

# The Ubiquitous Guardian: Ambient Intelligence's Impact on Healthcare

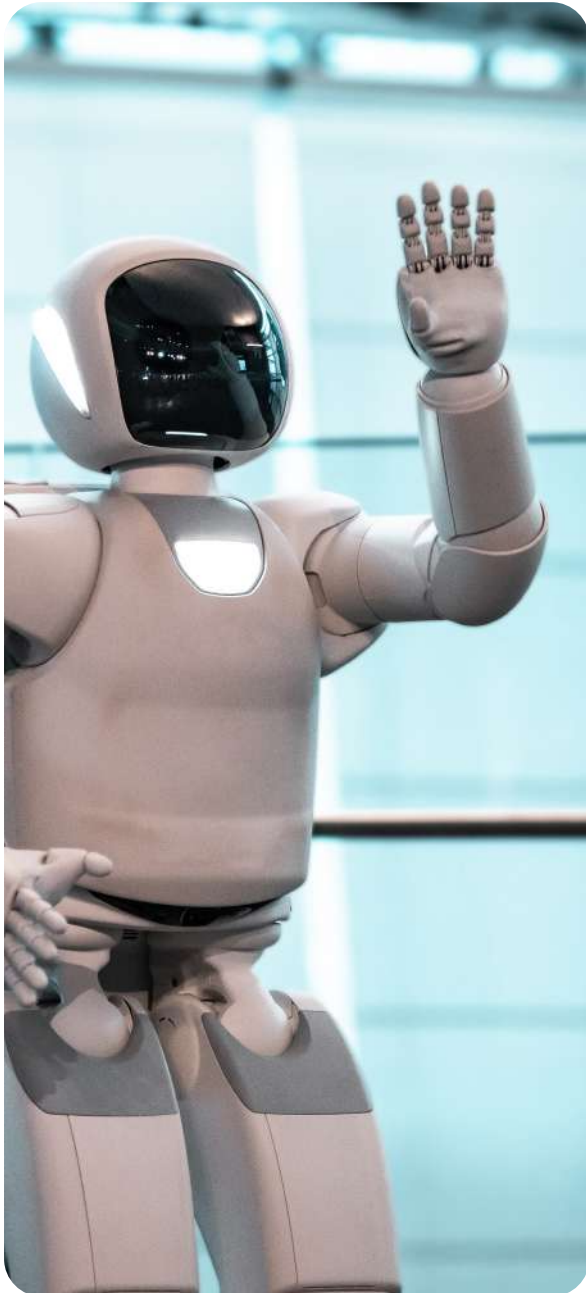


# Table of contents

About The Centre	03
Introduction	04
Ambient Intelligence	05
Building Blocks Of Ambient Intelligence	06-08
Body Area Networks	06
Wireless Mesh Sensor Networks	07
External Systems Integrations	07
Understanding Behavioral Patterns In Smart Systems	07-08
Unleashing Potential: Ami Use Cases In Healthcare	09-10
Automating Critical Care Support	09
Operating Rooms	09
Application In The Control Of Hospital Infections	10
Elderly Living Spaces And Ageing	10
Chronic Disease Management	10
Mental Health	10
Persuasive Wellbeing	10
Improving Hospital Operational Efficiency	10
Predict And Prevent Medical Emergencies	10
Challenges Of Ami In Healthcare	11-12
Standardization	11
Social And Cultural Equity In Design	11
Uncertainty	11
Privacy	11
Sensor Security	11
Security In Ami Systems	12
Surveillance Concerns	12
Lack Of Interoperability	12
Moving Ahead: A Trustworthy, Reliable, User-Centric, Secure, Transparent, And Interoperable Ami For Healthcare	13-14
Conclusion	15
End Notes	16-19

# About the Centre

The Centre for Trustworthy Technology is a World Economic Forum's Centre for the Fourth Industrial Revolution.



## Our vision

Our vision is to empower all through the responsible integration and use of innovative and potentially disruptive technologies.



## Our mission

Our mission is to guide organizations in understanding, preparing for, and leveraging transformative and trustworthy technologies, thereby promoting a future where technological innovation benefit all.



## Our core values

Our core values include Collaboration, Global inclusivity, Human-Centered outcomes, Being Action-Oriented, Passionate, and Committed to Learning & Educating.



# Introduction

Ambient Intelligence (Aml) is reshaping the healthcare landscape, presenting an intelligent and responsive environment that seamlessly integrates into our lives. Propelled by advancements in Internet of Things (IoT), Artificial Intelligence (AI), and ubiquitous computing, Aml now stands at the forefront of healthcare innovation. From utilizing a range of ambient sensors to synthesizing data with AI, Aml systems are redefining how healthcare spaces interact with and adapt to human needs.

The global ambient intelligence market was valued at \$19.2 billion in 2022 and is projected to reach \$185.5 billion by 2032.<sup>i</sup> This growth represents a compound annual growth rate (CAGR) of 25.7% from 2023 to 2032. In 2022, the healthcare sector dominated the market, contributing to almost one-third of the total revenue in the ambient intelligence industry. This segment is expected to continue leading the market throughout the forecast period.

Characterized by context awareness, personalization, anticipatory function, adaptability, and ubiquity, Aml systems are being designed to enhance healthcare delivery. These systems emphasize user-centric design, ensuring seamless and intuitive interaction, while also prioritizing reliability and security. The heart of Aml lies in its ability to understand and respond proactively to its environment, making healthcare spaces more intelligent and adaptable.

However, the journey of Aml in healthcare is not without challenges. It faces issues of standardization, the necessity for social and cultural sensitivity in design, managing uncertainties, ensuring privacy, and addressing security concerns. Despite its potential impact on advancing the quality of healthcare, a Pew Research survey showed that 60% of Americans are uncomfortable with medical care that uses technologies reliant on AI.<sup>ii</sup> To truly realize the impact of these technologies, there needs to be a concerted effort to understand Aml technologies and provide a trustworthy perspective for adopting them. This paper explores its capabilities, architecture, use cases, challenges, and the path forward for this nascent but potentially highly impactful emerging field. The roadmap ahead involves building systems that are trustworthy, secure, transparent, and interoperable, ensuring they are responsive to the diverse needs and challenges of modern healthcare.

This vision of Aml in healthcare is not just about technological advancement; it's about building systems that are empathetic and understanding of human emotions and behaviors. It's about creating a healthcare environment that is not only intelligent and efficient but also compassionate and responsive to the emotional and physical needs of individuals.



# Ambient Intelligence

Aml refers to spaces that are sensitively crafted to engage, adapt, and respond to human activity.<sup>iii</sup> Spaces are imbued with technology that operates discreetly in the background, designed to be responsive to our needs. It imagines our environment as an intelligent partner, proactively shaping itself to our behaviors, needs, and changing circumstances with subtle agility.

The concept of Aml was initially introduced in 1998 through research conducted for Philips.<sup>iv</sup> This research envisioned the future of computing and technology in domestic settings, aiming to integrate a diverse array of electronic devices into a cohesive, expandable, and adaptable system. Concurrently, similar initiatives were undertaken, notably by the Information Society and Technology Advisory Group (ISTAG) at the European Commission. In 2001, a report under ISTAG brought forth scenarios and use cases, key system components, and critical research areas necessary for Aml's development.<sup>v</sup> Since then, the development of the Internet of Things (IoT), Artificial Intelligence (AI), and ubiquitous computing has greatly advanced the use of Aml.<sup>vi</sup>

The deployment of a range of ambient sensors, including video cameras, depth sensors, thermal imagers, radio-frequency identifiers, acoustic monitors, and wearables like smartwatches, facilitates sensing of a space. When the perceptual data from these sensors are synthesized with diverse AI technologies, they can become intelligent and powerful tools to address a multitude of healthcare challenges.

## An Aml system has a unique set of characteristics<sup>vii viii ix x:</sup>

- i. **Context Awareness:** It effectively utilizes context and situational information to enhance functionality.
- ii. **Personalization:** It is tailored to cater to the specific needs of each user.
- iii. **Anticipatory Function:** It possesses the ability to predict and respond to the needs of an individual without requiring active inputs.
- iv. **Adaptability:** It can adjust to the evolving needs of its users.
- v. **Ubiquity:** It is seamlessly integrated into environments becoming pervasive in its background.
- vi. **Environmental Framework:** It includes varied components of the system, such as users, devices, and other interconnected systems.
- vii. **Sensing Mechanism:** It involves entities including people and devices which generate contextual data.
- viii. **Intermediary Systems:** It uses tools like Application Programming Interfaces and network devices that facilitate system distribution, data collection, processing, and command execution.
- ix. **Decision-Making Core:** It focuses on utilizing a knowledge base for making proactive or reactive adjustments and decisions within the system.
- x. **Evolution and Knowledge Acquisition:** It is dedicated to enhancing the decision-making core by integrating new experiences and learnings across the entire system.

These principles can be integrated with technical specifications detailed in the 2001 ISTAG report.<sup>xi</sup> An Aml system is expected to fulfill the following requirements:

- i. **Inconspicuous Hardware:** The hardware should be discreet and minimally intrusive.
- ii. **Integrated Web-Based Communication:** The system should possess a seamless, web-based communication framework.
- iii. **Dynamic Distributed Network of Devices:** It should feature networks that are both dynamic in nature and widely distributed.
- iv. **User-Friendly, Intuitive Interface:** The interface should be easy to interact and engage with for users.
- v. **Reliability and Security:** The system must be dependable and secure.

# Building Blocks of Ambient Intelligence

Aml is rapidly evolving due to a suite of groundbreaking technological developments that are transforming spaces into responsive and intuitive spaces. These technologies, ranging from Body Area Networks (BANs) and Wireless Mesh Sensor Networks (WMSNs) to systems for activity recognition and emotional analysis, are pioneering a future where interactions with technology become seamless. These technologies reveal layers of innovation that bring Aml to life, significantly transforming the healthcare sector.

## Body Area Networks

The development of Body Area Networks (BANs) has been significantly enabled by the widespread use of wireless networks and the miniaturization of electrical devices.<sup>xii</sup> BANs consist of various sensors that use biometric sensing and can be worn on clothing, attached to the body, or implanted under the skin.<sup>xiii</sup> They offer innovative applications by continuously monitoring vital health parameters such as heart rate, body temperature, physical activity, blood pressure, and various other physiological signals. These networks allow for the remote transmission of sensor data to medical professionals for real-time diagnosis, to medical databases for record-keeping, or to systems that can autonomously manage this information and take requisite action. BANs are scalable and can integrate with other network infrastructures like wireless sensor networks, RFID, Bluetooth technologies, video surveillance systems, the Internet, and cellular networks. BANs can be broadly encapsulated in consisting of sensor nodes and actuators, wireless and body-centric communication modules, and central and distributed network topology.<sup>xiv</sup>

- i. **Sensory Nodes and Actuators:** Sensory nodes within BANs record sensory data and may prompt actuators to take medical action (for instance delivery of drugs through a pump).<sup>xv</sup>
- ii. **Wireless Communication Modules:** Most BAN devices transmit sensory data (that was captured with sensory nodes) through Bluetooth and other wireless protocols. Additionally, the human body and its electric properties may be leveraged to transmit specific biological signals.<sup>xvi</sup>
- iii. **Network Topology:** BAN topologies have typically used central hubs that require sensory nodes to directly transmit with central gateways. In these cases, the central hubs will collect and interpret data from its distributed nodes before transmitting its results to external databases. Increasingly BAN topologies include the “mesh topology”, which allows sensory nodes to communicate with each other instead of a central gateway. The mesh topology is often thought to be more scalable and secure as there is no central point of network failure.<sup>xvii xviii</sup>

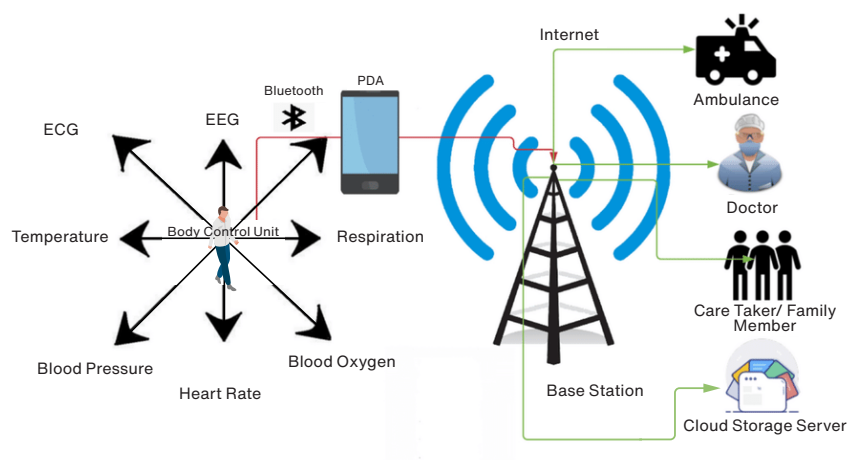


Figure 1 – Body Area Networks (BAN) Architecture<sup>xix</sup>

# Wireless Mesh Sensor Networks

Wireless Mesh Sensor Networks (WMSNs) play a pivotal role in transforming living spaces into intelligent and proactive environments. These networks involve embedding sensors and processors into everyday objects — from clothing to household appliances and furniture.<sup>xx</sup> Referred to as ‘ambient sensors’, these devices collect data to analyze and predict the inhabitants’ activities, aiming to improve their comfort and quality of life. In this system, each sensor node not only captures and processes its data but also relays information from other nodes, ensuring comprehensive data coverage across the network. This collaborative mechanism enhances the network’s efficiency. One of the standout features of WMSNs is their ability to self-organize and self-configure. This means the network can autonomously

establish and maintain connections between sensors, adapting dynamically to the environment. Such a flexible and responsive network design is key to creating supportive and adaptive environments.<sup>xxi</sup>

## External Systems Integrations

BANs need to communicate the information collected to external systems for analysis and decision making. In the context of Aml for Healthcare, data exchanges rely on Application Programming Interfaces (APIs) that integrate the BANs with external cloud-based servers and electronic health record systems. These data integrations require standardized data formats (like JSON or XML) that allow the data from BANs to be accurately recorded, translated, and stored on external systems.

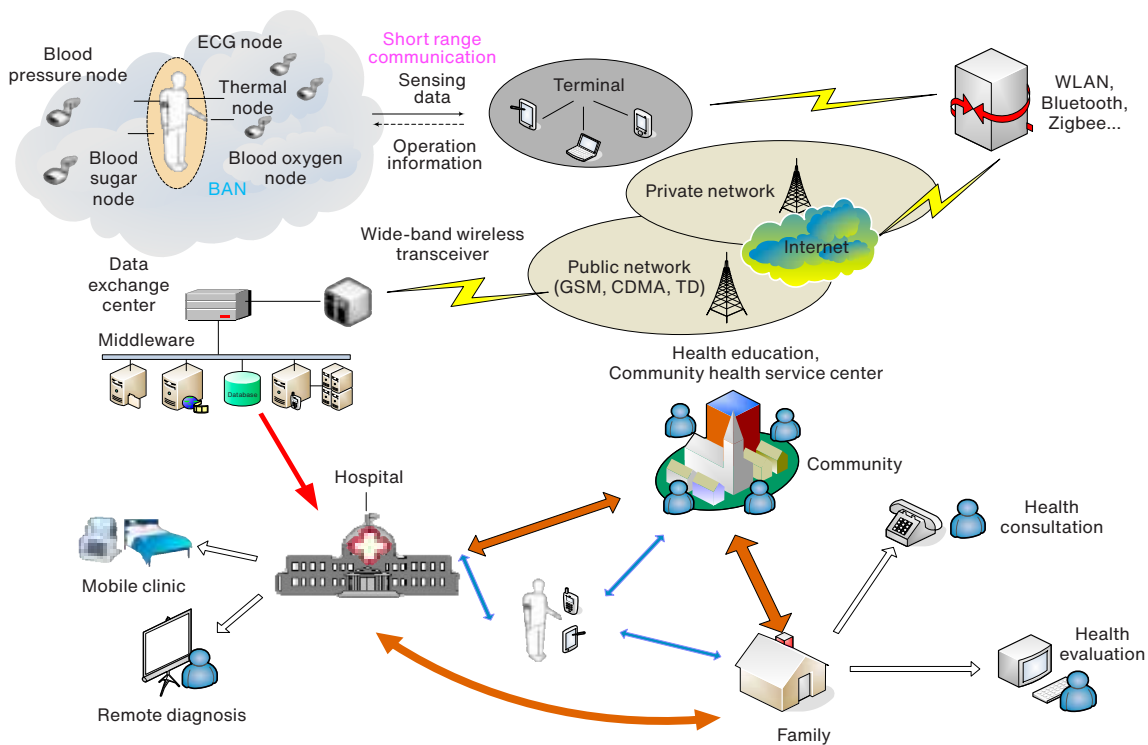


Figure 2 – BAN External Systems Integrations<sup>xxii</sup>

# Understanding Behavioral Patterns in Smart Systems

The most important aspect of Aml is to enable the system to learn about individual activity and behaviour. While traditional activity recognition often uses supervised learning (where activities are predefined), unsupervised learning proves crucial for

identifying new, unlabeled sequences of activities that represent potentially important behaviors.<sup>xxiii</sup> Progress in AI is augmenting our capabilities at both noticing and understanding these patterns without having a curated dataset to reference.<sup>xxiv</sup> Consequently, systems are becoming better at predicting our needs and behaviors over time, like a smart thermostat learning to adjust the temperature or a health monitor recognizing signs of stress.



- a. **Activity Recognition:** Activity recognition, a well-explored yet challenging area, involves identifying activities using data from sensors. These can broadly be divided into two types:
  - i. **Wearables:** Wearable sensors, either attached to the body or integrated into clothing provide information on body orientation and movement, aiding in recognizing actions like walking, running, sitting, and gesturing.<sup>xxxv xxxvi</sup>
  - ii. **Environmental Sensors:** Environmental sensors such as infrared motion detectors, door sensors, and pressure mats are being used to monitor more complex activities like cooking, sleeping, and eating.<sup>xxvii</sup> They are particularly effective for location-based activity recognition in indoor settings.<sup>xxviii</sup>
- b. **Gesture, Emotion and Body Language Recognition:** One of the most complex domains within Aml is the recognition of gestures, facial expressions, and body language.<sup>xxix</sup> Recognizing body language, such as gestures and facial expressions, enables the interpretation of non-verbal communication and emotions.<sup>xxx</sup> The most cutting-edge research in this field is now capable of understanding emotional expressions through subtle body movements, much like

human perception.<sup>xxxi</sup> A prominent example is emotion recognition using wireless signals. In this technique, radio frequency signals that bounce off the human body are used to detect individual heartbeats with precision comparable to wearable ECG monitors. This helps in identifying specific emotions, such as happiness or sadness.<sup>xxxii</sup>

- c. **Natural Language Processing:** Aml has seen a surge in applications not only with rising abilities to interpret physical actions but also vocal commands through natural language processing. Recent progress in the field highlights that using neural networks and machine learning approaches are yielding exemplary success at sensing and interpreting natural language.<sup>xxxiii</sup>
- d. **Predicting Human Behavior:** The traditional model of technology interaction, based on a request-and-response format, has been prevalent for a while. Current research is delving into the transition from this reactive model to a predictive approach.<sup>xxxiv</sup> This new paradigm aims to alleviate the routine mental tasks of daily life by anticipating upcoming tasks and either automatically completing them or providing reminders, thus reducing the need to remember them.<sup>xxxv</sup>





# Unleashing Potential:

## Aml use cases in Healthcare.

Aml in healthcare is transforming the landscape of medical services, bringing forth an era where the environment around a patient is aware, responsive, and informed. This intelligence is not confined to a single application; rather, it spans a spectrum of use cases that are transforming healthcare approaches. From automating critical care support, which ensures the continuous monitoring of patient vitals, to optimizing operating rooms for safety and efficiency, Aml stands as a testament to innovation in healthcare. It extends its capabilities to the control of hospital infections, where it becomes an ally in the battle against Hospital Acquired Infections (HAI) by tracking pathogen spread. For the elderly and those with chronic diseases, it offers a blanket of security and personalized care, facilitating independence and proactive

health management. Even in the realm of mental health, Aml offers a vigilant eye, detecting subtle changes that could signify a need for intervention. It streamlines patient flow and administrative processes, cutting down on waiting times, and improves clinical workflows by guiding healthcare providers through their daily tasks. Most notably, it holds the promise of enabling preventive persuasive strategies for better healthcare practices and also predicting medical emergencies, acting as a guardian that preempts crises before they unfold. Each of these use cases underlines the profound impact Aml can wield in reshaping how healthcare is perceived and delivered. It is bringing a future where healthcare is not only reactive but also predictive and preventive.

Some of its use cases can be highlighted as:

### Automating Critical Care Support

In critical care, Aml systems can monitor patient vitals continuously, providing real-time data to healthcare professionals. This can lead to quicker response times in emergencies and more informed decision-making, ultimately improving patient survival rates. The integration of advanced filtering systems allows for the distillation of pertinent data from the extensive influx of information into Electronic Health Records (EHR), providing clinicians with real-time, context-specific, and valuable insights.<sup>xxxvi</sup> In the context of patient mobility monitoring, ambient sensors placed within ICU rooms can be instrumental in assessing patient movements, recognizing the employment of assistive devices, and monitoring interactions with the physical environment.<sup>xxxvii</sup>

### Operating Rooms

Aml within the operating room serves a critical role in supervising surgical procedures. It ensures adherence to protocols, verifies the proper functioning of equipment, and maintains optimal environmental conditions, all of which are crucial for patient safety and the success of the surgery.<sup>xxxviii</sup> Employing ambient cameras to record video during operations, coupled with computer vision, offers a significant opportunity for assessing the surgical skills of surgeons. This technology can provide immediate feedback, allowing for the honing of surgical techniques, enhancing technical efficiency, and potentially reducing the rate of complications.

<sup>xxxix</sup> XI

## Application in the Control of Hospital Infections

By tracking and analyzing the spread patterns of pathogens, ambient intelligence can guide infection control strategies. It can help in identifying high-risk zones within a hospital and enforce strict hygiene controls, reducing the incidence of HAIs.<sup>xii</sup>

## Elderly Living Spaces and Ageing

In the living spaces of the elderly, Aml systems equipped with integrated contactless sensors play a vital and varied role in enhancing safety. They swiftly detect falls, alert caregivers, trigger emergency responses, and enable timely interventions, all contributing to the prevention of morbidity and mortality.<sup>xiii</sup>

## Chronic Disease Management

Ambient intelligence can offer personalized monitoring for individuals with chronic illnesses, ensuring that their condition is managed effectively.<sup>xiii</sup> It can prompt medication adherence, recommend lifestyle adjustments, and alert medical personnel of any concerning changes in health status.

## Mental Health

Aml brings a significant advancement in mental health care by being able to recognize behavioral changes that suggest a decline in a patient's mental state. It is adept at early detection of mental health symptoms, facilitating tailored responses to avert worsening conditions. Moreover, it provides continuous monitoring for customized treatment plans, thus increasing the accuracy and impact of mental healthcare provision.<sup>xliv xlv</sup>

## Persuasive Wellbeing

Persuasive wellbeing strategies using Aml are emerging as a transformative approach to positively shape individuals' attitudes and behaviors towards healthier lifestyles.<sup>xvi xvii</sup> This approach is crucial in both prevention and treatment, signifying a new phase in how people interact with technology. By fusing principles from behavioral science with cutting-edge computing, these technologies creatively prompt healthier lifestyle choices such as encouraging physical activity, fostering healthy eating habits, cessation of tobacco addiction, and minimizing sedentary behavior.<sup>xviii xlix l</sup>

## Improving Hospital Operational Efficiency

Ambient intelligence can revolutionize healthcare efficiency by overhauling administrative operations and optimizing the allocation of resources, which in turn can drastically cut down on patient waiting times.<sup>lii</sup> This not only enhances patient satisfaction by ensuring they receive timely care but also streamlines the clinical workflow.<sup>liii</sup> It also enables seamless coordination of clinical operations, ensuring that healthcare professionals are precisely where they need to be, equipped with the right information and tools at the right time.

## Predict and Prevent Medical Emergencies

This is one of the most promising aspects of ambient intelligence is its potential to predict medical emergencies before they occur.<sup>liv iv</sup> By identifying early warning signs and risk factors, these systems can prompt preemptive measures, safeguarding against potentially life-threatening events.<sup>lvii lviii</sup>



# Challenges of Aml in Healthcare

## Standardization

Aml currently faces a significant challenge due to the lack of standardization across its systems.<sup>lix lx</sup> This issue is particularly relevant when considering the global interaction standards that need to be adopted by commercial manufacturers of Aml systems.<sup>lxi</sup>

## Social And Cultural Equity in Design

When developing intelligent systems, it's crucial to consider social and cultural factors, as these play a significant role in shaping the effectiveness and appropriateness of Aml. For instance, significant challenges remain, particularly in comprehending the vast array of accents and dialects present in each language.<sup>lxii lxiii</sup> Biases in current models illustrate the importance of being mindful of diverse social and cultural contexts. Additionally, aspects such as gestures, body language, and verbal language vary widely across cultures. Behaviors considered polite or acceptable in one region might be seen as offensive in another. The way these systems adapt to, and respect social and cultural norms is likely to have a greater impact on their global acceptance and effectiveness than hypothetical scenarios of super-intelligent machines dominating humanity. This underscores the importance of integrating cultural sensitivity into the design and operation of Aml systems.

## Uncertainty

A key challenge is dealing with uncertainties in a healthcare space for decision-making.<sup>lxiv</sup> Aml systems often use complex rules for decisions based on the user's context and data. However, these rules, created from limited data, can be error prone. This issue is especially pertinent in healthcare, where personalized medicine's focus on individual context and data inherently includes uncertainties and limitations.<sup>lxv</sup>

## Privacy

Aml in healthcare brings with it a host of privacy challenges that necessitate careful consideration. Firstly, traditional physical boundaries like walls and doors are no longer sufficient in an environment where sensors and smart devices are pervasive.<sup>lxvi</sup> People often become oblivious to the presence of always-on microphones and video cameras, inadvertently exposing private moments. Challenges in this domain include issues like 'digital leakage', where a camera's field of view unintentionally violates the privacy of others by capturing areas beyond its intended scope.<sup>lxvii</sup>

Another privacy concern arises from physiological sensors, such as health monitoring wristbands, which have the potential to reveal emotions and health conditions that individuals might prefer to keep private. This situation is compounded by the vast increase in personal data that becomes available for data mining by both public and private organizations, often beyond the control of the individual.

Lastly, the erosion of trust, which is traditionally built through human-to-human interactions, becomes a concern in environments dominated by impersonal technology. This erosion can impact the patient-provider relationship and the overall experience of healthcare.<sup>lxviii</sup>

## Sensor Security

The use of sensors especially wearable which use biometric authentication poses eroding privacy rights issues.<sup>lxix lxx</sup> Moreover, since many Aml sensors and devices rely on wireless communication, which is susceptible to interception, there is a pressing need for encrypted and secure communications.

## Security in Aml Systems

The extensive data collection inherent in Aml systems, especially in healthcare, brings significant security concerns. These risks range from unauthorized access to nodes within the Aml networks to malicious manipulation of data within the system. When unauthorized devices are granted access, not only are they privy to sensitive and protected information, but they may be able to manipulate data which can adversely affect the entire system's analysis.<sup>lxxi</sup>

## Surveillance Concerns

Extensive data collection could lead to the creation of an almost invisible yet comprehensive surveillance network.<sup>lxxii lxxiii</sup> Additionally, there are issues with the one-way flow of information in Aml systems, which can result in an uneven distribution of data. For instance, while health providers might have access to extensive personal health information, individuals themselves may not have the resources or understanding needed to navigate

this complex information landscape or to make informed decisions about their healthcare providers.<sup>lxxiv</sup>

## Lack of Interoperability

The primary technical challenge for implementing ambient intelligence is the lack of interoperability between BANs and existing legacy systems at medical facilities.

As discussed above, BANs will require Bluetooth low energy (BLE), Zigbee, IEEE 802.15.6, and other standards and communication protocols. Meanwhile, legacy healthcare systems consist of standards and systems such as Health Level 7 (HL7),<sup>lxxv</sup> Digital Imaging and Communications in Medicine (DICOM),<sup>lxxvi</sup> Integrating the Healthcare Enterprise (IHE),<sup>lxxvii</sup> and other exchange, storage, and communication protocols that are not currently explicitly compatible with many BAN requirements. The interoperability challenges are not limited to the simple transfer of data. Even more challenging to address are the systems' differences in medical terminologies and representation of data formats, structures, and models.





# Moving Ahead:

## A Trustworthy, Reliable, User-centric, Secure, Transparent, and Interoperable Aml for Healthcare.

In the evolving landscape of Aml in healthcare, a multifaceted approach is key to building a system that is not only technologically sophisticated but also ethically grounded and user focused. This encompasses integrating AI with social and cultural sensitivity, enhancing decision-making reliability through data augmentation and user input, and ensuring clear explainability of processes. Simultaneously, it's crucial to fortify security measures, uphold stringent data privacy protocols, and foster interoperability between Aml and existing healthcare systems. These collective efforts will establish an Aml ecosystem in healthcare that is as effective in practice as it is ambitious in vision.

### i. Trustworthy Social and Cultural Integration

**Multilingual and Cultural Sensitivity:** Implement AI algorithms capable of understanding diverse accents, dialects, and cultural nuances in communication.<sup>lxxviii lxxix</sup>

**Contextual Behavior Analysis:** Develop Aml that recognizes and adapts to cultural differences in gestures, body language, and verbal communication to avoid misinterpretations.<sup>lxxx lxxxi lxxxii</sup>

### ii. Reliability in Decision-Making by managing uncertainty

**Data Augmentation:** To maximize the potential of data, it's essential to contemplate the long-term value of the data. The methodology and context of data collection significantly influence its future usability. Data collected without adequate descriptions of the circumstances and processes involved in its generation can render even vast datasets ineffective. Therefore, the interaction of Aml devices with their surroundings should be strategically guided by the prospective usefulness of the actions they perform and the data they collect.<sup>lxxxiii</sup>

**User-Informed AI:** Develop systems that actively seek user input when uncertainty in decision-making is high.<sup>lxxxiv</sup>

### iii. Understanding and Explainability:

**In Aml ecosystems, as decisions increasingly rely on data, two crucial requirements surface:**  
a) providing clarity to individuals on how these

decisions are made, and b) guaranteeing the fairness and non-discrimination of these decisions.<sup>lxxxv</sup> This will aid in limiting possibilities of unwarranted surveillance of patients while also ensuring they are provided with quality services. It's vital to unravel the complexities of machine learning decision-making processes, incorporating these insights into autonomous Aml systems. Concurrently, there should be emphasis on crafting algorithms and technical solutions that promote fairness and counteract bias, thereby enhancing transparency and equity in decision-making.

### iv. Security in Aml Systems

**Secure Wireless Protocols:** Aml systems in healthcare need to invest in both identifying and building a taxonomy of threats and then building advanced security protocols across its entire ecosystem to garner trust and scale its applications in healthcare.<sup>lxxxvi</sup>

**Advanced Encryption:** Utilize sophisticated encryption methods for data storage and transmission to safeguard patient information. Invest in solutions that process encrypted data locally within the healthcare environment's network.<sup>lxxxvii lxxxviii lxxxix</sup> This would ensure that sensitive health information is not exposed to external networks, significantly enhancing security of patient data in Aml healthcare settings.

**Biometric Authentication:** Use biometrics for user authentication in sensing devices to prevent unauthorized access.<sup>xc</sup>

v. **Transparency in Data Privacy**

**Selective Data Collection:** Collect only the data that is essential for the healthcare service, reducing the risk of 'digital leakage'.<sup>xcix xcii</sup>

**Novel Privacy Methods:** Navigating the delicate equilibrium between user privacy and the data needs of Aml systems is complex. The more user data these systems access, the better they can tailor their services to individual preferences. However, achieving this balance hinges on clear communication regarding the precise data required for these intelligent services. Importantly, users should be informed about the data being disclose, its intended application, and the duration of its availability to the system.

Various privacy protection methods, such as differential privacy, face anonymization, body masking, federated learning, and homomorphic encryption, are being explored as solutions to manage the pervasive nature of ambient sensing. These techniques aim to safeguard personal data while enabling the functionality of Aml intelligence systems.

**Federated Learning:** The machine learning techniques trains models across decentralized devices while securing the data within an organization.<sup>xciii</sup>

**Homomorphic Encryption:** This is a unique encryption method of computing ciphertexts and allows encrypted medical data to be used in computations.<sup>xciv</sup>

**Differential Privacy:** Differential privacy is a system for sharing information about a dataset by describing patterns of groups within the dataset while withholding personal information about individuals in the dataset.<sup>xcv</sup>

vi. **Innovating for interoperability:**

**Making healthcare legacy systems interoperable with BANs requires middleware solutions and the**

**appropriate APIs to integrate varied systems. A few of these middleware solutions may include:**

- a. **Health Information Exchange (HIE) Platforms:** These platforms allow various healthcare systems to standardize, normalize, and share data.<sup>xcvi</sup> Given the appropriate APIs, HIEs may help facilitate the data transfers from BANs to legacy platforms like HL7 and IHE.
- b. **Integration Engines:** As HIE platforms focus on facilitating data sharing between healthcare organizations, integration engines focus on data transfer within healthcare organizations.<sup>xcvii</sup> Like HIE platforms, integration engines may theoretically be used to transmit BAN data to legacy systems.
- c. **Fast Healthcare Interoperability Resources (FHIR):** FHIR systems are APIs that also operate as data formats, allowing them to standardize and facilitate data exchanges.<sup>xcviii</sup> FHIRs operate by standardizing data structures to specific clinical or administration requirements. In the context of BANs, data would be transmitted to the external FHIR systems which would subsequently map the BAN data. The FHIR systems may standardize sensory data as 'observations', categorize BAN sensory nodes as 'devices', and include demographic information under 'patient' labels.
- d. **Semantic Interoperability Layers:** Semantic interoperability layers may address data discrepancies that are not explicitly mapped with FHIR. Although FHIR can and does map data forms, they are more commonly used to exchange data. Meanwhile, semantic interoperability layers are designed to focus on mapping a shared understanding of data formats across different platforms.<sup>xcix</sup> For example, semantic interoperability layers can standardize specific data formats and representations, clinical terminologies, and data interpretations between BANs and legacy systems.





## Conclusion

Aml in healthcare is not merely a technological revolution; it is a paradigm shift towards a more empathetic, responsive, and intelligent healthcare ecosystem. The healthcare sector, as the leading beneficiary of this technology, stands on the brink of a transformative era where care is not just reactive but also predictive and deeply personalized.

The journey ahead, however, is not devoid of challenges. Issues of standardization, privacy, security, and the need for cultural sensitivity in design are pivotal hurdles that need to be addressed. Moreover, building public trust and understanding of these technologies is crucial for their widespread acceptance and effective utilization.

Yet, the potential benefits are immense. There

is a real potential to build a healthcare system that not only treats illness but anticipates it, adapting to everyone's unique needs. A system where the care environment itself is an active participant in the healing process, seamlessly integrated and inherently secure. This is the promise of Aml.

As we advance, we must focus on creating Aml systems that are not only technologically robust but also ethically sound and socially responsible. These systems should be transparent, secure, and interoperable, designed with a deep understanding of the diverse cultural and social contexts they will operate in.

In essence, the future of healthcare with Aml is not just about smart systems; it's about creating a healthcare experience that is more human, intuitive, and inclusive. It's about building a world where technology does not just support life but enhances its quality in the most profound ways.

# End notes

- i. Ambient intelligence market size, share: Forecast - 2032 Allied Market Research. Available at: <https://www.alliedmarketresearch.com/ambient-intelligence-market> (Accessed: 24 November 2023).
- ii. Survey: 60% of adults are uncomfortable with AI in their healthcare. (2023). Retrieved from <https://www.mobihealthnews.com/news/survey-60-adults-uncomfortable-ai-their-healthcare>.
- iii. Mahmood, M.R. et al. (2023) Ambient intelligence and internet of things: Convergent technologies. Hoboken: Wiley-Scrivener.
- iv. E. Zekha, B. Epstein, S. Birrel, and C. Dodsworth. 1998. From devices to "Ambient Intelligence." In Proceedings of the Digital Living Room Conference.
- v. ISTAG (1999) Information Society Technologies Advisory Group (ISTAG): Orientations for work programme 2000 and beyond. <ftp://ftp.cordis.europa.eu/pub/ist/docs/istag-99-final.pdf>.
- vi. Ambient intelligence BotPenguin AI Chatbot Maker. Available at: <https://botpenguin.com/glossary/ambient-intelligence> (Accessed: 10 November 2023).
- vii. G. Acampora, D. J. Cook, P. Rashidi and A. V. Vasilakos, "A Survey on Ambient Intelligence in Healthcare," in Proceedings of the IEEE, vol. 101, no. 12, pp. 2470-2494, Dec. 2013, doi: 10.1109/JPROC.2013.2262913.
- viii. Augusto J, McCullagh P. 2007. Ambient intelligence: concepts and applications. Computer Science and Information Systems 4(1):1-27 DOI 10.2298/CSIS0701001A.
- ix. Dunne R, Morris T, Harper S. 2021. A survey of ambient intelligence. ACM Computing Surveys 54(4):1-27 DOI 10.1145/3447242.
- x. Juan C. Augusto, Vic Callaghan, Diane Cook, Achilles Kameas, and Ichiro Satoh. 2013. Intelligent environments: A manifesto. Human-Centric Computing and Information Sciences 3, 1 (2013), 12. DOI:<https://doi.org/10.1186/2192-1962-3-12>.
- xi. ISTAG (1999) Information Society Technologies Advisory Group (ISTAG): Orientations for work programme 2000 and beyond. <ftp://ftp.cordis.europa.eu/pub/ist/docs/istag-99-final.pdf>.
- xii. M. Chen, S. Gonzalez, A. Vasilakos, H. Cao, and V. C. Leung, "Body area networks: A survey," Mobile Netw. Appl., vol. 16, no. 2, pp. 171-193, Apr. 2011.
- xiii. B. Latre', B. Braem, I. Moerman, C. Blondia, and P. Demeester, "A survey on wireless body area networks," Wireless Netw., vol. 17, no. 1, pp. 1-18, Jan. 2011.
- xiv. Tavera, C. A., Ortiz, J. H., Khalaf, O. I., Saavedra, D. F., & H. Aldhyani, T. H. (2021). Wearable Wireless Body Area Networks for Medical Applications. Computational and Mathematical Methods in Medicine, 2021. <https://doi.org/10.1155/2021/5574376>.
- xv. G. Fang, E. Dutkiewicz, M. A. Huq, R. Vesilo and Y. Yang, "Medical Body Area Networks: Opportunities, challenges and practices," 2011 11th International Symposium on Communications & Information Technologies (ISCIT), Hangzhou, China, 2011, pp. 562-567, doi: 10.1109/ISCIT.2011.6089699.
- xvi. Zhong, L., He, S., Lin, J., Wu, J., Li, X., Pang, Y., & Li, Z. (2022). Technological Requirements and Challenges in Wireless Body Area Networks for Health Monitoring: A Comprehensive Survey. Sensors (Basel, Switzerland), 22(9), 3539. <https://doi.org/10.3390/s22093539>.
- xvii. Zafar, J.A.F. (2012) Review of Body Area Network Technology & Wireless Medical Monitoring. International Journal of Information and Communication Technology Research, 2, 186.
- xviii. Vallejos de Schatz, C.H., Medeiros, H.P., Schneider, F.K. and Abatti, P.J. (2012) Wireless Medical Sensor Networks: Design Requirements and Enabling Technologies. Telemedicine and e-Health, 18, 394-399.
- xix. Ananthi, J. V., & Jose, P. S. H. (2021). A Perspective Review of Security Challenges in Body Area Networks for Healthcare Applications. *International journal of wireless information networks*, 28(4), 451-466. <https://doi.org/10.1007/s10776-021-00538-3>.
- xx. D. He, C. Chen, S. Chan, J. Bu, and A. Vasilakos, "Retrust: Attack-resistant and lightweight trust management for medical sensor networks," IEEE Trans. Inf. Technol. Biomed., vol. 16, no. 4, pp. 623-632, Jul. 2012.
- xxi. I. F. Akyildiz, X. Wang, and W. Wang, "Wireless mesh networks: A survey," Comput. Netw., vol. 47, no. 4, pp. 445-487, 2005.
- xxii. Zhong, L., He, S., Lin, J., Wu, J., Li, X., Pang, Y., & Li, Z. (2022). Technological Requirements and Challenges in Wireless Body Area Networks for Health Monitoring: A Comprehensive Survey. *Sensors (Basel, Switzerland)*, 22(9), 3539. <https://doi.org/10.3390/s22093539>.
- xxiii. P. Rashidi, D. Cook, L. Holder, and M. Schmitter-Edgecombe, "Discovering activities to recognize and track in a smart environment," IEEE Trans. Knowl. Data Eng., vol. 23, no. 4, pp. 527-539, Apr. 2011.
- xxiv. M. Ruotsalainen, T. Ala-Kleemola, and A. Visa, "Gais: A method for detecting interleaved sequential patterns from imperfect data," in Proc. IEEE Symp. Comput. Intell. Data Mining, 2007, pp. 530-534.
- xxv. A. Yang, R. Jafari, S. Sastry, and R. Bajcsy, "Distributed recognition of human actions using wearable motion sensor networks," J. Ambient Intell. Smart Environ., vol. 1, no. 2, pp. 103-115, 2009.
- xxvi. H. Harms, O. Amft, G. Troster, and D. Roggen, "Smash: A distributed sensing and processing garment for the classification of upper body postures," in Proc. ICST 3rd Int. Conf. Body Area Netw., 2008, p. 22.
- xxvii. Acampora G, Cook DJ, Rashidi P, Vasilakos AV. A Survey on Ambient Intelligence in Health Care. Proc IEEE Inst Electr Electron Eng. 2013 Dec 1;101(12):2470-2494. doi: 10.1109/JPROC.2013.2262913. PMID: 24431472; PMCID: PMC3890262.
- xxviii. C. Nugent, M. Mulvenna, X. Hong, and S. Devlin, "Experiences in the development of a smart lab," Int. J. Biomed. Eng. Technol., vol. 2, no. 4, pp. 319-331, 2009.
- xxix. Yassin Kortli, Maher Jridi, Ayman Al Falou, and Mohamed Atri. 2020. Face recognition systems: A survey. Sensors (Switzerland) 20, 2 (2020), 342. DOI:<https://doi.org/10.3390/s20020342>.
- xxx. Yu Luo, Jianbo Ye, Reginald B. Adams, Jia Li, Michelle G. Newman, and James Z. Wang. 2020. ARBEE: Towards automated recognition of bodily expression of emotion in the wild. International Journal of Computer Vision 128, 1 (2020), 1-25. DOI:<https://doi.org/10.1007/s11263-019-01215-y> arxiv:1808.09568.



- xxxii. Haoyu Chen, Xin Liu, Xiaobai Li, Henglin Shi, and Guoying Zhao. 2019. Analyze spontaneous gestures for emotional stress state recognition: A micro-gesture dataset and analysis with deep learning. Proceedings of the 14th IEEE International Conference on Automatic Face and Gesture Recognition (FG'19). DOI:<https://doi.org/10.1109/FG.2019.8756513>.
- xxxiii. Mingmin Zhao, Fadel Adib, and Dina Katabi. 2018. Emotion recognition using wireless signals. Communications of the ACM 61, 9 (2018), 91–100. DOI:<https://doi.org/10.1145/3236621>.
- xxxiv. Mariya Toneva and LeilaWehbe. 2019. Interpreting and improving natural-language processing (in machines) with natural language-processing (in the brain). arxiv:1905.11833.
- xxxv. Aitor Almeida and Gorka Azkune. 2018. Predicting human behaviour with recurrent neural networks. Applied Sciences (Switzerland) 8, 2 (2018), 305. DOI:<https://doi.org/10.3390/app8020305>.
- xxxvi. Piotr Augustyniak and Grazyna Ślusarczyk. 2018. Graph-based representation of behavior in detection and prediction of daily living activities. Computers in Biology and Medicine 95 (2018), 261–270. DOI:<https://doi.org/10.1016/j.compbimed.2017.11.007>.
- xxxvii. Piotr Augustyniak and Grazyna Ślusarczyk. 2018. Graph-based representation of behavior in detection and prediction of daily living activities. Computers in Biology and Medicine 95 (2018), 261–270. DOI:<https://doi.org/10.1016/j.compbimed.2017.11.007>.
- xxxviii. Haque, A., Milstein, A. & Fei-Fei, L. Illuminating the dark spaces of healthcare with ambient intelligence. Nature 585, 193–202 (2020). <https://doi.org/10.1038/s41586-020-2669-y>.
- xxxix. Mingmin Zhao, Fadel Adib, and Dina Katabi. 2018. Emotion recognition using wireless signals. Communications of the ACM 61, 9 (2018), 91–100. DOI:<https://doi.org/10.1145/3236621>.
- xl. Chadebecq, F. et al. (2020) 'Computer vision in the surgical operating room', Visceral Medicine, 36(6), pp. 456–462. doi:10.1159/000511934.
- xli. Khalid, S. et al. (2020) 'Evaluation of deep learning models for identifying surgical actions and measuring performance', JAMA Network Open, 3(3). doi:10.1001/jamanetworkopen.2020.1664.
- xlii. How mayo clinic is combating information overload in Critical Care Units (2020) Harvard Business Review. Available at: <https://hbr.org/2018/03/how-mayo-clinic-is-combating-information-overload-in-critical-care-units#:~:text=A%20rules%2Dbased%2C%20ambient%2D,insights%20from%20clinicians%20and%20patients> (Accessed: 09 November 2023).
- xliii. Haque, A., Milstein, A. and Fei-Fei, L. (2020) Illuminating the dark spaces of healthcare with ambient intelligence, Nature News. Available at: <https://www.nature.com/articles/s41586-020-2669-y> (Accessed: 09 November 2023).
- xliiii. Acampora, G., Cook, D.J., Rashidi, P. and Vasilakos, A.V., 2013. A survey on ambient intelligence in healthcare. Proceedings of the IEEE, 101(12), pp.2470–2494.
- xliv. Frank, A.C. et al. (2023) 'Wearable and mobile technologies for the evaluation and treatment of obsessive-compulsive disorder: Scoping review', JMIR Mental Health, 10. doi:10.2196/45572.
- xlv. Arevian, A.C. et al. (2020) 'Clinical state tracking in serious mental illness through computational analysis of Speech', PLOS ONE, 15(1). doi:10.1371/journal.pone.0225695.
- xlvi. Aouedi, O., Tobji, M.A.B. and Abraham, A., 2018. Internet of things and ambient intelligence for mobile health monitoring: A review of a decade of research. International Journal of Computer Information Systems and Industrial Management Applications, 10(1), pp.261–271.
- xlvii. Kaptein, M.C., Markopoulos, P., de Ruyter, B. et al. Persuasion in ambient intelligence. J Ambient Intell Human Comput 1, 43–56 (2010). <https://doi.org/10.1007/s12652-009-0005-3>.
- xlviii. Aldenaini, N. et al. (2020) 'Trends in persuasive technologies for physical activity and sedentary behavior: A systematic review', Frontiers in Artificial Intelligence, 3. doi:10.3389/frai.2020.00007.
- xlix. Frąckiewicz, M. (2023) Ambient Intelligence for Psychology and Behavioral Analysis, TS2 SPACE. Available at: <https://ts2.space/en/ambient-intelligence-for-psychology-and-behavioral-analysis/> (Accessed: 09 November 2023).
- l. Orji, R. and Moffatt, K. (2016) 'Persuasive technology for health and wellness: State-of-the-art and emerging trends', Health Informatics Journal, 24(1), pp. 66–91. doi:10.1177/1460458216650979.
- li. M. C. Kaptein, P. Markopoulos, B. E. R. de Ruyter, and E. H. L. Aarts, "Persuasion in ambient intelligence," J. Ambient Intell. Humanized Comput., vol. 1, no. 1, pp. 43–56, 2010.
- lii. Haque, A., Milstein, A. & Fei-Fei, L. Illuminating the dark spaces of healthcare with ambient intelligence. Nature 585, 193–202 (2020). <https://doi.org/10.1038/s41586-020-2669-y>.
- liii. Kartakis S, Sakkalis V, Toulakis P, Zacharioudakis G, Stephanidis C. Enhancing health care delivery through ambient intelligence applications. Sensors (Basel). 2012;12(9):11435–50. doi: 10.3390/s120911435. Epub 2012 Aug 24. PMID: 23112664; PMCID: PMC3478791.
- liv. The Case for Ambient Intelligence in Healthcare. Available at: <https://www.ouva.co/blog/the-case-for-ambient-intelligence-in-healthcare> (Accessed: 24 November 2023).
- lv. Science-based approaches to respond to Covid and other public health threats (2021). InTech.
- lvi. Ross, C. (2023) Hospitals look to computers to predict patient emergencies before they happen, STAT. Available at: <https://www.statnews.com/2019/05/13/artificial-intelligence-hospital-command-centers-predict-emergencies/> (Accessed: 24 November 2023).
- lvii. Acampora, G., Cook, D.J., Rashidi, P. and Vasilakos, A.V., 2013. A survey on ambient intelligence in healthcare. Proceedings of the IEEE, 101(12), pp.2470–2494.
- lviii. Qadri Y.A., Nauman A., Zikria Y.B., Vasilakos A.V., Kim S.W. The future of healthcare internet of things: A survey of emerging technologies. IEEE Commun. Surv. Tutor. 2020;22:1121–1167. doi: 10.1109/COMST.2020.2973314.
- lix. Amina El murabet, Anouar Abtoy, Abdellah Touhafi, Abderahim Tahiri, Ambient Assisted living system's models and architectures: A survey of the state of the art, Journal of King Saud University - Computer and Information Sciences, Volume 32, Issue 1, 2020, Pages 1-10, ISSN 1319-1578, <https://doi.org/10.1016/j.jksuci.2018.04.009>.

- Ix. Stankovic, J.A. et al. (2021) 'Challenges and directions for ambient intelligence: A cyber physical systems perspective', 2021 IEEE Third International Conference on Cognitive Machine Intelligence (CogMI) [Preprint]. doi:10.1109/cogmi52975.2021.00038.
- Ixi. Junaid SB, Imam AA, Balogun AO, De Silva LC, Surakat YA, Kumar G, Abdulkarim M, Shuaibu AN, Garba A, Sahalu Y, Mohammed A, Mohammed TY, Abdulkadir BA, Abba AA, Kakumi NAI, Mahamad S. Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey. *Healthcare (Basel)*. 2022 Oct 3;10(10):1940. doi: 10.3390/healthcare10101940. PMID: 36292387; PMCID: PMC9601636.
- Ixii. Irakli Kardava, Jemal Antidze, and Nana Gulua. 2016. Solving the problem of the accents for speech recognition systems. *International Journal of Signal Processing Systems* 4, 3 (2016), 235–238. DOI:<https://doi.org/10.18178/ijps.4.3.235-238>.
- Ixiii. Jerry Kaplan. 2017. Artificial intelligence: Think again. *Communications of the ACM* 60, 1 (2017), 36–38. DOI:<https://doi.org/10.1145/2950039>.
- Ixiv. Stankovic, J.A. et al. (2021) 'Challenges and directions for ambient intelligence: A cyber physical systems perspective', 2021 IEEE Third International Conference on Cognitive Machine Intelligence (CogMI) [Preprint]. doi:10.1109/cogmi52975.2021.00038.
- Ixv. Streitz, N. et al. (2019) 'Grand challenges for ambient intelligence and implications for design contexts and smart societies', *Journal of Ambient Intelligence and Smart Environments*, 11(1), pp. 87–107. doi:10.3233/ais-180507.
- Ixvi. Noah Aphorpe, Dillon Reisman, and Nick Feamster. 2017. A smart home is no castle: Privacy vulnerabilities of encrypted IoT traffic. arxiv:1705.06805.
- Ixvii. James Pierce. 2019. Smart home security cameras and shifting lines of creepiness: A design-led inquiry. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, 1–14. DOI:<https://doi.org/10.1145/3290605.3300275>.
- Ixviii. I. Maghiros, Y. Punie, S. Delaitre, P. de Hert, S. Gutwirth, W. Schreurs, A. Moscibroda, et al. 2006. Safeguards in a world of ambient intelligence. In *Proceedings of the 2nd IET International Conference on Intelligent Environments (IE'06)*. v2–245. DOI:<https://doi.org/10.1049/cp:20060702>.
- Ixix. Majumder S., Mondal T., Deen M.J. Wearable sensors for remote health monitoring. *Sensors*. 2017;17:130. doi: 10.3390/s17010130
- Ixx. Mamdiwar S.D., Shakruwala Z., Chadha U., Srinivasan K., Chang C.-Y. Recent Advances on IoT-Assisted Wearable Sensor Systems for Healthcare Monitoring. *Biosensors*. 2021;11:372. doi: 10.3390/bios11100372
- Ixxi. Junaid SB, Imam AA, Balogun AO, De Silva LC, Surakat YA, Kumar G, Abdulkarim M, Shuaibu AN, Garba A, Sahalu Y, Mohammed A, Mohammed TY, Abdulkadir BA, Abba AA, Kakumi NAI, Mahamad S. Recent Advancements in Emerging Technologies for Healthcare Management Systems: A Survey. *Healthcare (Basel)*. 2022 Oct 3;10(10):1940. doi: 10.3390/healthcare10101940. PMID: 36292387; PMCID: PMC9601636.
- Ixxii. J. Bohn, V. Coroama, M. Langheinrich, F. Mattern, and M. Rohs, "Living in a world of smart everyday objects social, economic, and ethical implications," *Human Ecological Risk Assessment*, vol. 10, no. 5, pp. 763–785, 2004.
- Ixxiii. H. Van Heerde, N. Anciaux, L. Feng, and P. Apers, "Balancing smartness and privacy for the ambient intelligence," in *Smart Sensing and Context*, vol. 4272. Berlin, Germany: Springer-Verlag, 2006, pp. 255–258, ser. Lecture Notes in Computer Science.
- Ixxiv. M. Friedewald, O. Costa, Y. Punie, P. Alahuhta, and S. Heinonen, "Perspectives of ambient intelligence in the home environment," *Telematics Inf.*, vol. 22, no. 3, pp. 221–238, 2005.
- Ixxv. Kimura M. [Outline of Health Level Seven (HL7) standard]. *Rinsho Byori*. 1999 Dec;47(12):1165–9. Japanese. PMID: 10639827.
- Ixxvi. Lim, J., Zein, R. (2006). The Digital Imaging and Communications in Medicine (DICOM): Description, Structure and Applications. In: Kamrani, A., Nasr, E.A. (eds) *Rapid Prototyping. Manufacturing Systems Engineering Series*, vol 6. Springer, Boston, MA. [https://doi.org/10.1007/0-387-23291-5\\_3](https://doi.org/10.1007/0-387-23291-5_3).
- Ixxvii. Dash, R. C., Jones, N., Merrick, R., Haroske, G., Harrison, J., Sayers, C., Haarselhorst, N., Wintell, M., Herrmann, M. D., & Macary, F. (2021). Integrating the Health-care Enterprise Pathology and Laboratory Medicine Guideline for Digital Pathology Interoperability. *Journal of Pathology Informatics*, 12. [https://doi.org/10.4103/jpi.jpi\\_98\\_20](https://doi.org/10.4103/jpi.jpi_98_20).
- Ixxviii. Yoav Goldberg. 2017. Neural network methods for natural language processing. *Synthesis Lectures on Human Language Technologies* 10, 1 (April 2017), 1–309. DOI:<https://doi.org/10.2200/S00762ED1V01Y201703HLT037>.
- Ixxix. Mariya Toneva and Leila Wehbe. 2019. Interpreting and improving natural-language processing (in machines) with natural language-processing (in the brain). arxiv:1905.11833.
- Ixxx. Dunne, Rob & Morris, Tim & Harper, Simon. (2021). A Survey of Ambient Intelligence. *ACM Computing Surveys*. 54. 1-27. 10.1145/3447242.
- Ixxxi. Presseau, J., McCleary, N., Lorencatto, F. et al. Action, actor, context, target, time (AACTT): a framework for specifying behaviour. *Implementation Sci* 14, 102 (2019). <https://doi.org/10.1186/s13012-019-0951-x>.
- Ixxxii. S. Chernbumroong, A. Lotfi and C. Langensiepen, "Prediction of mobility entropy in an Ambient Intelligent environment," 2014 IEEE Symposium on Intelligent Agents (IA), Orlando, FL, USA, 2014, pp. 65-72, doi: 10.1109/IA.2014.7009460.
- Ixxxiii. Streitz, Norbert et al. 'Grand Challenges for Ambient Intelligence and Implications for Design Contexts and Smart Societies'. 1 Jan. 2019 : 87 – 107.
- Ixxxiv. ibid
- Ixxxv. ibid
- Ixxxvi. Apostolos Gerodimos, Leandros Maglaras, Mohamed Amine Ferrag, Nick Ayres, Ioanna Kantzavelou, IoT: Communication protocols and security threats, *Internet of Things and Cyber-Physical Systems*, Volume 3, 2023, Pages 1-13, ISSN 2667-3452, <https://doi.org/10.1016/j.iotcps.2022.12.003>.
- Ixxxvii. Mian Ahmad Jan, Wenjing Zhang, Muhammad Usman, Zhiyuan Tan, Fazlullah Khan, and Entao Luo. 2019. Smart-Edge: An end-to-end encryption framework for an edge-enabled smart city application. *Journal of Network and Computer Applications* 137 (March 2019), 1–10. DOI:<https://doi.org/10.1016/j.jnca.2019.02.023>.

- lxxxviii. L. González-Manzano, José M. de Fuentes, Sergio Pastrana, Pedro Peris-Lopez, Luis Hernández-Encinas, PAgIoT – Privacy-preserving Aggregation protocol for Internet of Things, *Journal of Network and Computer Applications*, Volume 71, 2016, Pages 59-71, ISSN 1084-8045, <https://doi.org/10.1016/j.jnca.2016.06.001>.
- lxxxix. Ahmed, Shakeel, Parvathaneni Naga Srinivasu, and Abdulaziz Alhumam. 2023. "A Software Framework for Intelligent Security Measures Regarding Sensor Data in the Context of Ambient Assisted Technology" *Sensors* 23, no. 14: 6564. <https://doi.org/10.3390/s23146564>.
- xc. G. Acampora, D. J. Cook, P. Rashidi and A. V. Vasilakos, "A Survey on Ambient Intelligence in Healthcare," in *Proceedings of the IEEE*, vol. 101, no. 12, pp. 2470-2494, Dec. 2013, doi: 10.1109/JPROC.2013.2262913.
- xci. James Pierce. 2019. Smart home security cameras and shifting lines of creepiness: A design-led inquiry. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*. ACM, New York, NY, 1-14. DOI: <https://doi.org/10.1145/3290605.3300275>.
- xcii. M. Langheinrich, "Privacy by design principles of privacy-aware ubiquitous systems," in *Ubicomp 2001: Ubiquitous Computing*, vol. 2201. Berlin, Germany: Springer-Verlag, 2001, pp. 273-291, *Lecture Notes in Computer Science*.
- xciii. Mothukuri, V., Parizi, R. M., Pouriye, S., Huang, Y., Dehghantanha, A., & Srivastava, G. (2021). A survey on security and privacy of federated learning. *Future Generation Computer Systems*, 115, 619-640. <https://doi.org/10.1016/j.future.2020.10.007>.
- xciv. Munjal, K., Bhatia, R. A systematic review of homomorphic encryption and its contributions in healthcare industry. *Complex Intell. Syst.* 9, 3759-3786 (2023). <https://doi.org/10.1007/s40747-022-00756-z>.
- xcv. A. E. Ouadrhiri and A. Abdelhadi, "Differential Privacy for Deep and Federated Learning: A Survey," in *IEEE Access*, vol. 10, pp. 22359-22380, 2022, doi: 10.1109/ACCESS.2022.3151670.
- xcvi. Menachemi, N., Rahurkar, S., Harle, C. A., & Vest, J. R. (2018). The benefits of health information exchange: An updated systematic review. *Journal of the American Medical Informatics Association : JAMIA*, 25(9), 1259-1265. <https://doi.org/10.1093/jamia/ocy035>.
- xcvii. Espinoza, J., Xu, N. Y., Nguyen, K. T., & Klonoff, D. C. (2023). The Need for Data Standards and Implementation Policies to Integrate CGM Data into the Electronic Health Record. *Journal of Diabetes Science and Technology*, 17(2), 495-502. <https://doi.org/10.1177/19322968211058148>.
- xcviii. Vorisek, C. N., Lehne, M., Ines Klopfenstein, S. A., Mayer, P. J., Bartschke, A., Haese, T., & Thun, S. (2022). Fast Healthcare Interoperability Resources (FHIR) for Interoperability in Health Research: Systematic Review. *JMIR Medical Informatics*, 10(7). <https://doi.org/10.2196/35724>.
- xcix. N. Loutas, E. Kamateri and K. Tarabanis, "A Semantic Interoperability Framework for Cloud Platform as a Service," 2011 IEEE Third International Conference on Cloud Computing Technology and Science, Athens, Greece, 2011, pp. 280-287, doi: 10.1109/CloudCom.2011.45.



[The Ubiquitous Guardian: Ambient Intelligence's Impact on Healthcare](#)

© 2023 by [Satwik Mishra](#)

is licensed under [Attribution-NonCommercial 4.0 International](#)