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Ambient assisted living technologies to support older adults' health and wellness: a systematic mapping review

M.-A. CHOUKOU[1,2,3], A. POLYVYANA[1], Y. SAKAMOTO[4], A. OSTERREICHER[5]

[1]Department of Occupational Therapy, College of Rehabilitation Sciences, University of Manitoba, Winnipeg (MB), Canada
[2]Riverview Health Centre, Winnipeg (MB), Canada
[3]Centre on Aging, University of Manitoba, Winnipeg (MB), Canada
[4]Department of Computer Science, Faculty of Science, University of Manitoba, Winnipeg (MB), Canada
[5]Neil John Maclean Health Sciences Library, University of Manitoba, Winnipeg (MB), Canada

Abstract. – While the proportion of the Older Adults (OAs) population is growing, this shift raises a challenging question: "How can we support OAs to lead independent and healthy lifestyle?". Many researchers have been studying Ambient Assisted Living Technologies (or AALTs) over the last three decades to tackle this challenge. However, no literature can provide an overall view of research in the field of AALTs and linkages between technical development and related healthcare needs. Thus, we conducted a systematic mapping review of literature focusing on AALTs (N = 7006) to explore three main research questions: 1) When, where, and how AALTs are studied?; 2) What is the technological maturity level of AALTs used to support a health and wellness, and where were they evaluated and/or implemented?; and 3) To which health and wellness purposes are AALTs deployed? We found several noticeable imbalances in literature and identified some strategies to move this field of investigation further and to bring AALTs applications closer to clinical practice. While research in the area is gradually blossoming, the area mainly leads in only a few countries. Furthermore, the majority of research targeted asymptomatic older adults living at home. We hope this paper will help researchers easily understand what type of research, with whom, and where are available in AALT now. Potential challenges associated with AALTs research are also discussed.

Key Words:
Aging, Technology, Digital health, Telemonitoring, Telerehabilitation, Telemedicine.

Introduction

As the mean age of the population increases due to longer life expectancy, healthcare systems are challenged by the rising number of older adults (OAs) requiring services to maintain at-home independence[1-3]. For example, according to a report released by Statistics Canada in September of 2019, the number of OAs aged 80 and older is expected to triple by 2068. This sizeable demographic shift will have wide-reaching effects on society, including increases in healthcare strain[2,3]. Effective strategies are thus needed to promote aging in place. Currently, OAs are aging in place with the help of assisted living, supportive housing, and home care solutions. Technology is a complementary solution to promote aging in place[4]. Over the last few decades, emerging technologies, such as the internet of things (IoT), artificial intelligence (AI), sensors, cloud computing, wireless communication technologies, and assistive robotics have promoted the development of various ambient or active assisted living approaches for supporting OAs to live independently and safely in their environment. These technologies further encourage OAs to participate in the activities of their choice within their community, thus supporting them to maintain their physical and mental health and enhancing their quality of life.

AALT could be defined as "technological solutions that enable the OAs to maintain their independence for a longer time than would otherwise be the case"[5]. AALTs consist of a "set of ubiquitous technologies … embedded in the living space of the patient to monitor and react to his contextual needs by providing computerized assistive services"[6]. As a result of automatic detection, AALTs can send alerts without being activated by the end-users, such as caregivers or

Corresponding Author: Mohamed-Amine Choukou, MD; e-mail: amine.choukou@umanitoba.ca

local emergency communication centers[7]. In addition, AALT provides an opportunity to monitor energy consumption and appliances in the home[8]. For example, if the stove has not been turned off physically by the user after some time has passed, an actuator switch can automatically turn it off instead, ensuring safety, efficiency, and comfort for the user and their family[8].

Although there is a plethora of AALTs documented in the literature, exploring older adults' health and wellness remains understudied from end users' and real-life conditions perspectives[7]. There are numerous scoping reviews exploring AALTs from the technological performance[9-17] and user research[4,7,11,12,18] perspectives. However, there are important questions about the clinical utility of AALTs that remain unanswered. Also, literature focusing on AALTs clinical relevance or user perspectives is sparse and hard to identify. Sensor research seems to lack *in-situ* implementation, and most of the research focuses on validating AALTs in laboratory settings when testing with persons with specific health conditions[7,19-22]. Therefore, there is a need for a clear map of AALTs deployed successfully in meaningful health applications to guide further explorations. It is perceived that deploying AALTs in naturalistic settings (e.g., home setting) presents some implementation challenges, mainly due to potential risks associated with the vulnerability of the targeted population (OAs) including, for example, user and family acceptance, cost, insurability, technical challenges, as well as social desirability. This may explain why the actual application of research-based AALTs to the daily care of OAs is still challenging; the lack of user perspective in research raises questions about the usability of these technologies for home-care. Indeed, there is a gap in AALTs research between the end users' wants and needs (e.g., engineers, researchers' perspectives of what needs to be implemented) in terms of health and wellness. The latter is in fact multifaceted. OAs may suffer from various physical, cognitive, and even social problems due to processes occurring in aging[13]. These often include impairment of physical functions (e.g., decreased mobility and walking speed, falls, frailty, difficulties in basic and instrumental activities of daily living) leading to poor quality of life, and even decline of cognitive functions (e.g., memory-related issues, decrease in sensory functioning, hearing loss, cataracts and refractive errors, presbyopia, decreased vestibular function, increased agitation, apathy, and social isolation)[23]. From time to time, these difficulties in turn lead them to behavioral disturbances and poor social participation. To move AALT research forward, there is a need to review the existing literature on AALT for OAs with a focus on health and wellness applications. Therefore, this study aims to provide an exhaustive overview of the field of AALT from health and wellness perspectives by mapping the purposes and functions of AALT as well as the targeted settings and user profiles.

Materials and Methods

Design: Systematic Mapping Study

This study follows the process of conducting a systematic mapping study described by Petersen et al[24] (Figure 1).

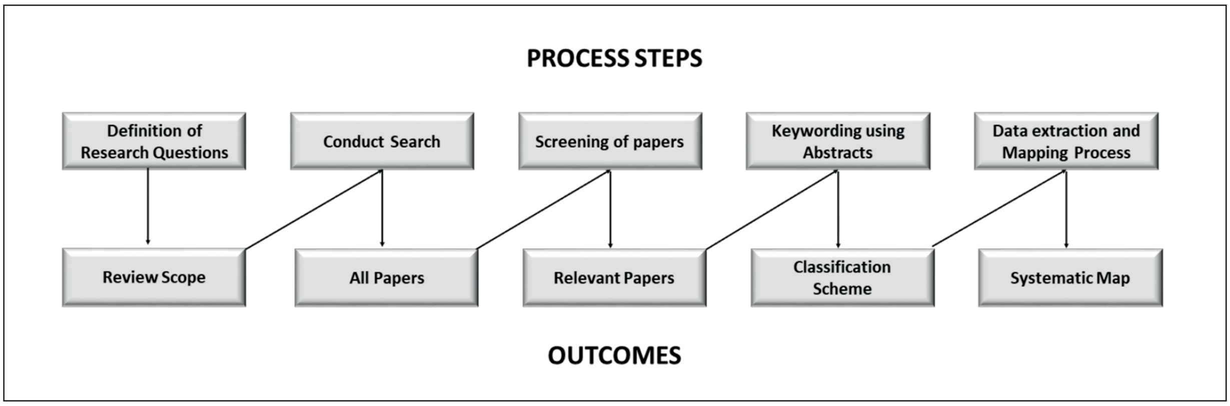

Figure 1. The systematic mapping process [Petersen et al (24)].

Research Questions

RQ1: When, where, and how AALTs are studied?
RQ2: What is the technological maturity level of AALTs used to support health and wellness and where were they evaluated and/or implemented?
RQ3: To which health and wellness purposes are AALTs deployed?

Search Strategy

A search strategy has been developed to find published literature following the Arksay and O'Malley framework for scoping studies[25]. A literature search was conducted in CINAHL (EBSCOhost), MEDLINE (OVID), and EI Engineering Village to harvest terminology. At this stage, text words in the title and abstract of retrieved articles and the index terms assigned to the articles were extracted and analyzed. A second round of comprehensive searching was performed in each of the following databases using the relevant text words and index terms: EMBASE (Ovid), MEDLINE (Ovid), CINAHL (EBSCOhost), and Web of Science. Engineering and computer databases were excluded as this review focuses on health outcomes when using non-wearable technology targeting the activities of daily living. The search included English and French articles, and it is not limited by years. A final search for additional studies was done by examining the reference lists of all literature meeting the inclusion criteria of this review. A full search strategy for EMBASE (Ovid) is included in **Appendix 1**.

Screening of Articles

Two independent reviewers performed the literature selection. Each paper was included only when the reviewers agreed on the inclusion. A third reviewer was consulted when consensus could not be reached between the two reviewers. To be included, the articles had to be written in English or French and present original results (qualitative or quantitative empirical data) related to the use of AALT. In this paper, we narrowly focused on AALTs, but not wearable devices nor mHealth. We made this distinction based on the fact that mHealth generally requires other available technologies on the market: Current mHealth relies on a sensorized device to collect data (i.e., commonly requires wearables). To the best of our knowledge, AALTs have not yet been deployed in mHealth applications. Thus, exceptions were made to the solutions involving AALTs that are paired with wearables. The articles had to include health-related outcomes evaluated with the use of ambient sensors. Articles including functional combinations of ambient technologies and wearables were included, whereas articles focusing on solely wearable technologies were excluded. Additionally, papers also had to be focused on OA and AALT(s) to support independent functioning and improved safety in the home or in a similar environment. Search results reporting technical papers, guidelines, literature reviews, and opinion papers were excluded.

Study Selection Process

Seven thousand six (7006) entries were identified (Figure 2). After the removal of the duplicates, 7005 entries remained. Based on the titles/abstract screening, 683 full-text articles were selected for further eligibility assessment. As detailed in Figure 2, 450 articles were excluded from the analysis, and a total of 233 studies was included in this systematic mapping review.

Data Extraction and Data Analysis

Two reviewers extracted the data independently, and a third reviewer revised the information extracted by both and adjusted and/or completed extraction if needed. This set of data allowed us to identify the location and year of publication of the included articles. Data about AALTs and their functions, status of development, context of use, and focus population for the study were gathered, charted, and underwent thematic analysis. The mapping process followed several iterations until consensus was reached among team members.

Results

This section includes the findings related to each of the three research questions, followed by a discussion.

When, Where, and How AALTs Are Studied? (RQ1)

Figure 3 shows the frequency of publications between 1993 and 2020. Articles were rare before 2006; only 7 over 13 years, and then, emerged at a frequency of ~15 articles per year over the next 15 years (Figure 3). While the development of AALTs has emerged after the 2000s and the advancement of information and communications technology e.g.,[27], interest in developing AALTs

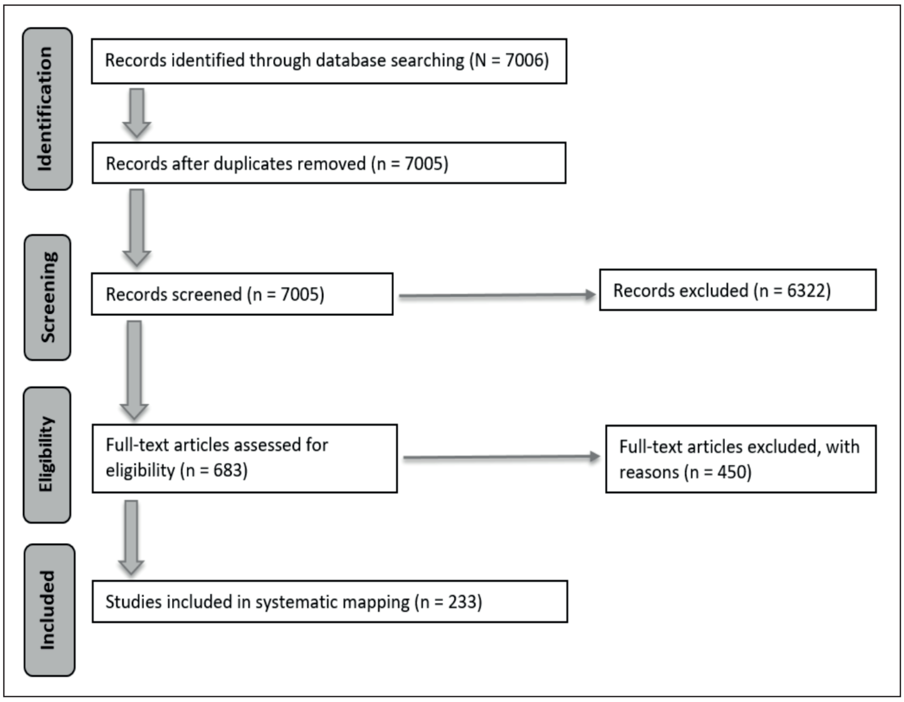

Figure 2. Literature selection process (26).

for health purposes has intensified around 2006. More than 80% of the literature included in this systematic mapping study is published between 2010 and 2020. Based on the trend, we predict more research will be conducted in this area and the advancement in AALT.

While included articles were published in 40 countries, approximately half of them (48.6%)

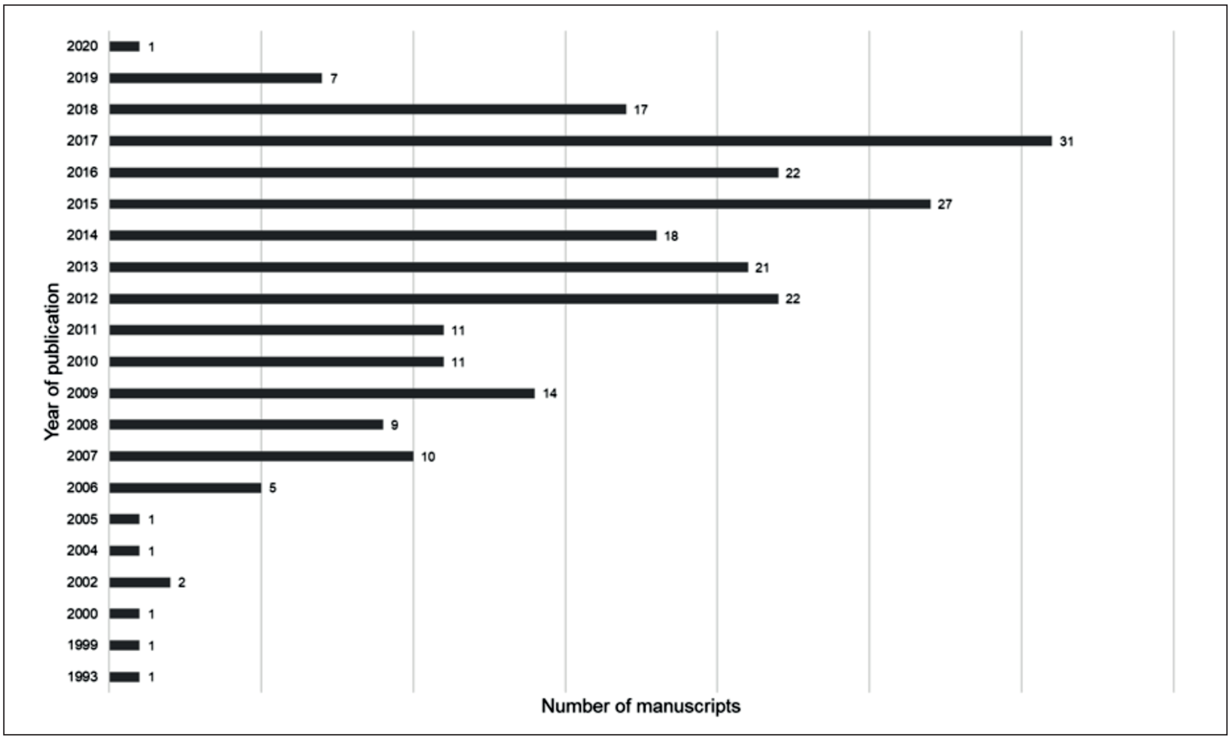

Figure 3. Frequency of publication by year.

originated in only 5 countries: United States of America (18%), United Kingdom (9.4%), and France (8.2%) followed by Japan and Canada (6.4%, each) (Figure 4). Overall, the development of AALTs seems related to the prevalence of aging in these countries. Interestingly, these five countries have a relatively lower fertility rate (M = 1.7 per woman while the world average was 2.415 in 2018) and higher life expectancy (M = 81 while the world average was approximately 73)[28]. These factors could have potentially, at least partly, contributed to the higher frequency of identified papers (i.e., ageing and AALT are highly relevant in these countries)[29]. If this is indeed the case, considering how the average fertility rate continues to drop, we might see more research in this area. Countries ranking high in Figure 4 have a quite high prevalence of aging and are more likely to drive technology development initiatives than low-ranking countries.

Most of the articles reported findings from quantitative studies (91.8%), with only a few being qualitative (7.3%) or mixed design (12.5%). The majority of the papers were peer-reviewed journal articles (58.4%) and conference papers (38.6%). 3% of the papers were book chapters. Overall, the papers included in this systematic mapping study are published by technology developers and researchers, making it plausible to think that they tend to use quantitative methodologies. While qualitative methods are not widely used among these authors, it is highly recommended to involve qualitative methods and mixed methods in research on AALTs. The use of quantitative methods is understandable considering how quantitative data could be more readily collected from many participants. In contrast, qualitative data requires more time and intensive data collection steps and data coding process (usually by more than two coders). However, to capture OAs' attitudes and perceptions regarding AALTs entirely, it is necessary that we explore qualitative data as well.

What is the Technological Maturity Level of AALTs Used to Support Health and Wellness, and Where Were

They Evaluated and/or Implemented? (RQ2).

Most of the AALTs retrieved in the literature focused on prototyping (95%, 411 occurrences). Only a few solutions were commercialized (4.4%, 19 occurrences).

AALTs were evaluated in seven different settings: more than half were evaluated in home

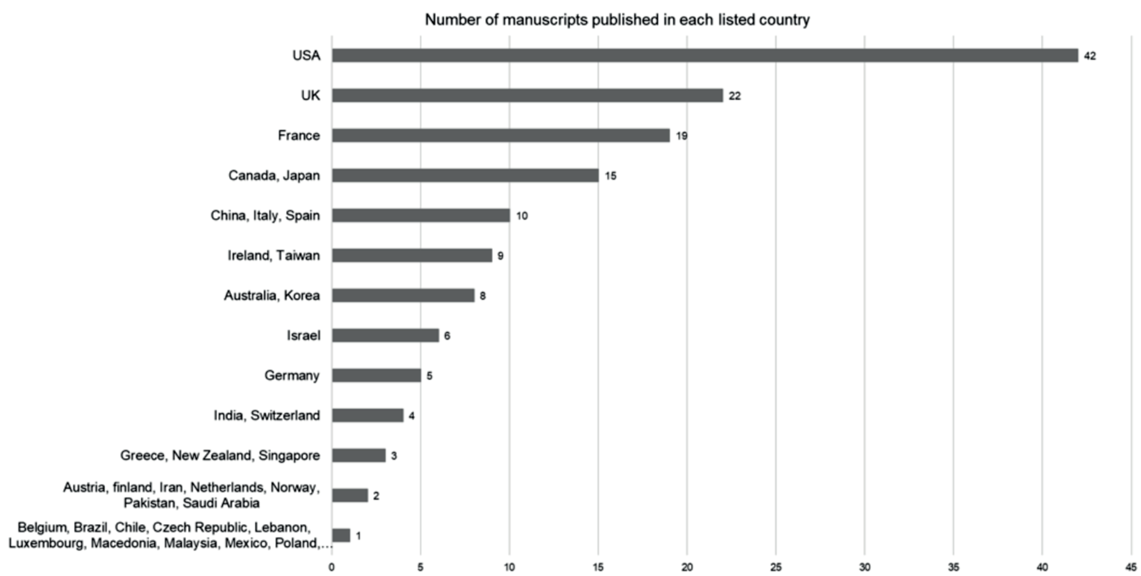

Figure 4. Country of origin.

settings (57.2% occurrences), followed by smart homes (27.6%), nursing homes (7.7%), hospitals (5.8%), public spaces (1.3%), and smart hospitals and smart offices (0.2% each).

A very small number of AALTs is tested in more than one environment. The range of locations where AALTs were tested varies from one to four:

- **Single location** (93%): "home", "smart home", "nursing home", "hospital" or "public spaces"
- **Two locations** (6%): "home and nursing home", "home and hospital", "home and smart home", "home and public space", "hospital and nursing home', "hospital and smart home", "smart home and smart office", or "smart home and smart hospital",
- **Three locations** (0.5%): "home, nursing home, and hospital"
- **Four locations** (0.5%): "home, hospital, nursing home, and public spaces".

AALTs were tested with targeted OAs (i.e., OAs with a specific condition) in 81.9% of cases (352 occurrences) and were tested with non-targeted users in 27.4% of the cases (118 occurrences). The manuscripts generally evaluated AALTs based on a range of characteristics except for one paper that related to more than one AALT. Thus, we used the number of occurrences as the counting method to determine the number of total evaluations for each AALT. Figure 5 shows the breakdown of health conditions or OA profiles on a logarithmic scale. Asymptomatic participants represented 74.9% of occurrences. OAs with dementia represented 12.1% of occurrences. The rest of the profiles were sparse and represented 13.2% of occurrences altogether.

To Which Health and Wellness Purposes Are AALTs Deployed? (RQ3)

Table I was created to guide researchers in their literature review. It summarizes the purposes and the functions of the AALTs, ranked by many occurrences. Twelve clinical purposes (see Purpose of ambient sensing in Table I[29-253]) have been identified primary, functions were classified based on the primary purpose of the study. Routine action monitoring was the most frequently focused clinical purpose with 42.7% of the occurrences with quite diverse (16 unique) functions:

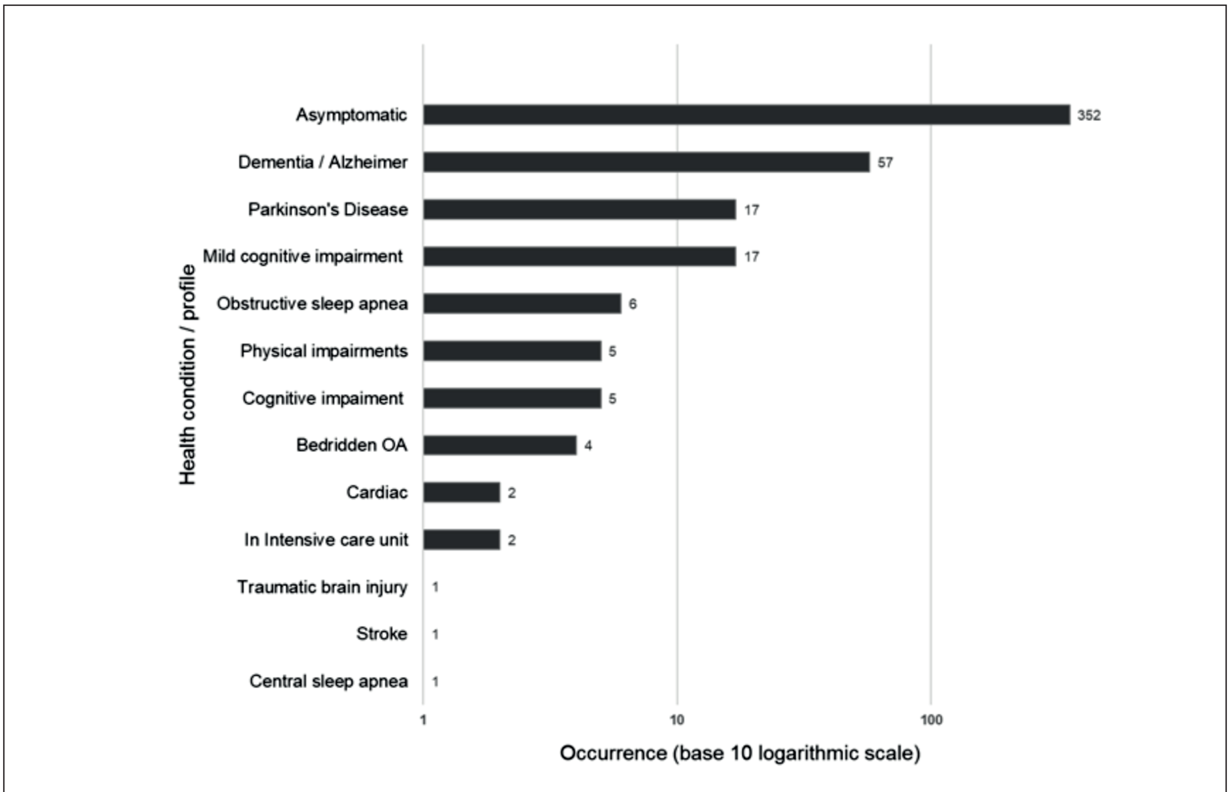

Figure 5. Breakdown of health condition/profile of the AALT users.

Table I. Purposes and health-related functions of ambient sensing solutions.

Purpose of ambient sensing (occurrences in %)	Function of the ambient sensors	Number of occurrences	References
Routine action monitoring (42.7%)	ADL	84	(6, 18, 73)
	Activity monitoring	46	(6, 34, 39, 41, 63, 74-105)
	Movement monitoring	34	(41, 47, 68, 70-72, 92, 94, 106-128)
	Posture analysis	7	(119, 129-134)
	Functional health monitoring	5	(135, 136)
	Multiple residents movement monitoring	4	(58, 137-139)
	Medication adherence monitoring	4	(47, 92)
	Food and drink intake monitoring	3	(92, 122, 140)
	Stand up notification	2	(141)
	Restlessness prediction	2	(142)
	Fainting prediction	2	(142)
	Running away prediction	2	(142)
	Phone use	1	(39)
	TV use	1	(143)
	Security monitoring	1	(144)
	Drowning prevention	1	(122)
Fall detection (13.7%)	Fall detection	64	(6, 40, 70, 76, 77, 85, 103-105, 107, 109, 115, 127-129, 132, 139, 142, 145-183)
Physiological parameters tracking (8.6%)	Breathing monitoring	17	(106, 122, 123, 130, 167, 184-194)
	Heart rate monitoring	12	(121, 130, 189, 192-197)
	Weight measurement	4	(77, 121, 194, 195)
	Body temperature	2	(77, 198)
	Excretion weight	2	(194, 195)
	Blood pressure measurement	1	(194)
	Nerve activity monitoring	1	(196)
	Urination speed	1	(194)
Presence detection (7.7%)	Presence detection	15	(34, 41, 42, 89, 95, 105, 141, 199, 200)
	Exiting/entering	15	(32, 33, 70, 72, 79, 94, 95, 113, 116, 117, 122, 125, 127, 141, 201)
	Identifying individuals	5	(139, 202-205)
	Speech recognition	1	(151)
Gait analysis (6%)	Gait analysis	28	(36, 79, 206-219)
Assessment of environment (6%)	Temperature	12	(39, 41, 63, 68, 71, 72, 87, 94, 121, 122, 124)
	Humidity	6	(41, 122, 124, 134, 220, 221)
	Light	4	(41, 42, 71, 94, 220)
	Brightness	2	(71, 220)
	Levels of CO_2	2	(121, 122)
	Well being	1	(128)
	Pressure	1	(122)
Sleep monitoring (5.8%)	Sleep monitoring	27	(114, 121, 130, 134, 194, 222-238)
Estimation of level of activity (4.3%)	Emergency detection	15	(36, 51, 77, 95, 134, 239-242)
	Detecting abnormal behaviors	3	(243, 243)
	Behaviour change tracking	2	(42)
Routine support (1.7%)	ADL support	8	(95, 127, 245-248)
Gesture recognition (1.5%)	Gesture recognition	4	(123, 132, 249, 250)
	Hand tremor sensing	3	(123, 167, 250)
Indoor localization (1.5%)	Localization	6	(58, 70, 199, 251-253)
	Visitor tracking	1	(79)
Wandering study (.4%)	Wandering	2	(6)

activity of daily living (ADL) was the most common function in the category (42.2% of the occurrences). Many papers focused on this purpose presumably because many of the functions associated with this purpose (e.g., ADL) allow family and the caregivers of OAs to monitor the OAs' routine behaviors before any serious issues arise. In this regard, these technologies could be seen as one of the "first phase" technologies, followed by more specific and/or crucial purposes (e.g., fall detection, breathing monitoring, and so on).

Discussion

Three research questions were explored to understand the general research trends in the field of AALTs: (RQ1 – When, where, and how AALTs are studied? RQ2 – What is the technological maturity level of AALTs used to support health and wellness, and where were they evaluated and/or implemented?; RQ3 – To which health and wellness purposes are AALTs deployed?). First, we found that five countries (USA, UK, France, Canada, and Japan) have been leading research in the area of AALTs so far. Indeed, these countries contributed to approximately half of the literature we focused on in this paper (48.5%). Interestingly, among these five countries, only one country (Japan) has a collectivistic cultural background. This cultural factor could reflect the fact that people with different cultural backgrounds might pursue different types of assistance for OAs. For example, people in individualistic cultures might be more interested in deploying AALTs than those who have a collectivistic cultural background. To support this view, China, for example, despite its substantial population (18.47% of the world population)[254], is reflected only in 10 publications identified with our literature search. This lack of use of AALTs in China, for example, could be in part because they might have a family-based assistive system embedded in their culture/lifestyle (i.e., extended family living together)[255,256]. To further understand this aspect, more research from diverse cultures will be crucial so AALTs can accommodate families with various cultural backgrounds. The goal would not be to generalize the use of AALTs across all the countries and cultures, but to have AALTs adapted to every context.

Our exploration of the second question revealed that many researchers started focusing on AALTs around 2006, with 4/5 of the literature published between 2010 and 2020. Further, we identified some research gaps among the questions they have investigated thus far (e.g., research focusing on public space setting is only 1.3% while 57.1% of research focused on home setting). More than a quarter of the papers included in this review tested technology with either the younger population (192 papers) or actors rather than the intended population (i.e., older adults). While necessary for assessing the general functionality of the AALTs, these tests are preliminary, and more targeted research is required to address the needs specific to OA population. Moreover, a large majority of AALTs research focused on asymptomatic individuals (81.9% of total occurrences). We suggest that this could be reflecting the fact that recruiting OAs with a condition might be more challenging than recruiting asymptomatic OAs. Recruiting OAs is generally more challenging than recruiting younger adult counterparts and looking for individuals with any specific condition would be naturally more difficult. Although these issues are hard to solve and probably are labor-intensive, more research in each subdivision (e.g., OAs in smart home or hospital settings) is needed to make AALTs truly useful. We strongly advocate for conducting more research in diverse subdivisions because of the variability in OAs' health status, as well as their lifestyles. Somewhat understandably, most of the research explored in this study focused on quantitative data. There are two possible explanations for this finding. First, this could be due to our inclusion criteria as we have excluded the papers that do not report on empirical data related to health outcomes collected as part of clinical studies. Secondly, collecting qualitative data (e.g., *via* interviews and observations) is often more challenging than collecting quantitative data, which the technologies themselves could collect. However, qualitative data is often crucial in this context as they allow us to understand people's perceptions, feelings, and ideas, all of which play a significant role in the wellbeing of an individual[257]. Therefore, this area of research would greatly benefit from the implementation of more mixed methods approaches to gather as much information as possible.

Finally, with our third research question, we learned that much research focuses on individuals' daily routines. We contemplate this could be partially due to the fact that the AALTs are still in the beginning phase of their progress, and hence, their research and development are focusing on a broader topic that could benefit the larger population. Wandering, medication adherence, blood pressure, and behavioral change tracking, among other functions, are considered very relevant to the wellbeing of older adults as aging involves gradual physical and mental deterioration. However, sensors addressing these functions were discussed in only a few papers. Targeting a group of people with specific medical conditions might eventually increase the risk of conducting research, and hence, ethical approval for such research might be harder to obtain, which might discourage some research initiatives. This barrier to researching AALTs could be a common challenge that many researchers in the area could be facing. However, once substantial research methodologies are established in the field, new research could follow their paths. Again, research targeting various goals in various cultural contexts will be crucial in moving the field of AALTs forward. Thus, this paper has provided a systematic map for researchers interested in this multidisciplinary field of investigation. Current literature includes narrative and scoping reviews; therefore, further systematic reviews are needed to focus on the clinical outcomes from the use of AALTs based on technology types or patient profiles.

Limitations

Although a systematic map is presented and discussed in this paper, this review suffers from two weaknesses. First, due to the diversity of papers, a high number of articles appeared in the initial searches leading us to focus the search on the bibliographic databases that are more likely to show articles, including health-related outcomes. Therefore, we have not explored engineering databases because articles in these databases are written by engineers and therefore could not include health-related outcomes. The readers of this paper should keep this in mind, and our pragmatic decisions may have hidden a few articles from appearing in our search results.

Conclusions

One of our primary goals was to provide a systematic map for researchers with interests in this multidisciplinary field of investigation, covering computer science and engineering and ethics and health, for instance. Therefore, this paper focused on AALTs to provide a scope and report on the progress in the area in terms of health outcomes in older adults. We learned that AALTs research is probably still in its beginning phase but will continue to expand rapidly, at least partly due to low fertility rate, growing life expectancy, and rapid technological progress. We identified that some countries' contribution to this field of research are disproportional to their population, contributing to the research of AALTs more than others. Surprisingly, the emergence of research in AALTs from engineering disciplines does not have the same breadth of empirical research. This research area has immense potential for growth, which could greatly benefit from more focus on structure and applicability. Specifically, we found this area would greatly benefit from more holistic, mixed-method evaluations that focus on addressing needs specific to OA population while directly involving OAs in assessments. Interdisciplinary collaborations involving science, engineering, psychology, social work, and health professionals would be beneficial for developing AALTs addressing the needs of OAs, since aging is a multifaceted process affecting all areas of an individual's life. Due to its scarcity, future research should explore the challenges of implementing AALTs in clinical settings as part of empirical research. Exploring both quantitative and qualitative data will be important in understanding the actual effect of AALTs. In addition, fine-tuning of evaluations to the intended locations of use (i.e., home, hospital, public spaces) and more culturally responsive assessments could further enrich this area of research and may provide additional insights into AALT development. To conclude, this paper has revealed some of the potential challenges that AALTs implementation may face. Family and cultural dynamics have been discussed as one of the potential underlying factors affecting acceptance and adoption of AALTs for healthcare purposes. This inter-user variability would imply the need for different business frameworks based on the socio-cultural characteristics in the users' environment. Therefore, future research should determine the most appropriate business frameworks and models that determine the implementation of AALTs in healthcare.

Conflict of Interest

The Authors declare that they have no conflict of interests.

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Authors' Contribution

M.-A.C. has initiated the ideas of this study. M.-A.C. and A.O. have made substantial contributions to the conception and design of the study. A.P., Y.S. and M.-A.C. have handled the screening and data extraction processes. M.-A.C. drafted the manuscript. All authors have read and agreed to the published version of the manuscript.

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