patient-centric, individual descriptors of complaints and symptoms. For example, Palacios et al. (2020) used an unsupervised learning approach to study heterogeneity of patients suffering from tinnitus by analyzing the complaints and symptoms described in an online patient forum. In addition to deterministic methods, it also facilitates the use of probabilistic methods that include uncertainty and likelihood to cope with the wide variability across individuals with hearing loss.

The application of algorithms in audiology is not new. Historically, it has been restricted mainly to cohort-level inference, for example, in understanding the incidence and degree of hearing loss in the general population (Mościcki et al. 1985), and the prescription of sound-amplification for different types and degrees of hearing loss (Byrne & Burwood. 2001). Individual refinement based on learning systems could be a promising way forward but raises many challenges to perform in an evidence-based manner (Barbour 2018).

Diagnostics

In general, diagnostic procedures in audiology consist of a sequence of psychometric and physiologic tests. Clinicians may benefit from computational augmentation because they need to deal with uncertainty, time constraints for testing, and the individual features of the patient. Clinical experts will typically evaluate test results visually and from summary statistics (e.g., average HL), which requires skill and experience but also introduces subjective variability in interpretation, restricts estimates on the certainty of the overall outcome, and impedes more advanced (multifactorial) analysis, which is difficult for humans (Kahneman 2011).

Limited time for testing is arguably the most significant constraint in collecting high-quality multidimensional data for an individual patient. However, machine learning allows, in principle, for flexible, efficient estimation tools that do not require excessive testing time. In an approach known as active learning, new computational tools actively determine which stimuli would be most valuable to deliver in order to converge onto an accurate estimate rapidly. Active learning was recently applied to diagnostic tests including basic audiometry (Schlittenlacher et al. 2018b; Barbour et al. 2019a), determination of the edge frequency of a high-frequency dead region in the cochlea (Schlittenlacher et al. 2018a), and hearing aid personalization (Nielsen et al. 2014). Also, when multiple factors that share some relationship are available, an active learning method can learn and exploit the relationships in real-time. For instance, data from the National Institute for Occupational Safety and Health database (Masterson et al. 2013) has been deployed as Bayesian "prior beliefs" to assess the similarity between ears of 1 million participants. A bilateral audiogram procedure that uses these priors speeds up testing considerably (Barbour et al. 2019b).

Principles of computational audiology may be applied to current research and clinical issues. For example, machine learning approaches to image analyses of otoscopy of the eardrum demonstrate the potential to supplement audiological tests with a diagnosis of potential outer and middle ear pathology (Myburgh et al. 2018; Cha et al. 2019). With a reported accuracy of between 81 and 94% and options for capturing and receiving diagnosis using mobile phone-based otoscopy, these approaches provide direct feedback to the clinician and therefore could allow point-of-care interventions and optimize current care (Myburgh et al. 2018; Cha et al. 2019).

Combining self-reported difficulty and genetic data may lead to potential candidate genes for hearing loss. Such a procedure, applied to the data from 250,000 people, identified 44 new genetic loci potentially associated with hearing loss (Wells et al. 2019). Individual, patient-centric (hearing) health care could become more comprehensive by collecting more extensive hearing profiles combined with other patient characteristics beyond the audiogram (Sanchez Lopez et al. 2018). For example, the genetic profile (Hildebrand et al. 2009) can be used to differentiate better various underlying causes leading to hearing loss (Dubno et al. 2013). A probabilistic interpretation of a patient profile can be further refined using auditory modeling (Verhulst et al. 2018) and AI and, among other applications, form the basis for prognosis. It is paramount to know the underlying pathology to determine a specific target therapy or rehabilitation strategy. By combining these examples, audiology may become a prime example of precision medicine.

Rehabilitation

When fitting cochlear implants or hearing aids, machine learning may help clinicians optimize parameters by minimizing a cost function. A recently developed clinical decision support system calculates a utility function based on a weighted combination of outcome measures (Meeuws et al. 2017). The utility function is continuously updated as the system learns from previous outcomes. The system also incorporates active learning by determining which of the collected outcomes are most clinically useful. Such a system can oversee the effect of considerably more fitting parameters than those commonly adjusted by audiologists. It can be used to make more accurate predictions of the expected outcome, enable cost-benefit evaluation by reducing the time needed by a trained professional to perform tests, and facilitate a more standardized CI fitting (Meeuws et al. 2017). In the future, the system might be extended to individualized cochlear implant surgery based on high-resolution medical images of the cochlea (Heutink et al. 2020). Also, users' preferences can be collected to make data-driven, individual adjustments to their cochlear implant or hearing aid. The internet of things provides suitable interfaces for users to provide feedback under ecologically valid circumstances (e.g., ecological momentary assessments; Wu et al. 2015), but also provides tools that monitor behavior that could serve as a proxy to derive user preferences (Johansen et al. 2018).

Another example of computational approaches to improve rehabilitation is applying neural networks to enhance speech-in-noise understanding in cochlear implant users (Goehring et al. 2019). Noisy speech signals were decomposed into time-frequency units, extracting a set of psychophysically verified features, fed into a neural network to select frequency channels with a higher signal-to-noise ratio. This preprocessing of the input signal significantly increased speech understanding, even of unfamiliar speakers (i.e., not used to train the network). The developers limited the required computational power and memory for their model to make it implementable on mobile devices.

Hearing Research

Machine learning techniques could also lead to better models of human auditory behavior and a better understanding of the auditory system. Recently, Ausili (2019) used a neural network to model experience-dependent sound localization for different hearing impairments. Deep neural networks are achieving parity with humans for some tasks, and it is possible that these networks could mimic aspects of representation and functional organization of the human brain (Güçlü & van Gerven 2017; Huang et al. 2018; Kell & McDermott 2019).

We can conclude that the trend of applying computational approaches in audiology could lead to more individualized hearing care and new services, as illustrated in Example 1. We base this claim on above-cited examples in diagnosis, rehabilitation, and hearing research, and on computational approaches in audiology already employed by digital hearing health technologies around the world (Swanepoel & Hall 2020). A part of these new services could be provided by companies that traditionally did not specifically target customers with hearing loss. For example, speech-to-text apps provide new functionality to people with hearing loss (Pragt et al. 2020), and AirPods Pro are nearing the functionality of hearing aids (Bailey 2020) but do not yet fulfill all FDA requirements and fall short in terms of amplification for the rehabilitation of people with moderate to severe hearing loss.

EXAMPLE 1: REHABILITATION SERVICE*

A person tests her hearing with an app to find out that her hearing profile is similar to that of 1.7 million other people in a global database who reported good results using hearing aids. She buys two hearing aids and signs up for a service, an app that sends programming instructions and settings to the hearing aids and asks for feedback to ascertain audibility and judge sound quality. Indications of momentary and remaining hearing problems, including expressions like "excuse me" or "what did you say?" are detected using automatic speech recognition. After a couple of weeks, the system provides fine-tuning based on her needs and similarity to other cases. It automatically determines that when entering her local subway station, substantial echo cancelation is needed. After a few years, the system detects specific changes in the spectral quality and patterns of sounds when she speaks. After tracking this trend for several months, the system suggests scheduling an appointment with a physician because these changes can correlate with heart disease.

HOW COULD COMPUTATIONAL APPROACHES IMPROVE ACCESS TO HEARING HEALTH CARE?

Hearing health care is challenging to deliver in low- and middle-income countries (LMICs) because it currently requires specialized equipment and trained professionals. Smartphone-mediated telehealth holds great promise to lower many of these barriers (Swanepoel & Clark 2019). Smartphone penetration now exceeds 80% in LMICs (Jonsson et al. 2019), and low-cost equipment and robust test procedures are becoming available to perform audiometric (Potgieter et al. 2018; Swanepoel & Clark 2019) and otologic (Chan et al. 2019) diagnostic measures with acceptable levels of quality and reproducibility. We foresee a

*Based on Crum (2019).

considerable growth in mobile app usage for self-administered hearing tests (Swanepoel et al. 2019; Hazan et al. 2020) and self-adjustment by hearing aid users (Søgaard Jensen et al. 2019) that in turn could lead to self-fitted hearing aids. In the simplest form of telehealth, the caregiver and patient are physically separated, and technology facilitates interaction. However, telehealth can be expanded by distributing expert knowledge across the health care delivery system, with clinical expertise incorporated into algorithms employed on devices used by patients or by local caregivers, making hearing health care possible and affordable in remote and underserved areas where experts are lacking, as illustrated in Example 2.

EXAMPLE 2: HEARING SCREENING IN EARLY CHILDHOOD†

Children in LMICs typically do not have access to hearing screening. However, a community-based project relying on AI assistance offers screening, diagnosis, and referral in underserved communities.

(1) Screening is conducted via an automated pure-tone-screening test facilitated on a smartphone for children from 3 to 4 years.
(2) Test quality is monitored locally on the smartphone and regionally via uploaded data on a cloud-based data management portal.
(3) If a child fails the screening test, an automated report is generated from the cloud-based data management portal and sent to caregivers by text message or email.
(4) If the child fails the screening a second time, automated threshold pure-tone audiometry facilitated by an operator and AI-supported middle ear function assessment is carried out. A clinical decision support system assists local caregivers in diagnosing hearing loss and referring to specialized care.

If screening and diagnosis of hearing loss can be improved in LMICs, the next requirement is to provide specialized care and affordable hearing loss rehabilitation. Global awareness for hearing loss has recently been spurred by the formation of a Lancet Commission examining strategies to reduce the burden of hearing loss (Wilson et al. 2019). Recommendations include stimulating the development of low-cost hearing prostheses, leveraging smartphone technologies for use as hearing assistive devices, and equipping a small number of specialist centers for medical and surgical management of ear disease. Computational audiology as an emerging field is uniquely positioned to combine inexpensive, ubiquitous hardware and software (e.g., smartphones with apps) and sophisticated multifactorial (meta)data modeling. By transforming cheap hardware and equipping it with (AI-based) software, LMICs can benefit from advanced automated diagnostic tools and interventions to address hearing loss. The overall cost of devices and services incurred per user will drop, which is expected to compensate for the resources needed for building and maintaining the computational infrastructure, defined here as all hardware, software, protocols, practices, and regulation needed to apply computational approaches on an international scale (O'Brien 2020). An interesting (but solvable) question is how governments, companies, health care providers, and users will together bear the cost of computational infrastructure, research & development, intellectual property, licenses, devices (e.g., smartphones), and other indirect costs. How to align the involved stakeholders together with the potential risks, privacy issues, and technical requirements are the topics that we consider in the next sections.

†Based on Barbour et al. (2019a), Chan et al. (2019), Swanepoel and Clark (2019).

ETHICAL CONSIDERATIONS AND TECHNICAL REQUIREMENTS CONCERNING COMPUTATIONAL APPROACHES IN HEARING HEALTH CARE

Whereas AI applications in audiology outlined previously should be considered an improvement, they may also involve some additional risks.

Unauthorized or Undesirable Use

For example, AI researchers recently introduced new lipreading technology to facilitate speech understanding in people with a hearing impairment. They trained their algorithm on TV footage, and it outperformed expert lip-readers. This solution could, in theory, allow people with hearing loss to augment their speech understanding (Shillingford et al. 2018). However, the technique could also be used for other purposes, including mass surveillance (Metz 2018). Footage from closed-circuit TV could be fed into the algorithm to track conversations of unknowing citizens, invading their privacy. A similar privacy issue may apply to devices that incorporate tracking technology. The Global Positioning System (GPS) can be used to track a smartphone on a rideshare journey, but it can also track smart hearing aids. Current hearing aids can log users' preferences in particular environments, monitor adjustments users make in each place, log those preferences, use global positioning system to detect when they return to those places, and automatically or manually reactivate the preferred settings (Wolfgang 2019). In courts, tracking the whereabouts of personal devices has already led to erroneous criminal accusations (Valentino-DeVries 2019).

Bias in the Data Used to Train an AI-System

Buolamwini (2017), for example, uncovered large gender and racial biases in face recognition systems sold by tech giants IBM and Microsoft. Errors in gender identification were substantially lower for lighter-skinned men (1% error rate) than darker-skinned women (35% error rate). One explanation was that the face recognition systems were trained on data sets containing many more men with light skin than women with dark skin. This example shows that real-world biases may translate to inherent biases in the outcome of AI systems, whether we are aware of those biases or not. As a result, it might be a risk to apply data collected in, for example, Western countries to solutions for non-Western regions with other ethnic characteristics, including race and lifestyle.

Violation of Privacy

Privacy protection has begun to be taken seriously in recent years, resulting in the EU's General Data Protection Regulation (GDPR; Regulation (EU) 2016/679, 2016). In addition to general privacy issues, one article of the GDPR explicitly states that individuals should not be subjected to a decision based on automatic processing, including profiling, except when explicit consent is given (Goodman & Flaxman 2017). Manufacturers of hearing devices and cochlear implants are already collecting large bodies of data (data profiles) beyond the view of (independent) publicly funded hearing health care providers and researchers. Clinicians use that data for counseling purposes, for instance, to evaluate hearing aid usage based on data-logging (Saunders et al. 2020). However, Mellor et al. (2018) reported that a hearing aid manufacturer did share a large dataset but did not share possibly relevant commercially sensitive information, which may limit insights drawn by researchers from the data. Automatic processing could be problematic with machine learning and big-data designs, even using anonymous data only. When a database uses many types of data from individual subjects, it will increase the likelihood that data can be traced back to individuals (reidentification; Leese 2014; Rocher et al. 2019). Privacy concerns and the sheer amount of data have led to the development of distributed learning, an approach that allows for decentralized training (Konečný et al. 2016). For example, in federated learning, models are trained locally on a local device (e.g., a smartphone connected to a hearing aid; Szatmari et al. 2020), and only aggregate meta-data (updated priors) travel from central databases to users and back.

Restricted Access and Control Over Data

All human stakeholders must have access to relevant information to make the right decision about the diagnosis, treatment, or rehabilitation that affects a patient's health. Data from which relevant information could be extracted is currently scattered across databases residing with different stakeholders (i.e., companies, hospitals, research institutions). The data are collected for distinct purposes and might have a particular status, for example, proprietary or open. In effect, data are vital for so many processes that control over them may lead to a strategic advantage in business, clinical care, or science. Companies might collect data to improve products (proprietary data) or evaluate services, but also because of legal requirements or for quality assurance. It is mandatory for health care professionals to keep a medical record that contains all information needed to provide accountable care according to good clinical practices* (article 454 WGBO; Eijpe 2014). The Health Insurance Portability and Accountability Act (HIPAA) in the United States and GDPR in the EU provide the legislative framework that enables patients and care providers access and control over personal data (Individuals' Right under HIPAA to Access their Health Information 2016; Forrest 2018). An individual can request access to his/her data stored by a health care provider (HIPAA) or any organization (GDPR). Therefore, in theory, it is possible to create a global system that can access patients' health history. In reality, however, appropriate data-exchange practices are lacking, which seriously hampers patients' control over their data. The (re)use of proprietary data can be restricted and is subject to trade secrets, patents, copyrights, or licenses (e.g., see for legal rights governing research data, Carroll 2015; and for property rights, Stepanov 2020). Vested interests, a motivation to influence factors for your benefit, is a considerable barrier to the reuse of proprietary data. Without access to relevant information, patients cannot make informed (shared) decisions. Clinicians will lack insight into decision support systems, regulators will be unable to inspect and audit, and researchers will be unable to appraise outcomes and methods critically.

Liability

For anyone working with new AI paradigms, it needs to be clear who is responsible if anything goes wrong. Is it the scientist who made the algorithm, is it the health care professional, or is it the patient who is ultimately responsible for their own decisions? For example, how can a clinician (or a patient) ascertain that an algorithm's outcome is correct and valid? An explicit example of a potentially invalid test result is an auditory steady-state response exam performed on a restless neonate that results in measurement conditions markedly different from the conditions on which the algorithm was trained (Sininger et al. 2018). The test result may not be accurate, but this shortcoming might not be noticeable to the clinician.

Oversight and regulation (in general for medicine; Maddox et al. 2019) for hearing-related AI also needs to be in place. The level of this oversight will need to be increased in cases of highly autonomous and self-learning clinical decision support systems operating in highly complex environments that have severe consequences for erroneous actions. Furthermore, AI-based clinical decision support systems need to be transparent to inspection and audit, and robust for application in a specified context (in general for health technology; Shuren & Califf 2016).

THE ROLE OF COMPUTATIONAL AUDIOLOGY IN PERSONALIZED HEARING HEALTH CARE

AI, automation, and remote care will become more widespread and better available in the coming years. Redesigning the clinical workflow, implementing AI technology, and changing the clinician's role should become a top priority (Rajkomar et al. 2019). Below we discuss what role clinicians and other stakeholders might play in the digital transition and its meaning for patients. Already, remote care has become more mainstream due to the COVID-19 pandemic that has provided an unprecedented impetus to develop and employ hearing health solutions that reduce physical contact (De Sousa et al. 2020; Swanepoel & Hall 2020). This situation has demonstrated that clinicians can adapt if appropriate benefits are clear (e.g., keeping practice doors open).

Clinicians' Role

Hearing health care professionals, including audiologists, have valuable insights needed to implement these new approaches successfully. For instance, algorithmic bias is reduced if a system is trained in a situation comparable to where it is employed. Therefore, early involvement by hearing care professionals in the design of algorithms could lead to products that better fit the clinical pathway. In a concept mapping study (a structured method to produce a conceptual representation), clinicians from Canada reported that structural training on implementation and best-practices of remote care is needed (Davies-Venn & Glista 2019). Also, the application of AI requires clinicians to have appropriate training to use AI tools and to be aware of their validity and limitations as well

*For the following examples, we chose to apply Dutch law to illustrate a legal framework.

as how to use them. Clinicians should also use their position (e.g., in a professional society) to advocate for necessary user requirements, including transparency and clarity, so that, as professionals, they can take responsibility for actions and decisions supported by those systems.

Not everything valuable in hearing health care is quantifiable and automatable. Machines do not easily replace a clinician in aspects of care based on clinical judgment, soft skills, and the personal touch that help the clinician understand the patient's needs. Clinicians need to see the patient's perspective while offering knowledge, creating realistic expectations, providing rehabilitation, and collecting feedback. They are also the mediators that counsel patients in using remote care options, translating outcomes to individual cases, and interpreting results from AI approaches.

Automation of routine diagnostic procedures might free up clinician time to design more elaborate therapeutic interventions, rehabilitation strategies, or even patient engagement/education initiatives. Technical tasks, including hearing tests and hearing aid fitting, will benefit from best practices for accuracy and efficiency standardized in automated routines. One example could be visual reinforcement audiometry for infants, which currently requires two clinicians to implement: one that conditions the child while the other selects each stimulus and the timing of its delivery. Suppose the stimulus selection is optimized through active learning. In that case, a single clinician could condition the child while also registering responses and selecting the timing of delivery with a handheld remote. The result would be more accurate test results with half the labor, potentially enabling a practice to double its patient throughput. In considering such scenarios, clinician concerns about becoming marginalized in the face of automation deserve consideration. AI technology can eventually standardize best practices of efficiency and effectiveness for all clinicians while preserving the necessary human element of care that only a person can provide. In no way are these ideas intended to take clinicians out of the loop or diminish their contribution. On the contrary, their new ability to reach more patients and provide better care is expected to expand their clinical impact.

Collaboration Among Stakeholders

This article attempts to start the dialogue needed to create a shared vision among stakeholders regarding computational audiology, one of the first steps towards effective collaboration. As examples, one could think of health care decision-making and advocacy groups including health departments; nongovernmental organizations including WHO and patient associations; but also hearing health care professionals including medical doctors and audiologists; device manufacturers, insurance companies, and researchers in audiology. The way to get there could be by stakeholder collaboration, for which Sekhri et al. (2011) provide successful examples within medicine. We regard such collaboration as a necessary step to implement the current advances in computational audiology on a large scale. Besides a shared vision, we also need to think about aligning the interests of stakeholders. By putting patients' interests first and creating the proper incentives (i.e., rewards that encourage people or organizations to do something), we may overcome professional inertia, defined here as the resistance to change. For this to occur, we need to assess and create awareness about vested interests that hamper innovation (e.g., reimbursement policies; Davies-Venn & Glista 2019) and find common ground. By collaboration, then, we can jointly overcome the barriers and all benefit fairly from the forthcoming advances.

An opportunity to further improve diagnostic and therapeutic procedures is to make anonymous data openly available so that algorithms can train on larger populations. All stakeholders involved who collect data should apply privacy guarded-by-design, which requires built-in safety measures to protect patients' privacy (A&L Goodbody 2016). These measures should require all stakeholders to assume responsibility for their specified share within the system. A prerequisite for collaboration is the standardization of clinical procedures and how data is stored and annotated within a computational infrastructure. Only then is pooling of high-quality data possible. The time of small-scale research with small (uniform) samples should be consigned to the past. Here, we may learn from other fields. For example, in neuroimaging and genetics, research groups started a consortium to facilitate data aggregation and sharing on a scale unprecedented in audiology (Bis et al. 2012).

Standardization would help clinicians collect evidence and create independent outcome measures to assess new tools and comparing them with established and validated methods. It also ensures that clinicians are talking about the same thing when operating within a network of distributed expertise. Besides, by enabling interoperability between manufacturers and clinics, clinical procedures can be more readily adopted. Interoperable systems in combination with licenses to protect proprietary data will reduce risk and costs for companies (e.g., missing out on a standard, maintaining a platform, adhering to regulatory requirements). These systems keep the option open to compete and excel, and tackle the problem of vendor lock-in that currently limits freedom of choice for clinics and patients.

What Does Computational Audiology Mean to Patients?

For many people worldwide, access to screening and diagnosis of hearing impairment will improve. The complexity of a patient's hearing problem and his/her self-reliance will determine the required degree of professional guidance. A large group with mild and moderate hearing loss may be helped with relatively simple devices and may even apply forms of self-care. More intensified professional help is needed for more complex fittings or for people who cannot apply self-care (e.g., those with specific comorbidities).

We believe it is still a significant challenge to make self-care by people with hearing loss possible even for those with sufficient autonomy and health literacy, for reasons including lack of trust in the transition and how digital information is presented and exchanged between patients, clinicians, and companies. If information is not clear to the patient, how can he/she act upon it? Clinicians will play an essential role in maintaining patient trust in the transition and adapting to new practices. Hearing health care may evolve to the point where parts of care are organized remotely, for instance, screening of hearing loss, monitoring the status quo, and making adjustments to rehabilitation depending on the patient's situation.

THE FUTURE OF AUDIOLOGY

Modernization of audiology towards greater quality, accessibility, and equity will benefit immensely from the emerging power of computational sciences. We envision a future where patient well-being is promoted by judicious evaluation of data shared between interoperable systems of public or private origin. Health care providers will adopt expanded roles within a network of distributed expertise that continually updates best practices as they are accumulated and quantified. Clinicians will be empowered to reach more patients by offloading decisions about data collection to supportive tools while reserving complex and rare clinical decisions for human experts. In the next decade, we foresee that widely available devices, including smartphones, will catalyze the democratization of audiology and benefit millions of people who suffer from the disabling effects of hearing loss by helping evaluate and treat them with support and guidance from advanced algorithms. For this to happen, we must join forces with experts in computational sciences, agree on global standards and evidence-based procedures, and carefully consider the possible challenges of big data and AI technology.

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Address for correspondence: Jan-Willem A. Wasmann, Department of Otorhinolaryngology, Donders Institute for Brain, Cognition and Behaviour, Radboud University Medical Center Nijmegen, Philips van Leydenlaan 15, P.O. Box 9101, 6500 HB Nijmegen, The Netherlands. E-mail: Jan-Willem.Wasmann@radboudumc.nl

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