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Sustainable and Adaptive Smart Homes with Personalised Edge AI: Technologies, Applications and Research Challenges

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ABSTRACT: The smart home concept has changed significantly since its inception, from primarily remote-controlled devices and timers to advanced systems that can sense, learn, and adapt to occupants' preferences and behaviour. This shift has been made possible by integrating personalised edge AI, which lets smart home devices operate locally without relying entirely on the cloud. By using personalised edge AI, smart homes can respond in real time, protect users' data by processing it locally, learn their preferences over time, and remain resilient to changes in network availability. This chapter reviews the fundamental architecture, critical technologies, learning techniques, and practical implementation of smart homes that utilise personalised edge AI. It addresses the advantages and disadvantages of placing AI at the edge, compares cloud-based and edge-based intelligence, and explores methods for achieving a balance between computational efficiency and end-user customization. It then describes how personalised edge AI systems are changing everyday life, drawing on a number of example applications: intelligent climate control, adaptive lighting and ambience, security and safety monitoring, voice interaction, and health monitoring. This chapter also discusses ethical and legal considerations, as well as user-experience design issues that enable wider adoption. Finally, this chapter concludes with suggestions for potential next steps on this interdisciplinary subject. Smart homes powered by personalised edge AI will revolutionise how AI is integrated into our daily lives by learning and adapting to us while ensuring our privacy and autonomy are respected. The result is homes that are more user-friendly, efficient, secure, and grounded in human-centred design.

1. INTRODUCTION

The smart home concept has evolved from basic automation to comprehensive sensing, processing, and action in intelligent environments that adapt to users' preferences. Smart home systems of the past mainly provided programmable control of various appliances (e.g., Lighting, heating, and security), enabling them to be operated remotely. The rapid growth of Internet of Things (IoT) technology has enabled smart homes to become connected ecosystems of sensors, actuators, communication networks, and embedded computers that create, transmit, and receive massive amounts of real-time data. A combination of technologies enables constant observation of both the environment and a user's activity; therefore, smart home devices can operate without user input, creating greater ease of use, safety, and efficiency. Smart homes are now moving from simple automation towards systems that adapt to and learn from user behaviour, enabling them to refine how every aspect of the home operates. Creating intelligent systems that provide personal assistant services and improve the comfort and efficiency of residential environments requires artificial intelligence (AI) — in particular machine learning, deep learning, and pattern recognition — to analyse the volume and complexity of the environmental data collected by IoT devices [1-3]. Examples include smart thermostats that detect whether a room is occupied and smart lighting systems that adjust brightness according to the available natural light and the user's preferences. In addition, smart home hubs and voice-activated assistants exploit natural language processing and context-aware reasoning to improve interaction between users and devices. Increased use of AI technology continues to improve smart home systems, making them more self-sufficient and adaptable while reducing the need for manual intervention [4-7].

Despite these advances, many smart home products still rely on a centralised cloud architecture for processing and decision-making: data collected from household devices such as sensors and appliances is sent to a cloud server, where computationally demanding tasks are performed. Although cloud computing offers substantial computational and storage capacity, cloud-based systems that depend on remote infrastructure remain poorly suited to smart home environments that must act on real-time data. Sending excessive amounts of sensor data back to a remote cloud server frequently creates significant network latency and consumes substantial bandwidth, resulting in service interruption or at least a lack of service during periods of instability in the Internet connection. In addition, storing and processing sensitive and private household data raises enormous privacy and security issues. These limitations indicate an immediate need for new computing paradigms that provide improved responsiveness, reliability, and data privacy for intelligent services [8–10]

Edge Computing has emerged as an option to address these issues by processing data closer to where it is created. Rather than sending sensor data to a cloud server that may be hundreds or thousands of kilometres from the data source, processing can occur at the edge of the network on devices like smart sensors, home gateways, and embedded processors. This distributed approach significantly reduces network latency, allowing many smart home applications to respond almost immediately. Edge intelligence is therefore considered to be an important enabling technology for the next generation of smart homes, which must support real-time decision-making, run on energy-efficient processors, and preserve data privacy during processing [11–14].

When machine learning models are deployed directly on edge devices, they can adapt to the specific preferences, routines, and behaviour patterns of individual users. Unlike traditional artificial intelligence systems that rely on generalised models trained on aggregated cloud data, personalised Edge AI systems learn from local user data, offering customised services that meet each household's needs. For example, a personalised climate control system can adjust the indoor temperature to match an individual user's comfort level. Intelligent lighting systems can adjust automatically according to the user's daily schedule and activities. Health monitoring systems can also be deployed at the edge to analyse individual behaviour and identify anomalies that may indicate health risks for elderly residents. By combining personalisation with local intelligence, personalised edge AI enables a smart home to offer highly responsive, privacy-preserving, and context-sensitive services [15–18]. Given the significant promise of personalised edge AI, numerous technical and societal challenges must be resolved to deploy these technologies successfully in smart home environments.

Edge devices are constrained by limited processing power, memory capacity, and energy, which makes it difficult to deploy complex machine learning models. Research challenges include ensuring interoperability between heterogeneous IoT devices, maintaining data confidentiality, and developing robust privacy-preserving mechanisms. Ethical issues surrounding user autonomy, transparency, and trust must also be addressed when designing AI-enabled smart home technologies. Addressing these challenges requires interdisciplinary cooperation among researchers in AI, edge computing, cybersecurity, and human–computer interaction to develop smart home technologies that are safe, dependable, and user-centred [19, 20]. This chapter discusses personalised edge AI in the context of smart homes and illustrates how it can be applied in several areas, including energy management, home automation, home security, and health monitoring. Finally, it identifies the major challenges, ethical considerations, and future areas of research regarding intelligent, adaptable, and privacy-conscious smart home ecosystems.

2. FUNDAMENTALS OF SMART HOME ECOSYSTEMS

A smart home ecosystem is a technologically integrated environment in which multiple devices, smart systems, and sensors work together to automate and enhance how homes function. Smart home ecosystems are formed by integrating IoT technologies, communication networks, and embedded computing systems, enabling seamless monitoring, control, and automation of home operations. Smart homes today consist of hardware and software components that collect, transmit, and process real-time information from activities in the home. These integrated devices and their associated systems support intelligent decision-making processes that enhance the safety, energy efficiency, and quality of life of people in residences [21, 22]. The standard architecture of a smart home ecosystem has three basic levels: the device layer, communication layer, and application layer. The device layer includes various IoT devices such as smart thermostats, lighting systems, surveillance systems, motion detectors, and environmental sensors. These devices collect data on physical quantities in the home such as temperature, humidity, occupancy, and energy use. The communication layer enables devices to send and receive data from one another using wireless or wired technologies. Popular protocols for establishing reliable connections between IoT devices in the smart home environment include Wi-Fi, Zigbee, Bluetooth Low Energy (BLE), and Z-Wave. The application layer collects and processes data using intelligent algorithms and user interfaces that allow for automation. This layered architecture allows smart home systems to operate through continuous, largely autonomous cycles of sensing, communication, and decision-making [23, 24].

From a structural perspective, most smart home infrastructure consists of IoT-enabled devices, as well as sensors and actuators that allow interaction with the environment. Smart homes use sensors primarily to collect data by measuring environmental conditions or user activity. The most common sensors measure temperature, motion, light level, humidity, air quality, and physiological signals. These sensors continually produce data streams that provide insight into activity levels in a home and the dynamics of a household. Actuators convert digital signals into physical actions. Smart locks, automated lights, motorised window coverings (blinds and shades), and HVAC systems are all examples of actuators. Coordinated interactions between sensors and actuators enable smart home systems to autonomously control the environment, improve safety, and optimise energy use [25, 26]. Smart home ecosystems depend on reliable, effective communication protocols that allow data exchange between devices. Multiple networking technologies have been developed to meet the various operational requirements of home-based environments. Wi-Fi is the most common protocol for connecting devices because of its high data transfer rate and its compatibility with existing home Internet infrastructure. However, low-power wireless communication technologies are becoming more popular in smart homes because they provide energy-efficient communication for battery-operated Internet of Things devices. These protocols allow devices to form mesh networks that extend coverage within the home while maintaining very low power use [27].

Context awareness refers to a system's ability to collect and process information about the environment and about users' behaviour in order to determine the current state of that environment. IoT devices generate data on user location, activity patterns, device usage, and environmental conditions. By processing these datasets, intelligent systems can discover behaviour patterns and make informed decisions about how to operate the smart home. For example, when combined with occupancy data, motion sensors can detect whether residents are in particular rooms, so lighting and temperature systems can adjust automatically. Similarly, environmental sensors can monitor indoor air quality and trigger ventilation when it falls below a defined safe threshold. Context-aware home systems are therefore key enablers of adaptive automation and personalised user experiences [28, 29]. The convergence of sensing technologies, communication networks, and contextual analytics has created more intelligent and adaptable home ecosystems that can learn from user actions and modify how they operate. However, the increasing complexity of the interrelated devices creates additional interoperability, data management, and scaling challenges. One of the biggest ongoing research challenges is ensuring that heterogeneous devices from different manufacturers communicate and work together in a single ecosystem. The large volumes of data generated by these devices require efficient processing and storage strategies to support both real-time decisions and long-term analytics. Meeting these challenges is critical to developing robust, scalable intelligent home ecosystems that can also support advanced technologies such as edge intelligence and personalised artificial intelligence [30].

2.1 Smart Home Architecture and Device Interaction

The interaction among sensors, gateways, and applications forms the operational core of the smart home ecosystem. The sensors monitor environmental conditions; gateways aggregate, transmit, and manage the data flow; and application platforms analyse that data to generate automated responses or notifications to users. As shown in Fig. 1, this interaction enables real-time monitoring and control of household systems, improving efficiency, safety, and convenience for the residents.

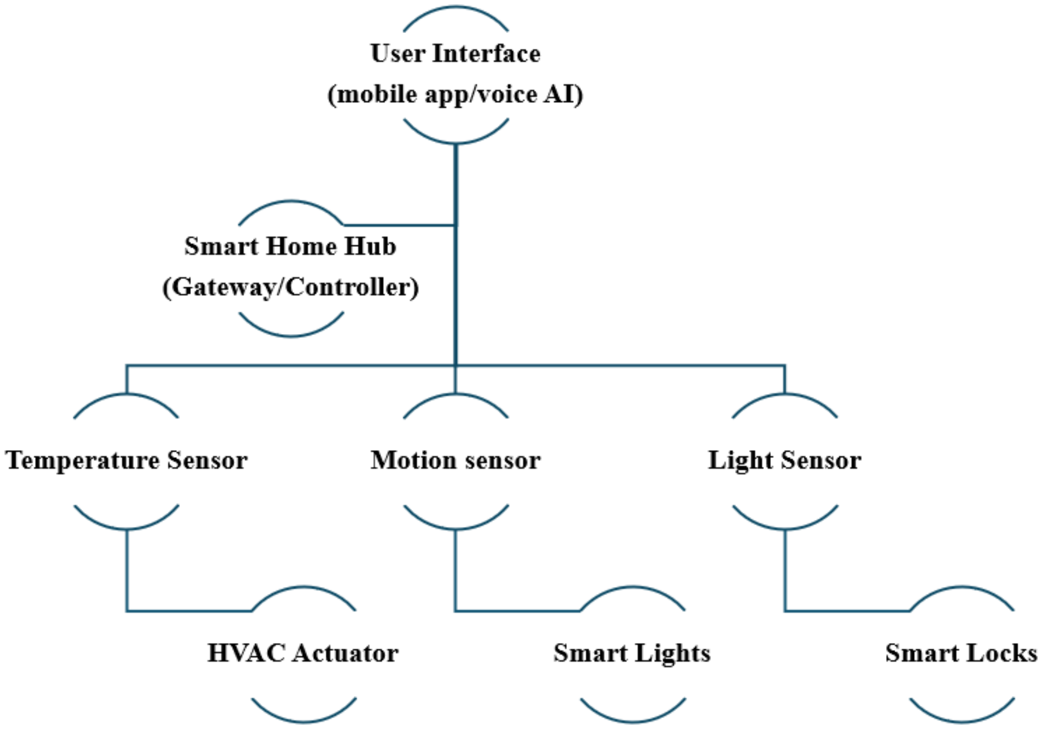

Fig. 1 Basic architecture of a smart home ecosystem illustrating interactions between sensors, gateway controllers, and automated devices.

3. EDGE INTELLIGENCE IN SMART HOME SYSTEMS

As smart home technologies develop rapidly, interconnected devices, appliances, and monitoring equipment now generate vast amounts of data. Historically, most smart home applications have relied on cloud computing to process this data and make intelligent decisions. Given the growing demand for real-time responsiveness, privacy protection, and efficient use of resources, the shift towards edge intelligence in the home continues to accelerate. Edge intelligence is defined as embedding AI capabilities within edge devices or local gateways near the point of data generation. By enabling local data processing and decision-making, edge intelligence reduces reliance on centralised clouds and helps smart home systems operate more efficiently and securely [31,32]. In a smart home environment, edge devices collect and process data locally and send only essential information back to the cloud when needed. This architecture minimises latency and bandwidth use while improving response time for time-critical applications. For example, a security camera that runs image-recognition models at the network edge can identify suspicious activity locally and alert the user without the delay introduced by cloud processing. Similarly, smart thermostats with embedded machine learning can use historical data to adjust to changes in indoor temperature as soon as they are detected. These characteristics make edge intelligence well suited to smart homes, since it responds immediately to user input and continues to operate when connectivity is lost [33].

3.1 Edge AI and Distributed Intelligence in Smart Homes

Edge AI combines AI and edge computing, allowing artificial intelligence to process data at the edge of a network. In smart home environments, edge AI devices run machine learning algorithms on smart hubs and embedded microcontrollers to perform tasks such as activity recognition, anomaly detection, and predictive control without relying on cloud-based processing. Distributed intelligence extends this approach by allowing multiple devices to collaborate on data evaluation and joint decision-making. Instead of each device sending all of its data to a central server, the smart home network distributes data processing across edge devices, improving scalability and reducing computational bottlenecks. With recent advances in lightweight machine learning models and hardware accelerators, many edge devices can now perform complex inference tasks in real time. As a result, voice recognition, gesture detection, and health monitoring can all be analysed in real time within the home [34].

3.2 Advantages and Challenges of Edge-Based Smart Home Intelligence

Edge AI in the home offers many benefits over cloud-centric systems; for instance, local data processing reduces latency because data no longer needs to be transmitted to distant cloud servers for processing. By processing sensitive data on a local network, the likelihood of unauthorised access is minimised, delivering privacy benefits. Additionally, local processing reduces the amount of data sent over the Internet, lowering bandwidth needs and increasing the system's resilience to network outages. Despite these advantages, implementing edge intelligence in homes poses several technical challenges. Edge devices have far less computational capacity, memory, and power than large cloud data centres, so deploying complex machine learning models on them requires both optimisation and model compression techniques. Another challenge is maintaining interoperability among many different device types from multiple manufacturers that make up the overall smart home environment. Additionally, security-related issues such as creating secure communication protocols for devices from various manufacturers and protecting edge systems from malicious cyber activity remain important challenges. Resolving these challenges is essential to the reliable and scalable deployment of edge intelligence in smart homes [35].

Table 1 Comparison Between Cloud AI and Edge AI in Smart Homes

Feature	Cloud AI	Edge AI
Data Processing Location	Centralised cloud servers	Local edge devices or gateways
Latency	Higher due to network transmission	Very low (real-time processing)
Privacy	Sensitive data sent to the cloud	Data processed locally
Bandwidth Usage	High network dependency	Reduced network traffic
Reliability	Dependent on internet connectivity	Can operate offline locally
Computational Power	Very high	Limited but improving

4. ARCHITECTURE OF PERSONALISED EDGE AI FOR SMART HOMES

Deploying personalised edge artificial intelligence (AI) effectively within a smart home ecosystem requires a well-designed architectural framework that supports distributed data processing, intelligent decision-making, and seamless communication between heterogeneous devices. Unlike traditional cloud-centric smart home systems, personalised edge AI architectures use computational intelligence located directly within local devices and gateways close to the data source. The personalised edge AI architecture enables real-time sensor data processing, adapts to users' behaviours, and reduces dependence on remote cloud infrastructure [35]. The architecture comprises three layers: the device layer (sensors, actuators, and embedded processors that collect environmental data and execute lightweight AI tasks); the edge gateway layer (an intermediate processing unit that aggregates data from multiple devices and performs more sophisticated analytics using local resources); and the cloud integration layer (which connects edge AI services to existing decision-support and enterprise systems). The cloud layer also provides additional capacity for large-scale data storage, model training, and system updates when required. By distributing workloads across these layers, personalised edge AI architectures reduce latency, improve energy efficiency, and strengthen data privacy in smart homes [36].

4.1 Edge AI Architecture Layers and Local Intelligence

The foundation of any personalised edge AI architecture is the device layer, which consists of numerous IoT devices such as smart thermostats and wearable health and environmental monitors. These devices typically contain low-power processors capable of running lightweight machine learning models directly on the device. Whereas traditional cloud-based AI systems rely on remote computation to analyse data and respond to change, embedded AI processing allows analysis and response to take place locally, without any connection to a remote service. For example, a smart camera with embedded edge AI can detect objects locally and alert users to possible security risks, and a smart thermostat can learn occupancy patterns and adjust the temperature according to those learned preferences [37]. The edge gateway layer above the device layer provides a central collaboration point in the smart home ecosystem by acting as a processing hub that connects multiple devices. Edge gateways typically have more powerful processors that support compute-intensive analytics. The gateway also enables communication among local devices and with external cloud services as needed [38]. Personalised edge AI systems can distribute intelligence between devices and gateways, enabling collaborative data processing while maximising resource efficiency within the smart home.

4.2 Hybrid Edge–Cloud Integration and Resource Management

Integrating cloud technology into smart home architecture is a critical element of any system's design; hybrid edge-cloud infrastructures combine the advantages of local edge processing with remote computing resources in a centralised data centre. The edge is best suited to time-sensitive tasks such as activity recognition, security monitoring, and environmental control, whereas the cloud is better suited to computationally intensive tasks such as training large-scale machine learning models and performing long-term analytics. Overall performance is therefore maximised by assigning latency-sensitive tasks to the edge while drawing on scalable cloud resources for the remainder [39]. Resource management and energy efficiency are other important considerations when designing personalised edge AI for smart homes. Because edge devices have limited processing capability, memory, and battery power, resources must be allocated efficiently. Model compression and lightweight neural networks are commonly used to improve performance while reducing energy consumption. Furthermore, distributing workloads across edge devices, gateways, and cloud servers is essential to ensure system stability and use computing resources efficiently. Effective resource management therefore makes personalised edge AI smart home technology considerably more scalable, reliable, and sustainable [40].

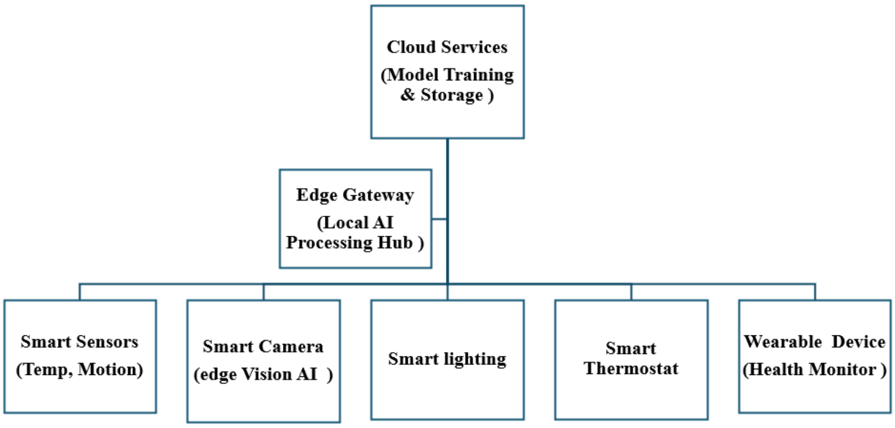

Fig. 2 Layered architecture of a personalised edge AI-enabled smart home system integrating devices, edge gateways, and cloud services.

5. LEARNING STRATEGIES FOR PERSONALISED EDGE AI

Smart home devices utilise advanced learning methods to provide customised services by monitoring user actions and adapting to changes in the environment. In contrast to traditional AI approaches that perform training and inference in a centralised cloud infrastructure, personalised edge AI focuses on local learning. These methods are designed to operate within the computational and energy limits of edge devices while remaining accurate and responsive. By combining contextual data analysis with machine learning methods, smart home devices can develop a more accurate understanding of how occupants behave in the home and improve household functionality [41]. By continuously analysing data from embedded sensors and connected devices, smart home systems can identify the preferences and interaction patterns of individual users. For instance, smart thermostats can use machine learning algorithms to learn from past occupancy patterns and preferred temperatures and automatically adjust heating or cooling to meet the occupant's comfort needs. Likewise, smart lighting systems can analyse usage histories and adapt light levels and schedules to the habits of the occupants. Personalised models increase the accuracy and relevance of automatic decision-making processes by tailoring the system's response to specific household members rather than to generalised behavioural patterns [42]. Context-aware and behaviour-aware learning are also highly relevant in smart home environments. Context-aware mechanisms represent information about the setting in which the system operates — location, time of day, user activity, and ambient conditions — while behavioural models draw on histories of user activity captured by sensors and wearables. Combining the two allows the system to anticipate user needs and improve interaction with household appliances, so that convenient and energy-efficient services can be delivered without manual intervention [43]. More recently, federated learning has emerged as a means of enabling collaborative learning across distributed edge environments. Each device trains a local model on its own data, and only the model parameters — never the raw data — are sent to a central server, where they are aggregated into a shared global model.

Devices can therefore improve the performance of a shared model without disclosing private user information to a third party or to the cloud. Federated learning strengthens privacy protection and reduces the risks associated with storing user data in a central location. Within the smart home ecosystem, devices such as thermostats, wearable health monitors, and security cameras can collaboratively improve predictive models while retaining strict control over sensitive user data [44]. On-device training and model adaptation offer a further route to improving personalised edge AI systems. Traditional AI models are trained once, centrally, for a fixed task, whereas edge AI models can learn incrementally and adapt to the user's needs from the real-time data generated on the device. As new data becomes available, AI models can continually adapt, allowing the smart home or building system to function according to the most up-to-date user preferences and changing environmental conditions. For example, a smart home health monitoring system can continually update its activity-detection models to match an older resident's changing mobility patterns. On-device learning therefore allows smart home systems to adapt more effectively to users' needs and to deliver tailored services in real time [45].

Running advanced learning models on edge devices raises numerous technical challenges, particularly because many IoT products have limited storage capacity and energy. To address these challenges, researchers have developed AI models that are both energy-efficient and small enough to run on edge devices. Techniques such as model compression, quantization, pruning, and knowledge distillation reduce the computational power and memory a model requires while limiting the accompanying loss of accuracy. Applying these methods makes it possible to build scalable and sustainable personalised edge AI systems that deliver efficient local processing at low energy cost [46]. Together, personalised machine learning models, context-aware learning, federated learning, and lightweight AI methods provide the basis for edge-based smart home systems that learn continuously from user behaviour, adapt to environmental change, and deliver tailored services while preserving data privacy and computational efficiency.

6. KEY TECHNOLOGIES ENABLING PERSONALISED EDGE AI

Implementing personalised edge AI in smart homes requires multiple supporting technologies to enable effective data processing, intelligent decision-making, and responsive real-time systems. Advances in embedded machine learning, hardware acceleration, optimised software frameworks, and edge analytics provide the computational foundation for running AI tasks on resource-constrained edge devices while delivering performance and energy savings [47]. One of the most influential enabling technologies in edge AI is TinyML, which concerns the deployment of machine learning models on low-power microcontrollers and embedded systems. Using compact neural network architectures and optimised inference engines, TinyML enables intelligent processing directly on small devices such as sensors, wearables, and home automation controllers, allowing tasks such as activity recognition, anomaly detection, and voice recognition to run without cloud connectivity.

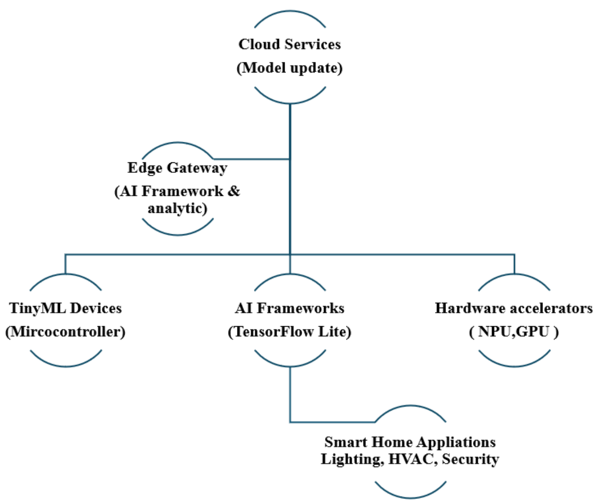

Fig. 3 Technological ecosystem enabling personalised edge AI through TinyML devices, hardware accelerators, AI frameworks, and edge analytics platforms.

AI platforms built on microcontroller and SoC architectures provide an efficient way to integrate hardware/software, allowing smart home devices to perform AI tasks independently while consuming very little power. These features make them especially valuable for battery-powered sensors and wearable health monitoring solutions often found in smart home ecosystems [48]. Edge hardware accelerators are another essential component, extending the computational capability of edge devices through processing units designed specifically for artificial intelligence workloads. Hardware accelerators (neural processing units, graphics processing units, and tensor processing units) are used to significantly increase the speed and efficiency of machine learning inference operations. Many smart home hubs and gateways already include these accelerators to support enhanced capabilities for computer vision, speech recognition, and predictive analytics. Such processors reduce latency and allow edge networks to support demanding AI applications [49]. In addition to hardware advances, several AI frameworks are available for edge applications, improving the development and implementation of machine learning models in embedded systems. Developers can use these frameworks to convert large-scale machine learning models into compact versions that run on edge devices while retaining an acceptable level of accuracy. These frameworks also lower the barrier to deploying and maintaining personalised edge AI in smart home applications [50].

7. APPLICATIONS OF PERSONALISED EDGE AI IN SMART HOMES

Personalised edge AI is changing how smart homes operate, making it possible to deliver intelligent, context-aware, and adaptive services based on each user's own preferences. Smart sensors, home gateways, and embedded processors handle data locally, giving users immediate access to services and preserving data privacy without reliance on central cloud infrastructure. Combining edge AI with Internet-of-Things technology enables a variety of devices to collaborate to provide greater comfort, security, energy savings, and healthcare monitoring in homes [51]. As summarised in Fig. 4, one of the most common applications of personalised edge AI is intelligent climate control. Intelligent thermostats combine occupancy monitoring, environmental sensing, and machine learning of personal preferences to build a model of the occupant's preferred settings, enabling real-time control of heating, ventilation, and air conditioning (HVAC) that maintains thermal comfort while minimising energy use. Edge analysis also supports adaptive lighting and energy management systems by adjusting light levels based on available natural light and user activity. Both applications improve household energy efficiency [52].

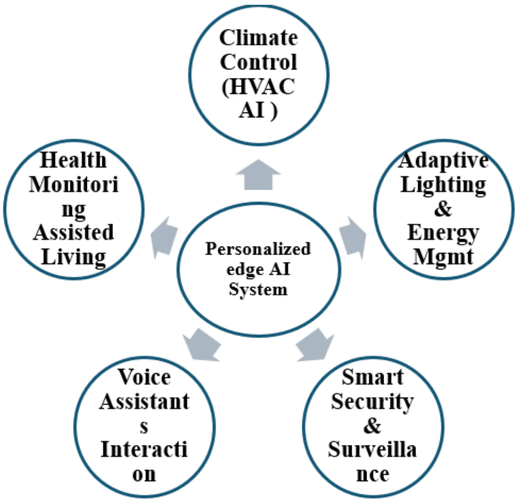

Fig. 4 Application areas of personalised edge AI in smart homes, including climate control, lighting management, security systems, voice interaction, and health monitoring.

Voice interaction is a further application area: natural language processing (NLP) models running on edge devices allow users to control appliances, receive information, and manage all aspects of home automation with spoken requests [53]. Personalised edge AI systems significantly contribute to health monitoring and assisted living for the elderly and people with chronic illnesses. Wearable devices and smart home systems can continuously monitor physiological data, activity levels, and behaviour. Edge AI can analyse this data locally to identify irregularities in activity patterns, falls, or potential health risks, triggering immediate alerts for caregivers or medical professionals. This capability helps create safer, more supportive living environments and enables vulnerable populations to live independently [54].

8. KEY CONSIDERATIONS FOR PERSONALISED EDGE AI

8.1 Privacy, Security, and Ethical Considerations

When personalised edge AI technology is integrated into smart homes, many concerns arise about data privacy, system security, and ethical governance. Smart home devices continuously generate sensitive and highly valuable data, including voice and video recordings, behavioural patterns, and health-related information. Users need assurance that their data is protected, together with effective means of preventing their misuse. Edge computing allows devices to process data locally rather than transmitting it to a central cloud server, which reduces the exposure of sensitive information to external attack and leaves users in control of their own data [55]. However, despite the advantages of edge computing, smart homes remain vulnerable to cyberattacks, including unauthorised access to devices, data interception, and malicious attacks on Internet of Things (IoT) networks. Weak authentication, unencrypted communication protocols, and software vulnerabilities can all be exploited to compromise these systems. If smart homes are to protect sensitive data while remaining fully functional, privacy-preserving techniques such as federated learning, encryption, and differential privacy will need to be adopted far more widely. These methods support collaborative learning and intelligent data processing while keeping raw user data confidential. Ethical considerations are equally prominent in the design and deployment of AI-enabled smart home systems: user consent should be explicit, algorithms transparent, and lines of accountability clear when systems fail. Previous studies suggest that personalised edge AI solutions will not be widely adopted in homes until clear regulatory frameworks and system transparency are in place [56].

8.2 Human–AI Interaction and User Experience Design

The success of AI-powered domestic devices depends on how well they are designed around human needs, and in particular on usability, accessibility, and behavioural factors. Personalised edge AI can be embedded in adaptive user interfaces that tailor a device's response to an individual's preferences, behaviour, and living conditions. Interaction models built on contextual sensor data — location, activity, and time of day — support proactive assistance and smoother automation. Interaction with intelligent home systems can be mediated in several ways, including voice assistants, gesture control, and mobile applications. Usability, accessibility, and behavioural factors are therefore central to design, since user acceptance and engagement determine the long-term adoption of AI-enabled smart home technologies [57].

8.3 Challenges and Research Opportunities

Despite advances in technology, multiple barriers currently limit large-scale adoption of individualised edge AI in smart homes. Edge devices generally have limited computing power, memory, and energy, which hinders the deployment of sophisticated machine learning models. Interoperability problems arise because heterogeneous IoT devices are produced by different manufacturers and use different communication protocols. Striking the right balance between generalisation and personalisation is a further challenge, since systems must adapt to individual behaviour while maintaining reliable performance across different settings. Research should focus on developing standardised approaches, secure infrastructures, and scalable deployment methods to build future smart home ecosystems [58].

8.4 Future Directions of Personalised Edge AI in Smart Homes

Current work anticipates a future in which 5G and next-generation 6G communications combine with personalised edge AI to deliver faster networking and improved device performance. Additionally, intelligent edge devices will create more autonomous home systems with self-maintenance functions, proactive assistance, and adaptive resource (energy) use. Advances in AI-driven sustainability will also help to reduce the energy consumption and ecological footprint of the home. Progress in explainable AI, federated learning, and distributed edge computing will make smart technologies more transparent and protect privacy while also scaling within the smart home space over the next decade [59].

Table 2 Challenges and Future Research Opportunities in Personalised Edge AI Smart Homes

Aspect	Current Challenges	Future Opportunities
Computational Resources	Limited processing power of edge devices	Development of lightweight AI models and specialised edge hardware

Interoperability	Diverse IoT standards and device incompatibility	Unified protocols and standardisation frameworks
Data Privacy	Risk of sensitive data exposure	Privacy-preserving AI techniques and federated learning
Energy Efficiency	High power consumption of AI processing	Energy-aware AI algorithms and sustainable smart home systems
System Scalability	Difficulty managing large numbers of connected devices	Distributed edge architectures and intelligent orchestration

9. CONCLUSION

The emergence of personalised edge artificial intelligence (AI) is transforming the design and use of next-generation smart home environments. Smart home systems use edge computing and intelligent algorithms to process data locally, tailor responses to individual user preferences, and deliver instantaneous automated actions without heavy reliance on centralised cloud infrastructure. This decentralisation improves responsiveness, enhances user privacy, and allows better management of residential resources. The convergence of Internet of Things (IoT) devices, AI, and edge-based analytics has extended the established automation model of smart homes into an intelligent environment capable of understanding and anticipating user activity. In this chapter, we discussed the architectural foundation and enabling technologies that underpin personalised edge AI in smart homes. Key elements that comprise the foundation for adaptive systems in a domestic setting include edge-based learning strategies, distributed intelligence, embedded AI platforms, and communications infrastructure. Examples of how AI can be implemented directly at the network edge include intelligent climate control, adaptive lighting, security monitoring, voice-based interaction, and health monitoring. These applications demonstrate benefits in convenience, energy savings, safety, and healthcare support. However, technical and social issues must be resolved before personalised edge AI can reach its full potential. Challenges remain, including the restricted processing capacity of edge devices, poor interoperability between IoT device types, and unresolved privacy and cybersecurity issues. Ethical considerations — transparency, consent, and trust — must also be addressed to ensure that these products are used responsibly. Developments in edge hardware, low-overhead machine learning algorithms, and fast communication networks (including 5G and beyond) will further expand the capabilities of personalised edge AI. Smart homes will eventually become autonomous, context-aware, and human-centric environments that seamlessly integrate intelligent services into daily life while maintaining strong privacy protections and operating in an energy-efficient manner.

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