Automated and machine learning approaches in diagnostic hearing assessment: a scoping review

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Abstract

Hearing loss affects one in five people worldwide and is estimated to affect one in four by 2050. Treatment relies on accurate diagnosis of hearing loss, but this first step is out of reach for more than 80% of those affected. Increasingly automated digital approaches are being developed for self-administered hearing assessment without professionals' direct involvement. This scoping review provides an overview of automated approaches, based on 56 reports from 2012 until June 2021, adding to the 29 published prior to 2012. Twenty-seven automated approaches were identified. An increasing number of approaches report similar accuracy as manual hearing assessments. Machine learning approaches are more efficient and personal digital devices make assessments more affordable and accessible. Validity can be enhanced by quality surveillance including noise monitoring and detecting inconclusive results. Employed within identified limitations, automated hearing assessments can support task-shifting, self-care, and clinical care pathways.

Introduction

Hearing loss affects 1·5 billion persons globally and is expected to increase by another billion by 2050.^{1,2} Hearing testing is the first step towards appropriate and timely treatment. Unfortunately, most affected persons are unable to access hearing assessments with less than one hearing health professional for every million people in regions such as Africa.^{2,3} Increasingly automated approaches (all aspects of the method associated with automated audiometry), including machine learning, are being developed and made available that provide self-administered hearing assessment without necessitating professionals' direct involvement, enabling health care pathways with the potential to increase accessibility, efficiency and scalability within a network of distributed expertise.⁴ Recent examples of automated hearing assessments include clinical- and consumer-grade applications.⁵ General global health trends suggest that increased availability of diagnostic tools could lower healthcare costs while improving quality of life.⁶ For example, in Parkinson's disease, remote care based on wearables provides ecologically valid methods for monitoring and evaluating symptoms.^{7,8} In tuberculosis screening in low-resource settings, automated diagnosis can increase sensitivity of identifying persons at risk while reducing cost.⁹

Timely detection and treatment of hearing loss is essential to enable optimal outcomes and quality of life across the life course.² Untreated hearing loss restricts language development and educational potential in children and

is associated with more rapid cognitive decline in adults.¹⁰ It may lead to social isolation, lower socioeconomic status, increased social disparities and decreased health, resulting in lower quality of life at the individual level and substantial costs at the community level.^{11,12} Importantly, treating hearing loss in mid-life has been identified as the largest potentially modifiable risk factor for developing dementia in later life.¹³ The global annual cost of untreated hearing loss is \$980 million.¹¹ Global health investment models indicate a significant return of investment both in hearing diagnosis and treatment.² The capacity of the entire clinical pathway should be increased since a bottleneck looms if the accessibility of diagnosis is increased faster than the availability of affordable treatment and rehabilitation.

Automated self-test options are important for detecting and diagnosing hearing loss to direct timely and appropriate treatments. The overwhelming majority of treatments are for permanent age-related and noise-induced hearing loss, but a significant portion of the population requires medical treatment for hearing loss.¹ The onset of COVID-19 has further emphasised the importance of self-test approaches.^{14,15} Automation is a powerful enabler for alternative diagnostic pathways that can include home-based testing, low-touch service models outside traditional clinic settings, and decentralised community-based models that rely on task-shifting to minimally trained facilitators.¹⁶

Automation in hearing assessment is not a new concept and dates back more than seven decades.¹⁷ In recent years, it has resurged with the convergence of digital and machine learning approaches. The primary tool for hearing assessment is pure-tone audiometry which describes the degree of hearing loss relative to normal hearing persons expressed in decibels Hearing Level (dB HL) across specific frequencies (125 - 8000 Hz). Pure-tone audiometry can also differentiate the type of hearing loss, i.e. sensorineural or conductive, when bone conduction and air conduction transducers are used. Machine learning-based threshold seeking approaches, known as Bayesian active learning, have demonstrated their potential to optimise efficiency and increase automated hearing assessments' precision.¹⁸ Increased precision comes naturally since Bayesian active learning provides an estimate of hearing threshold as a continuous function of frequency.^{19,20}

In 2012, a systematic review that included 29 reports on automated audiometry showed that automated procedures have comparable accuracy as manual procedures when performing air conduction audiometry. However, few validated automated procedures that included automated bone conduction audiometry had been

reported, machine learning based audiometry approaches were not reported yet, and approaches were rarely validated in children or hard to test populations.²¹ Since 2012, there has been significant work and innovation in this area, which calls for an update and extension of the previous review. This scoping review aims to provide the current status of automation and machine learning approaches in hearing assessment using pure-tone audiometry with potential indicators of accuracy, reliability and efficiency of these approaches.

Method

We conducted a systematic scoping review of peer-reviewed literature on automated and machine learning approaches to pure-tone threshold audiometry and their accuracy, reliability, and efficiency. This review followed the methodological framework outlined in Arksey & O'Malley.²²

Identifying potentially relevant records

A search across the electronic databases from PubMed, IEEE, and Web of Sciences was conducted to identify relevant reports from peer-reviewed literature. Complementary and redundant search terms were applied to ensure thorough coverage and cross-checking of search findings. In the PubMed database, medical subject headings and relevant keywords were collected to determine all records relating to the study aim. The following synonyms of, and closely related terms to, automated audiometry were used: automatic audiometry, self-administered audiometry, self-assessment audiometry, and user-operated audiometry. The complete set of terms and applied search strategy are provided in the supplemental materials, Table 1. The IEEE database is engineering-oriented, and only relevant keywords based on audiometry were used since it was assumed that any result in audiometry would be highly associated with automated audiometry. The Web of Science database is known to index the PubMed and IEEE databases and was explored using similar search terms as for the PubMed search. After preliminary explorations to identify appropriate keywords, we conducted a search on 8 July 2020 and updated it on 12 January 2021 and 6 July 2021. The search includes all reports that meet the inclusion criteria published from 1 January 2012 until 30 June 2021. The start date was chosen as we regard this scoping review as an extension and generalisation of a previous (systematic) review by Mahomed et al.,²¹ which included studies up to 20 July 2012.

Selecting relevant records

There were three inclusion criteria the reports had to meet; (i) the report had to be about automated or machine learning, pure-tone frequency-specific threshold audiometry; (ii) written in English; (iii) the automated threshold audiometry had to be compared against the gold standard or reasonable standard. The gold standard is defined as manual audiometry in a sound booth according to ISO standards. The automated audiometry also needed to be performed inside a sound booth, and results needed to be compared to the gold standard. A reasonable standard for validation was defined as either a within-subject comparison between the gold standard and automated audiometry in an unconventional setting (for example, a quiet room), or a within-subject comparison between a validated automated audiometry approach and an experimental approach of audiometry in the same unconventional setting.

We excluded reports on screening audiometry (e.g. gave pass/refer as an outcome) rather than threshold audiometry, review papers and studies reporting approaches that were not compared to the gold or reasonable reference standard.

The first phase of the screening was based on title. If the title indicated that content was within the scope of the research question (i.e. automated or machine learning approaches in diagnostic hearing assessment), the report was included into the second screening phase. In the second phase, the remaining reports' abstracts were assessed using the inclusion and exclusion criteria stated above.

Two authors (LP and JWW) conducted the abstract screening. They were blinded from each other to avoid confirmation bias. After the screening, the authors discussed any disagreements to reach an agreement. When in doubt, the report was admitted to the third, full-text review phase. In this phase, all remaining reports were reviewed in full to determine if the inclusion criteria were met. As can be seen in the PRIMSA flow diagram, Figure 1, the resulting selection of reports was complemented by additional reports. After some reports were clustered as having identical approaches (explained under the heading "*Collating approaches, summarising, and reporting the results*"), additional reports were added to avoid missing validation data of these clustered approaches. These reports were published before the inclusion date criteria (from before 1 January 2012) or did not appear in the search and were added based on the reference lists of the already included reports.

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Extracting data items

A template for grading the reports was agreed upon by all authors (supplementary materials, Table 2). Two authors (LP and JWW) independently extracted the information directly relevant to the scoping review question. In cases of disagreement, a consensus was reached after discussion between these two authors. The compulsory data fields were: test frequency and intensity range; response method; test equipment including the type of transducers; calibration; hardware; test quality control; accuracy; validation; and test population. Where available, accuracy was expressed in decibel (dB) using the overall root-mean-square-deviation (RMSD) between the automated approach and the gold (or reasonable) standard or between test and retest. Based on the work by Margolis et al.²³ and the minimum acceptable accuracy recommended by clinical guidelines,²⁴ a RMSD of 6 dB and 10 dB was chosen as criteria for desired and minimal accuracy, respectively. The data collected from the reports provided key information about each report's scope and details, enabling the authors to assess commonalities between the approaches.

Collating approaches, summarising, and reporting the results

When multiple reports described the same underlying approach, these reports were pooled in one approach-cluster. The first report describing an approach and subsequent studies that validated or extended that approach were included. The name of the approach, citations to the initial report and/or common authorships were used to cluster the reports. The grading table was completed for each cluster separately to provide a structure for the subsequent content analysis. In the last part of the grading table, under the heading "validation approach", all validation studies are described together. For every approach-cluster a key contribution for the audiological field was derived from the associated report(s). A key contribution is a finding or claim made by the author(s) significant for the approach in general, stated in either the conclusion or discussion of a report in accordance with their objective.

Results

A total of 64 reports were included in this study. Fifty-six of the 64 reports were included according to the inclusion- and exclusion criteria, and eight reports were added to the approach-clusters. After clustering identical approaches, 27 approach-clusters remained including two that used machine learning. Extracted data items and grading of results on approaches are provided in the supplemental material, Table 3.

Accuracy and Validity of Automated Approaches

Specifications of the reported accuracy and validity are described in Table 1. The accuracy is represented as a comparison against the gold standard and test-retest reliability. Twenty-two approaches were validated on normal-hearing and hearing-impaired people. Four studies were performed using normal-hearing subjects.^{25–27} One approach-cluster was only validated in a hearing-impaired population, using hearing aids as transducers.²⁸ Automated audiometry was applied across a range of populations. All approaches were applied to adults except for Patel et al²⁹ who only included children in their study. Eight approaches were validated in children, including three approaches that designed a child-friendly user-interface.^{29–31} Other test populations were elderly,³² veterans,³³ and persons exposed to occupational noise³⁴ or ototoxic substances.³⁵ Automated audiometry has also been applied as an alternative in low-resource environments for traditional manual audiometry.^{36–38} The user-interface plays an important role in making self-testing feasible in all populations and may require an iterative design process (including clinical pilot-studies).^{37,39}

Table 1. Review of the validation, accuracy, and test population for automated and machine learning audiometry approaches 2012 – 2021.

Validity		Descriptions of clustered approaches
Accuracy	comparison against conventional audiometry	<i>Air conduction (n=23 approach-clusters):</i> 4 RMSD < 6 dB 7 RMSD < 10 dB 9 statistical equivalence 3 no statistical equivalence
		<i>Bone conduction (n=1 approach-cluster)</i> 1 statistical equivalence
		<i>Both air and bone conduction (n=3 approach-clusters)</i> 2 RMSD < 6 dB compared for air-conduction 1 RMSD < 10 dB compared for air-conduction 1 RMSD < 10 dB compared for bone-conduction 2 statistical equivalence for bone-conduction
	Test-retest	<i>Air conduction (n=23 approach-clusters):</i> 4 RMSD < 6 dB 1 RMSD < 10 dB 9 statistical equivalence 9 test-retest not reported
		<i>Bone conduction (n=1 approach-cluster)</i> 1 test-retest not reported
		<i>Both air and bone conduction (n=3 approach-clusters)</i> 1 RMSD < 6 dB compared for air-conduction 2 RMSD < 10 dB compared for air-conduction 1 RMSD < 6 dB for bone-conduction 2 test-retest not reported
Validation (n=64 reports)		49 against the gold standard 14 against the reasonable standard 1 proof of concept
		26 normal hearing

Test population (<i>n</i> =27 approach-clusters):	23 tested hearing impaired
	23 tested adults
	8 tested children

Test parameters and specifications

Tests were all self-administered from the point the test starts. Four approaches had the option to switch to a manual audiometry mode. Table 2 summarises an overview of test parameters and specifications of the 27 approach-clusters, and Table 3 highlights key contributions. Most of the approaches used adaptive procedures that rely on the previous response only (here referred to as partially adaptive procedures). The most common example was the (modified) Hughson-Westlake staircase procedure (*n*=20), which is based on the classical method of limits.⁴⁰ Other partially adaptive procedures applied the method of adjustment, such as the Bekesy tracking method⁴¹ or the ‘coarse-to-fine focus’ algorithm.²⁸ There was a single report of an approach that did not define the threshold seeking method, but had a built in protocol to alternate between ears during testing.⁴² Fully adaptive procedures, in contrast, use the complete set of all previous responses. Examples include Bayesian active learning procedures (also referred to as machine learning audiometry; *n*=2)^{18,20} and maximum likelihood estimation (*n*=2).^{27,43}

Most of the approaches used conventional calibration (20/27) according to ISO-standards. Six approaches used an unconventional calibration technique. Patel et al.²⁹ determined a reference equivalent threshold level (RETSPL) for air conduction for the specific phone-headphone combination using manual audiometry as a reference. Masalski et al.⁴⁴ used reference levels for calibration for smartphone and transducer combinations, collected in uncontrolled conditions in normal-hearing persons. Other calibration techniques were setting the volume of the device to 50%,⁴⁵ comparing and adjusting the output level to the input using a sound level meter^{26,46} or using Thévenin-equivalent probe calibration.⁴¹

Table 2. Review of test parameters and specifications for automated audiometry approaches 2012 – 2021.

Test parameters & specifications	Descriptions of approach clusters (<i>n</i>=27)
Threshold seeking method <i>Underlying algorithm to determine the thresholds</i>	20 (modified) Hughson-Westlake 2 machine learning 1 Bekesy tracking 4 other method
Test range <i>Limits of the frequency and intensity that can be tested</i>	18 full frequency range 125 – 8000 Hz 4 extended high frequencies 125 – 16000 Hz 5 reduced frequency range
	14 Intensity range 0 – 100 dB HL 10 reduced intensity range 3 intensity range not reported
Masking	9 automated masking 1 manual masking

<i>Needed to prevent responses from the non-test ear and obtain the true threshold of the test ear</i>	13 no masking 4 masking not reported
Response method <i>Method of recording subject's responses to test stimuli</i>	9 forced-choice 12 single response 4 forced-choice and single response 2 not reported
Transducers <i>Method of presenting stimuli, e.g. insert phone or supra or circumaural headphone</i>	23 air conduction transducers 3 air- and bone conduction transducers 1 only bone conduction transducer
Calibration <i>Unconventional calibration methods are explained in the text</i>	20 conventional calibration 6 unconventional calibration 1 calibration not reported
Digital devices <i>Reported Hardware needed to run the test.</i>	2 portable audiometer 9 computer-based 1 web-based (requires connectivity) 15 smartphone- or tablet-based
Quality control measures <i>Indicators of the reliability of the test</i>	5 detect false-responses 6 have noise control 7 detect false-responses and have noise control 9 quality control measures not reported

Table 3: key contributions of the automated and machine learning approaches to the audiological field; ^a smartphone-based hearing test application, not yet commercialized; ^b automated hearing test commercialized by hearX™ group.

Approach-Cluster (first author, year, publications, approach name)	Key contribution(s) to the field
Bean et al, 2021 ⁴⁷ OtoKiosk	It has the potential to be used in test environments like exam rooms as a clinical tool for identifying hearing loss via air conduction separating persons with normal and impaired hearing
Chen et al, 2019 ²⁸	A demo smartphone-based hearing self-assessment (SHSA) that runs on a hearing aid which has statistical equivalence to manual audiometry
Colsman et al, 2020 ²⁵	Portable devices that use calibrated headphones result in much higher accuracies than the uncalibrated devices.
Corry et al, 2017 ²⁶	The reliability of audiometer apps should not be assumed. Issues of accuracy and calibration of consumer headphones need to be addressed before such combinations can be used with confidence.
Dewyer et al, 2019 ⁴⁸ Earbone	A proof of concept for smartphone-based bone conduction threshold testing
Foulad et al, 2013 ^{36,46,49} Eartrumpet	An iOS-based software application for automated pure-tone hearing testing without need for additional specialized equipment, yields hearing test results that approach those of conventional audiometry
Jacobs et al, 2012 ^{35,50} Oto-ID	Automated (remote) hearing tests can provide clinicians information for ototoxicity monitoring
Kung et al, 2021 ³¹ Kids Hearing Game	Tablet based audiometry using game-design elements can be used to test and screen for hearing loss in children who may not have adequate access to resources for traditional hearing screening
Liu et al, 2015 ⁵¹	An interactive hearing self-testing system, consisting of a notebook computer, sound card, and insert earphones is a valid, portable and sensitive instrument for hearing thresholds self-assessment
Manganella et al, 2018 ⁴²	If the application detects increased levels of ambient noise, it is programmed to stop the testing.
Margolis et al, 2007 ^{23,52-55} AMTAS	Fits in the clinical care pathway and incorporates a quality assessment method (QUALIND®) that predicts the accuracy of the test

Margolis et al, 2016 ^{33,56,57} Home Hearing Test	It is developed and well suited to provide increased access to hearing testing and support home telehealth programs.
Masalski & Kręćicki, 2013 ^{44,58,59}	This automated method uses smartphone model-specific reference sound levels for calibration in the app. These biological reference sound levels have been collected in uncontrolled conditions in normal-hearing persons.
Meinke et al, 2017 ^{60,61} WHATS	Comparable performance is obtained with a mobile wireless automated hearing-test system in occupational audiometry and obtaining hearing thresholds in diverse test locations without the use of a sound booth
Patel et al, 2021 ²⁹ HearTest^a	A novel subjective test-based approach was used to calibrate a smartphone-earphone combination with respect to the reference audiometer
Poling et al, 2016 ⁴¹	Specific tracking patterns are identifiable in subjects who experienced difficulty converging to a reliable threshold. This behavioral information can be used to develop algorithms that detect loss of engagement or lack of attention and create a warning system to draw the listener back to the task.
Schlittenlacher et al, 2018 ²⁰	Bayesian active-learning methods provide an accurate estimate of hearing thresholds in a continuous range of frequencies
Schmidt et al, 2014 ⁴³	A user-operated two-alternative forced-choice in combination with the method of maximum likelihood does not require specific operating skills and the repeatability is acceptable and similar to conventional audiometry
Song et al, 2015 ^{18,62–64} MLAG	Bayesian active-learning method determines the most informative next tone leading to fast audiogram procedure and threshold estimation in a continuous range of frequencies with potential to measure additional variables efficiently.
Sun et al, 2019 ⁶⁵	Active noise control technology to measure outside the sound booth
Swanepoel et al, 2010 ^{32,38,66–71} KUDUwave	An automated portable diagnostic audiometer using improved passive attenuation and real-time environmental noise monitoring making audiometry possible in unconventional settings
Swanepoel et al, 2014 ^{37,39,72–77} HearTest^b	A smartphone-based automated hearing test applicable in low resource environments
Szudek et al, 2012 ^{45,78,79} Uhear	uHear is applicable in the initial evaluation of patients with sudden sensorineural hearing loss before a standard audiogram is available
Van Tasell & Folkeard, 2013 ⁸⁰	Method of adjustment and the Hughson-Westlake method embedded in automated audiometry can be considered equivalent in accuracy to conventional audiometry
Vinay et al, 2014 ^{27,34} NEWT	The New Early Warning Test (NEWT), which is incorporated inside an active communication earplug, serves as a reliable and efficient method to measure auditory thresholds, especially in the presence of high background noise
Whitton et al, 2016 ⁸¹	This study provides a proof of concept that several self-administered, automated hearing measurements at home are statistically equivalent to conventional audiometry in the clinic.
Yeung et al, 2015 ^{30,82–86} Shoebbox	A method for threshold hearing assessments outside conventional sound booths and with an interface suitable for children.

Test efficiency

No standard measure expressing test efficiency was reported across studies. The two machine learning approaches reported lower bounds of the test efficiency by comparing the number of required trials for the manual gold standard method and the machine learning method. Machine learning methods converged to a 5 dB precision for unmasked air conduction audiograms within 18 to 28 trials for one side²⁰ or 19 to 44 trials bilaterally.⁶³ The gold standard method required 93 to 114 trials on average, depending on the hearing loss configuration.⁶³ Heisey et al.⁶³ also expressed the efficiency gains by comparing the total overall test time of 2·1 to 4·8 minutes for bilateral air conduction audiometry using the machine learning based procedure versus 6·9 to 9·9 minutes using the gold standard procedure. The two maximum likelihood approaches reported test time per

ear²⁷ or per frequency.⁴³ Vinay et al.²⁷ reported an average test time of 3·0 minutes for bilateral air conduction audiometry in 2 dB steps on an unconventional number of frequencies (1, 3, 4, 6 kHz) using a method based on maximum likelihood versus 5·5 minutes measured manually. However, this was achieved in normal-hearing persons for the purpose of monitoring occupational hearing health. Schmidt et al.⁴³ aimed for high accuracy and reliability at the expense of efficiency, which is for example reflected in the requirement to have at least 30 responses before terminating the test and their use of a forced choice paradigm. They reported a test time of 2·2 minutes per frequency that could be reduced to 1·0 minute if only thresholds above 10 dB HL are relevant.

Discussion

In 2012 evidence for automated audiometry demonstrated similar reliability and accuracy as manual audiometry across limited reports especially for children and using bone conduction.²¹ In less than a decade, twenty-two novel approaches and developments across five existing approaches have appeared in 56 publications. Promising new developments include machine learning techniques for more efficient hearing assessment (n=2), use of tablets or smartphones as audiometer interface (n=15), and child-friendly user-interfaces (n=3) including game-design elements. The number of approaches that include bone conduction is still limited (n=4), only two more than already existed in 2012.²¹

Accuracy

The required accuracy, reliability, and efficiency depend on the clinical aims and consequences. The ultimate aim for automated hearing assessment is to deliver clinical actionable estimates of hearing status (i.e. the clinician or patient acts appropriately for treatment given the diagnostic test results). In fully adaptive procedures, the level of precision and confidence needed to conclude the assessment can be set to any level by choosing the proper termination criteria, resulting in different trade-offs. Schmidt et al.,⁴³ for instance, aimed for high accuracy and reliability, whereas Heisey et al.⁶³ aimed for high efficiency. Overall, several different measures were used to demonstrate accuracy across the identified reports. In our view, RMSD is the preferred indicator for accuracy with proven clinical relevance assuming, it has already been demonstrated that there is no bias between the automated and manually determined hearing thresholds (e.g. signed differences). In traditional clinical terms, automation is equal in accuracy to manual audiometry if the difference is within 6 dB RMSD. Six

of the twenty-seven automated approaches meet this strict accuracy criterion. For many applications, however, the less strict 10 dB RMSD criterium is sufficient, which is achieved by seven additional automated approaches.

For bone conduction measurements, the accuracy is inherently lower than air conduction measurements due to conductor placement.²³ However, this accuracy is typically sufficient to address the clinical question of whether conductive/mixed hearing loss is present and to choose and evaluate appropriate treatment. The feasibility of bone conduction assessments outside of a clinical setting (sound booth) remains difficult. Alternatively, this clinical question can be addressed with other tests, including tympanometry, otoscopy, or a combination of air conduction thresholds for tone and speech stimuli.⁸⁷ At least 13 automated techniques have accuracy comparable to traditional manual air conduction audiometry as expressed in RMSD. Eighteen of the twenty-seven approaches did not report on test-retest accuracy or used a measure of statistical equivalence that does not allow us to assess the accuracy.

One limit to the impact of achieved test accuracy is the high variation in the interpretation of audiograms by clinicians, regardless if those audiograms are determined using an automated or manual approach.⁸⁸ Automation can assist clinicians and patients to interpret the measurement by data-driven automated reporting of accuracy and reliability (including signalling for suspicious outcomes) such as QUALIND^{®53} or by automated classification for diagnostic purposes (including type and degree of hearing loss). Examples of automated classification include AMCLASS,⁸⁹ Autoaudio,⁹⁰ and data-driven audiogram classification.⁹¹

Reliability

Reliability is based on representative validation, which means that the approach is demonstrated in the prospective population in an operational environment. Twenty-three approaches have been validated in a hearing-impaired population and eight studies tested in children. Other examples of validation in hard-to-test populations were not found. Further advances in automated audiometry that increase reliability included procedures to identify invalid responses (n=5), monitoring environmental noise (n=6), and do both (n=7) to warn for invalid test conditions, making these tests applicable in more populations and environments. The digital devices, including smartphones and tablets, lend themselves to quality control measures for increased reliability with the host of integrated sensors

Efficiency

A fair indicator of efficiency is the overall time required to conduct a test. Most approaches (n=20) use the modified Hughson-Westlake procedure, which would have a similar test duration as manual audiometry. Maximum likelihood procedures demonstrated a 45% reduction in test time in normal hearing persons.²⁷ Machine learning based automated procedures have demonstrated a 70% reduction in test time compared to manual audiometry for air conduction audiograms both in normal and hearing impaired persons.⁶³ No machine learning approaches have incorporated bone conduction yet. Therefore, efficiency gains compared to full audiogram procedures are not available but are expected to yield similar efficiency gains. Another indicator for test efficiency is the number of stimuli required to reach the desired accuracy. This indicator is helpful to optimise the threshold seeking part of the approach. Reporting the equivalent time gains is recommended since this can be readily compared to other efficiency gains, including the reduced travelling time if a visit to the outpatient clinic can be replaced for an at-home test, or time savings by automating other parts of the clinical care pathway such as interpretation of the outcome.

Future developments required

To get an overall indicator of the technical maturity of an approach, developers are encouraged to use the technology readiness level (TRL) to report the development phase of a technology. Technology readiness levels were initially developed in aerospace to estimate the maturity of technology from basic concept to flight-proven product.⁹² To apply the TRL to automated audiometry would require an adjustment of the definition of TRL by the European Union to fit the hearing healthcare sector better. For those approaches that are ready for operational use, certification (e.g. CE and FDA) can further stimulate clinical adoption and iterative improvements based on clinical feedback. In addition, standards and consensus on what meta-data are needed in health applications to describe the test conditions and facilitate interpretation are currently missing.

Limitations

This scoping review included peer-reviewed reports taken from widely used and recognised scientific databases. A potential limitation is that some of the commercialised automated approaches may have been developed without peer-reviewed reports. Some automated approaches could therefore be more mature than reported.

There is no gold standard for reporting audiometry validation studies, which limits a consistent comparison among approaches. Lastly, automated procedures may well be embraced by early adopters first, which could lead to projections on suitability that are overly optimistic for users with poorer digital proficiency.

Conclusion and recommendations

Since 2012 an increasing number of automated audiometry approaches have similar accuracy and validity as conventional manual audiometry. New developments offer features, versatility, and cost-effectiveness beyond manual audiometry. Fully adaptive procedures, including machine learning techniques, seek hearing thresholds more efficiently. Inexpensive devices such as smartphones can be turned into audiometers, increasing accessibility and availability. Higher reliability is achievable by signalling invalid test conditions, and child-friendly user-interfaces offer a solution to the hard to test population. These approaches can be implemented in the clinical care pathway, remote hearing healthcare, community-based services, and occupational healthcare to address the global need for accessible hearing loss diagnosis.

For successful adoption, standardised measures of accuracy, reliability and efficiency are needed for comparative purposes (including certification) and to gain the trust of prospective users. Further reliability can be achieved by determining which difficult to test populations may not be appropriate for automated testing and how to detect and then triage these patients to specialised centres. More user-friendly and failsafe procedures that include remote surveillance and quality control can support automated hearing assessment at-scale in specific populations and in concert with diagnostic assessments in other medical domains. Further contextual information, e.g. standardised meta-data, is needed to help clinicians interpret test outcomes' context and limitations. If researchers and clinicians deal carefully with its limitations, automated hearing assessments can be designed such that it forms an effective part of service delivery for many people who have or are at risk of hearing loss. Automated audiometry can be part of existing care pathways but also enable new service models, including task-shifting to community health workers delivering decentralized care and over-the counter or direct-to-consumer hearing aid dispensing.

Authors' contributions

LP and JWW made equal contributions and share first authorship. LP, JWW and DWS conceptualised the study.

LP and JWW conducted the abstract screening. LP and JWW independently extracted the information directly relevant to the scoping review question. All authors contributed to the data interpretation. LP and JWW took the lead in drafting the manuscript. RHE and DWS provided supervision, reviewed the results, and edited the manuscript.

Declaration of interests

DWS has a relationship with the hearX™ Group (Pty) Ltd, which includes equity, consulting, and potential royalties. DWS holds a patent for Smartphone based audiometry, as inventor.

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