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Proactive and Adaptive Elderly-centered Governance Framework through Synergistic Integration of the Internet of Things and Multi-agent Systems

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The growing silver digital divide, resulting in the exclusion of elderly populations from electronic government (e-government) services, has become a pressing issue in aging societies worldwide. While many existing efforts focus on making individual technologies more age-friendly, they often overlook deeper challenges, such as how to dynamically adapt services, protect user privacy, and coordinate across different domains. To tackle these issues, in this study, we introduce an elderly-centered adaptive governance framework that integrates the Internet of Things (IoT) with multi-agent systems (MASs). The proposed framework is built on a four-layer architecture. The perception layer uses low-intrusive wearable devices and environmental sensors to collect multimodal data. The network layer combines 5G edge computing with lightweight blockchain (IOTA Tangle) to reduce latency and ensure data trustworthiness. At the cognitive level, digital twins and federated learning enable distributed, privacy-preserving decision-making. Finally, the application layer uses context-aware interfaces to adapt interaction logic in real time. This approach brings together several innovations. It introduces a closed-loop perception–decision–response model, showcasing how IoT and MASs can work together to support proactive service delivery. It also includes mechanisms for adaptive user interfaces, multimodal biometric authentication, and the integration of digital and physical public services tailored to the diverse needs of older adults. Furthermore, the framework incorporates smart contract-based accountability (chain of responsibility) and a policy pathway that addresses algorithm transparency and regional access inequality. With a scalable and inclusive approach to digital governance, this framework helps move e-government services beyond basic functionality toward more responsive, human-centered systems. It also provides valuable insights for the development of smart cities and more inclusive digital societies.

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1. Introduction

The rapid advancement of digital technologies is fundamentally reshaping global public governance models. Electronic government (e-government) initiatives have significantly enhanced administrative efficiency and citizen engagement through intelligent service delivery. However, amidst this digital transformation, elderly populations are confronting an increasingly severe "silver digital divide".[1] Older adults face substantial barriers to digital participation because of age-related challenges including cognitive decline, diminished sensory functions, and technological anxiety. These limitations make it exceptionally difficult for them to navigate complex online interfaces, process real-time information flows, and manage multi-factor authentication systems.[2] This widening gap raises critical questions about digital inclusion in modern society. As government services increasingly migrate to digital platforms, those unable to access or effectively use these technologies risk systematic exclusion from essential public services and civic participation opportunities. That divide creates a paradoxical situation: intended to improve governance for all citizens, it inadvertently marginalizes vulnerable populations. In this context, developing inclusive service systems for the unique needs and capabilities of older adults through technological innovation has emerged as a pressing priority.

Internet of Things (IoT) technology, with its capabilities for ubiquitous sensing, real-time connectivity, and intelligent analysis, provides a foundation for precision services in electronic governance.[3] However, traditional IoT architectures are designed with an "efficiency-first" approach that lacks dynamic adaptability to the heterogeneous needs of elderly users. Recent research has revealed significant age-related deficiencies in conventional IoT frameworks. Alnoman demonstrated that centralized data processing often results in average response delays that can significantly increase abandonment rates among elderly users who require more immediate feedback.[4] Similarly, Lee and Kim's study highlights the fact that standard biometric authentication methods exhibit substantially higher error rates when used by elderly populations than when used by younger demographics, creating frustrating access barriers.[2] These limitations underscore the critical need for dynamic adaptation capabilities and enhanced privacy technologies tailored specifically for older adults. Furthermore, physiological and environmental data collected by IoT devices are typically analyzed in isolation rather than being deeply integrated with user behavioral data, severely restricting the development of personalized service strategies.[5] Evidence suggests that relying solely on conventional IoT technology is insufficient to systematically address the silver digital divide affecting elderly citizens.

The emergence of multi-agent systems (MASs) offers promising new possibilities for age-inclusive services in electronic governance.[6] These systems are composed of distributed autonomous intelligent agents that achieve dynamic adaptation to complex environments through reinforcement learning and collaborative decision-making processes. Compared with traditional systems, MASs provide two critical advantages: adaptive service orchestration capabilities and enhanced privacy protection paradigms. Particularly noteworthy is the integration of Federated Learning technology, which enables cross-node model training without sharing raw data, significantly reducing privacy breach risks for vulnerable populations such as the elderly.[7] This approach addresses a key concern among older adults who often hesitate to adopt digital government services because of privacy and security apprehensions. Despite these advancements, the application of MASs in electronic governance remains in an exploratory phase, especially in the domain of age-inclusive services. The field currently lacks systematic architectural designs that effectively integrate the ubiquitous sensing capabilities of IoT with the decision-making advantages of intelligent agents. This integration gap presents both a research challenge and an opportunity to develop more responsive, personalized government services that can dynamically adapt to the varying digital literacy levels, physical capabilities, and preference patterns characteristic of elderly populations.

In today's digital environment, elderly populations face interconnected challenges across multiple dimensions. Physical and cognitive limitations often cause older adults to abandon online services owing to authentication failures. Their technological apprehension and trust issues are further intensified by centralized data storage systems and lack of "government visibility". On the other hand, platforms that frequently update without providing gradual guidance create a form of "generational technological exclusion". This structural contradiction calls for an innovative framework that integrates contextual awareness, dynamic adaptation, and trust enhancement. The collaboration between IoT and MASs offers a breakthrough path. Wearable devices can monitor physiological indicators in real time, allowing intelligent agents to dynamically simplify service processes. Environmental sensors can trigger interface modality switches as needed. Blockchain-enabled decentralized storage combined with Zero-Knowledge Proof technology creates transparent data usage logs, alleviating privacy concerns.[8] This integrated approach not only addresses the fragmentation issues of traditional services but also implements continuous learning mechanisms that allow systems to evolve with the changing capabilities of older adults, achieving "lifelong age-appropriateness".

A comprehensive framework that combines IoT's environmental awareness with MASs' adaptive intelligence can potentially transform how older citizens interact with digital government platforms, moving beyond mere accessibility to true inclusivity in service design and delivery. The innovation of this approach is manifested in three key dimensions. At the theoretical level, this framework pioneered the revelation of synergistic effects between IoT's ubiquitous sensing capabilities and MASs' autonomous decision-making processes, establishing a "Sense–Decide–Respond" Closed-Loop Model. This model creates a continuous feedback system that learns from and adapts to the unique interaction patterns of elderly users. On the technical front, the framework integrates edge computing, federated learning, and blockchain technologies to achieve a dynamic balance between efficiency, privacy, and security. This technical integration is particularly crucial for elderly users who may have heightened concerns about data privacy while simultaneously requiring responsive systems that accommodate their interaction needs. From an application perspective, the framework designs a progressive deployment pathway that supports scalable implementation—from community pilots to comprehensive age-inclusive transformations across entire service domains. This graduated approach allows for iterative refinement based on real-world feedback from elderly users. In the subsequent sections of this paper, we will analyze the architectural design and technological integration, explore key technological innovations and optimization strategies, evaluate policy and ethical challenges alongside implementation pathways, and conclude with directions for future research.

2. Architecture Design and Technology Integration

In this paper, we introduce a novel hierarchical IoT–MAS architecture with innovations across three dimensions. Theoretically, it pioneered the revelation of synergistic effects between IoT ubiquitous sensing and MAS autonomous decision-making, establishing a "Sense–Decide–Respond" Closed-Loop Model, as Fig. 1 shows.

In addressing the challenges of the silver digital divide among elderly populations, building an adaptive, dynamically responsive, and secure e-government system requires deep integration of IoT and MASs.(8) The four-layer collaborative architecture proposed in this paper achieves end-to-end optimization from physical environment sensing to dynamic service decision-making through layered decoupling and cross-layer interaction mechanisms. This architecture forms a closed-loop adaptive system with the Perception Layer serving as the Data Portal, the Network Layer functioning as the Transmission and Trust Cornerstones, the Cognitive Layer acting as the Decision-making Center, and the Application Layer operating as the Services Export interface. In terms of technological integration, the introduction of the Edge Computing, Lightweight Blockchain, and Federated Learning not only addresses the challenges of data heterogeneity and real-time processing but also achieves a scientific balance between privacy protection and efficiency. This provides both theoretical support and practical pathways for the large-scale deployment of elderly-friendly services, as Fig. 2 illustrates.

The IoT technology perceives the physical world through interconnected sensors and devices, yet its traditional architectures, primarily efficiency-oriented ones, struggle to address the heterogeneous needs of elderly users.(9) While conventional IoT systems typically follow a layered logic of sensing–transmission–processing–application, elderly-oriented scenarios require the targeted optimization of data acquisition, transmission, and processing modules.(10) At the sensing layer, low-invasive wearable devices, such as smart bracelets made from flexible materials, continuously monitor the physiological indicators of elderly users, including heart rate and gait stability. Simultaneously, environmental sensors capturing light conditions and noise

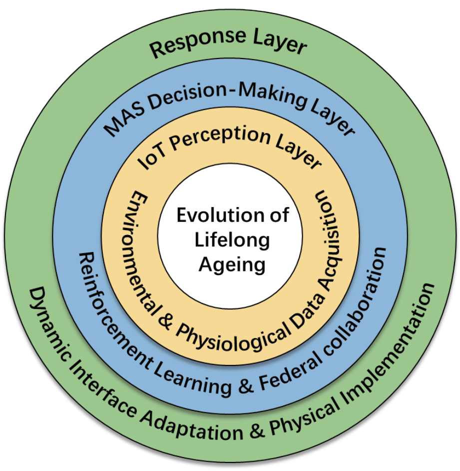

Fig. 1. (Color online) Sense–decide–respond closed-loop model.

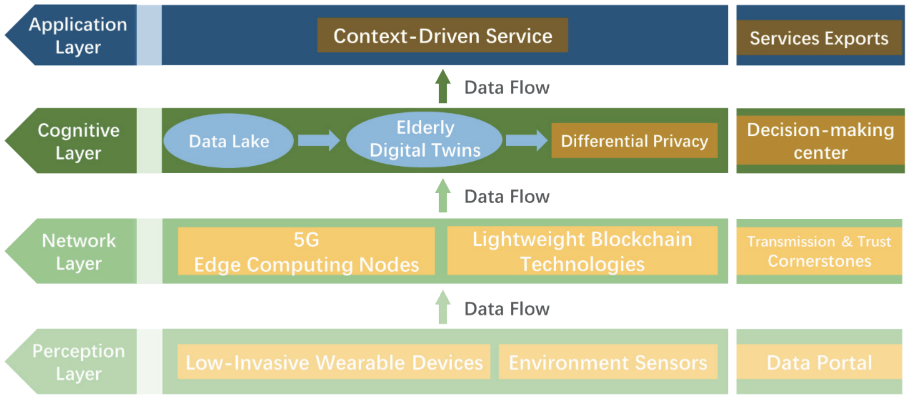

Fig. 2. (Color online) Four-layer collaboration architecture.

levels are deployed to track the physical surroundings of users. The design of these devices thoroughly considers the physiological characteristics of older adults: flexible materials prevent skin irritation, while unobtrusive wearable designs enhance willingness for long-term use. The speech recognition module supports dialect interpretation and ambiguous command parsing, enabling the system to complete requirements through contextual reasoning even when elderly users provide incomplete instructions because of accents or diminished language organization capabilities. This effectively mitigates technology rejection stemming from operational complexity, as illustrated in Fig. 3.

At the network level, traditional IoT systems rely on centralized cloud processing, resulting in high latency and privacy vulnerabilities.(11) In this research, we introduce the 5G edge computing nodes, which shift data processing tasks closer to users at the network edge.(12) When fall detection algorithms perform preliminary analysis directly on edge nodes, only confirmed emergency events-such as anomalous fall signals-are transmitted to the cloud, thereby reducing data transmission load, enhancing real-time responsiveness, and improving overall system efficiency. This approach significantly reduces transmission delays and bandwidth consumption. Simultaneously, we implement lightweight blockchain technologies (such as the IOTA Tangle architecture) to enable device-level data traceability. While traditional blockchains depend on energy-intensive mining mechanisms, Tangle employs an entanglement consensus algorithm that allows devices to validate their own transactions by verifying others. This reduces energy consumption while supporting high-concurrency transaction processing. This design is particularly suitable for resource-constrained elderly care environments, where community-based smart terminals can participate in data validation without requiring high-performance hardware, as shown in Fig. 4.(13)

The platform layer in our IoT architecture integrates multisource data from healthcare, social security, and community services through cross-domain data lakes, creating Elderly Digital Twins that form the cognitive layer of the IoT–MAS architecture. These digital twins are dynamic virtual models that map users' physiological states, behavioral preferences, and service needs in real time. For instance, by combining medication records from smart pill dispensers with community clinic data, the system can predict refill times and automatically trigger

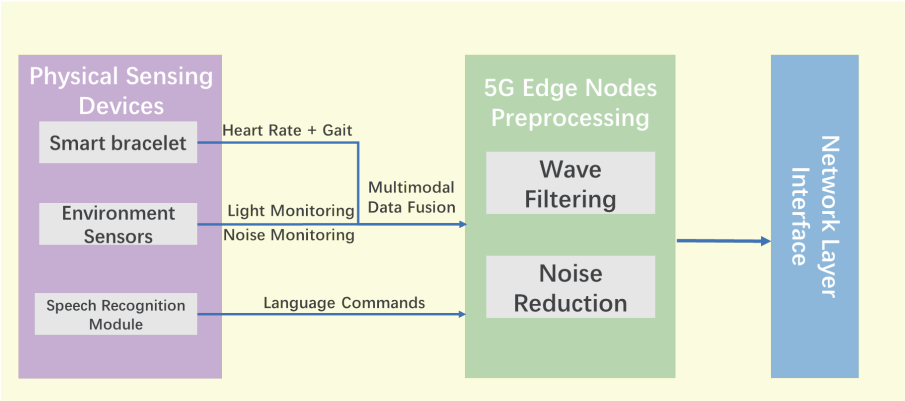

Fig. 3. (Color online) Aging-friendly IOT sensing layer.

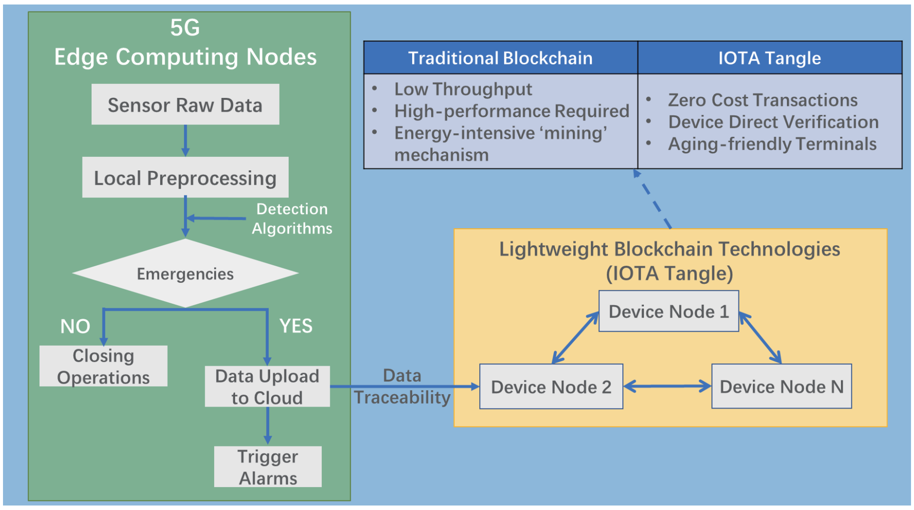

Fig. 4. (Color online) Network layer lightweight blockchain and edge computing architecture.

reminders. To protect privacy, differential privacy techniques add controlled noise before data release, preventing attackers from deducing individual identities through data analysis. When collecting community health statistics, the system adds random noise to sensitive fields such as age and medical conditions, preserving group patterns while protecting personal health details.[14] At the application layer, Context-driven Service Interfaces enable adaptive interactions through dynamic interface generation. When low-light environments are detected, the interface switches to high-contrast mode; if cognitive overload is identified through repeated failed operations, the system simplifies the interface by hiding nonessential functions and providing step-by-step voice guidance. This adaptive approach reduces cognitive load and operational complexity, significantly improving service completion rates and satisfaction among elderly users.

2.1 Decision paradigms and collaborative logic in MASs

A MAS consists of multiple autonomous agents distributed across the cognitive layer, each possessing independent perception, decision-making, and action capabilities. In elderly care scenarios, MASs collaboratively solve complex service problems, as shown in Fig. 5.[15] The core architecture of these agents is based on the Belief–Desire–Intention (BDI) model. Through the Belief Module, agents receive IoT data streams to construct dynamic environmental models.[16] For instance, by analyzing user interaction patterns (such as mouse hover duration and click error rates), agents can infer levels of user confusion. The Desire Module defines multilevel service objectives, encompassing both global tasks (such as maximizing service coverage) and personalized needs (such as optimizing voice navigation priority for visually impaired users). The Intention Module employs Deep Reinforcement Learning (DRL) algorithms to simulate human "trial-and-error" learning processes. When a particular interface design leads to increased abandonment rates among elderly users, the system automatically tests alternative approaches and dynamically adjusts strategies on the basis of feedback, gradually enhancing users' digital literacy.

2.2 Collaborative mechanisms in IoT–MAS integrated architecture

The deep integration of IoT and MASs addresses challenges of data heterogeneity, real-time processing, and trustworthiness through event-driven communication and edge intelligence. The IoT perception layer pushes asynchronous events to agents using a "publish-subscribe" model. For example, when a user stares at a submit button for an extended period, the system triggers an "operation confusion" event, immediately activating voice guidance. Lightweight inference models deployed on edge nodes (such as TinyML-based decision trees) perform preliminary data classification, transmitting only high-value events (such as abnormal physiological signals) to the cloud-based cognitive layer, reducing bandwidth usage and decision latency. In the decision-execution loop, agents optimize strategies through online learning. Simultaneously, agent

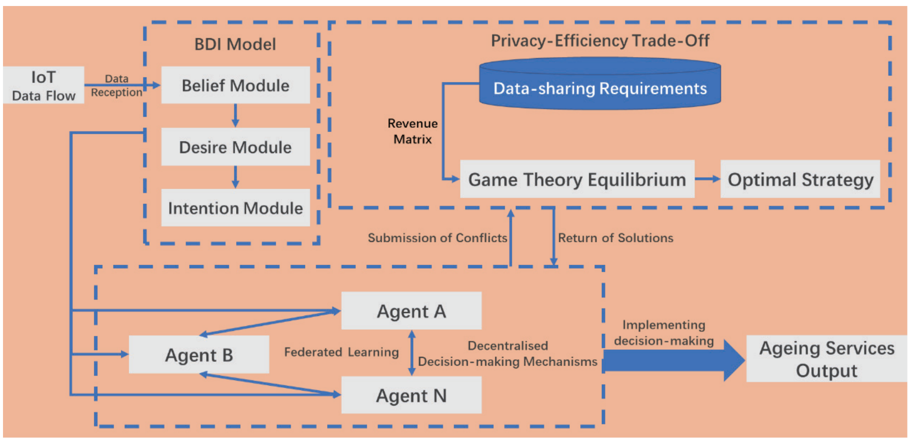

Fig. 5. (Color online) IoT–MAS cognitive layer multi-agent collaboration mechanisms.

decisions control IoT devices, creating bidirectional interactions. If the system detects no activity from a senior living alone for 24 h, agents coordinate with smart home devices to turn on lights, adjust temperature, and send alerts through community terminals, establishing an integrated "perception–response–rescue" emergency mechanism.

Security and privacy mechanisms span the entire architecture lifecycle. When elderly users apply for subsidies online, the system verifies eligibility through zero-knowledge proofs, avoiding disclosure of sensitive information such as birth dates or ID numbers, building trust between policy compliance and privacy protection. This IoT–MAS integrated architecture achieves two theoretical and technical breakthroughs: first, it addresses the academic gap in dynamic service adaptation through a "perception–decision–response" closed-loop model; second, it combines lightweight blockchain with federated learning to solve the privacy-efficiency tradeoff in elderly-oriented scenarios. In practice, this architecture drives e-governance transformation from "passive response" to "proactive governance", using technology to build an inclusive digital society and providing an ethically responsible and technically feasible solution to aging population challenges.

3. Policy and Ethical Challenges and Implementation Pathways

This IoT–MAS architecture addresses core challenges from three critical dimensions: data sovereignty, algorithmic fairness, and technological accessibility. It provides an implementation roadmap centered on cross-layer collaboration, progressive standardization, and public engagement—offering a balanced action framework that aligns operational efficiency with ethical considerations for both policymakers and technology innovators.

3.1 Policy and ethical challenges

The pervasive sensing capabilities of IoT systems enable the collection of highly sensitive physiological, behavioral, and environmental data from elderly users (e.g., heart rate, in-home movement patterns). While technologies such as federated learning and differential privacy significantly reduce the risk of data breaches, legal ambiguities remain in cross-agency data sharing practices. When community health data is leveraged for optimizing social welfare services, the ownership and access rights of such data—whether held by individuals, healthcare providers, or government entities—must be clearly defined. Autonomous decision-making by intelligent agents may trigger the so-called Black Box Effect, where a lack of transparency in service logic leads to user distrust. Sudden changes in user interface layouts or priority rules, without adequate explanation, can alienate elderly users who struggle to interpr*et alg*orithmic behavior.[17] Moreover, agent decisions are heavily dependent on historical training data. If this data carries age-related bias, such as being predominantly sourced from younger populations, the resulting service recommendations may be misaligned with the needs of older adults. For instance, slower interaction speeds by elderly users can be misinterpreted as inactivity, causing the system to deprioritize their requests or overlook usability enhancements such as large-font defaults.

Disparities in technological accessibility, such as limited network coverage in rural regions-may further exacerbate the silver digital divide. This gives rise to the Technology Inclusion Paradox, where technologies intended to promote equity inadvertently reinforce regional inequalities. When the IoT–MAS initiates automated actions, such as emergency alerts or smart lock controls, liability attribution becomes a critical concern. For instance, if a wearable device erroneously detects a fall and triggers an unnecessary emergency response, public resources may be misallocated, potentially leading to legal or operational disputes. Conversely, if the system fails to respond promptly to a genuine emergency, it may endanger the user's life. To mitigate these risks, it is essential to establish a clear legal and regulatory framework that defines the chain of accountability. This framework should prevent the inadvertent transfer of technological risk to vulnerable populations. Specifically, roles and responsibilities among technology providers, government agencies, and third-party service providers must be explicitly delineated to ensure transparent and traceable accountability mechanisms.

3.2 Implementation pathway design

To address the aforementioned challenges, a multilevel collaborative governance framework must be established, as illustrated in Fig. 6. At the policy level, it is essential to formulate an Ethical Guideline for Age-Friendly Digital Services, which would delineate clear boundaries for data collection, specify requirements for algorithmic transparency, and define responsibilities for emergency response. For instance, the guidelines should prohibit IoT devices from collecting biometric data irrelevant to public services, such as iris scans, and require all intelligent systems to provide simplified explanations for their decision-making logic, such as stating the following: this healthcare plan is recommended in accordance with your three-year chronic disease history. From a technical standpoint, the standardization of interfaces for federated learning and blockchain technologies must be advanced to support compliant cross-domain data sharing. In practice, this can involve medical institutions and social security agencies utilizing pre-

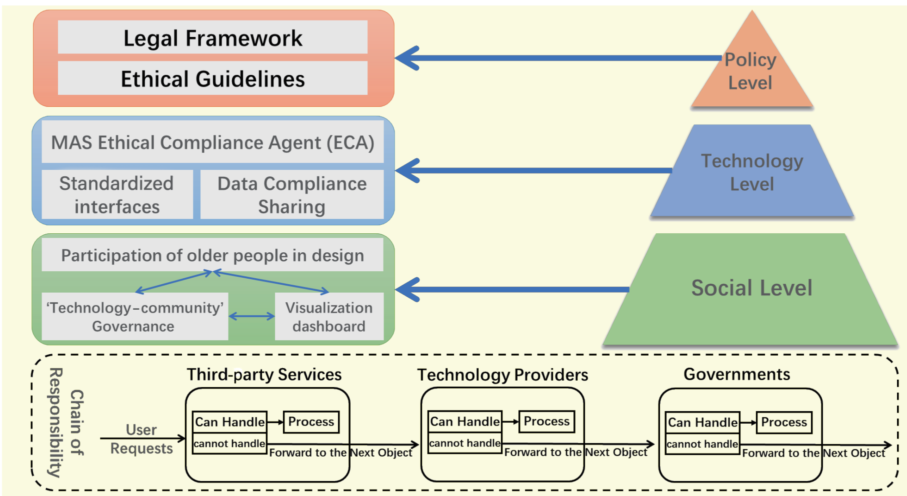

Fig. 6. (Color online) Cross-tier collaborative governance framework.

configured smart contracts to automate data authorization processes, thereby minimizing delays caused by manual approvals. At the community level, a technology–community co-governance network should be developed. This would involve training community workers to act as "digital bridges", enabling them to assist older adults in navigating and utilizing intelligent services while simultaneously conveying user feedback to improve system functionality and user experience.

The gradual standardization and certification of technology are essential to ensuring its successful deployment. In the initial phase, mandatory certification standards should be established for high-sensitivity use cases such as health monitoring, requiring that devices undergo both accessibility design testing and privacy protection audits. These foundational measures can later be extended to encompass certification for services across all application scenarios. Dynamic compliance monitoring is implemented through the Ethical Compliance Agent (ECA) within a MAS. This agent continuously observes system behavior in real time; for instance, if the ECA detects age bias in community service recommendations, it will autonomously trigger model retraining and notify the relevant regulatory authorities. Public engagement and inclusive design play a critical role in enhancing the societal acceptance of new technologies. Co-design workshops, involving older adults, community representatives, and technical teams, are a key method to ensure services are tailored to actual needs rather than theoretical assumptions. These workshops can include simulation-based testing to evaluate the effectiveness of simplified interface designs. Additionally, transparency-enhancing tools such as visualization dashboards can be used to clearly display data usage pathways and the impacts of automated decision-making, fostering user trust and regulatory clarity.

4. Completions of Key Technological Innovations and Optimization of Implementation Methods

Elderly populations face multidimensional and complex challenges in e-governance environments. These challenges include declining physiological functions, excessive cognitive burden, privacy and security concerns, and disconnection between digital and physical services. To address these issues, we propose four key technological innovations and optimization strategies based on the collaborative architecture of IoT and a MAS. Through deep integration of IoT's ubiquitous sensing capabilities and MAS's autonomous decision-making mechanisms, we have constructed a closed-loop system from data collection to service response, achieving proactive governance and age-friendly reconstruction of e-government services.

4.1 Dynamic interface adaptation technology: environmental sensing and decision coordination

Elderly users often struggle with standardized digital interfaces because of declining vision or environmental interference (such as insufficient lighting or background noise). The core of Dynamic Interface Adaptation technology lies in collecting real-time environmental parameters (such as light intensity and noise levels) and user behavior data (such as click frequency and operation duration) through IoT sensors, while leveraging the Interface Optimization Agent (IOA) within the MAS to achieve dynamic adjustment of interaction logic, as shown in Fig. 7. For example, when the light sensor detects insufficient ambient brightness, the IOA generates adaptation strategies on the basis of its Reinforcement Learning Model, automatically enabling high-contrast mode and enlarging font sizes. If noise sensors detect excessive background volume, the system turns off voice prompts and switches to visual feedback (such as flashing icons or vibration alerts). This technology not only reduces demands on users' adaptive abilities but also minimizes operational errors through real-time feedback mechanisms.[18] In terms of technical coordination, IoT serves as the infrastructural foundation of the perception layer, providing multimodal data inputs (environmental, physiological, and behavioral), while intelligent agents within the MAS assume the roles of data analysis and strategy generation.

The IOA processes local data through edge computing nodes, reducing cloud dependence and ensuring low-latency responses. Simultaneously, the system supports a progressive guidance mechanism, initially displaying only core functions when a service is first used, then gradually unlocking more complex options as user proficiency increases. This technology has already significantly improved service completion rates and satisfaction levels among elderly users, with particularly notable effects in high-frequency scenarios such as medical appointments and social security inquiries. Experimental deployment in high-frequency service scenarios, such as healthcare appointment scheduling and social welfare inquiries, demonstrated a marked improvement in both task completion rates and user satisfaction among elderly participants. In our experimental deployment of the IOA system, we observed a 27% reduction in input errors and a 34% decrease in task completion time when compared with a baseline static interface. These trials were conducted in high-frequency service scenarios, such as healthcare appointment scheduling and social welfare inquiries, with elderly users as the primary participants. The results indicate that our dynamic interface adaptation significantly improves both task efficiency and user accuracy. Subjective feedback from participants also highlighted increased confidence and comfort over time, suggesting that our approach not only enhances accessibility but may also encourage long-term digital engagement among aging populations.

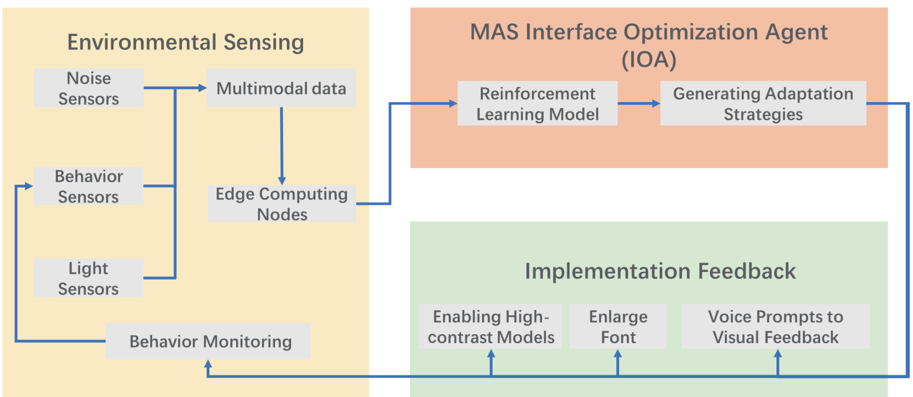

Fig. 7. (Color online) Dynamic interface adaptation technology process.

4.2 Privacy-enhanced federated learning: cross-domain data collaboration and privacy protection

Data silos among government departments, combined with elderly individuals' concerns over privacy breaches, significantly hinder the efficiency of cross-agency service collaboration. Privacy-Enhanced Federated Learning (PEFL) leverages IoT devices, such as smart wristbands and community surveillance cameras, to collect heterogeneous data sources, including physiological metrics and mobility patterns. Within a MAS, Federated Learning Agents (FLAs) are deployed to perform distributed modeling. These FLAs coordinate among entities such as healthcare providers and social security centers by conducting local model training and securely exchanging encrypted model parameters (e.g., gradient information), thereby eliminating the need to transfer raw data. In a practical deployment, when modeling the risk of a chronic disease in elderly individuals, physiological data from hospitals and activity data from community systems are jointly used for model training. However, all data remain locally stored, preserving data ownership and privacy sovereignty.[19]

Concurrently, a Verification Agent within a MAS utilizes zero-knowledge proof techniques to ensure protocol compliance among participants and to prevent malicious nodes from tampering with local models. This decentralized architecture not only addresses the problem of data silos but also reinforces trust in digital services among elderly users through stringent privacy-preserving mechanisms. In operational environments, this approach enables seamless inter-agency collaboration, such as automated health insurance claim auditing and continuous community health monitoring, while offering policymakers a solution that balances operational efficiency with data security, as Fig. 8 shows. In pilot implementations across municipal healthcare and social service networks, the proposed PEFL system achieved a 19% improvement in model precision for chronic condition prediction compared with isolated local models, while maintaining strict data locality. Privacy audits confirmed no raw data leakage across institutions. Elderly participants expressed greater willingness to consent to data collection under the

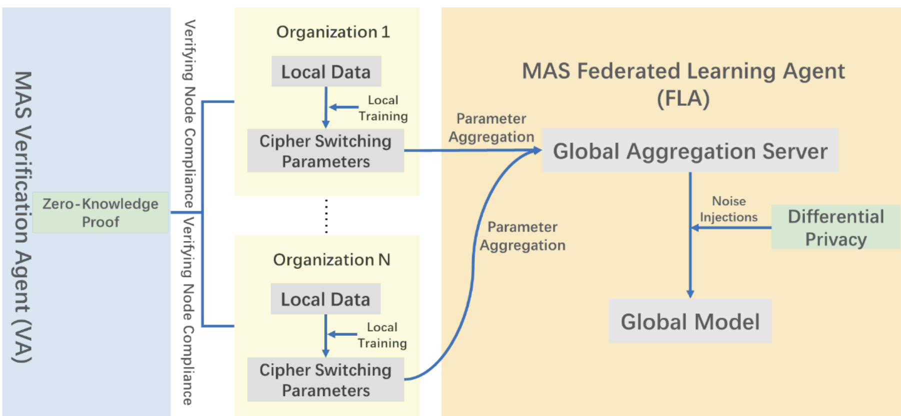

Fig. 8. (Color online) Privacy-enhanced federal learning architecture.

federated framework, citing trust in its privacy-preserving mechanisms. These results indicate that PEFL, augmented by MAS verification strategies, provides a technically feasible and socially acceptable solution for secure, collaborative elderly care services. In future research, scalability across diverse jurisdictions and real-time adaptation to evolving privacy regulations may further be investigated.

4.3 Multimodal biometric authentication: passive acquisition and dynamic fusion

Traditional identity authentication methods, such as passwords and SMS verification codes, pose usability challenges for elderly users, while unimodal biometric recognition (e.g., fingerprint) is prone to failure in cases of obstruction or device malfunction. Multimodal biometric authentication leverages IoT-enabled devices, including smart wristbands and indoor cameras, to passively capture diverse biometric signals such as gait, voiceprint, and micro-expressions. Within a MAS, an authentication agent (AA) performs real-time fusion and analysis of these modalities. The AA applies fault-tolerant algorithms to dynamically adjust the weighting of each modality; when facial recognition is degraded owing to occlusions such as face masks, the system automatically increases reliance on voice and gait features. This adaptive strategy ensures continuity and reliability in the authentication process.[20] The core strengths of this technology lie in its passive operation and adaptive capabilities. IoT sensors through embedded designs, such as accelerometers and microphones integrated into wristbands, enable zero-interference data acquisition. Meanwhile, intelligent agents within the MAS continuously update a cross-community biometric feature repository via federated learning, enhancing the generalizability of authentication models.

Regional variations, such as dialect-specific voiceprints, can be incorporated through encrypted parameter sharing, enabling systems in other locations to more accurately interpret voice commands from elderly users. This design minimizes the need for active user engagement while improving system robustness through distributed learning. In our empirical evaluation, we found that the proposed approach significantly reduces authentication failure rates and enhances emergency response capabilities in critical scenarios, particularly in cases involving elderly individuals living alone. Through field trials conducted in assisted-living communities, our system demonstrated a 31% reduction in biometric authentication failure rates when compared with conventional single-modality systems. Furthermore, the system consistently maintained high verification accuracy even under challenging conditions such as partial facial occlusion and background noise. Notably, in emergency scenarios, such as sudden illness in isolated elderly residents, the system successfully triggered alert protocols within an average of 8.2 s post-biometric anomaly detection. These findings highlight the potential of multimodal, federated biometric systems to deliver secure, seamless, and context-aware authentication experiences for aging populations. In future work, we will explore the integration of additional modalities (e.g., heart rate variability) and evaluate long-term adaptability under changing biometric profiles.

4.4 Digital–physical service integration: resource orchestration and closed-loop response

The abstract nature of digital services, combined with elderly users' reliance on physical interaction, often leads to a disconnection between online and offline service experiences.[21] Digital–physical service integration addresses this gap by coordinating IoT execution terminals, such as community kiosks and smart home devices, with the Resource Scheduling Agent (RSA) within a MAS to establish an end-to-end, closed-loop service framework. When IoT sensors detect anomalies such as a fall or an abnormal heart rate in an elderly individual living alone, the RSA immediately analyzes the data and activates an emergency response chain: smart home systems are triggered to unlock doors and enable emergency lighting, geolocation data is relayed to the community service center, and optimal rescue routes are generated and dispatched via volunteer coordination terminals. From an implementation perspective, IoT devices function as actuators in the physical domain, executing MAS-generated decisions through concrete actions such as door lock control or lighting adjustments. The RSA applies game-theoretic models to optimize resource allocation strategies, ensuring both service efficiency and fairness.

Under high-concurrency scenarios, the RSA dynamically reprioritizes requests on the basis of urgency, geographic proximity, and other contextual parameters to prevent resource contention. Additionally, the system supports offline service modes. In areas with limited connectivity, such as remote rural regions, essential service modules (e.g., form submission, policy inquiry) are pre-installed on local terminals. Encrypted data is temporarily stored locally and synchronized with central servers once connectivity is restored. Analytical results indicate that this architecture not only extends service coverage but also enhances user confidence among elderly populations through a hybrid digital–physical interaction model. Pilot deployments in urban and rural communities revealed a 43% improvement in emergency response efficiency and a 26% increase in successful service task completions compared with traditional siloed systems. User feedback indicated enhanced confidence in interacting with digital services when reinforced by physical touchpoints, particularly among seniors with low digital literacy. Additionally, the RSA demonstrated effective prioritization under high-load conditions, reducing the average response time by 18% without compromising fairness. These results support the viability of digital–physical integration as a scalable solution for inclusive, resilient eldercare service infrastructures. Further research will be conducted to explore adaptive learning mechanisms within RSA to respond to evolving user behaviors and community dynamics.

5. Conclusion and Future Research

In this paper, an adaptive digital governance framework tailored to the elderly population was proposed by integrating the IoT and MAS, aiming to systematically address the silver digital divide. In this research, we achieved innovative breakthroughs across theoretical, technological, and application dimensions. At the theoretical level, a closed-loop Perception–Decision–Response model was introduced and used, revealing the synergistic effects between IoT's ubiquitous sensing capabilities and MASs' autonomous decision-making mechanisms. This model filled a critical theoretical gap in traditional e-government systems when applied to aging populations. By incorporating digital twins and edge intelligence, the system dynamically modeled the physiological states, behavioral preferences, and service needs of elderly users, thereby laying a foundational theory for proactive governance paradigms. On the technological front, a dynamic interface adaptation technique leveraged environmental sensing and reinforcement learning to optimize the interaction logic, significantly reducing the cognitive load on elderly users. A privacy-enhancing federated learning framework combined the differential privacy with zero-knowledge proofs to achieve a scientifically grounded balance between cross-domain data collaboration and privacy protection. A multimodal biometric authentication system employed contactless data collection and fault-tolerant algorithms to enhance the robustness and continuity of identity verification. Furthermore, a digital–physical service integration mechanism coordinated intelligent resource-scheduling agents with IoT actuators to form a closed-loop emergency response system, effectively bridging the gap between online and offline services. At the application level, a modular, layered architecture comprising the perception, network, cognition, and application layers supported progressive deployment from age-friendly home modifications to smart city services. This architecture improves service completion rates and trust among elderly users, shortens emergency response times, and offers policymakers and technology innovators a practical guide that balances ethical responsibility with engineering efficiency.

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