Ambient Assisted Living: A Scoping Review of Artificial Intelligence Models, Domains, Technology and Concerns

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Abstract

Background: Ambient Assisted Living (AAL) is a common name for various Artificial Intelligence (AI)-infused applications and platforms that support their users in need in multiple activities, from health to daily living. These systems use different approaches to learn about their users and make automated decisions, known as AI models, for personalizing their services and increasing outcomes. Given the numerous systems developed and deployed for people with different needs, health conditions, and dispositions towards the technology, it is critical to obtain clear and comprehensive insights concerning AI models employed, along with their domains, technology, and concerns, to identify promising directions for future work.

Objective: This study provides a scoping review of the literature on AI models in AAL. In particular, we analyze: 1) specific AI models employed in A?L systems, 2) the target domains of the models, 3) the technology using the models, and 4) the major concerns from the end-user perspective. Our goal is to consolidate research on the topic and inform end-users, healthcare professionals and providers, researchers, and practitioners in developing, deploying, and evaluating future intelligent AAL systems.

Methods: The study was conducted as a scoping review to identify, analyze and extract the relevant literature. It used a natural language processing (NLP) toolkit to retrieve the article corpus for an efficient and comprehensive automated literature search. The relevant articles were then extracted from the corpus and analyzed manually. The review included five digital libraries: the Institute of Electrical and Electronics Engineers (IEEE), PubMed, Springer, Elsevier, and the Multidisciplinary Digital Publishing Institute (MDPI).

Results: The annual distribution of relevant articles shows a growing trend for all categories from January 2010 to November 2021. The AI models started with unsupervised approaches as the leader, followed by deep learning (dominant from 2020), instance-based learning, and supervised techniques. Activity recognition and assistance were the most common target domains of the models. Ambient sensing, wearable, and mobile technologies mainly implemented the models. Older adults were primary beneficiaries, followed by patients and frail persons of various ages. Availability was a top beneficiary concern, and to less extent, reliability, safety, privacy, and security.

Conclusions: The study presents the analytical evidence of AI models in AAL and their domains, technologies, beneficiaries, and concerns. Future research on intelligent AAL should: involve healthcare professionals and caregivers as designers and users, comply with health-related regulation, improve transparency and privacy, integrate with healthcare technological infrastructure, explain their decisions to the users, and establish evaluation metrics and design guidelines.

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Abstract

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Results:
We included a total of 108 papers. The annual distribution of relevant articles shows a growing trend for all categories from January 2010 to July 2022. The AI models mainly employed unsupervised and semi-supervised approaches. The leading models are deep learning, natural language processing, instance-based learning, and clustering. Activity assistance and recognition were the most common target domains of the models. Ambient sensing, mobile technology, and robotic devices mainly implemented the models. Older adults were primary beneficiaries, followed by patients and frail persons of various ages. Availability was a top beneficiary concern.

Conclusions:
The study presents the analytical evidence of AI models in AAL and their domains, technologies, beneficiaries, and concerns. Future research on intelligent AAL should: involve healthcare professionals and caregivers as designers and users, comply with health-related regulation, improve transparency and privacy, integrate with healthcare technological infrastructure, explain their decisions to the users, and establish evaluation metrics and design guidelines.

Trial Registration:
PROSPERO International Prospective Register of Systematic Reviews CRD42022347590; https://www.crd.york.ac.uk/prospero/display_record.php?ID=CRD42022347590

Introduction

Background

AAL is an umbrella term describing a general approach to technology design to construct safe environments around assisted users and help them maintain independent living [1]. Over time, it has focused mainly on older adults (people over 65 years) as target users.
Developing technology for this group is an increasingly important design challenge because of specific deficits in later life [2]. Beyond usability, there is an increased emphasis on designing technology for older adults that will enable them not merely to satisfy their needs but use it to transform their mental and physical health and well-being [3, 4]. The challenge is made particularly significant because older people are becoming the largest demographic group. In 2020, more than one-fifth (20.6%) of the EU population was aged 65 and over [5], and by 2030, 16.6% of the world's population will be aged 60 or above [6].

Over the last decade, many technological devices have been developed to support an active lifestyle as people age concerning health promotion [4, 7, 8]. Health promotion refers to *"the process of empowering people to increase control over their health and its determinants through health literacy efforts and multisectoral action to increase healthy behaviors"* [9]. Concerning technology design, the objective is to find cost-effective solutions to help independent living and provide healthcare and well-being [10]. A comprehensive analysis of Information and Communication Technology (ICT) research and development reveals common goals of these technologies as the provision of health, accessibility, and safety [11, 12]. Many technologies seek to assist older adults in everyday activities [4, 11, 13-15].

To support disability-free and independent living and the well-being of older users, AAL systems use automated decision-making mechanisms that integrate, analyze and interpret complex multimodal and multi-device information [7]. These systems have focused on two general scenarios of automated decision-making involving older users - *health monitoring* and *activity recognition* [8, 16, 17].
Different *monitoring* contexts were targeted by a variety of technological systems, ranging from monitoring systems for fall prevention using wearable and ambient sensing technology [18] and social robots for the well-being of people with dementia and mild cognitive impairments [13] to games for leisure and maintaining user engagement during therapy and rehabilitation [14].
Robotic technologies have been widely exploited as tools to support health monitoring and mobility capacities, such as strength, balance, and range of motion [15], or acting as companions [19] to assist older adults in daily and social activities at home. The former may be non-social robots, whereas the latter are social robots with the primary goal of offering companionship.
Remote telepresence robots have been successfully used to support the autonomy of older adults in doing daily activities at home. The Giraff was a telepresence robot that used a video interface to allow caregivers and relatives to visit older people in their homes virtually [20]. It ran implicit data collection (blood pressure, body temperature, movement, and fall), then analyzed to alert the caregivers for emergencies. Similarly, Matilda was a social robot with human attributes (such as baby-face-like appearance, human voices, gestures, and body movements) that could recognize voices and faces and perform activities such as playing music, dancing, and playing card games [21].
Although it cannot stop biological aging, regular exercise can minimize its physiological effects, increase life satisfaction, and prolong the decline of functional abilities in older adults [22]. Studies on favorite activities of older adults show the prominence of physical activities such as walking,

jogging, and outdoor maintenance [23]. Specific technologies, such as exergames [10] or Web-based exercises and activities [24, 25], have motivated, sustained, and monitored physical and social activities at older adults' homes. Coupling with the features from theories of human behavior, such as goal-setting, self-monitoring, achievements, and personalized feedback and progression, has been associated with the higher effectiveness of these applications for older adults (i.e., increased engagement in physical activities and associated health outcomes) [26].

In the context of AAL, *activity recognition* concerns tracking the daily behavior of older and frail people. It can detect falls and recognize activities of daily living (ADL), which is crucial for identifying complex patterns associated with the development of specific diseases. Authors of [27] suggested an automated approach for analyzing multivariate time series originating from various sensors and facilitating robust classification of daily activities.

Wearable [28] and *mobile* technologies [29, 30] have been used for implicit data collection and analysis to recognize older adults' activities for tracking their health and detecting emergencies.

From a technical side, the energy efficiency of wearable technologies appears to be the primary constraint for continuous measurement and activity recognition [28]. It further affects the provision of timely and informative feedback and recommendations for the users. The major user-related concerns are privacy and acceptance [28] due to unclear use cases and difficulties in device pairing with a smartphone for older adults. A more stable commitment to wearables requires use cases with apparent benefits and reduced effort of use for older adults.

Mobile technologies represent a versatile source for older adults' health and activity data collection [29, 30]. They facilitate home care and self-management of the health and well-being of older adults. These applications implement various services based on target activity/health recognition features to support healthcare and independent living (i.e., reminders, companionship, or recommendation of favorite activities or treatments). However, the significant obstacles of using mobile technologies in practice include privacy [30] and technological literacy and usability of touch-screen interaction styles [31].

The AAL technologies use a variety of AI models in learning about their users' habits and health conditions to provide adequate services with automated decision-making. Table 1 shows common AI classification, whereas Table 2 summarizes existing AI models concerning their learning/decision-making techniques, and problems they address (with corresponding algorithms) [32, 33, 34]. We separated classification and models since multiple models can belong to the same class. Vice versa, some models can implement different classes (i.e., clustering can be done in both supervised and unsupervised manner).

Table 1. The AI classification as common learning approaches [32, 33, 34].

Name	Description	Problem/Algorithm
Supervised learning	Input (training) data or examples are labeled with known output values. The model uses the data in a training process to make predictions and is corrected when the predictions are false. The process runs until the model achieves a required level of the predictions' accuracy.	Classification, regression
Unsupervised learning	Input data are not labeled, and output values are unknown. Instead, the model is trained by removing structures from the input data to extract general rules, reduce redundancy, or organize data by similarity.	Clustering, dimensionality reduction, association rule learning
Semi-supervised learning	Input data contains labeled and unlabeled examples. The model learns the structures to organize the data to create predictions. It models the unlabeled data.	Classification, regression

Reinforcement learning	The model rewards desired behaviors and/or eliminates undesired ones. It is represented by a learning agent (process) that perceives and interprets its environment, takes actions, and learns through trial and error.	Markov Decision Process, Q learning, Monte Carlo methods

Table 2. The summary of AI models [32, 33, 34].

Model	**Learning technique**	**Problem/Algorithm**
Regression learning	Models a relationship between input and output data (or variables). The relation is iteratively refined by measuring error in the model's predictions.	Variations such as linear and logistic regression
Instance-based learning	Models a decision based on instances of input data that are considered relevant or necessary. Creates a database of reference examples used to compare with new data to find optimal matches using similarity metrics to make a decision.	k-Nearest Neighbor (kNN), Support Vector Machines (SVM)
Regularization learning	The extension or modification of another model (e.g., regression learning) in a way that reduces the complexity of the model by converting it into a simpler form.	Ridge Regression, Elastic Net
Decision tree learning	Models a decision based on the values of the input data attributes. It follows a tree structure in making a decision for given input data.	Classification and Regression Tree, Conditional Decision Tree
Bayesian learning	The models use Bayes' Theorem to solve problems of classification and regression.	Naive Bayes, Gaussian Naive Bayes
Clustering learning	The model organizes the input data into groups (or clusters) where group membership/commonality criteria are taken or derived from the data (e.g., centroid-based or hierarchical).	K-Means, K-Medians, Hierarchical Clustering
Association rule learning	The model discovers associations in input data to make a decision. It extracts rules that describe relationships between observed variables in input data.	Apriori algorithm, Eclat algorithm
Artificial neural network (ANN)	The model is driven by the structure and function of the human neural networks. Represents a class of pattern matching models and their commonly used variations for regression and classification problems.	Perceptron, Multilayer Perceptrons (MLP), Back-Propagation
Deep learning (DL)	Special category of large and complex neural networks for handling vast amounts of labeled input data, including text, images, audio, and video.	Convolutional Neural Network (CNN), Recurrent Neural Networks (RNNs), Long Short-Term Memory Networks (LSTMs)
Dimensionality reduction learning	The model analyzes the input structure in the data to represent and describe the data with less information. The simplified data can be visualized and used by other learning methods.	Principal Component Analysis (PCA), Principal Component Regression (PCR), Linear Discriminant Analysis (LDA)
Ensemble learning	Multiple models that are independently trained, where individual predictions are combined to make the final prediction. The models are combined due to their weaknesses in making the desired prediction.	Boosting, Random forest, AdaBoost, Weighted Average (Blending)

Natural language processing (NLP)	Specific for Conversational AI and includes natural language understanding (NLU), dialog management (DM), and natural language generation (NLG).	Rule-based algorithms, statistics, neural networks, DL

Goal of the Study

This paper investigates the AI models of existing AAL technologies to support independent living. The quality of the models' decision making can benefit positive behavior change to maintain an active and healthy lifestyle for older adults and other user groups in need of assistance. This is critical for preventing functional decline and supporting health treatments. Our work aims to identify positive sides and gaps in research and practice to provide implications for future AAL systems.

This scoped analysis focuses on the following research questions (RQs).
RQ1: What AI models are implemented in AAL systems? First, we identify, describe and systematize AI classification and models in the current landscape of AAL systems. For this purpose, we extracted common terminology to describe current AI models and AAL.
RQ2: What are the domains of the models? Second, we describe existing target domains with their concrete activities to propose suitable application strategies that reinforce positive aspects and highlight critical parts in which further research is necessary.
RQ3: What technologies are using the models? Third, we investigate different technologies employing AI models to consolidate and provide design and development guidelines for intelligent AAL systems.
RQ4: What are the significant concerns regarding the models from an end-user perspective? Finally, we examine end-users groups and their perceptions of AAL systems' usage to indicate specific requirements that the systems should meet or improve.

The study reviews AI models in AAL concerning their domains, technologies, and concerns published in the literature covering 2010 to 2022. The findings are intended for (health)care professionals, researchers, technology providers, and end-users to consult when developing, deploying, and evaluating intelligent AAL technologies.

The paper continues as follows: Section 2 includes the methodology of the scoped literature review; Section 3 describes the results of the analysis of the N=108 selected papers; Section 4 contains the discussion of the review's findings concerning the RQs and outlines conclusions, limitations, and implications for future work.

Method

Study type

This paper has been organized as a scoping review, involving the synthesis and analysis of the existing literature to provide a conceptual framework that systematizes and clarifies the specific phenomena - AI models in AAL systems. We identified the articles to be reviewed by conducting a systematic literature search within the IEEE, PubMed, Springer, Elsevier, and MDPI research article databases. The study implemented the PRISMA workflow for systematic reviews [35], as illustrated in (Figure 1).

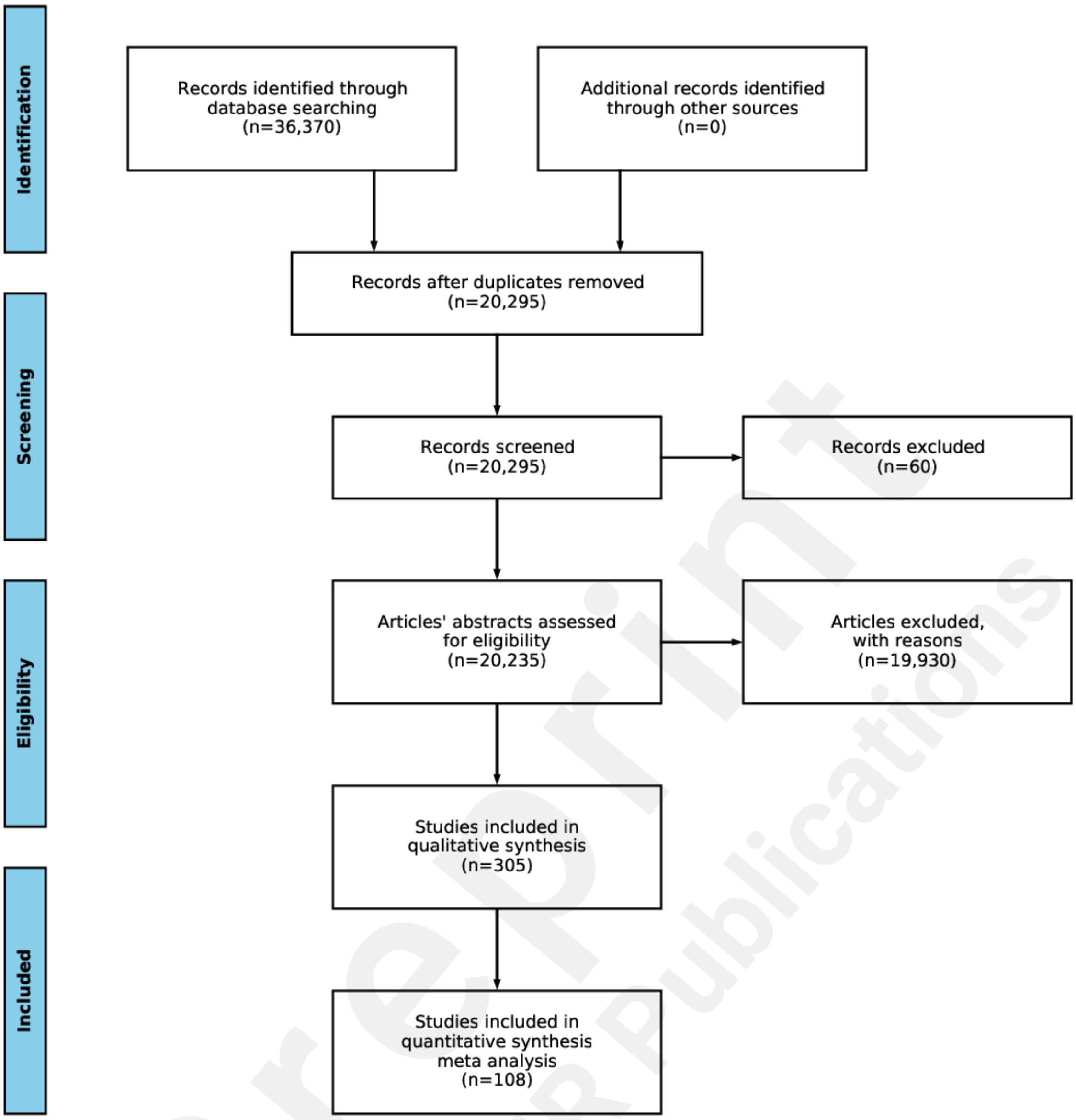

Figure 1. The PRISMA flow of the review process illustrates identification, screening, eligibility, and inclusion of relevant articles.

Identification

During the search, the titles, abstracts, and keywords of the libraries' articles were queried with the search terms structured as from (Table 3). The search terms of AAL and AI classification and models categories were mandatory for all papers, and the remaining categories were optional. We ran the search based on categories as properties and contained keywords. For this purpose, we used the NLP toolkit we had developed for automated literature search, screening, and analysis [36]. The toolkit accepts a collection of keywords as an input to retrieve potentially relevant articles, combined with the set of properties (or categories) and property groups (as sub-categories) to be satisfied by the articles. The input can be expanded with keywords' and properties' synonyms to fine-tune the search and screening process. The details of the toolkit can be found in [36].

The search was conducted in July 2022 and included research papers written in English and published between 2010 and 2022. Given the rapid advancements in AI that also influenced the significant growth of technology-supported AAL, we wanted to cover the sufficient research landscape concerning the time frame.

Table 3. Key terminology for the scoping review's NLP search toolkit.

Category	Criteria	Keywords
AAL	Mandatory	Ambient assisted living, ambient-assisted living, assisted living, active and assisted living, active-assisted living
AI Class	Mandatory	Supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning
AI Model	Mandatory	Classification, regression, clustering, dimensionality reduction, association rule learning, instance-based learning, regularization learning, decision tree learning, Bayesian learning, ANN, DL, ensemble learning, natural language processing
Domain	Optional	Activity recognition, health monitoring, activity assistance, rehabilitation, therapy, interaction, communication, entertainment
Technology	Optional	Mobile technology, mobile device, smartphone, tablet, touch-screen, wearable technology, wearable device, robot, robotic device, ambient sensing, ambient sensors, game, gamification, conversational agent, chatbot, virtual assistant, virtual companion
Beneficiaries	Optional	Older adults, frail persons, patients, healthcare staff, caregivers, family
Concerns	Optional	Acceptance, adoption, availability, accessibility, privacy, usability, reliability, safety, security

The search process sometimes identified the same article by multiple keywords and phrases from Table 3. For example, the article could describe use of multiple AI models or classifications. In these situations, we count the article multiple times, per each found keyword, and present it in the charts in the Results section.

Screening

In the screening phase, we evaluated retrieved articles to assess their relevance to the review based on the following independent inclusion criteria:

- AI classes and models of AAL applications and platforms, where specific classes and models are explicitly considered, not mentioned without description, analysis, or evaluation.
- Papers contributing to the AI models' domains to support or assist in specific health-related or daily activities, in line with RQ2.
- Papers demonstrating different AAL technologies that use the models and deliver the AAL systems' automated decisions to the end-users, as per RQ3.
- Papers describing end-users concerns regarding the model's automated decision-making outcomes, according to RQ4.
- The primary end-users are older adults, but also other user groups.

The exclusion criteria were as follows:

- Papers containing the search terms but AAL, AI classes and models, domains, technology, and end-users concerns were not scrutinized. Thus, they were not relevant to RQ1-4.
- Literature reviews and surveys on the related topics.

The first three authors manually screened the content of each paper independently and coded it to indicate its relevance concerning the inclusion criteria. The inclusions were cross-checked, resolved, and confirmed during regular discussions among the authors.

Extraction

In this phase, we analyzed each included article in detail. We identified and extracted AI classes and models in AAL systems, the models' target domains and technologies, and the end-user's categories and concerns, where available per article. The extracted information from the articles was kept in a shared spreadsheet to facilitate coding and discussion among the authors. The extracted information included: publication venue and date, a summary of the paper, AI model(s) employed including corresponding AI algorithms and tools, the models' target domains if available, the technology using the models, if any, and information on the end-users and their concerns regarding the models if available.

Analysis

We conducted a manual, thematic analysis of the extracted information during this phase. Our goal was to categorize the AI classes, models, domains, technologies, and concerns for AAL systems. Coded data were the basis to address the review's research questions. In particular, we grouped papers based on their primary outcomes to guide the analysis as follows:

- Papers that describe AI classes and models of the AAL systems,
- Papers dealing with the models' domains,
- Papers that present the technologies using the models, and
- Papers with the models' beneficiaries and usage concerns.

We describe the general approach to analyzing the particular paper groups.

Analysis of AI classes and models in AAL systems concerned identifying and describing the systems' automated learning and decision-making functionalities, including the particular AI algorithm/tool.

Analysis of AI models' domains considered specific application scenarios with supported activities.

Analysis of the AI models' technologies through which the automated decisions were generated and communicated to the end-users.

Analysis of the models' concerns included various end-users perceptions and dispositions towards the models' functions and outcomes.

Results

Screening process and number of articles

The NLP search toolkit initially identified 36,370 potentially relevant papers (Figure 1). Duplicates were then eliminated, reducing the number to 20,295. The automated screening process further removed 60 articles published before 2010 or for which the title and/or abstract could not be analyzed due to parsing errors, unavailability, or other reasons. The NLP toolkit's advanced functions assessed the eligibility of the remaining 20,235 papers and kept 305 articles. After automated processing, the articles were analyzed in detail, according to the inclusion and exclusion criteria. Finally, 108 articles were deemed eligible for the in-depth manual investigation to identify and articulate research results, trends, and implications.

We describe the results by responding to the RQs that guided our review.

Distribution of relevant articles and categories

Figure 2 illustrates the annual occurrences of the relevant articles containing different AI classes and models. The term 'Assisted Living' has been commonly used in the literature to describe the systems with similar context and purpose of use as per the definition of AAL [1, 4]. It outperformed the number of papers in some years (e.g., 2019) and was comparable to the AAL in 2018 and 2020. In minor cases, the abbreviation was used solely. In general, there has been a growing trend throughout the search time frame, occasionally decreasing in specific years. The decreases are due to our search conditions and inclusion criteria. Many papers dealt with AAL without explicit mentions of AI models concerning their application and outcomes.

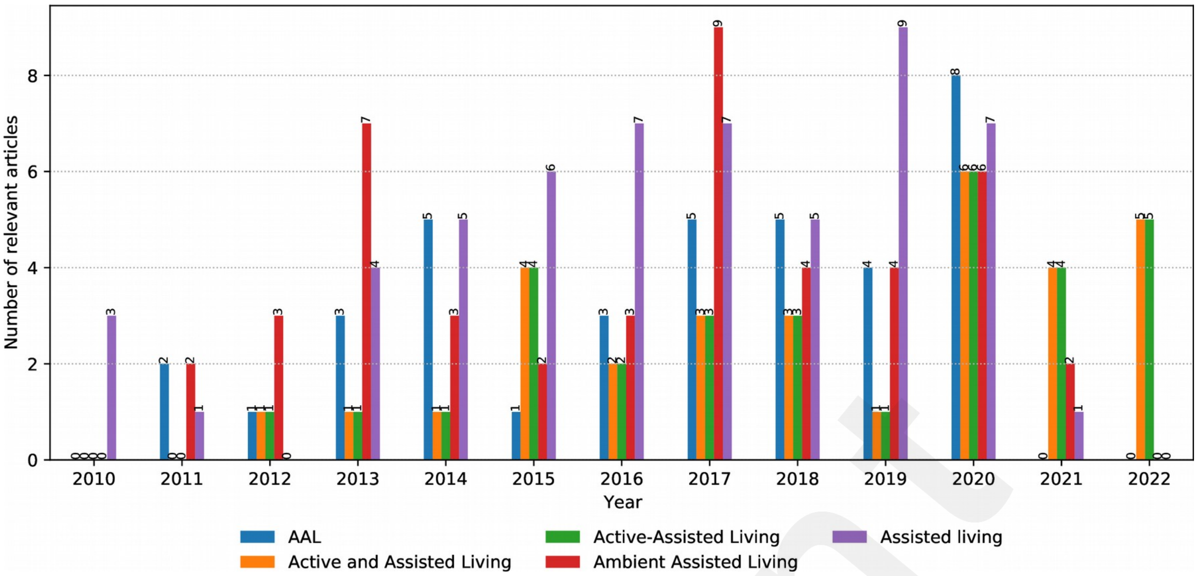

Figure 2. The number of relevant articles concerning Ambient Assisted Living with AI Classes and Models per year from January 2010 to July 2022.

The combined information on the digital library and publication year of the relevant articles demonstrates IEEE is a leader, with an increasing trend reaching a peak in 2020 (Figure 3). This is expected as the publisher is oriented towards technology with many venues relevant to AI models and AAL. PubMed follows, dealing more with the end-user aspects of the topics, such as different types of user evaluations. We can notice a growing trend until 2020 and an oscillatory period afterward. The Springer library combines technical with user-oriented articles. A smaller number of the relevant articles with an irregular annual trend was found in the Elsevier library, while MDPI published relevant articles from 2020.

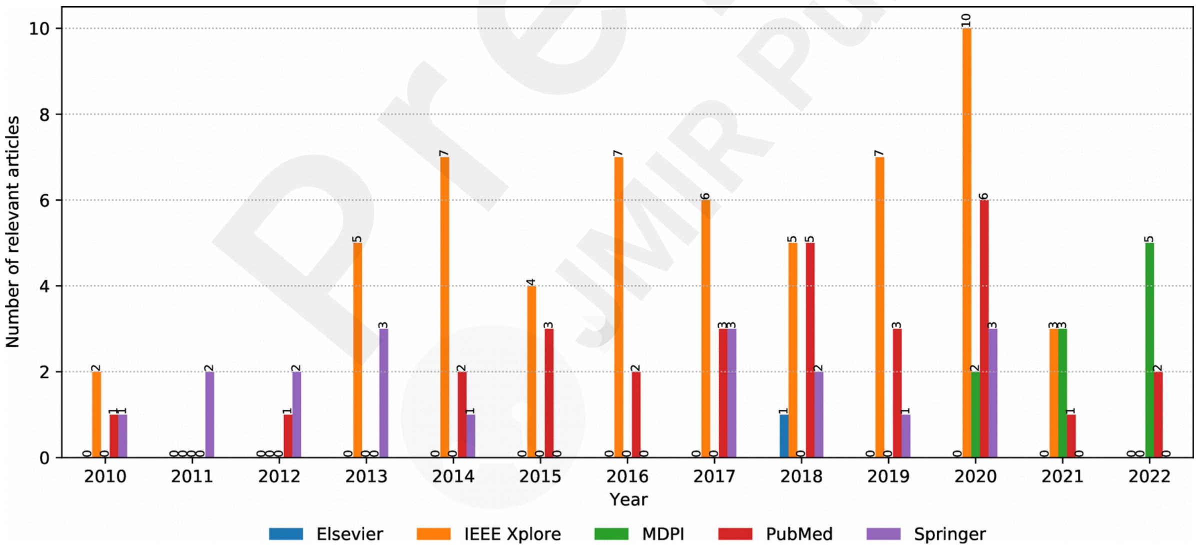

Figure 3. The number of relevant articles per year from January 2010 to July 2022, grouped by the respective digital library.

As the total number of relevant articles increases within the review's time frame, the number of articles pertinent to the associated categories changes accordingly (Figure 4). As for the three mandatory categories (*AAL, AI classification,* and *AI model*), there is a general growing trend up to 2020, with occasional drops in the previous year and a decrease in 2021. As an optional category, the *domain* follows the leading trend but with fewer articles indicating that sometimes it was not considered (i.e., AI models used or tested in a domain-independent way). The *beneficiaries* follow the leading trend but is smaller than the domain, showing that the AI models are sometimes studied without relating to a particular user group(s). The *beneficiaries* are comparable to the technology in total amount but with annual oscillations due to different types of AI models' verifications across relevant papers (i.e., deployments and/or evaluations with or without users). The *concerns* appear in the smallest amount that grows in time and oscillates in some years, showing that relevant articles focused on various aspects of AI models in AAL, beyond and different from users' concerns (i.e., algorithmic accuracy and performance).

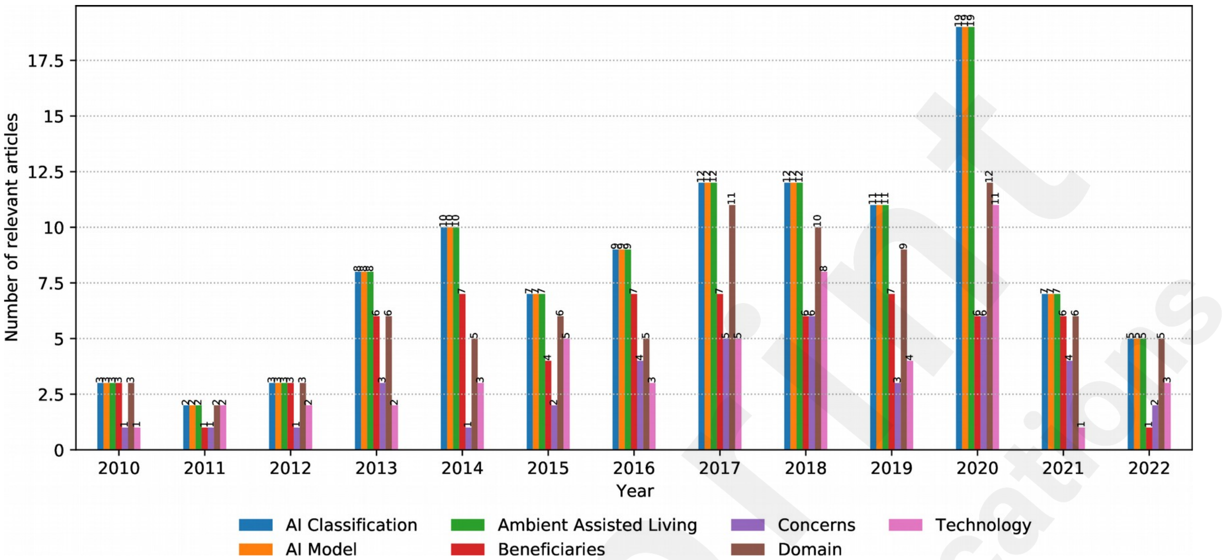

Figure 4. The number of relevant articles for each category per year from January 2010 to July 2022.

Connections between and within categories

Our analysis revealed overlap between searched categories. We aimed to represent all categories equally while highlighting particular connections as informative (e.g., notably higher co-occurrences of instances from distinct or within the categories).

Figure 5 shows associations of AI models and the classes they employ. The semi-supervised learning is a dominant approach for DL and NLP models (51 co-occurrences). Unsupervised learning appears mainly in clustering (14), instance-based (12), and DL (11). Supervised learning prevails for instance-based and DL (9 per model). Finally, reinforcement learning was the occasional approach for DL and NLP (7 per model).
The study reveals specific synergies within categories. Regarding the classes, 20 papers combined supervised and unsupervised learning. Reinforcement learning was used together with the former 17 times per class. The papers combined the classes in a sequence or for mutual comparison in solving concrete problems. Concerning the models, we notice that NLP tasks have been mainly tackled with DL algorithms and tools (51).

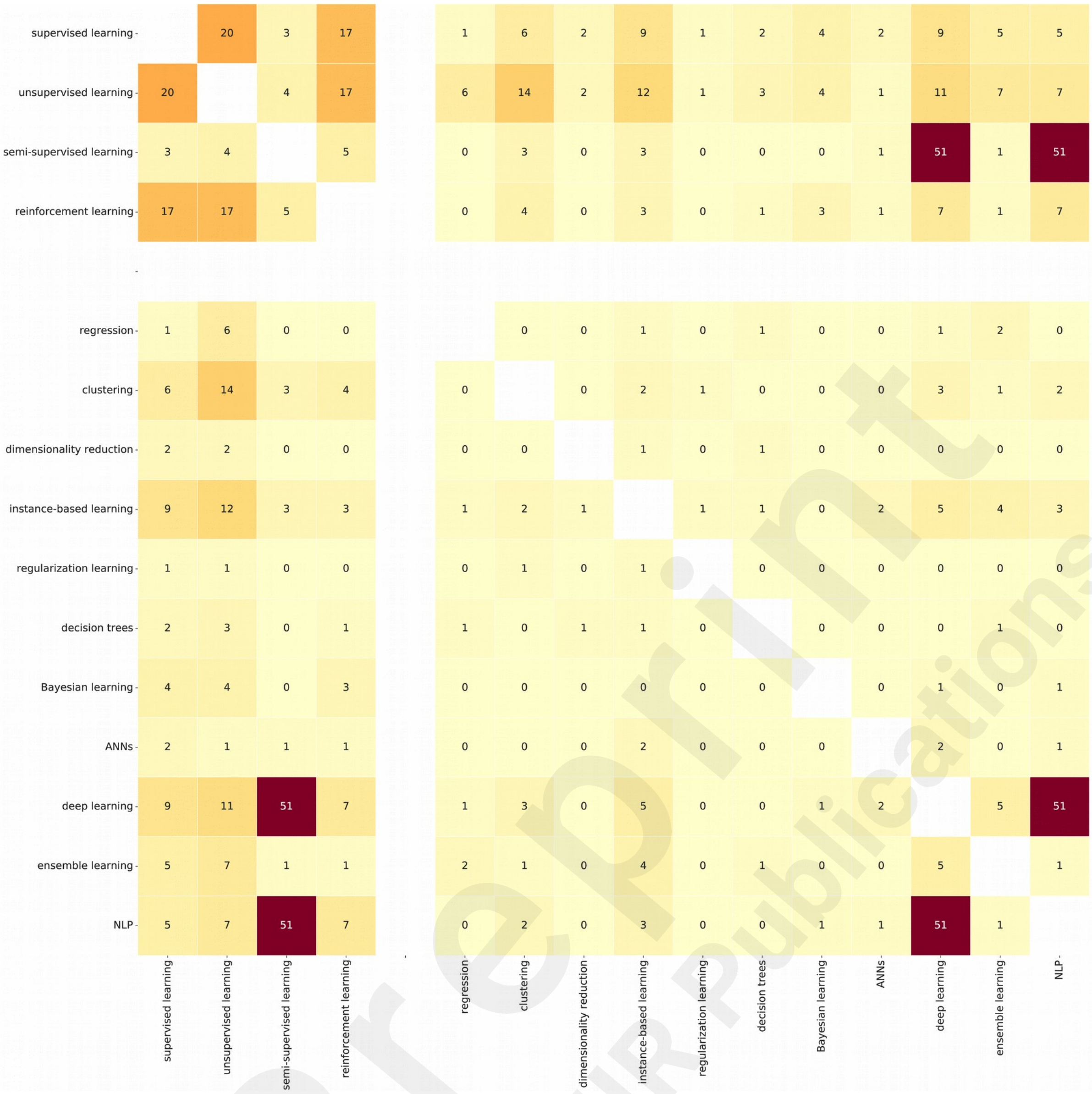

Figure 5. The heatmap describing co-occurrences of AI classes and models in relevant papers.

Figure 6 presents combinations of AI models, domains, and beneficiaries. Activity assistance (33), activity recognition (25), and interaction (14) mainly utilized DL models. Similarly and to a smaller extent, NLP models helped with activity assistance (26), activity recognition (19), interaction (15), and communication (10).

Combinations of AI models and beneficiaries highlight older adults as leading users of DL (27) and NLP (26). Patients and frail persons co-existed with DL models 11 times each.

Co-appearance of beneficiaries and domains reveals activity assistance targeted mainly older adults (27), followed by activity recognition (17) and communication (10).

As for connections within categories, activity recognition is a common form of assistance (38), followed by communication (12) and interaction (12), and health monitoring (10). Patients and frail persons co-occur 11 times. Older adults are referred to as frail persons and patients 9 times each, indicating that AI models mainly serve healthy senior users. Family, caregivers, and healthcare staff rarely appear together in the articles.

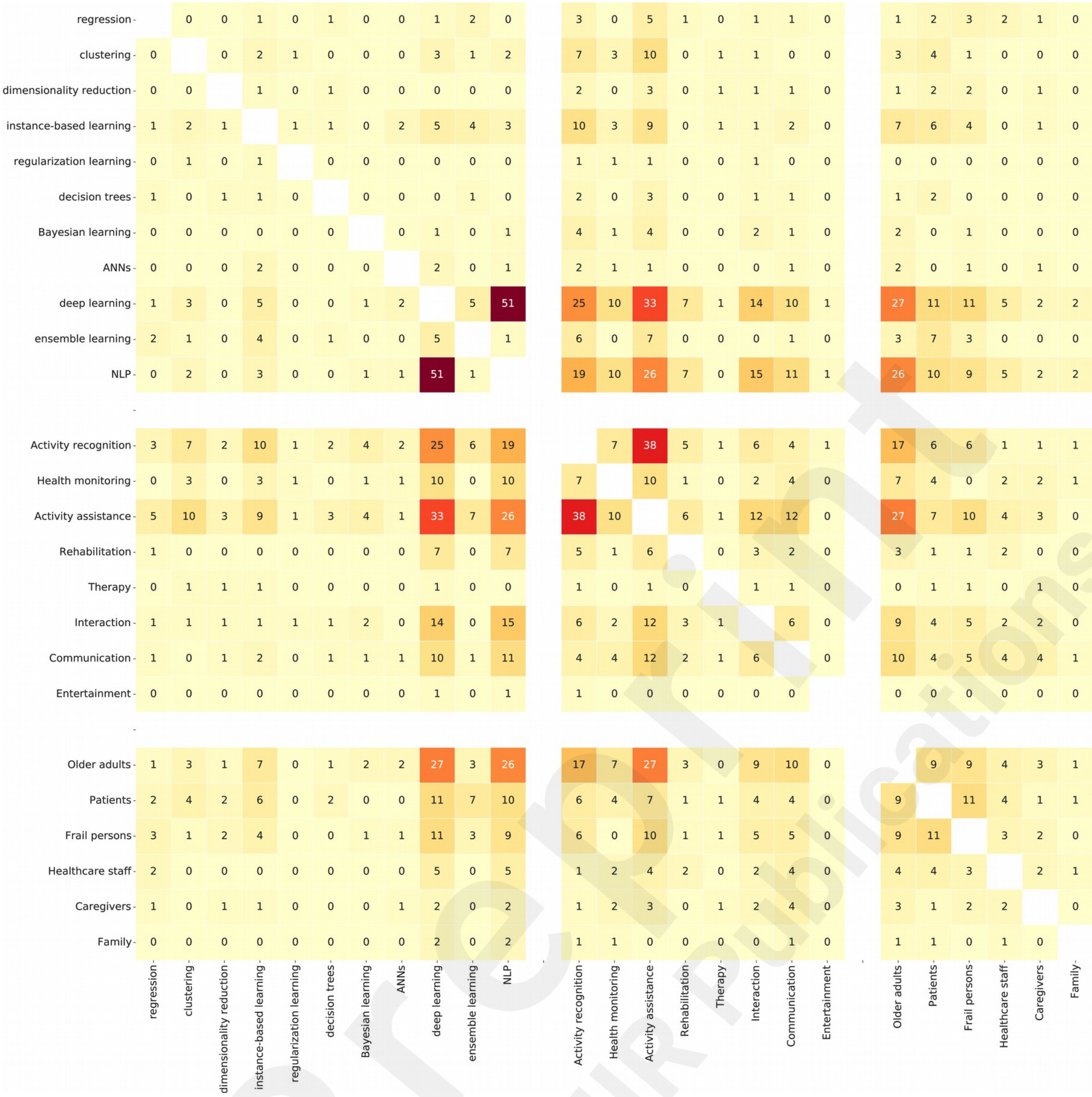

Figure 6. The heatmap describing co-occurrences of AI models, domains and beneficiaries in relevant papers.

Figure 7 shows instances and connections between the technology, beneficiaries, and concerns. Relationships between the nodes from different categories reveal that older adults commonly used ambient sensing technology (9), mobile devices (7), and robots (6). At the same time, their primary concerns were availability (7), usability (5), and safety and accessibility (4 per each). Availability is a concern for patients (4). Moreover, availability is the primary concern in wearable technology (5), along with ambient sensing and mobile technology (4 per each).

Links between the instances within a category indicate occasional use of ambient sensing and wearable technology with mobile devices, 4 and 3 times, respectively.

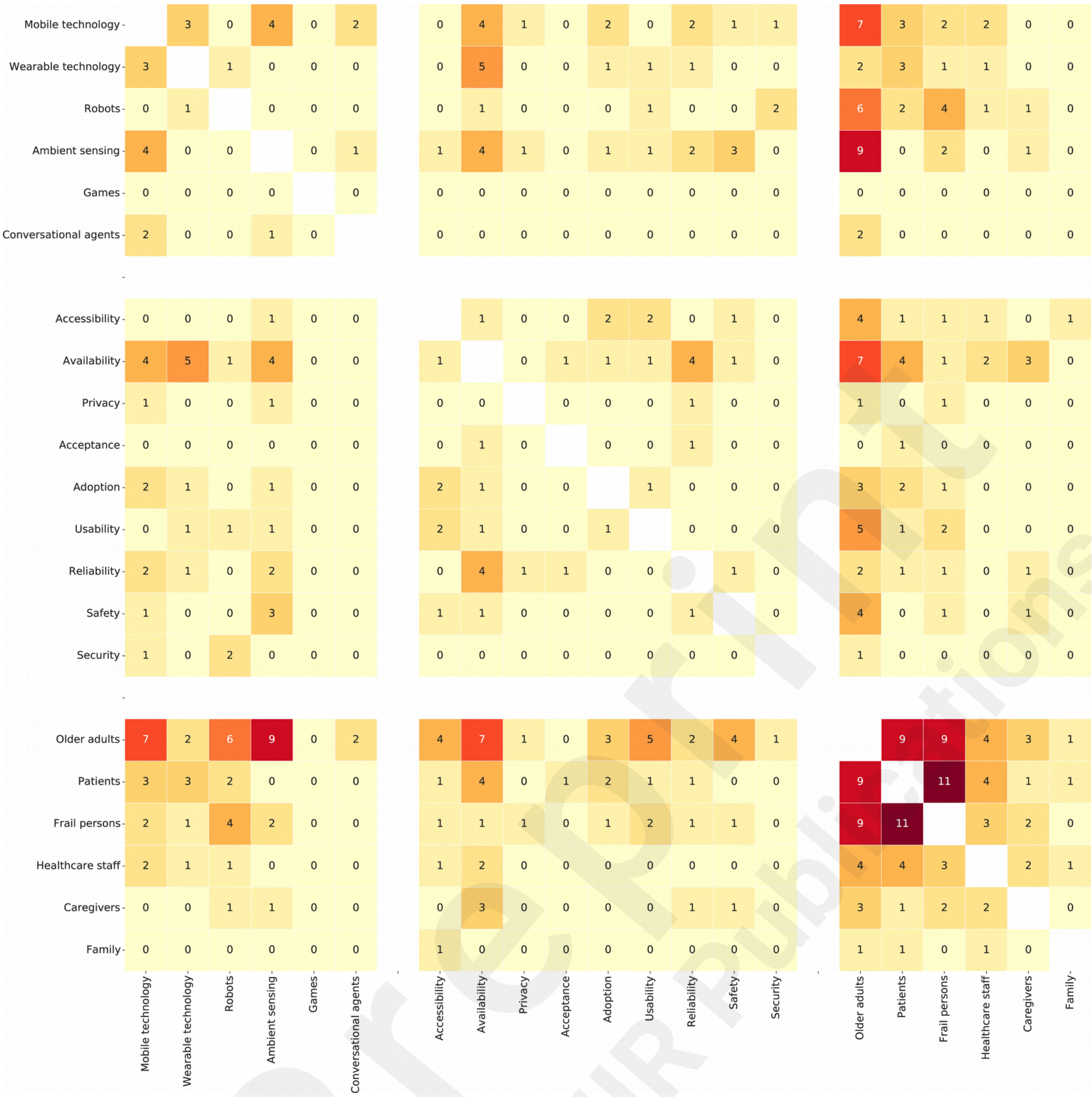

Figure 7. The heatmap describing co-occurrences of technology, beneficiaries and concerns in relevant papers.

AI Classes and Models in AAL

Concerning the classes, the analysis of the relevant articles (Figure 8) shows the highest presence of semi-supervised learning (52 occurrences), followed by unsupervised learning (50), supervised learning (29), and reinforcement learning (20).

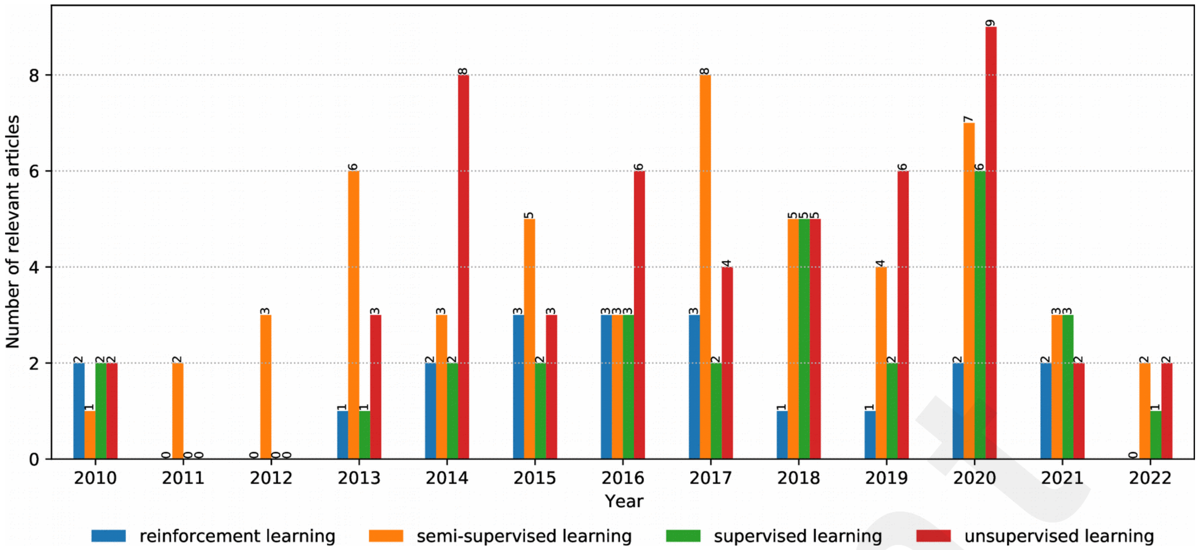

Figure 8. The number and annual distribution of the relevant articles concerning AI classes from January 2010 to July 2022.

The distribution of AI classes shows *that semi-supervised learning* models had prevailed since the 2010s, with an irregular growing trend till 2017, when they compensated for the lack of a sufficient amount of labeled data for particular inputs. Concrete examples include clustering for physical activity recognition [37], finding relevant input features for improving activity recognition [27], and detecting user-object interaction from sequences of images [38].

The *unsupervised learning* models trend follows the previous category with a slightly smaller amount of appearances. Their use was motivated by a general lack of annotated (or labeled) training data for various activities that early AAL solutions aimed to support [4, 8]. Such problems were tackled mainly by either grouping according to shared properties or simplifying input data. The growing trend that followed was caused by the emergence of new health-related domains and activities that solutions were targeting and for which the labeled data did not exist. The examples include recognition and measurement of everyday activities from unlabeled data [39], clustering to create an ontology of human activities [40], or classification for predicting user movements indoors [41].

The *supervised learning* models show general growth till 2020. They have complemented other approaches (e.g., unsupervised and reinforcement learning as from Figure 5) for particular user activities for which labeled data existed. They were used in various *classification* tasks within the AAL, such as user re-identification with RGD-D cameras [42] and ADL recognition using wearable sensors [43].

Reinforcement learning models were used from 2010, increasing to 2015 and reducing usage after 2017. They have served as an alternative to data-driven approaches (i.e., clustering and regression) by promoting desirable and eliminating undesirable user behaviors. Hidden Markov models are the most common algorithms in applications, including user activity recognition from appliance consumption data [44] or with multiple Kinect devices [45].

Regarding the models, the study reveals the prevalence of DL (63), followed by NLP (54), instance-based learning (20), clustering (17), ensemble learning (12), regression (7), Bayesian learning, decision tree learning and dimensionality reduction (4 per each), ANN (3) and regularization learning (2).

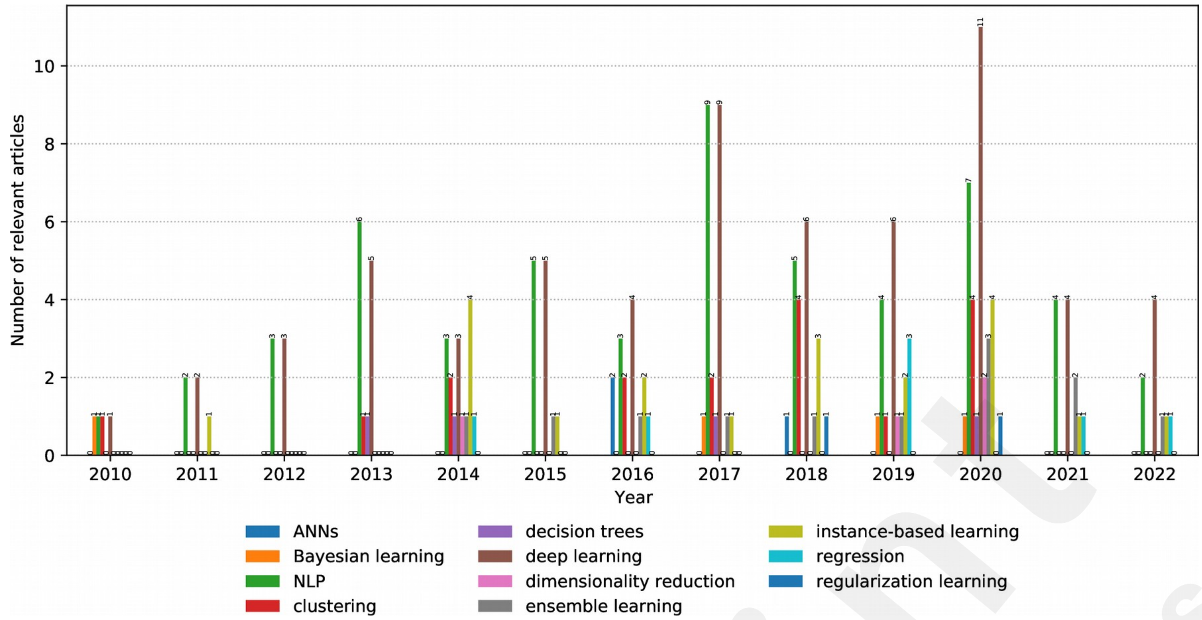

Figure 9. The number and annual distribution of the relevant articles concerning AI models from January 2010 to July 2022.

In the following, we describe each model according to its prevalence (Figure 9).

DL models gained momentum in 2017, expanding their use cases up to date. Their application assumes labeled input data of different structures and semantics, generated at scale. CNNs are the most common algorithms used independently or combined within this model. Examples are activity recognition by transforming data from smartphone sensors into image-based representation [46] or detecting human postures from RGBD cameras [47].

NLP models' usage can be divided into two stages - earlier applications (up to 2015) that focused on speech recognition (SR) and NLU, and later applications that could also perform DM and NLG. We can explain this trend with the critical advancements in Conversational AI facilitated by the DL algorithms that overlap with our search time frame [34]. For example, detection of acoustic events (e.g., knock, cough, clap) for older adults in ADL [48] versus conversation with a companion robot [49].

Instance-based learning models were used throughout the search period, with an irregular trend and a recent drop from 2020. They employed mainly kNN and SVM algorithms. The use cases include recognizing physical activity patterns at home with a multi-view infrared motion sensing system [50] or detecting ADL from human joint trajectories captured with a depth camera [51].

Clustering learning models were employed in specific years of the search time frame, mainly unsupervised, as an alternative approach in the absence of labeled data concerning particular use cases. The use cases include predicting a sequence of connected users' actions in a robotic device [52] or detecting dining-related postures from motion sensors' data [53].

Ensemble learning models were used starting from 2014. The Boosting and Random Forest are the main algorithms from this model, including physical activity classification from wearable sensors [54] and seizure and fall detection from a smartphone's accelerometer data [55], respectively.

The remaining models were utilized to a smaller extent during the search time frame.

Regression learning models were mainly linear regression, such as real-time energy expenditure estimation when walking with loads and on inclines assisted by ankle exoskeleton [56] or ADL recognition from hand grasps using electroencephalography (EEG) [57]. *Bayesian learning* models were applied to classification problems, such as ADL recognition (i.e., detection and classification) using data collected from wearable motion sensors [43]. *Decision tree* and *dimensionality reduction* models were used for classification tasks. The respective examples classify physical activities based on step counts [58] or Wi-Fi and wearables' data [59]. *ANNs* were applied to classification problems as a predecessor of DL models, such as activity recognition in safety-critical environments (e.g., fall detection) [60]. Finally, *regularization learning* models were applied to regression tasks, such as selecting predictive input features for person identification with RGBD cameras [42].

Although they were mentioned in some papers in the context of previous, relevant, or future work, our analysis did not reveal the examples of *association rule learning* models' algorithms in AAL.

Domains of AI Models

AI Models were applied in multiple domains, per domain or combining them (Figure 10). The most popular domains found were *activity assistance* (61 occurrences) and *activity recognition* (45). The domains expose a growing trend till 2020, with periodic oscillations during the time frame. As indicated earlier, they were mainly interconnected in previous studies (38 co-occurrences from Figure 6). Activity assistance has been a significant target in ALL and assistive technologies in general. Mobility was a common assisted activity, such as a robotic walker for mobility of older adults [61] or smart glasses helping visually impaired users navigate in physical spaces [62]. Human activity recognition (HAR) was a commonly used term to describe the recognition of various physical activities. These activities are usually classified into ADL (health-focused) and IADL (well-being-focused), indicating that intelligent AAL systems support health and quality of life. An essential challenge in activity recognition was predicting longer-term behavior [63]. Similarly, some research dealt with the problem of multisensor data fusion in a robotic walker for indoor assistance [64].

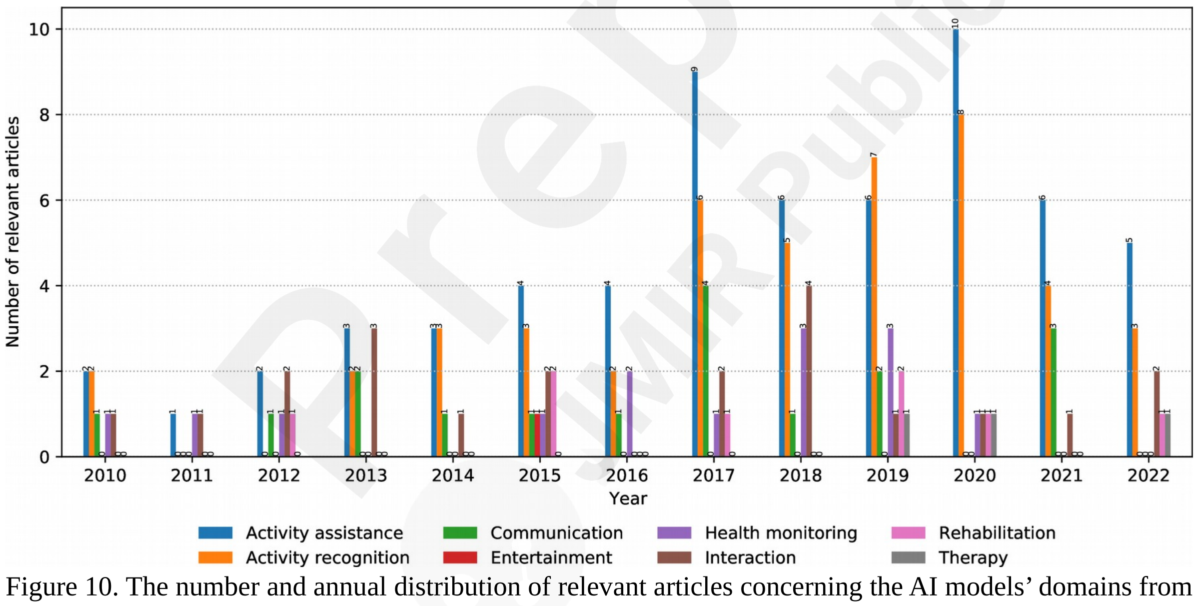

Figure 10. The number and annual distribution of relevant articles concerning the AI models' domains from January 2010 to July 2022.

Interaction (21) referred to the use of different AAL systems, whereas *communication* (17) was mainly considered from a technical perspective (e.g., communicating between sensors, servers, and cloud-based systems). The former examples include interacting with an innovative home platform for FER [47] or a medication delivery application [65]. The latter is distributed multimedia system for patient data capture [66] or digital footprint applications for activity prediction of assisted users [67].
Health monitoring (14) was commonly referred to as observing users' vital signs to detect changes in health conditions and emergencies, such as health-related data collection for users at their homes [66] or in-home gate analysis from radar sensors [63].
Rehabilitation (8), therapy (3), and entertainment (1) received less attention from the research

community in the search time frame. The rehabilitation example is a home system suggesting medications and exercises during fall recovery [68].

Technologies Using AI Models

Ambient sensing and *mobile technology* (15 occurrences per each) prevail in ALL, as shown in Figure 11. It is an umbrella term that connotes various sensors that measure the parameters of the observed environment (or ambient) to detect and analyze user behavior. In this respect, studies used a particular sensor or combined multiple sensors. In the former case, vision [51] and radar [69] sensors were used for recognizing activities and measuring vital signs, respectively. In the latter case, studies merged signals from various sensors for energy efficiency and improved accuracy and performance (known as sensor fusion). For example, activity recognition combined depth image sequences and audio data [70].

Mobile technologies exposed two typical roles. A *passive role* in using their embedded sensors and providing a user interface for measuring the conditions in the users' environments or the state of their behaviors [55]. An *active role* in promoting healthy habits and behaviors with users for a positive lifestyle change by suggesting activities [67].

Robotic technology (14) has been used during the time frame, with an irregular trend. Robots fit well with the AAL paradigm as they replicate human abilities and characteristics, but the cost of development and deployment may influence their use. In line with related work, we notice their *assistive* and *companionship* purpose. The former concerns upper-limb gesture recognition to help users with ADL [71]. The latter is demonstrated by interacting with older adults to prevent social isolation and mediating between the older adult, the environment, and the AAL system [49].

Wearable technology was used less than the previous (10). On the one hand, it can introduce a certain level of intrusiveness compared to the ambient sensors when used independently. On the other hand, it is available through mobile devices (e.g., smartwatches and bracelets), and the study identified 3 overlaps (as from Figure 7). The study from [56] used wearable sensors attached to users' ankles to estimate energy consumption when walking. Another example is activity recognition which accounts for measurement uncertainty in wearable sensors [43].

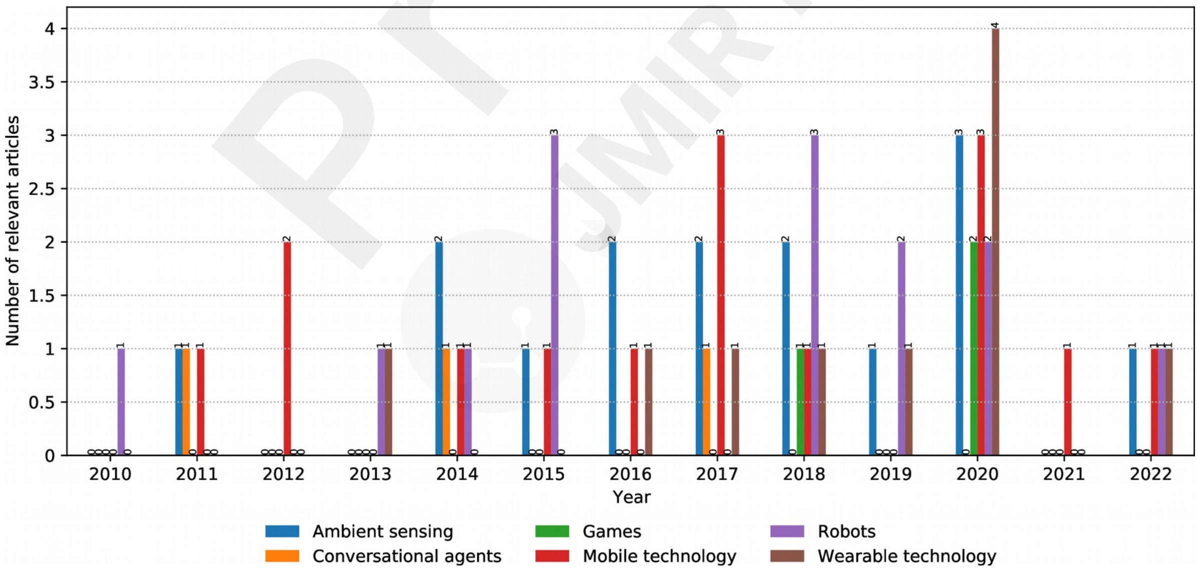

Figure 11. The number and annual distribution of relevant articles concerning the AI models' technology from January 2010 to July 2022.

Conversational and *gaming* technologies have 3 occurrences each. The conversation example is a social robot that conducted simplified small-talk dialogs with users [49]. Overall, the dialogs were rare compared to many occurrences of NLP models used for speech and text recognition. Games were mentioned as the usage of gaming technologies (e.g., Kinect's RGBD camera) that recognized human activity [72].

Beneficiaries of AI Models

Older adults are the primary beneficiaries of intelligent AAL systems (42 occurrences), as from Figure 12. The shared elements emerging from different AAL systems using AI models for this target group include HAR and measuring vital signs. Accordingly, the study described in [73] used radar sensors' data to infer activities of community-dwelling older adults, while research from [74] detected falls by analyzing accelerometer and barometric pressure sensor data.

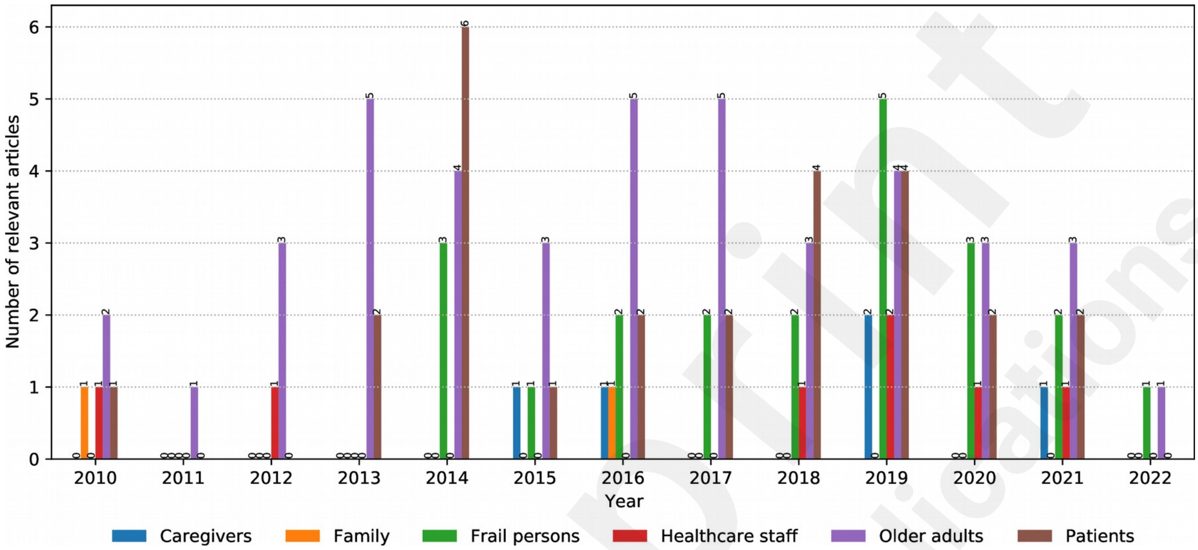

Figure 12. The number and annual distribution of relevant articles concerning the AI models' beneficiaries from January 2010 to July 2022.

Patients (26) were persons with health declines who underwent different medical treatments. The examples include activity prediction for fall prevention of patients at risk [45] and diagnosing clinical abnormalities of patients using multiple vital signs (e.g., heart rate, blood pressure, and respiratory rate) [75]. The overlap with the older adults (9 times from Figure 6) indicates that for most older people, the purpose of AAL systems was more assistive and aimed toward health promotion rather than therapy.

Frail persons (21) were in a specific state of vulnerability with increased risks of falling or disability. The AAL support for these beneficiaries manifested in diagnosing various health declines. Examples include diagnosing Alzheimer's disease from magnetic resonance images [76], and detecting emergencies with users' mobility [56].

Healthcare staff (7), *caregivers* (5), and *family* (2) were considerably less present than the previous. Due to the AAL technology used, they appeared as beneficiaries concerning more efficient and effective caregiving. For example, supporting medical staff in monitoring patients at home [68] and notifying doctors and family if patient conditions decline [66].

Concerns in AI Models

Availability of intelligent AAL systems was the primary user concern (17 occurrences), shown in Figure 13. It was mentioned mainly concerning a particular technology. For example, beneficiaries preferred off-the-shelf technologies such as mobile devices due to their availability regarding services they can offer and cost [55]. Conversely, the availability of particular devices, such as exoskeletons [56] or multiple Kinect devices [72], was highlighted as a potential barrier to their use.

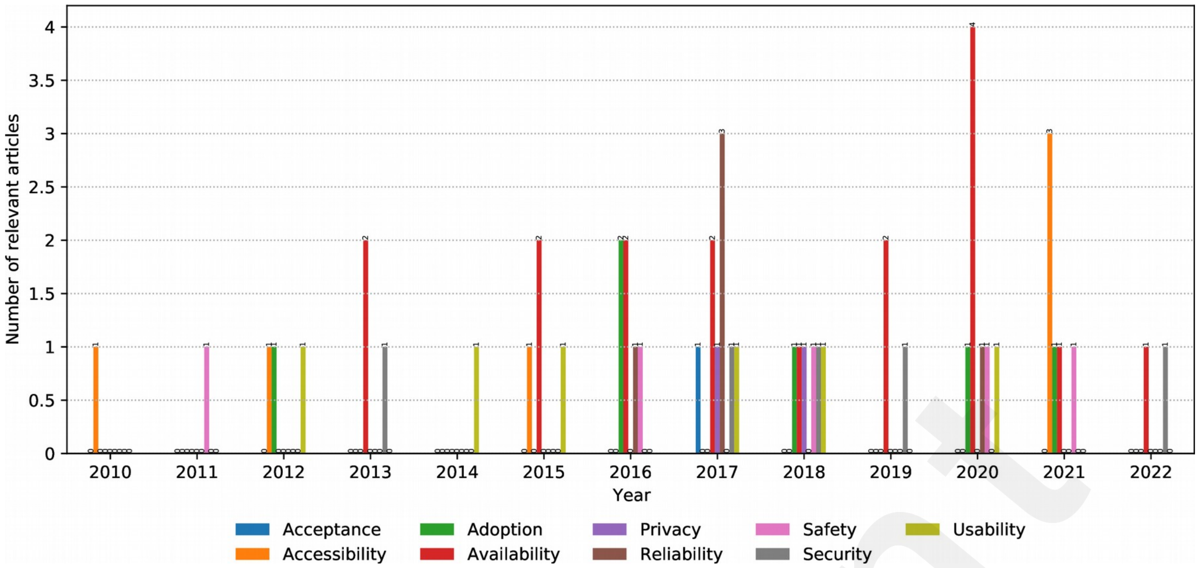

Figure 13. The number and annual distribution of relevant articles regarding the beneficiaries' concerns from January 2010 to July 2022.

The *accessibility*, *adoption*, and *usability* appear 6 times each. The accessibility of the AAL systems' services reflected the convenience of reaching them, such as the functions of an IoT device that generates user profiles from their activities [77]. The adoption referred to more sustained and stable use and integration of the introduced technology into the beneficiaries' routine, such as the usage of widely-adopted technologies (i.e., smartphones) for HAR [46]. The usability was described as the ease of use of various AAL systems, including the percentage of successful task completion when using a medication management application [65].

The *reliability*, *safety*, and *security* have 5 occurrences each. Reliability described the reliability levels of the AI models' outcomes from the beneficiaries' perspective, such as the perceived accuracy of activity trackers [58]. Safety was a requirement for AAL applications to prevent any harm to their users, such as detecting abnormal human behaviors to avoid dangerous situations [78]. Security refers to protecting users from external threats when using AAL technology, for example, when utilizing users' appliance consumption data to infer their activities [44].

Privacy (2) and *acceptance* (1) received the least attention. The privacy manifested as a need for protecting beneficiaries' data during collection, analysis, and use by the AAL system, such as protecting persons' identities [42]. The acceptance emerged as desired qualities of the AAL technology that facilitate the attitude, such as the unobtrusiveness of radar-based sensors for patient monitoring [63].

Discussion

This section summarizes the results of the scoping review. The AI models are key drivers of AAL systems. In this respect, the study clarifies their role and significance over the previous decade by considering domains, technologies, and end-users. At the same time, it highlights critical user concerns to identify gaps that require further research.
The overall goal was to provide an overview and synthesis of the research on AI classes and models in AAL (RQ1), domains in which they were applied (RQ2), technologies that employed them (RQ3), and their beneficiaries, along with usage concerns (RQ4).
The following discusses the principal findings concerning the evolution of the AI models and related categories and implications for different stakeholder groups, including well-being and healthcare, technology, and research.

Principal Results

Evolution of Categories in AAL

The time frame has seen a variety of AI *models*' contributions that target a range of *domains*, *technologies*, and *beneficiaries*.
Semi-supervised and unsupervised learning classes dominate the intelligent AAL landscape. Their prevalence was due to an increase in the variety of the health and living domain and the gradual appearance of labeled input data describing related ADL/IADL the learning aimed of support [37-39]. The supervised approaches been used for classification tasks [42].
DL and NLP models have been mainly used throughout the search time frame. DL models combined NN-based algorithms, such as CNN and RNN [79]. These algorithms can be both supervised or unsupervised, but it was rarely considered explicitly in relevant articles. However, in-depth, manual article analysis showed they were mainly supervised. The algorithms dealt with multi-dimensional input data from heterogeneous sources. The data described various human activities to support or infer health conditions [46, 47]. In the first half of the frame, NLP models mainly recognized users' spoken input [48]. During the second, they enabled conversations with users [49]. The models using reference examples (i.e., instance-based) and clustering were used for classification tasks [50-53]. Ensemble approaches, by definition, combine separate models to compensate for individual drawbacks [54, 55] and were used later in the time frame (from 2014). Other approaches were notably less employed.
Activity assistance and recognition were leading domains with the generally growing trend. In most cases, the activity assistance assumed recognition (38 out of 61 occurrences, 62%), while the remaining instances focused on specific activities known in advance. A range of ADL and IADL were supported, where different indoor/outdoor mobility (i.e., walking, physical exercise, and transportation) prevailed [61, 62]. The interaction referred to the systems as seen by their end-users [65]. The communication denoted internal inter-relations between AAL system components [66]. Health monitoring concentrated on deviations in vital functions and detection of abnormal behaviors [63].
Ambient sensing and mobile technology are mainly used in AAL. Sensing uses different sensors to detect available signals that carry specific information on user behavior [70]. Mobile technologies were convenient to use (i.e., market availability, affordability, and wide adoption) on an application level as lifestyle applications for health and well-being [67] and device-level as a platform with integrated sensors [55]. Robots appeared as either assistive devices helping users carry out their activities [71] or companions for pleasurable activities [49].
The study found notably fewer wearables, followed by conversational and gaming technologies.
Older adults were the primary beneficiaries of AI models in AAL within the search time frame [73]. Patients followed, and the co-existence with the previous (9 out of 26, or 35% found cases with older adults as per Figure 6) shows that other ages benefited from AI models [45, 75]. Frail persons were less present and co-appeared with older adults in 9 out of 2 or 43% of instances. Healthcare staff, caregivers, and family were under-represented than the former and occasionally mentioned.
Availability prevails as a beneficiary concern. In general, off-the-shelf, affordable technology [55] is preferred compared to more expensive equipment concerning cost and/or deployment [56]. The remaining concerns had fever cases.

Implications for Healthcare and Well-being

Based on our observations concerning domains, beneficiaries, and concerns, we identified gaps in the existing literature and articulated the following directions for future work.

- *Collaborative decision making* - current AAL systems make their decisions autonomously, driven by the models' algorithms and input data. The involvement of expert users (i.e., healthcare staff and caregivers) in the decision-making process can improve its accuracy, facilitate automated learning about users, and reduce the burden on healthcare professionals.

- *Augmenting caregivers and recipients* - by its definition, the AAL occurs outside healthcare facilities. In such a scenario, consideration of caregiving and caretaking is critical for adherence to healthcare services that should address the participants' concerns. Active participation of these beneficiaries is crucial for a successful digital healthcare intervention, from their AI model comprehension to a particular technology design and deployment.
- *AAL interventions* - studies included various technologies and platforms to support independent living. Our analysis did not reveal knowledge exchange among studies concerning their results and experiences. Technology-supported healthcare interventions have been designed for various medical domains. Systematized knowledge on models, domains, technologies, and beneficiaries can guide AAL interventions tailored to specific healthcare requirements. Such knowledge can reinforce best practices and mitigate potential risks.
- *Regulations and compliance* - at present, AAL design and deployment space is not regulated, nor is their compliance acknowledged and endorsed by regulatory authorities globally. AAL systems must comply with regulations at both a national and international level. This is crucial for their implementation in medical practice and general adoption. To meet this need, we advocate for a repository of evaluation methods and design guidelines that would support compliance and provide a clear view of how to incorporate critical aspects during AAL system design.

Implications for Technology

The analysis of the models, technologies, and concerns discovered unsolved matters that require more attention.

- *Transparency and privacy* - AI models, by their very nature, need, produce and process large amounts of various user-related data. From intensive data collection and analysis to delivering their decisions as personalized recommendations to users. First, the technology should be transparent on why and how user data are collected, analyzed, and utilized. Second, it should respect a user’s right to control their private data and communications and that they are free from intrusion. Satisfying these user needs is critical for trust in AAL systems.
- *Integration with healthcare services* - AAL systems are usually built and deployed as stand-alone platforms, independent of institutional healthcare systems. Connecting with existing medical technological infrastructure and digital services can increase the efficiency and effectiveness of healthcare provision. The benefits are mutual. The AI models could be fed with existing user medical records and procedures for improved decision making. In turn, medical actors could be timely informed on emergencies or changes in users’ behaviors that are difficult to observe in clinical settings.
- *Inclusive AAL* - AI models focus on individual users as a user-system relation. Group dynamics are not supported, such as user-system-doctor relations or forming peer groups of similar users. The future intelligent AAL systems should equally engage and moderate among multiple beneficiaries: patients, families, caregivers, and healthcare staff. This also represents a general implication for healthcare systems.

Implications for Research

Looking at the results as RQs’ responses, following research directions emerged.

- *Explainable decision making* - as capabilities of AI models increase, the absence of explanations behind automated behaviors raises uncertainty with users due to a lack of understanding of how specific decisions are made [80]. The explanatory behavior of the models can ingrain positive behaviors to maintain a healthy lifestyle [81]. Thus, a general requirement for future AI models is the provision of explanations understandable to beneficiaries without background or knowledge in AI (i.e., non-experts).

- *Evaluation techniques* - studies proposed evaluation techniques that could be broadly categorized into functional (i.e., technical) and non-functional (i.e., medical and usability). They used existing instruments to measure AI models' algorithms (accuracy and performance) or medical/user-related outcomes (standard scales for particular medical conditions, interviews, and questionnaires). Moreover, they focused on a single or several measures from the same category. To obtain a clear and valid assessment of the effectiveness and efficiency of the AI models employed in AAL, we need a more comprehensive and coherent set of cross-category evaluation metrics to be proposed and verified in practice.
- *Design recommendations* - discovery of design guidelines from relevant papers depends on how they are described. In the analysis phase, the identification and extraction of guidelines were not straightforward. The design contributions were mainly presented as suggestions derived from the conducted studies. Other forms included development and deployment practices concerning specific models, domains, and technologies. These contributions are difficult to apply and reproduce, being a barrier to their uptake. Standard reporting procedures and the knowledge bases could help address the issue and provide actionable guidelines to interested communities. A number of independent studies will be needed to implement and validate the guidelines.

Limitations

We acknowledge the proposed AI/ML class/model categorization that served as a basis for our search is not comprehensive, exhaustive, and exclusive. While there are other taxonomies, our goal was to highlight the underlying mechanisms of these classes and models for the review to provide a proper understanding of their roles in AAL systems.

Moreover, the categories and associated keywords may have limited the search results. Thus, we included common synonyms found in the literature for the keywords to capture more results at the cost of more non-relevant articles. Still, we may have missed relevant material using other terms or not using searched keywords explicitly.

Another limitation of our study is the necessity of setting a time frame for the articles included in the review. We selected to cover work by early reviews of AAL systems and advancements in AI learning algorithms. Yet, as with any date restriction, there is a risk of not considering potentially relevant work.

A further limitation concerns manual extraction and categorization of retrieved articles (for inclusion) that may introduce a subjective perception of coders. The risk was addressed by cross-analysis and discussion of each other's results for agreement. Relatedly, the findings on prevalence/trend may primarily represent the researchers' interest but not an objective sampling of all the stakeholders' perspectives, including that of the users.

Finally, the study considered 5 digital libraries, among others. Considering the size, coverage, and diversity of the digital libraries regarding RQs, we deem that the obtained results sufficiently respond to them.

Comparison with Prior Work

In comparison with relevant work, we focus on previous (meta-)reviews on related topics and comparative studies, giving preference to AI models. The (meta-)reviews' and studies' scope was generally more constrained than ours.

The meta-review presented in [16] examined video-based lifelogging technologies for AAL of older adults. Lifelogging assumes recording personal data of a user's daily life. It produces a dataset as a computational knowledge about a person (also known as quantified self) that could be used for different purposes, such as detecting emergencies and predicting user behavior. The target model was DL, domain HAR, and technology RGBD sensing devices. The study articulates ethical implications for these applications.

The review described in [82] analyzed existing fall detection systems through implementations of existing sensor technologies. It provides a descriptive framework to help choose appropriate sensors for particular deployment scenarios and locations. The main areas for technical improvements were unobtrusiveness, installation costs, and power requirements.

The survey from [83] discussed ML and DL algorithms for sensor-based HAR of older adults concerning their accuracy and quantity (coverage of recognized activities). ML models require fewer data and computational resources, whereas DL models better recognize complex activities.

A review of mobile applications for dementia [84] showed that caregivers were the primary users, and the app content mainly provided information on dementia. The barrier to the availability of these applications is a lack of navigating the app marketplace and quality metrics for their dementia information.

The review of DL techniques used in smartphone and wearable sensor-based HAR systems [85] demonstrated that DL techniques outperform other ML ones. However, they were verified on pre-existing datasets, not the data acquired in real-time.

An in-depth analysis of DL algorithms for HAR using mobile and wearable sensor networks [79] raised the need for higher computational resources in mobile and wearable devices to enable online and real-time decision making.

A more comprehensive review of assistive technologies for older adults classified technologies into clusters such as general ICT (e.g., computer and internet applications), robotics, telemedicine, sensor technology, medication management applications, and video games [17].

A study analyzed RCTs on the effectiveness of assistive technology for memory support in people with dementia [86]. Measured outcomes included ADL, level of dependency, clinical and care-related outcomes, and perceived quality of life and well-being. The evidence was mixed and inconsistent and drew no generalized conclusions.

Another review investigated mHealth interventions for adults who had experienced stroke [87]. The interventions targeted different patient functions, mostly upper extremity function, functional mobility, and language and speech skills. However, they were mainly preliminary, focused on technology development up to pilot testing, lacking evidence from large-scale trials.

Off-the-shelf voice assistants were used by persons with motor, linguistic and cognitive disabilities [88]. While these systems are widespread, inexpensive, and non-stigmatizing compared to other assistive technologies, participants' performances depended on their level of cognitive and linguistic skills.

A comparative study of different ML algorithms for HAR [89] used existing datasets and indicated that sensor-based techniques were preferred over vision-based since they better preserve user privacy. A similar study [90] examined particular algorithms, namely DT, KNN, SVM, NB, LDA, and ensemble learning, in recognizing specific ADL (meal preparation, eating, housekeeping, etc.). In general, the algorithms performed equally well on the chosen dataset.

Conclusions

We have described a scoping review based on systematic search and analysis, which identified research trends concerning AI models, domains, technologies, and beneficiaries along with their concerns. The AI models, domains, technologies, beneficiaries, and concerns extracted from the literature represent a knowledge base that can be consulted and utilized when developing and deploying AI-infused AAL systems. Its findings can: 1) inform end-users, healthcare professionals, and caregivers on available technologies and their target medical domains, 2) guide healthcare providers and engineers in implementing and deploying these technologies, and 3) help end-users understand the benefits and trade-offs of the technologies.

Research activity increased awareness of AI models in AAL and revealed gaps in the field. Further work is needed in making AAL systems more efficient, effective, and user-friendly. In particular, hybrid doctor-model decision making, the inclusion of caregivers by technology design, and compliance with health-related regulation will uptake AAL by a society. Moreover, improving transparency and privacy, integration with legacy systems, and equal inclusion of different beneficiaries will improve the acceptance and availability of AAL systems. Finally, efforts to explain automated decision-making, adopting standard evaluation metrics, and verified design guidelines will recognize different AAL approaches to ensure them in digital healthcare.

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Conflicts of Interest

No conflicts to declare.

Abbreviations

AAL - Ambient Assisted Living
ADL - Activities of Daily Living
AI - Artificial Intelligence
AL - Assisted Living
ANN - Artificial Neural Network
CNN - Convolutional Neural Network
DL - Deep Learning
DM - Dialog Management
DT - Decision Tree
EEG - Electroencephalography
EU - European Union
FER - Facial Emotion Recognition
HAR - Human Activity Recognition
HMM - Hidden Markov Models
IADL - Instrumental Activities of Daily Living
ICT - Information and Communication Technology
IEEE - Institute of Electrical and Electronics Engineers
IMU - Inertial Measurement Unit
IoT - Internet of Things
kNN - k-Nearest Neighbor
LDA - Linear Discriminant Analysis
LSTM - Long Short-Term Memory Network
MDPI - Multidisciplinary Digital Publishing Institute
ML - Machine Learning
MLP - Multilayer Perceptron
MRI - Magnetic Resonance Imaging
MTC - Multi-task Clustering
NB - Naive Bayes
NLG - Natural Language Generation
NLP - Natural Language Processing
NLU - Natural Language Understanding
NN - Neural Network
PCA - Principal Component Analysis
PCR - Principal Component Regression
RGBD - Red Green Blue Depth

RNN - Recurrent Neural Network
SR - Speech Recognition
SVM - Support Vector Machines

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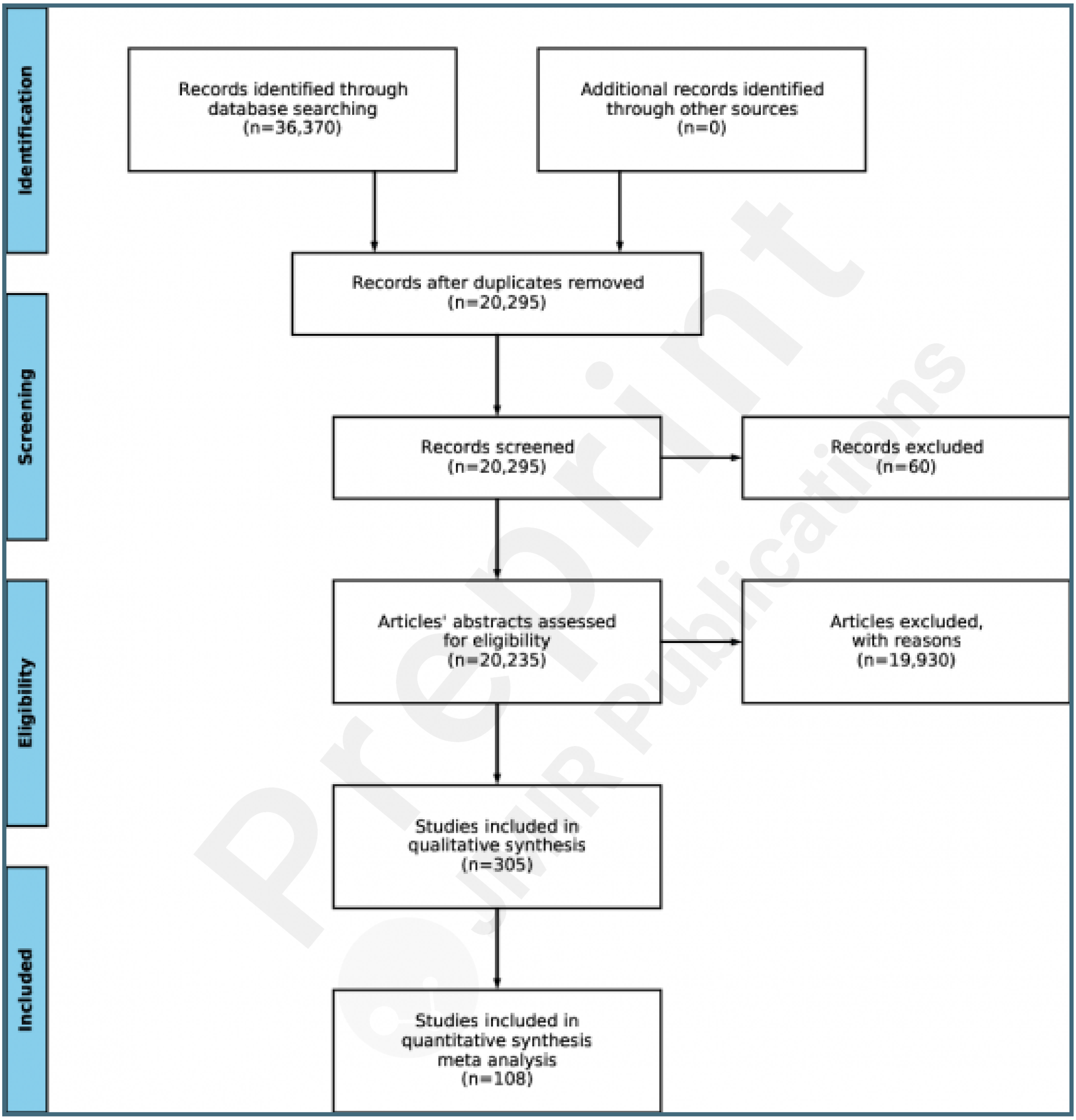
doi: 10.1007/978-981-32-9682-4_29

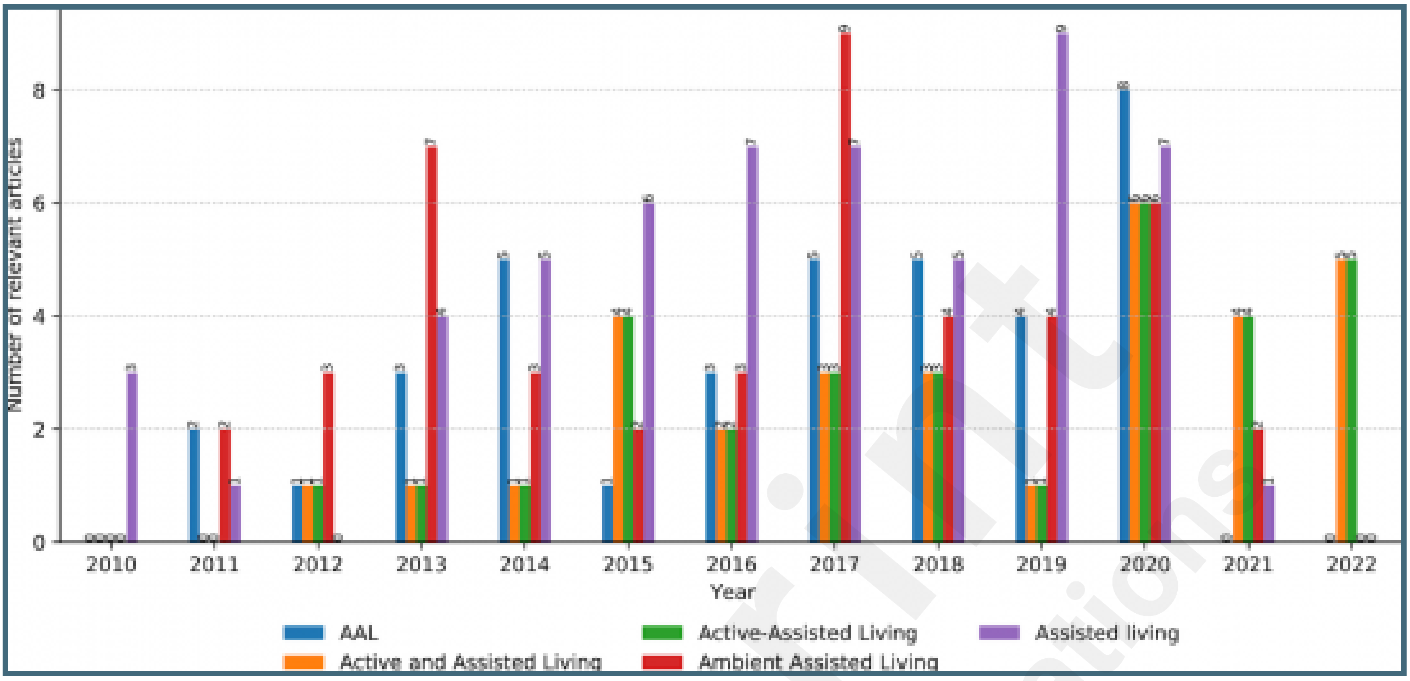
Supplementary Files

Figures

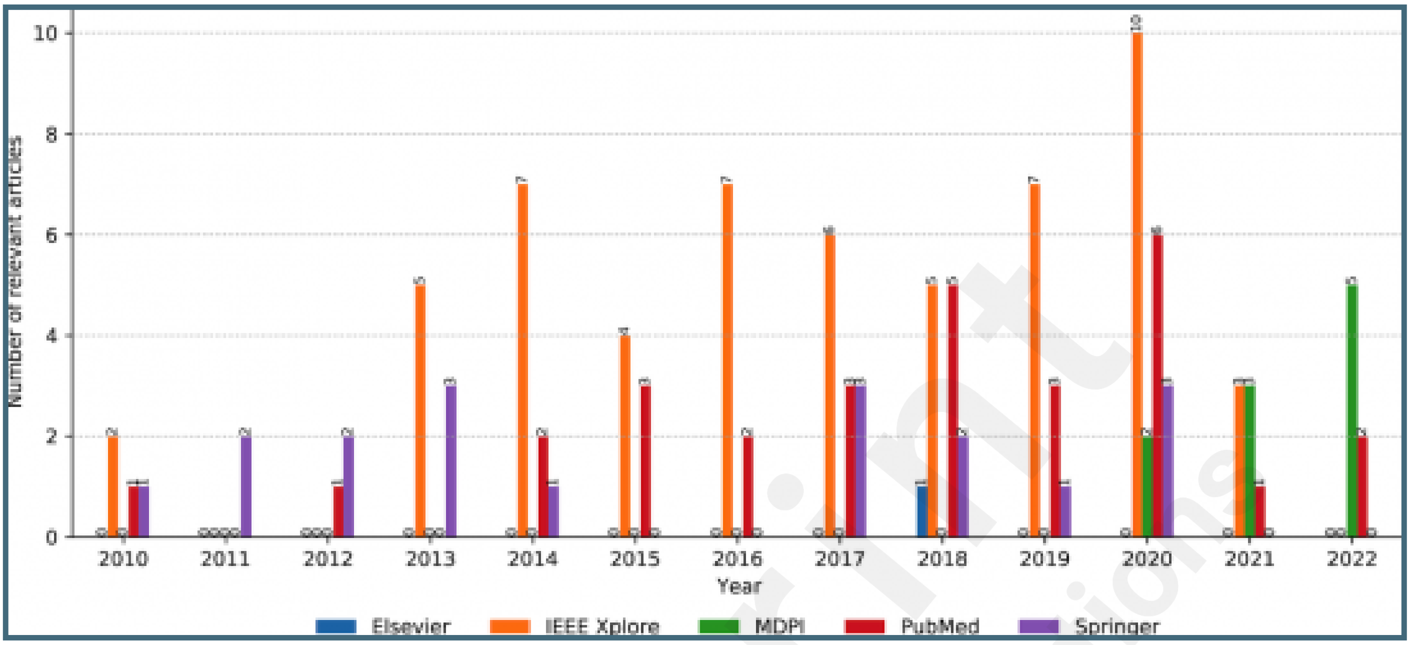
The PRISMA flow of the review process illustrates identification, screening, eligibility, and inclusion of relevant articles.



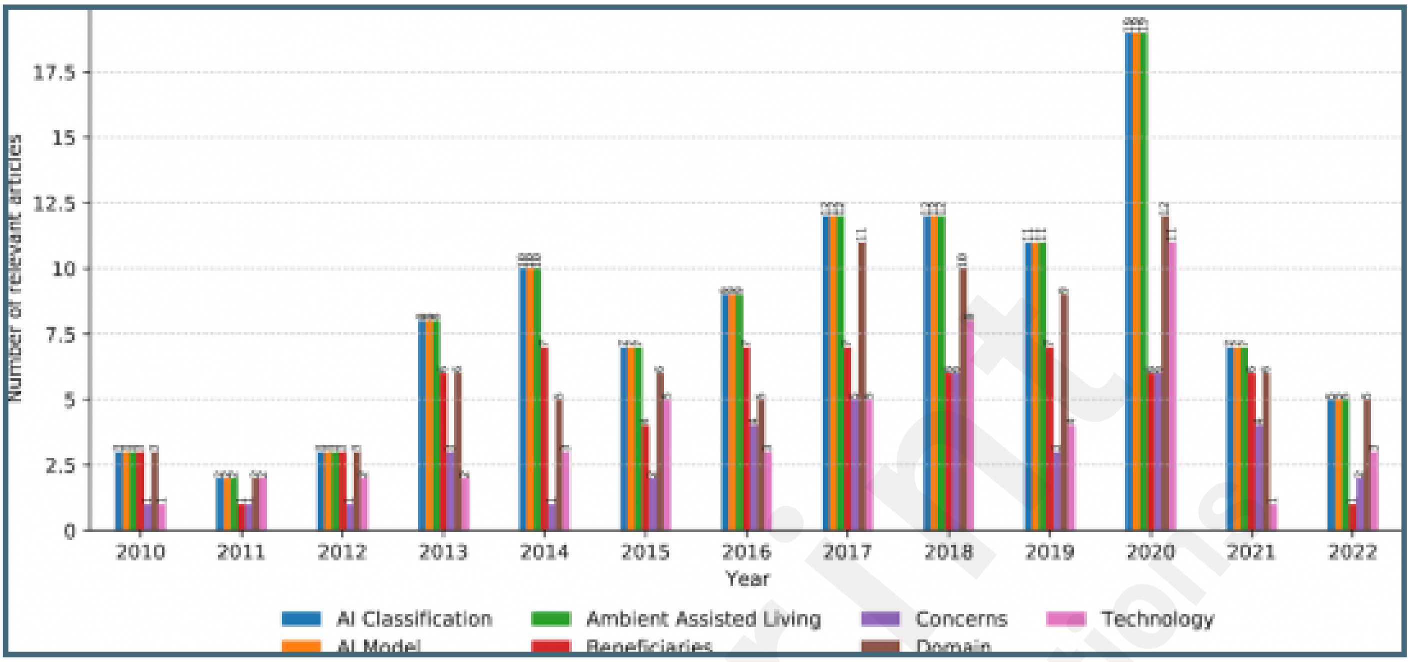
The number of relevant articles concerning Ambient Assisted Living with AI Classes and Models per year from January 2010 to July 2022.



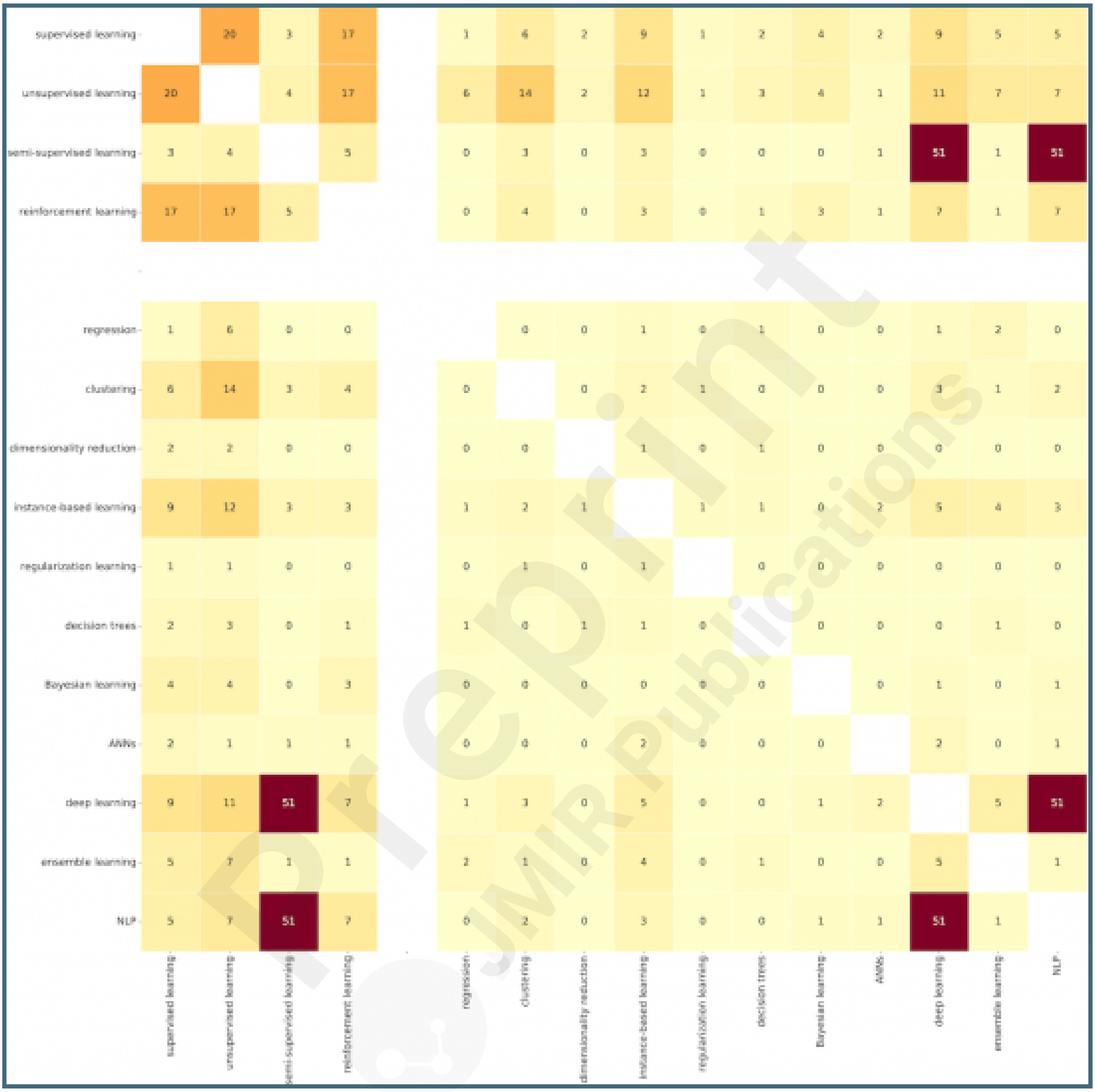
The number of relevant articles per year from January 2010 to July 2022, grouped by the respective digital library.



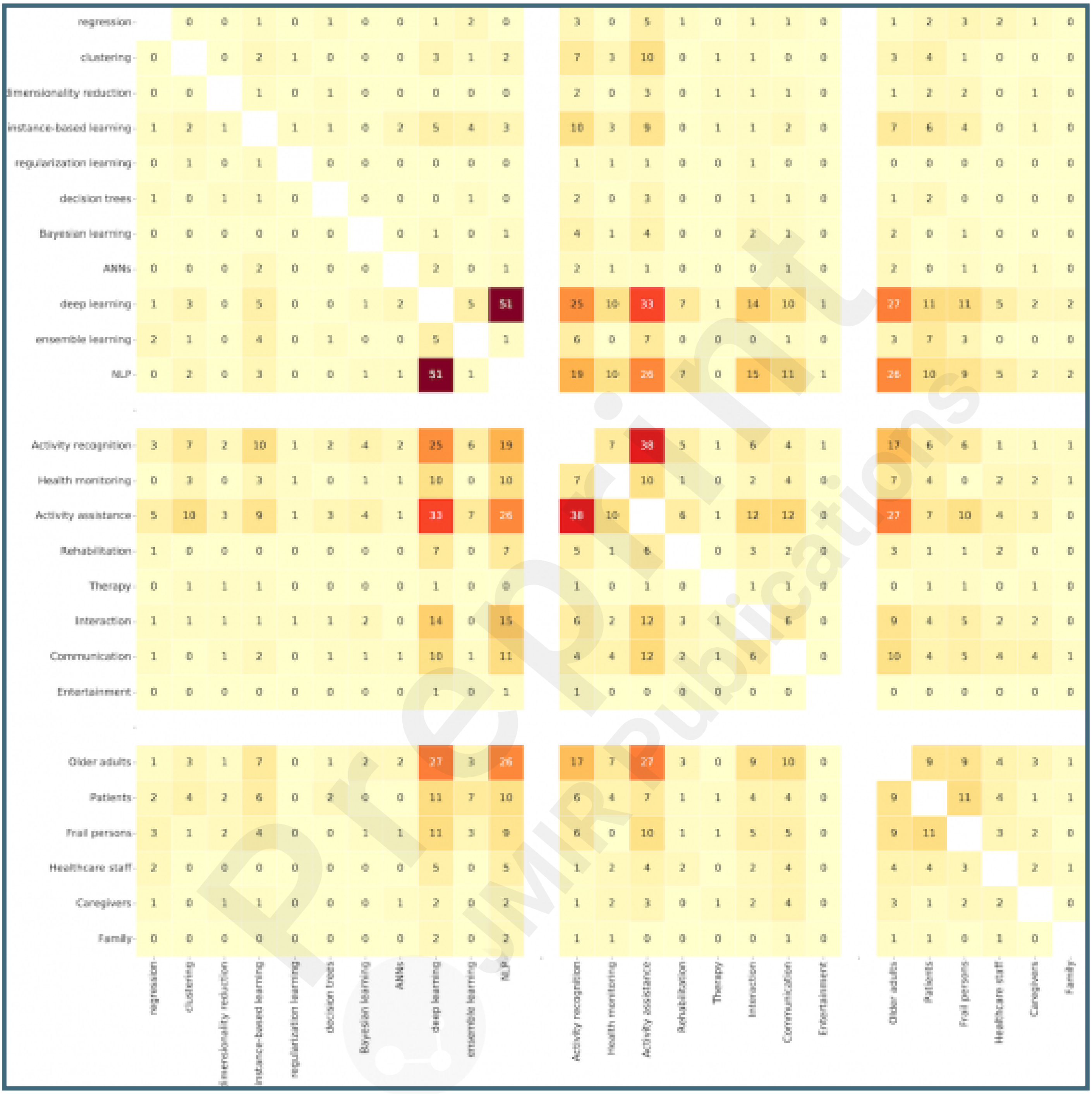
The number of relevant articles for each category per year from January 2010 to July 2022.



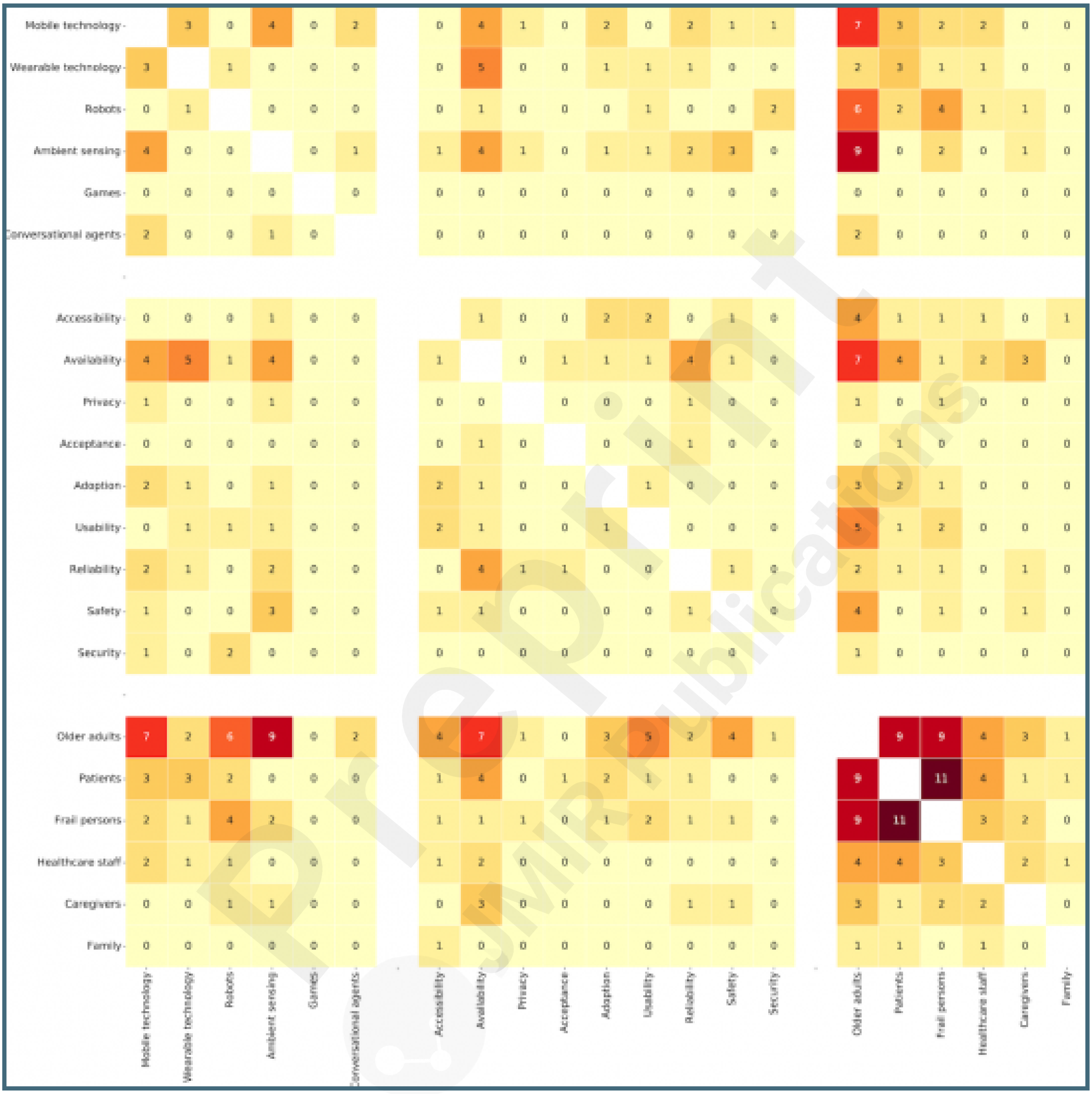
The heatmap describing co-occurrences of AI classes and models in relevant papers.



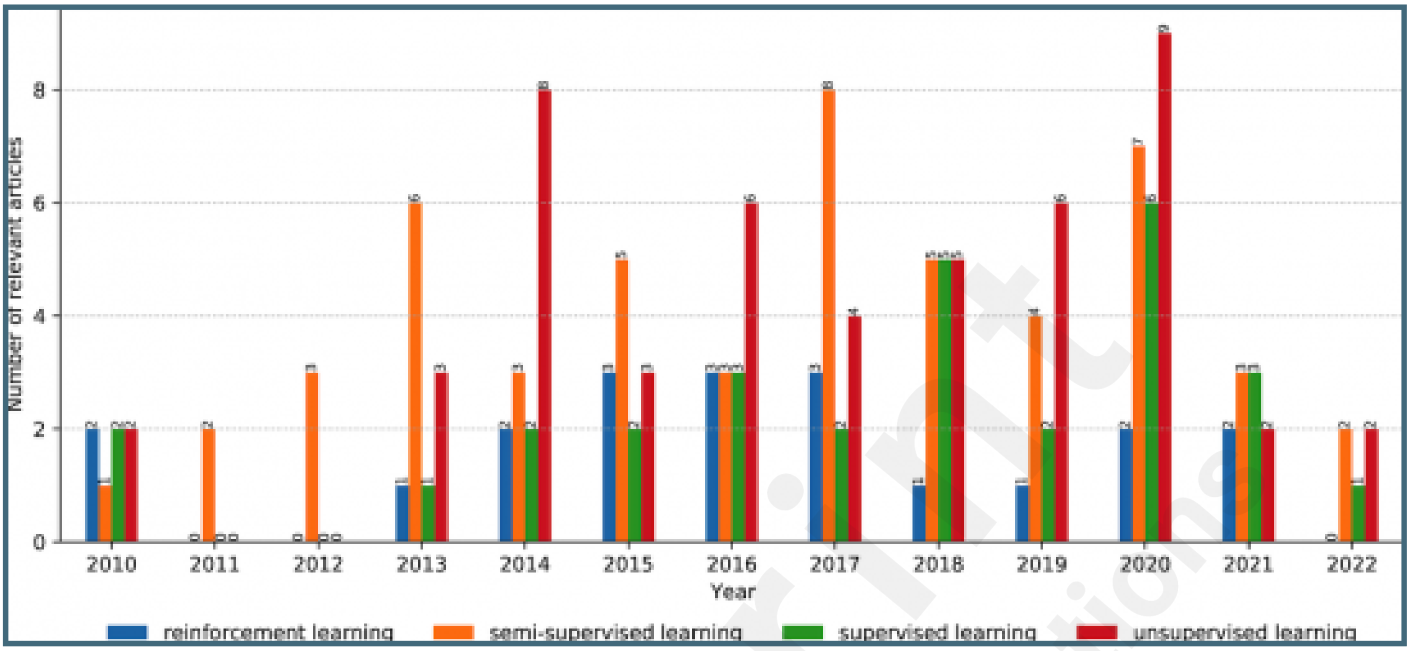
The heatmap describing co-occurrences of AI models, domains and beneficiaries in relevant papers.



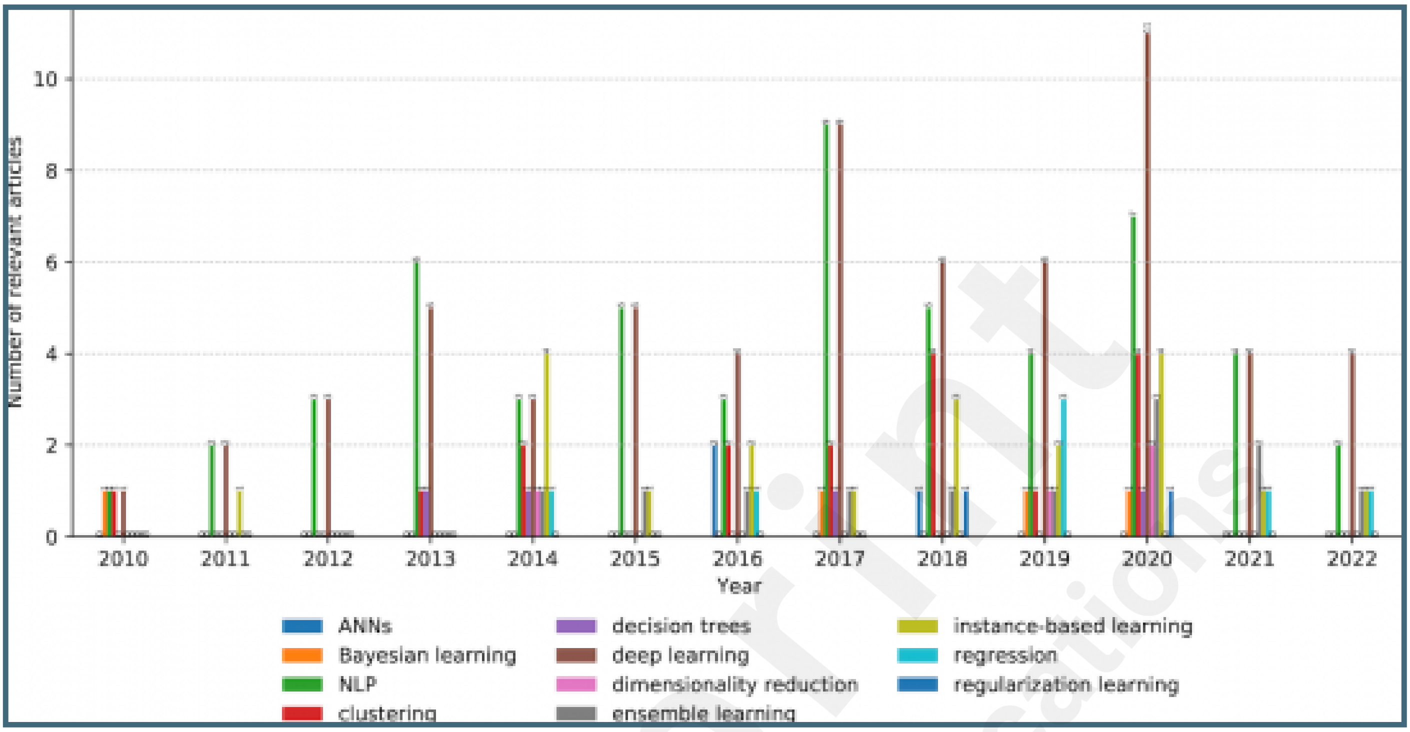
The heatmap describing co-occurrences of technology, beneficiaries and concerns in relevant papers.



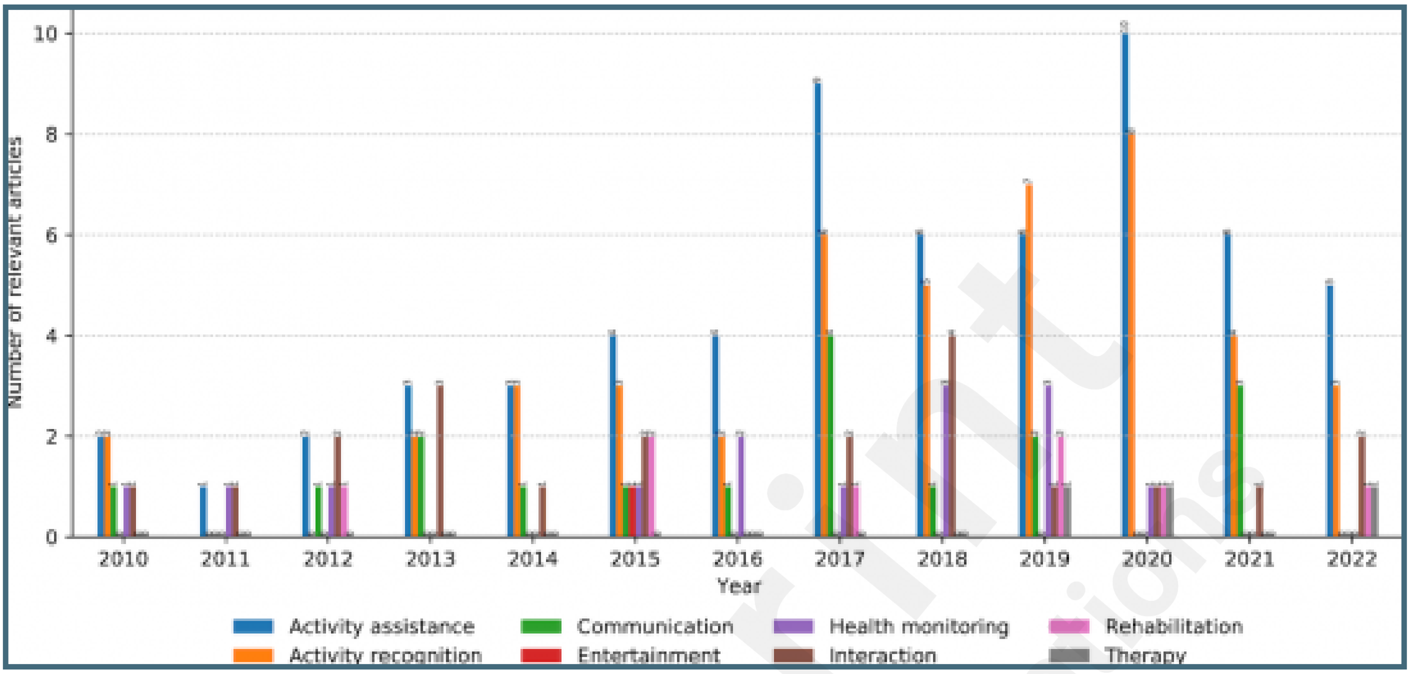
The number and annual distribution of the relevant articles concerning AI classes from January 2010 to July 2022.



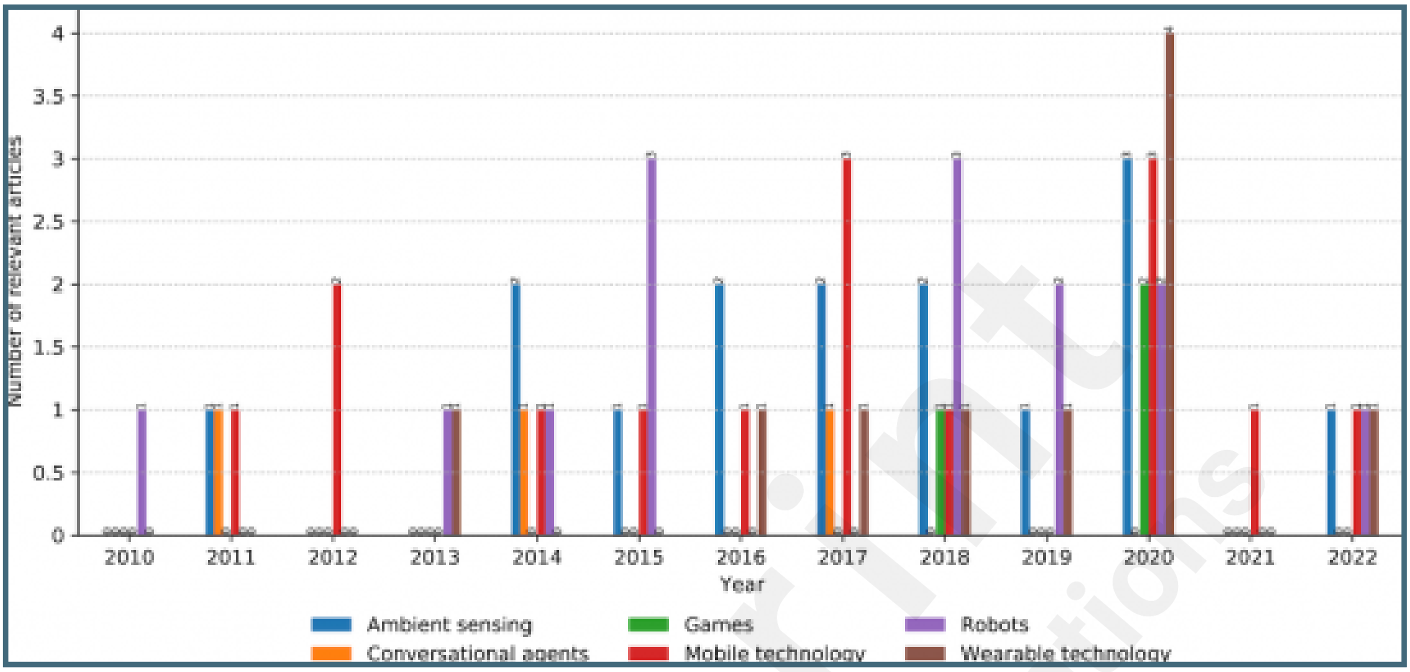
The number and annual distribution of the relevant articles concerning AI models from January 2010 to July 2022.



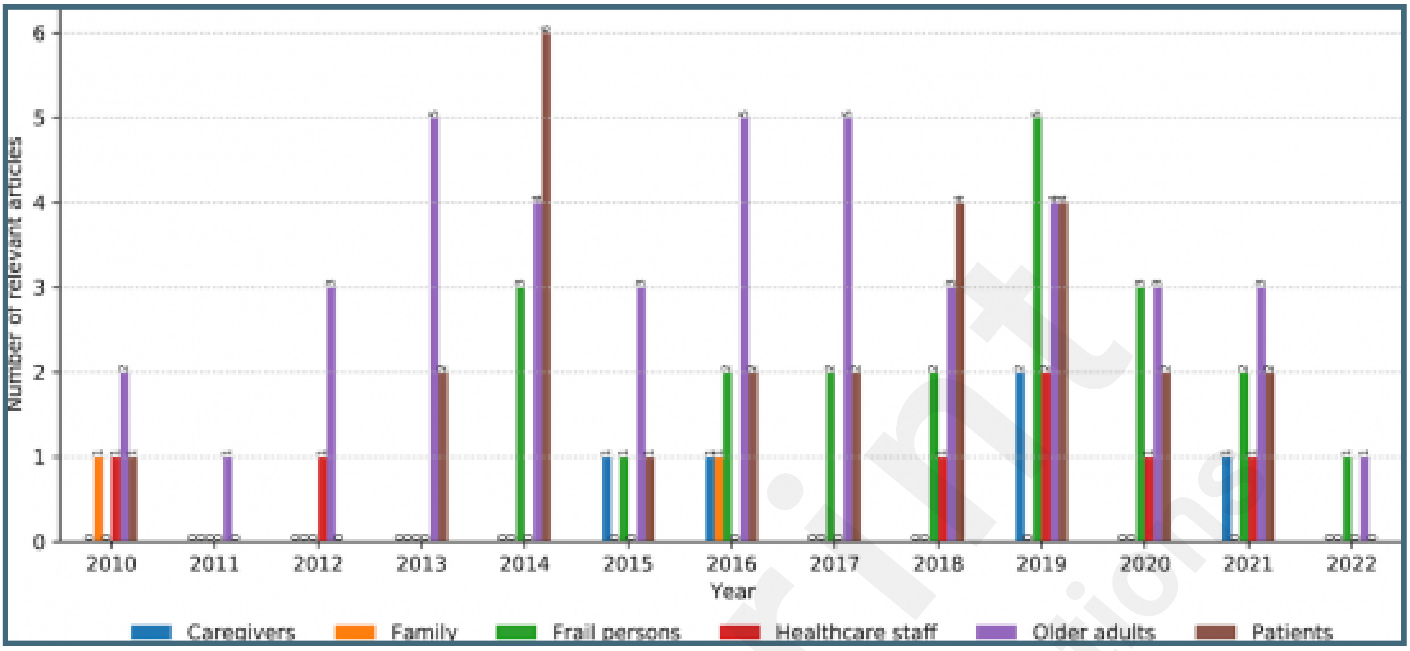
The number and annual distribution of relevant articles concerning the AI models' domains from January 2010 to July 2022.



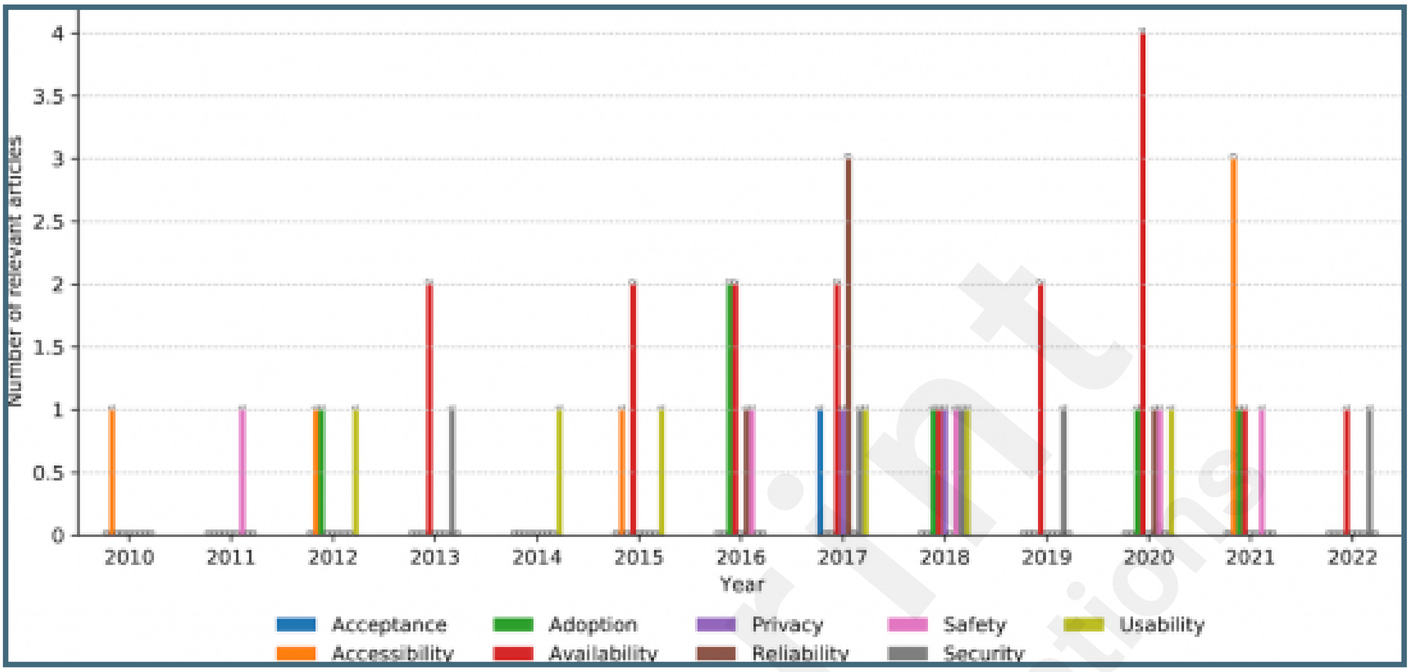
The number and annual distribution of relevant articles concerning the AI models' technology from January 2010 to July 2022.



The number and annual distribution of relevant articles concerning the AI models' beneficiaries from January 2010 to July 2022.



The number and annual distribution of relevant articles regarding the beneficiaries' concerns from January 2010 to July 2022.



Multimedia Appendixes

The list of the relevant articles retrieved from the five digital libraries.
URL: http://asset.jmir.pub/assets/64ea7130a1622cab8d82b76bf3b373ba.xlsx