



February 23, 2026

VIA Electronic Submission to <https://www.regulations.gov/>

Thomas Keane, MD, MBA  
Assistant Secretary for Technology Policy and the Office of the National Coordinator for Health Information Technology,  
Department of Health and Human Services,  
Mary E. Switzer Building  
7033A, 330 C Street SW,  
Washington, DC 20201

***Re: Request for Information: Accelerating the Adoption and Use of Artificial Intelligence as Part of Clinical Care [RIN 0955-AA13]***

The American Health Care Association and National Center for Assisted Living (AHCA/NCAL) represent over 15,100 long term and post-acute care facilities, or 1.1 million skilled nursing facility (SNF) beds and over 300,000 assisted living (AL) beds. With such a membership base, the Association represents the majority of SNFs and a rapidly growing number of assisted living communities as well as residences for individuals with intellectual and developmental disabilities (ID/DD). We appreciate the opportunity to comment on the *Request for Information: Accelerating the Adoption and Use of Artificial Intelligence as Part of Clinical Care [RIN 0955-AA13]*.

We agree that effective and responsible adoption of artificial intelligence (AI) clinical technology has the potential to empower care providers, patients and their families and caregivers to make informed decisions for their health and well-being and welcome this discussion of the market of digital health products for Medicare beneficiaries as well as the state of data interoperability and broader health technology infrastructure. **However, any discussion of AI adoption must reinforce that reimbursement, interoperability, and population relevance are the binding constraints for long-term and post-acute care (LTPAC) providers.**

We believe that it is imperative that the federal government provide leadership, governance, and support to encourage more widespread adoption of accessible, safe, secure, and user-friendly interoperable digital health technology for providers and their patients. The Assistant Secretary for Technology Policy (ASTP)/Office of the National Coordinator for Health Information Technology (ONC) (collectively, ASTP/ONC), in coordination with the Centers for Medicare & Medicaid Services (CMS) and other agencies within the interconnected health information ecosystem, are best positioned to provide the leadership to facilitate infrastructure progress enable beneficiary access to effective digital capabilities needed to make informed health decisions, and to increase secure health information data availability for all stakeholders contributing to health outcomes.

We are eager to work with ASTP/ONC in identifying a pathway to finding clinical AI solutions that are attainable to all stakeholders across the information health technology ecosystem. If you have questions about any of our comments, please contact Daniel Ciolek at [dciolek@ahca.org](mailto:dciolek@ahca.org).

Sincerely,

Daniel E Ciolek  
Associate Vice President, Therapy Advocacy

## RFI Summary

This RFI outlines the Department of Health and Human Services (HHS) strategy to support the responsible adoption of artificial intelligence (AI) in clinical care, focusing on **regulation, reimbursement, and research & development**.

HHS aims to establish a clear, predictable, and risk-based regulatory approach for clinical AI that enables rapid innovation while safeguarding patient safety, protecting identifiable health information, and maintaining public trust. The agency is seeking input on how existing regulations affect the development and use of AI in clinical settings.

The document emphasizes that current fee-for-service payment systems often slow innovation, encourage inefficiencies, and fail to align spending with value. HHS highlights the need to modernize reimbursement policies, so payers are incentivized to support high-value AI clinical interventions, promote competition among AI developers, and improve access and affordability for patients. Feedback is requested on payment policy reforms to achieve these outcomes.

Finally, HHS underscores its role in supporting one of the world's largest health research ecosystems. Through investments in applied AI research, implementation science, public-private partnerships, and cooperative research agreements, the agency seeks to accelerate the translation of AI technologies from concept to clinical use, creating long-term market opportunities and improving people's health and wellbeing.

## Who We Are and Who AHCA/NCAL Members Provide Care To

Before we can provide responses to the ten specific questions this RFI seeks comment on, we believe it is important to share contextual information about our AHCA/NCAL provider members, the resident populations they serve, their current fragmented baseline digital capabilities, and historical financial, legislative, and regulatory barriers to initiating or accelerating the adoption of and use of AI as part of clinical care. We believe a critical issue that ASTP/ONC needs to consider as strategies are developed in response to the comments received to this RFI, is that increased adoption of AI in clinical care will remain extremely challenging if not impossible for LTPAC providers without first providing adequate support to eliminate the digital interoperability infrastructure gaps. True functional interoperability capacity across the healthcare ecosystem would provide the comprehensive information necessary to permit a secure, safe, and effective use of AI in clinical care.

### 1. SNF/NF, AL, and ID/DD Provider Setting Profiles and the Populations of Individuals Served

Of importance, and relevant to our comments, is that unlike other healthcare facility-based provider settings that address acute and sub-acute conditions for a limited time-window, or office-based primary care and other practitioners that encounter patients intermittently, most of the individuals our members care for are long-term residents – it is their home. Except for a portion of SNF short-stay post-acute patients who require certain nursing and/or rehabilitation therapy services to return to the community, most people in nursing facilities (SNF/NF) and those in AL or ID/DD residences require residential care to manage chronic conditions reflected through physical and/or cognitive impairments.

Regarding the long-term and post-acute care (LTPAC) provider settings represented by our membership, we first describe the types of healthcare and healthcare-related services they furnish and the characteristics of the residents they serve. Next, we highlight the diversity of payor sources since a provider's reliance on fixed federal and state payors impacts a provider's capacity to assume the significant hardware, software, and administrative costs associated with interoperable digital health technology, including AI. Finally, we share information regarding the diversity of the resident population across the SNF, AL, and ID/DD provider community as a reflection of the digital health needs footprint of these residents within the health information technology (HIT) ecosystem.

Most of the 14,742 SNFs nationwide serve a dual purpose with 93 percent being dually certified for furnishing Medicare and Medicaid services. As mentioned above, SNFs provide short-term post-acute services to patients who require skilled nursing and/or rehabilitation services on an inpatient basis. Additionally, SNF's/NFs furnish long-term care for residents requiring 24/7 care due to various medical, mobility, activities of daily living, cognition, and behavioral challenges that cannot be addressed adequately in the community. Health care services from various professions may be furnished to residents in the facility, at the offsite office or facility, or via telehealth and remote patient monitoring (RPM) technology. While a small number of SNFs serve pediatric populations, the vast majority serve adults with chronic conditions and related disabilities, predominantly for adults over the age of seventy-five. Overall, Medicaid accounts for sixty-three percent of SNF residents while private and other payers represent twenty-three percent, and Medicare only fourteen percent.<sup>1</sup>

According to the MedPAC March 2025 Report to Congress<sup>2</sup>, SNF facilities range from small to large organizations and operate on minimal net margins:

- **The SNF all-payer profit margin in 2023 was 0.4 percent (negative 1.3 percent in 2022).**
- **The median SNF had 100 beds, while ten percent of facilities had 176 or more beds and ten percent of facilities had 50 or fewer beds.**

There are over 32,000 AL communities that serve older individuals or those with limited disabilities who typically need help with everyday activities and some health care services but do not require 24-hour skilled nursing services for extended periods of time<sup>3</sup>. These communities offer a unique mix of companionship, independence, privacy, and security in a home-like setting. The philosophy of assisted living is built on the concept of delivering person-centered care and services to each individual resident. Some assisted living communities specialize in serving individuals with specific needs. These may include, but are not limited to, Alzheimer's disease or other forms of dementia (such as memory care units), intellectual and developmental disabilities, and particular medical conditions (e.g., Parkinson's disease) or other needs. AL communities do not directly provide certain health care services, such as physical therapy or pharmacy, but work with other providers to offer these services.

- **AL services are not included in Medicare benefits, and Medicaid does not cover AL room and board, so most costs are private-pay, with only one in five residents being eligible for Medicaid home and community-based services (HCBS) such as personal care and supportive services.**
- **Forty-three percent of AL residents are small and serve 4-10 residents at a time, while only ten percent have 100 or more residents.**

There are also over 5,300 ID/DD residences, or Intermediate Care Facilities for Individuals with Intellectual Disabilities (ICF/IID) serving over 56,000 residents of all ages daily, with over seventy-five percent being between the ages of 22 and 65<sup>4</sup>. Many of these individuals are non-ambulatory, have seizure disorders, behavior problems, mental illness, visual or hearing impairments, or a combination of the above. ICFs provide active

---

<sup>1</sup> A Look at Nursing Facility Characteristics in 2025. KFF. <https://www.kff.org/medicaid/a-look-at-nursing-facility-characteristics/> [accessed February 11, 2026]

<sup>2</sup> March 2025 Report to Congress: Medicare Payment Policy: Chapter 6: Skilled Nursing Services. Medicare Payment Advisory Commission. <https://www.medpac.gov/document/march-2025-report-to-the-congress-medicare-payment-policy/> [accessed February 11, 2026]

<sup>3</sup> Assisted Living Facts & Figures. AHCA/NCAL. <https://www.ahcancal.org/Assisted-Living/Facts-and-Figures/Pages/default.aspx> [accessed February 11, 2026]

<sup>4</sup> AHCA/NCAL internal analysis of the following public and proprietary data sources: A-Certification and Survey Provider Enhanced Reporting (CASPER) data. B-Medicaid Budget and Expenditure System/State Children's Health Insurance Program Budget and Expenditure System (MBES/CBES). C-IMPLAN Group LLC, IMPLAN System (data and software)

treatment and services for people with significant support needs. They offer 24-hour supervision, health care, therapies, activities, and training intended to maximize residents' autonomy and independence.

- **Virtually all funding for ID/DD residents is under Medicaid benefits.**
- **The average number of beds per residence is 14, ranging from 9 for private ID/DD residences to 52 for public residences.**

## **2. Digital Capabilities Across SNF/NF, AL, and ID/DD Provider Settings**

A sizable portion of AHCA/NCAL member care providers are directly tied to the healthcare information exchange ecosystem whether reimbursed by federal, state, commercial, or private health coverage. Many payer quality- and value-based payment models – including long-term care-focused Medicare fee-for-service (FFS) Accountable Care Organizations (ACO), bundled payment models such as the Transforming Episode Accountability Model (TEAM), and the Medicare Advantage (MA) Institutional Special Needs Plan (I-SNP) model of care – involve integrated care across care providers. This would be significantly enhanced by improved digital capabilities, including AI that can efficiently leverage critical health information across all provider types involved with resident care.

All the care provider settings represented by our membership have access to and store Personal Health Information (PHI). Of these, many store this information electronically to varying degrees and generally have limited interoperable connectivity in the current digital health technology ecosystem. The variations in digital capabilities across our LTPAC provider membership is directly the result of historical federal prioritization of hospital inpatient and primary care interoperability support through the implementation of the Health Information Technology for Economic & Clinical Health (HITECH) Act of 2009 and in subsequent coordinated care, bundled care, and other integrated care value-based payment models advanced by CMS. Since LTPAC providers were not specifically identified in the HITECH Act, the federal administrative support necessary to facilitate seamless secure interoperable electronic exchange of the patient information between providers, and to the patient, particularly at transitions of care, has been quite limited. Additionally, bundled incentive programs have not historically included mechanisms to ensure that the bundle holder shares incentive payments to partner SNF, AL, and ID/DD providers to support investment in interoperable technology capabilities. Moving forward, the lack of explicit recognition and scaling of SNF, assisted living, and ID/DD setting challenges in federal AI regulatory guidance not only creates compliance uncertainty for providers, but also discourages vendors from developing and tailoring AI tools for these settings—reinforcing a cycle of market neglect for LTPAC care environments.

In the absence of a federal coordinated effort to support Information Technology (IT) integration, LTPAC providers that have adopted HIT have instead developed non-standardized HIT, including electronic health records (EHR) to support setting-specific clinical and operational activities. In addition to EHR systems, many of the SNF, AL and ID/DD providers in our membership utilize other digital technologies to support resident care. Telehealth technologies are used to expand beneficiary access to care and reduce unnecessary hospitalizations. Remote patient monitoring (RPM) and sensor technologies can provide valuable information to improve resident safety and more timely and effective care interventions. Clinical decision support systems (CDSS) including artificial intelligence (AI) driven analytics help to improve treatment decisions and outcomes. Resident care management activities are also supported by tools for purposes such as electronic nursing documentation, medication administration, incident reporting and quality assurance, and resident engagement tools such as patient portals and apps. Moreover, HIT tools are also used to facilitate communication with various internal and external clinical support services including pharmacy, laboratory, radiology, rehabilitation therapy professionals, and for administrative purposes such as scheduling, claim processing, compliance programs and more.

However, the current digital ecosystem for many of these technologies today is fragmented and interconnectivity – when present – is commonly built upon customized non-standardized digital ‘work arounds’. This fragmentation is a significant barrier to attaining the level of effective digital capabilities needed to support patients, families and their caregivers in making informed health decisions, and for provider stakeholders to improve health outcomes.

For example, as recently as December 23, 2023, the Office of the Assistant Secretary for Planning and Evaluation (ASPE) within HHS published a report titled *Health Information Technology Adoption and Utilization in Long-Term and Post-Acute Care Settings*<sup>5</sup> which found that most LTPAC providers, including SNFs, have generally adopted EHRs to support clinical and business needs at a rate comparable to hospitals and primary care providers, but adoption of EHRs in residential care settings such as AL and ID/DD is limited.

***“Yet despite the lack of a federally-funded program and policy requirements, estimates of EHR adoption rates among nursing home and SNF providers, as well as HHAs, were greater than 78% in 2018, which is on par with EHR adoption in office-based primary care settings. Residential care settings were estimated to be much lower overall, at 26% -- higher than that for larger facilities and much lower for small facilities.”***

However, the authors also emphasized that interoperable exchange of health information is not routine or widely used. In other words, LTPAC providers utilize their internal EHR, but modernization to improve interoperability capabilities remains slow without focused and realistic policy levers. Despite barriers, the authors concluded that there are opportunities for emerging policies to support secure interoperability in LTPAC.

The breadth of this digital divide was reflected in a recent May 2024 ONC Data Brief titled *Interoperable Exchange of Patient Health Information Among U.S. Hospitals: 2023*<sup>6</sup>.

**Specifically, ONC indicated that only 17 percent of hospitals are able to routinely send interoperable health information to LTPAC providers and only 8 percent of hospitals were able to routinely receive such information from LTPAC providers.**

While we appreciate the recent ONC efforts in late 2023 in launching the Trusted Exchange Framework and Common Agreement (TEFCA) to enable nationwide health information exchange that could provide opportunities for LTPAC providers with nonstandard health IT to exchange information through a Health Information Exchange (HIE), an August 2024 Health Affairs Scholar article titled *The state of health information organizations and plans to participate in the federal exchange framework*<sup>7</sup> has revealed that this alternative method for information exchange will likely be insufficient to resolve the interoperability gap for LTPAC providers as 32 percent of the current Health Information Organizations (HIOs) that could facilitate this information exchange through their HIEs have indicated they may not participate in TEFCA. As the authors summarized,

***“While TEFCA appears to have successfully engaged the majority of HIOs, achieving nationwide exchange will require policy efforts to either attract the remaining HIOs or ensure that nonparticipating HIOs' providers have another option for TEFCA participation.”***

Another barrier to interoperable HIT adoption in some LTPAC providers is the lack of adequate high-speed internet infrastructure in specific geographic locations. For example, KFF Health News recently published a

---

<sup>5</sup> Health Information Technology Adoption and Utilization in Long-Term and Post-Acute Care Settings. Office of the Assistant Secretary for Planning and Evaluation (ASPE) at the U.S. Department of Health & Human Services by RTI International. December 2023.

<sup>6</sup> Interoperable Exchange of Patient Health Information Among U.S. Hospitals: 2023. Office of the National Coordinator for Health Information Technology (ONC). May 2024.

<sup>7</sup> Jordan Everson, Wei Chang, Vaishali Patel, Julia Adler-Milstein, the state of health information organizations and plans to participate in the federal exchange framework, *Health Affairs Scholar*, Volume 2, Issue 8, August 2024

report<sup>8</sup> that included a national map, by county, where there is broadband ‘deserts’ where providers who may be motivated to obtain interoperable HIT that could support AI to improve the quality of care cannot do so.

Finally, with increased digital interconnectedness necessary to support comprehensive AI technology in LTPAC settings, the risk for cybersecurity breaches increases and will require additional investments in financial and personnel resources to manage and to establish and maintain emergency plans during digital blackouts including emergency backups for data recovery, and manual procedures to assure resident safety and care quality is maintained at times when the AI or other digital information is offline.,

Since the enactment of the HITECH Act, AHCA/NCAL, other LTPAC Associations and the LTPAC Health IT Collaborative<sup>9</sup> have commented on various Agency HIT programs and have sought the support of HHS both in funding and policy. HHS has provided limited support to support secure HIT interoperability and cybersecurity infrastructure to support AI adoption within the constraints of the current statutory framework, but we believe more is necessary. Unlike large health systems with dedicated IT departments and capital reserves, most LTPAC providers lack the staffing and financial capacity to engage in complex, enterprise-style procurement processes, underscoring the need for direct infrastructure support rather than adopting poor fitting AI models designed for hospitals.

## AHCA/NCAL Overarching Comments on Regulation, Reimbursement, and Research & Development

### Regulation

AHCA/NCAL supports the HHS vision of transitioning to a regulatory framework that is proportionate, transparent, and enables innovation while protecting vulnerable populations. For AI tools deployed in LTPAC settings, regulatory clarity recognizing the unique challenges of providing care to individuals is essential regarding:

- Clinical Decision Support (CDS) versus Decision Support Interventions (DSI): Under the HTI-1 Final Rule, distinctions between CDS software and DSI must account for workflow-critical interventions in LTPAC settings, such as glucose monitoring in diabetes management, delirium detection, fall risk assessment, and polypharmacy optimization. Many AI tools operating in these domains directly impact patient safety and outcomes.
- Algorithmic Transparency and Accountability: AI tools targeting LTPAC populations must undergo validation against population-relevant cohorts including geriatric and chronic impairments and demonstrate transparency in their decision-making logic and auditability of the AI outputs, particularly when involving generative AI technology. Vendor accountability for algorithmic bias affecting safety outcomes should be enforced, particularly for tools addressing conditions prevalent in older adults and those with multiple chronic conditions.
- Age-Inclusive Standards: Regulatory frameworks should mandate age-stratified data collection and validation in real-world data (RWD) studies to mitigate age bias in AI algorithms. Current clinical trials frequently underrepresent geriatric patients, leading to biased algorithms that may recommend inappropriate care pathways for older adults.
- Cybersecurity and HIPAA Compliance: Accelerating appropriate adoption of AI in clinical care is desirable, but not at the expense of exposing patients and providers from bad actors that could leverage/intercept AI technology without appropriate security measures to improperly obtain a residents personally identifiable information (PII) or personal health information (PHI). AI development guardrails that are scaled to risk of cybersecurity breach or HIPAA violations should be established as

<sup>8</sup> Dead Zone. KFF Health News. May 31, 2025. <https://kffhealthnews.org/dead-zone/>

<sup>9</sup> LTPAC Health IT Collaborative: <https://www.ltpachit.org/>

providers do not have the technical expertise to assess such protections in proprietary, and often ‘black box,’ vendor technology.

## Reimbursement

Payment policies, particularly federal technology investment and support prioritization, significantly influence technology adoption in LTPAC settings. AHCA/NCAL recommends:

- Value-Based Payment Alignment: Payment models should incentivize the use of high-value AI interventions that improve outcomes for complex, high-need populations. Alternative payment models (APMs) and value-based care arrangements should explicitly include quality measures and risk-adjustment methodologies that account for LTPAC populations.
- Coverage for AI-Enabled Remote Monitoring: Medicare and Medicaid should expand coverage for AI-enabled remote patient monitoring (RPM), ambient AI, and other technologies regardless of where the beneficiary is residing that support aging in place, resident safety, and reduce preventable hospitalizations and emergency department visits.
- Infrastructure Investment: Reimbursement mechanisms should support the underlying infrastructure required for AI adoption, including interoperability investments, workforce training, and technical assistance for small and rural providers.
- Reduction of Administrative Burden: AI tools that automate documentation, quality reporting, and administrative tasks should be incentivized through payment policy to facilitate workflow transitions to reduce provider burden and allow clinicians to focus on direct patient care.

## Research & Development

HHS should prioritize R&D investments that address the unique needs of aging, geriatric, and LTPAC populations with multiple chronic conditions including physical, cognitive, and behavioral impairments:

- Inclusion of LTPAC Populations in Research: The National Institutes of Health (NIH), the Agency for Healthcare Research and Quality (AHRQ), and other HHS research agencies should require inclusion of LTPAC and geriatric populations in AI research funding. Pilot programs should focus on AI applications in nursing homes (SNF/NF), home health, assisted living, and other post-acute settings.
- Inclusion of LTPAC Standardized Patient Data Elements (SPADES) in Research: Any national AI validation or testing infrastructure should explicitly include SPADES assessment items such as the SNF Minimum Data Set (MDS) required by the IMPACT Act as well as the PACIO aligned datasets to correct longstanding bias against aging and long stay populations and to ensure AI tools are evaluated using data representative of LTPAC care delivery. While simulation or synthetic data methods may supplement evaluation efforts, real world validation in SNF, assisted living, and ID/DD settings must remain the standard for assessing any regulated AI performance and safety.
- Interoperability Research: Support development and validation of Fast Healthcare Interoperability Resources (FHIR) implementation guides that capture geriatric-specific data elements, including functional status, cognitive assessments, social determinants of health, and caregiver support data.
- Public-Private Partnerships: Establish cooperative research and development agreements (CRADAs) with LTPAC providers, health IT vendors, and academic institutions to co-develop and validate AI tools in real-world settings.
- Longitudinal and Multimorbidity Research: Fund large, longitudinal studies on aging trajectories, multimorbidity trials, polypharmacy optimization, and research on family caregivers and aging in place.

## AHCA/NCAL Detailed Responses to the RFI Questions

### Question 1: What are the biggest barriers to private sector innovation in AI for health care and its adoption and use in clinical care?

#### Example feedback from our frontline AHCA/NCAL member providers includes:

*“The biggest barrier to the private sector is price and the lack of reimbursement. Many facilities would embrace more AI; however, the question is how it will be paid for. Also, many individuals still have a fear of AI and the interpretation of certain medical conditions; and are worried about an error in the interpretation as often happens with denials. There is also some concern about network capability and computer literacy.”*

#### Specific concerns across LTPAC providers regarding the most significant barriers for AI adoption include:

**Population Bias and Data Exclusion:** Clinical trials and AI training datasets systematically underrepresent older adults, particularly those in LTPAC settings. This leads to biased algorithms that perform poorly or produce harmful recommendations when applied to geriatric populations. AI models trained predominantly on younger cohorts may recommend inappropriate medication dosages, fail to account for age-related pharmacokinetics, or overlook fall risk factors specific to frail older adults.

**Data Interoperability Limitations:** LTPAC providers face significant challenges in achieving interoperability with acute care hospitals, primary care providers, specialty clinics, service partners including therapy providers, pharmacies, and labs, and more recently, health information exchanges. The healthcare ecosystem is not designed to be inclusive of LTPAC populations. Limited adoption of standardized data exchange formats, particularly HL7 FHIR implementation guides relevant to LTPAC (such as those developed by the PACIO Project), hinders the flow of critical patient information across care transitions. Without access to longitudinal, interoperable data, AI tools, particularly clinical decision support tools, cannot effectively support person-centered, holistic care.

**Infrastructure and Resource Constraints:** Many LTPAC providers, particularly small, rural, and under-resourced facilities, lack the technical infrastructure, broadband connectivity, and financial resources needed to adopt AI technologies. The digital divide in LTPAC settings creates disparate access to innovation. Additionally, workforce challenges—including limited health IT expertise and high staff turnover—impede successful AI implementation. While AI literacy and training are important considerations, workforce instability in LTPAC settings—characterized by chronic staffing shortages, high turnover, and care models reliant on a high proportion of Certified Nursing Assistants (CNAs) as the primary personal needs caregivers—remains the more binding constraint on such technology adoption absent reimbursement and operational support.

**Regulatory Uncertainty:** Lack of clarity regarding liability, indemnification, privacy, and security for non-medical device AI tools creates hesitation among LTPAC providers and AI developers. Questions about who bears responsibility when an AI tool produces an adverse recommendation, how HIPAA applies to AI-generated insights, and what standards govern AI tool validation remain inadequately addressed. As AI technologies evolve, additional clarity regarding how HIPAA applies to AI generated outputs and data use could further protect LTPAC providers and residents, provided such guidance prioritizes provider safeguards and resident privacy over technical enablement or research flexibility.

**Reimbursement Barriers:** Fee-for-service payment and other HIT investment incentive program structures provide limited incentives for LTPAC providers to invest in AI tools, even when such tools could improve outcomes and reduce costs over time. Coverage and reimbursement decisions for AI-enabled services are slow,

and current payment models do not adequately account for the value of AI interventions that prevent adverse events, reduce hospitalizations, or improve quality of life.

**Lack of Geriatric-Specific Clinical Guidelines Integration:** AI-powered clinical decision support tools often lack integration with geriatric-specific clinical practice guidelines. Evidence-based guidelines tailored for older adults—such as those published by the Post-Acute and Long-Term Care Medical Association (PALTmed)—address conditions like diabetes management, falls prevention, delirium detection, polypharmacy, and pressure ulcer prevention in geriatric populations. AI tools that do not incorporate these guidelines may produce recommendations that are inappropriate for LTPAC patients.

Below are numerous government, academic, and stakeholder analyses and commentary regarding the digital divide impacting AHCA/NCAL member settings that creates a barrier that needs to be resolved for accelerating adoption of AI technology in LTPAC settings.

### **Interoperability Capacity and AI Adoption and Costs in Nursing Homes and Assisted Living References**

Amazon Web Services (AWS). 2025. Elaprolu, Sri, Alla Simoneau, Paul Amadeo, and Laura Kulowski. “Physical AI in Practice: Technical Foundations that Fuel Human Machine Interactions.” AWS Machine Learning Blog. <https://aws.amazon.com/blogs/machine-learning/physical-ai-in-practice-technical-foundations-that-fuel-human-machine-interactions/>.

Argentum. “Argentum and A Place for Mom Highlight Current Technology Trends, Growing AI Optimism and Industry Collaboration in Senior Living Technology Report.” July 1, 2025. <https://www.argentum.org/argentum-and-a-place-for-mom-highlight-current-technology-trends-growing-ai-optimism-and-industry-collaboration-in-senior-living-technology-report/>.

Ciolek, Daniel. “Federal Report on Interoperability of Health IT in Long-Term Care.” Provider Magazine, Spring 2024. <https://www.providermagazine.com/Issues/2024/Spring/Pages/Federal-Report-on-Interoperability-of-Health-IT-in-Long-Term-Care.aspx>.

Ciolek, Daniel. “Influences on Health Technology Adoption in Nursing Facilities.” Provider magazine, Winter 2025. <https://www.providermagazine.com/Issues/2025/Winter/Pages/Influences-on-Health-Technology-Adoption-in-Nursing-Facilities.aspx>.

Ciolek, Dan. “New Federal Report on Adoption of Health Information Technology Includes SNF and AL Settings.” AHCA/NCAL Blog, January 5, 2024. <https://www.ahcancal.org/News-and-Communications/Blog/Pages/New-Federal-Report-on-Adoption-of-Health-Information-Technology-Includes-SNF-and-AL-Settings.aspx>.

Code, Scott. “Building Interoperability: A Call for Investment, Not Penalties.” LeadingAge. July 14, 2025. <https://leadingage.org/building-interoperability-a-call-for-investment-not-penalties/>.

Cognitive World. 2025. “The Infrastructure Decade: Why Healthcare’s AI Future Is Being Built in Layers, Not Launched Overnight.” Cognitive World. <https://cognitiveworld.com/articles/2025/11/8/the-infrastructure-decade-why-healthcares-ai-future-is-being-built-in-layers-not-launched-overnight>.

Forrester Consulting. The Total Economic Impact™ of PointClickCare’s Skilled Nursing Solution. April 2020. <https://pointclickcare.com/wp-content/uploads/2021/07/the-total-economic-impact-of-pointclickcares-skilled-nursing-solution-study.pdf>.

Kandel, Ben, Cheryl Field, Jasmeet Kaur, Dean Slawson, and Joseph G. Ouslander. “Development of a Predictive Hospitalization Model for Skilled Nursing Facility Patients.” Journal of the American Medical Directors Association 26, no. 1 (January 2025): 105288. [https://www.jamda.com/article/S1525-8610\(24\)00710-2/fulltext](https://www.jamda.com/article/S1525-8610(24)00710-2/fulltext).

KFF Health News. Dead Zone. Published May 31, 2025. <https://kffhealthnews.org/dead-zone/>.

LeadingAge CAST. “Adoption of Advanced EHRs Stalls in the Aging Sector.” LeadingAge, June 10, 2024. <https://leadingage.org/adoption-of-advanced-ehrs-stalls-in-the-aging-sector/>.

LeadingAge CAST. “Case Study: Using AI to Help Detect and Prevent Falls.” PDF. [https://leadingage.org/wp-content/uploads/2023/03/Case-Study\\_Village-Assisted-Living-Detect-Falls.pdf](https://leadingage.org/wp-content/uploads/2023/03/Case-Study_Village-Assisted-Living-Detect-Falls.pdf). Accessed February 11, 2026.

Lin, Sunny C., and Ozcan Tunalilar. “Rapid Adoption of Electronic Health Record and Health Information Exchange among Assisted Living Communities, 2010–2018.” *Journal of the American Medical Informatics Association* 29, no. 5 (2022): 953–957. <https://doi.org/10.1093/jamia/ocac021>.

McHugh, John P., Hayara Cardoso, Ngan Bui, and Gregory L. Alexander. “Market and Organizational Characteristics Associated with Nursing Home Health Information Technology Maturity.” *Journal of Gerontological Nursing* 51, no. 10 (October 2025): 10–16. <https://journals.healio.com/doi/abs/10.3928/00989134-20250916-01>.

Nguyen, Thuy D., Christopher M. Whaley, Kosali Simon, and others. “Adoption of Artificial Intelligence in the Health Care Sector.” *JAMA Health Forum* 6, no. 11 (November 21, 2025): e255029. <https://jamanetwork.com/journals/jama-health-forum/fullarticle/2841460>.

Office of the Assistant Secretary for Planning and Evaluation (ASPE). *Health Information Technology Adoption and Utilization in Long-Term and Post-Acute Care Settings*. Prepared by RTI International. Washington, DC: U.S. Department of Health and Human Services, December 2023. <https://aspe.hhs.gov/reports/hit-adoption-utilization-ltpac-settings>.

Office of the National Coordinator for Health Information Technology (ONC). *Trusted Exchange Framework and Common Agreement (TEFCA) Overview*. U.S. Department of Health and Human Services, 2025–2026. <https://www.healthit.gov>.

Orlov, Laurie M. *The Future of AI in Senior Living and Care: What’s Now and Next*. October 2024. <https://www.ageinplacetechnology.com/files/aip/Future%20of%20AI%20in%20Senior%20Living%20and%20Care.pdf>.

Poon, Eric G., Christy Harris Lemak, Juan C. Rojas, Janet Guptill, and David Classen. “Adoption of Artificial Intelligence in Healthcare: Survey of Health System Priorities, Successes, and Challenges.” *Journal of the American Medical Informatics Association* 32, no. 7 (July 2025): 1093–1100. <https://doi.org/10.1093/jamia/ocaf065>. Accessed February 11, 2026.

The King’s Fund. 2025. “Infrastructure for Innovation: Getting the NHS and Social Care Ready for AI.” The King’s Fund. <https://www.kingsfund.org.uk/insight-and-analysis/long-reads/infrastructure-nhs-social-care-ai>.

## **Question 2: What regulatory, payment policy, or programmatic design changes should HHS prioritize to incentivize the effective use of AI in clinical care and why?**

### **Example feedback from our frontline AHCA/NCAL member providers includes:**

*“Prioritization should be given to memorializing the source(s) of the AI generated information and documentation trail by providing regulatory clarity under HIPAA to clarify understanding who or what technology is responsible for what is written; such as “documentation on this was generated and entered by AI” [insert technology here] or , “recommended by AI [insert technology here]and verified by [insert human approver/editor];.From a payer standpoint, this could involve statements such as “This approval/denial generated and determined by AI[insert technology here]” Some vendors are already using such capabilities in Acute Care, VA and Physicians’ offices...but regulatory standardization across all provider settings regarding documenting when and how AI impacted care decisions should leverage existing models customized to long term care needs rather than reinventing the wheel.”*

## Specific LTPAC provider recommendations include the following priority changes:

### *Regulatory Changes*

- Mandate Age-Stratified Validation (42 CFR Part 412, 413, 482, 483, 484, 485): Require AI tools used in clinical care to undergo validation testing on age-stratified cohorts, particularly for tools intended for use in Medicare populations. Validation should include performance metrics specific to geriatric patients and demonstrate absence of age-based bias.
- Algorithmic Transparency Requirements (45 CFR Part 170): Under the ONC Health IT Certification Program, establish certification criteria for AI-enabled clinical decision support tools that require disclosure of training data characteristics, model performance on diverse populations, and explanation of decision logic. FHIR-based event-condition-action rules per HL7 Clinical Reasoning modules should be used to enforce transparency.
- Interoperability Standards for Geriatric Data (45 CFR 170.315): Expand the United States Core Data for Interoperability (USCDI) to include geriatric-specific data elements captured in PACIO Project FHIR implementation guides: functional status (ADLs/IADLs), cognitive assessments (PHQ-9, CAM), advance directives, standardized medication profiles, social determinants of health, and caregiver support information.
- Privacy and Security Safeguards (45 CFR Parts 160, 164): Clarify HIPAA applicability to AI-generated clinical insights and establish standards for de-identification, consent management, and audit trails for AI tools that access or generate protected health information.
- Certification Agility as Burden Reduction (All above relevant CFT sections) Certification pathways for AI enabled health IT should also be designed to avoid imposing repeated compliance and administrative burdens on LTPAC providers as tools are updated, emphasizing predictability and simplicity rather than development speed.

### *Payment Policy Changes*

- Medicare Coverage for AI-Enabled RPM (42 CFR Part 405, 410, 414): Expand Medicare Part B coverage for AI-enabled remote patient monitoring, ambient AI monitoring, and wearable devices that support aging in place. Reimbursement should cover device costs, data transmission, clinical interpretation, and care coordination activities.
- Value-Based Payment Incentives (42 CFR Part 425, 512): Incorporate AI adoption and outcome metrics into Medicare Shared Savings Program (MSSP), Accountable Care Organization (ACO) models, and other APMs. Quality measures should reward use of AI tools that demonstrate improved outcomes for high-risk, complex patients. Similar alignment should be tied to Medicare Advantage requirements (42 CFR Part 422). Additionally, while AI can be used to improve workflow address clinical questions and relieve administrative burden (conversational AI), the use of agentic AI without proper regulations can threaten the quality of care received by beneficiaries in VBC programs.
- Infrastructure Investment Payments (42 CFR Part 413, 484, 485): Create a Medicare/Medicaid infrastructure payment mechanism to support LTPAC providers' investments in interoperability, health IT upgrades, and AI readiness. This could be modeled after the Medicare Promoting Interoperability Program but tailored for LTPAC settings.
- Documentation Burden Reduction (42 CFR Part 483, 484): Allow AI-generated documentation to satisfy regulatory documentation requirements in skilled nursing facilities (42 CFR 483.20, 483.21) and home health agencies (42 CFR 484.55, 484.60), provided the AI tool meets transparency and accuracy standards.

## ***Programmatic Design Changes***

- **CMMI Innovation Models**: Develop Center for Medicare and Medicaid Innovation (CMMI) models specifically focused on accelerating AI adoption in LTPAC settings with appropriately funded models. Test payment incentives, technical assistance models, and shared savings approaches for providers implementing AI tools.
- **LTPAC-Focused FHIR Adoption**: Provide grants and technical assistance through the Office of the National Coordinator (ONC) to accelerate LTPAC provider adoption of PACIO Project FHIR implementation guides and onboarding to Qualified Health Information Networks (QHINs) under the Trusted Exchange Framework and Common Agreement (TEFCA).
- **Geriatric AI Validation Testbeds**: Establish regulatory-science testbeds in partnership with the Food and Drug Administration (FDA), Veteran’s Affairs (VA), and CMS to validate AI tools for safety, efficacy, and appropriateness in LTPAC settings. Require real-world evidence from diverse care settings for regulatory approval.

## **AI in Healthcare Federal and State Legislative & Regulatory Barriers Research**

Congressional Research Service (CRS). 2025. Wells, Nora. “Artificial Intelligence (AI) in Health Care: Recent Federal Activity.” Congress.gov. <https://www.congress.gov/crs-product/IF13135>.

International Comparative Legal Guides (ICLG). 2025. “Artificial Intelligence Tools in Health Services – An Overview of Current and Evolving US Federal and State Health Regulatory Structures.” ICLG Digital Health. <https://iclg.com/practice-areas/digital-health-laws-and-regulations/03-artificial-intelligence-tools-in-health-services-an-overview-of-current-and-evolving-us-federal-and-state-health-regulatory-structures>.

Manatt Health. 2025. Seigel, Randi, Jared Augenstein, Maya Shashoua, Cassidy Slater, and Christine Irlbeck. “Manatt Health: Health AI Policy Tracker.” Manatt Phelps & Phillips. <https://www.manatt.com/insights/newsletters/health-highlights/manatt-health-health-ai-policy-tracker>.

National Law Review. 2025. de la Houssaye, Nadia, Andrew R. Lee, Jason M. Loring, and Graham H. Ryan. “Healthcare AI in the United States — Navigating Regulatory Evolution, Market Dynamics, and Emerging Challenges in an Era of Rapid Innovation.” National Law Review. <https://natlawreview.com/article/healthcare-ai-united-states-navigating-regulatory-evolution-market-dynamics-and>.

### **Question 3: For non-medical devices, what novel legal and implementation issues exist related to AI in clinical care, and what role should HHS play?**

#### **Example feedback from our frontline AHCA/NCAL member providers includes:**

*“If AI declines a Medicare Advantage prior authorization request...who is ultimately responsible if the nursing home resident has a poor outcome? What is the validity of ongoing modifications.... should we have specific AI medical system standards, so facility personnel know that these standards are followed when looking at systems. Also, there is a lack of knowledge on how to choose which AI and the ongoing review of development and changes.... with each update is there an upcharge”*

#### **Specific LTPAC provider recommendations include considering the following on the HHS role:**

***Liability and Accountability***: When an AI tool recommends a clinical intervention that results in patient harm, liability questions arise: Is the provider liable for following the recommendation? Is the AI vendor liable for the algorithm’s output? Is the health system liable for deploying an inadequately validated tool? Current medical malpractice frameworks do not clearly address AI-mediated decision-making. HHS should work with state

medical boards, professional liability insurers, and legal experts to develop guidance on shared accountability models.

**Indemnification Agreements:** Many AI vendors require healthcare organizations to sign indemnification agreements that shift liability risk entirely to the provider. This is particularly problematic for under-resourced LTPAC providers who lack the financial capacity to assume such risk. HHS should establish model contract language and standards for balanced risk-sharing between vendors and providers.

**Privacy and Security:** AI tools often require access to large volumes of patient data for training and operation. Questions remain about:

- Whether AI-generated clinical insights constitute protected health information (PHI) under HIPAA;
- How consent should be obtained for AI processing of patient data;
- What security standards apply to AI model storage, transmission, and updates; and
- How to address privacy risks when AI tools use consumer-generated health data from non-HIPAA-covered wearables and apps.

HHS should issue guidance clarifying HIPAA applicability to AI systems and establish security standards for AI tools used in clinical care.

**Algorithmic Bias and Discrimination:** AI tools that exhibit bias against protected classes (age, race, disability status) may violate civil rights laws. However, detection and remediation of algorithmic bias require technical expertise that many healthcare organizations lack. HHS Office for Civil Rights (OCR) should develop guidance on algorithmic patient population appropriateness requirements and establish complaint mechanisms for patients who believe they have been harmed by biased AI tools.

**Data Ownership and Control:** When AI tools generate clinical insights, predictions, or risk scores based on patient data, questions arise about who owns these outputs and how they can be used. HHS should establish clear data governance frameworks that respect patient autonomy while enabling appropriate secondary use for research and quality improvement.

**Workforce Competency:** Effective use of AI in clinical care requires workforce education on AI capabilities, limitations, and appropriate supervision. HHS should support development of training programs and competency standards for clinicians, administrators, and health IT professionals who will deploy and oversee AI tools.

**Question 4: What are the most promising AI evaluation methods for clinical care, and how should HHS support them?**

**Example feedback from our frontline AHCA/NCAL member providers includes:**

*“Need interoperability between practice settings...is this a way to “mandate” everyone knows the same information; need to support grants and operative agreements that show human and technology intervention; any grants or agreements should be fairly spread across the healthcare continuum; it cannot be allocated the same way as money for EMR’s was allocated.”*

**Specific LTPAC provider recommendations for HHS to support AI evaluation include the following:**

### ***Pre-Deployment Evaluation Methods***

- Prospective Validation on Diverse Cohorts: AI tools should undergo prospective validation testing on age-diverse, racially diverse, and clinically diverse populations before deployment. For tools intended for geriatric populations, validation cohorts must include adequate representation of older adults with multimorbidity and polypharmacy.
- Bias Auditing and Fairness Testing: Independent bias audits should assess AI tool performance across demographic subgroups (age, race, ethnicity, sex, disability status) and clinical subgroups (disease severity, functional status, cognitive status). Disparities in performance should trigger remediation before approval.
- Explainability Assessment: AI tools should be evaluated for their ability to provide clinically meaningful explanations of recommendations. Black-box models that cannot explain their reasoning pose risks in clinical settings where clinicians must understand rationale to appropriately supervise AI outputs.
- Workflow Integration Testing: Human-centered design evaluations should assess how AI tools integrate into clinical workflows (such as in SNF, AL, and ID/DD residential care settings), including cognitive load, alert fatigue, and usability for diverse users (including staff with varying levels of health IT literacy).

### ***Post-Deployment Evaluation Methods***

- Continuous Performance Monitoring: Real-world performance monitoring should track AI tool accuracy, adoption rates, override rates, and clinical outcomes over time. Performance should be stratified by patient characteristics to detect emerging bias or model drift.
- Clinical Outcome Studies: Rigorous implementation science research should evaluate whether AI tools actually improve patient outcomes, reduce costs, or enhance clinician efficiency in real-world settings. Studies should include LTPAC sites and geriatric populations.
- Safety Surveillance: HHS should establish voluntary or mandatory adverse event reporting mechanisms for AI tools, similar to FDA MedWatch for medical devices. This would enable detection of safety signals and patterns of harm.
- Equity Monitoring: Ongoing monitoring should assess whether AI tool deployment widens or narrows health disparities. Particular attention should be paid to access barriers for under-resourced providers and vulnerable populations.

### ***HHS Support Mechanisms***

HHS should support these evaluation methods through:

- Contracts and Cooperative Agreements: Fund development of standardized evaluation frameworks, toolkits, and benchmarking datasets that include geriatric populations.
- Grants: Support independent research on AI tool performance, safety, and bias minimization through NIH, AHRQ, and Patient-Centered Outcomes Research Institute (PCORI).
- Regulatory-Science Testbeds: Establish collaboration among FDA, ONC, CMS, and VA to create shared infrastructure for AI validation.
- Prize Competitions: Incentivize development of novel evaluation methods, bias detection tools, and explainability techniques through HHS prize competitions.

The most impactful approach would be a combination of contracts (for infrastructure development), grants (for independent research), and cooperative agreements (for multi-stakeholder collaboration).

### **Question 5: How can HHS best support private sector activities to promote innovative and effective AI use in clinical care?**

HHS should adopt a supportive posture toward industry-driven quality assurance mechanisms while establishing baseline standards to protect patients:

**Specific LTPAC provider recommendations for HHS to promote AI in clinical care include the following:**

#### *Accreditation and Certification*

- Support development of voluntary AI tool accreditation programs through organizations like The Joint Commission, NCQA, or URAC that assess AI tools for safety, effectiveness, and equity.
- Expand the ONC Health IT Certification Program (45 CFR Part 170) to include certification criteria for AI-enabled clinical decision support tools, with specific requirements for validation, transparency, and bias testing.
- Recognize and incentivize (through payment policy) use of certified or accredited AI tools in value-based payment arrangements.

#### *Industry-Driven Testing and Standards*

- Partner with standards development organizations (HL7, IEEE, ASTM) to create technical standards for AI tool interoperability, data requirements, and performance reporting.
- Support industry consortia (such as the Coalition for Health AI, Partnership on AI) that develop best practice frameworks, model cards, and datasheets for AI transparency.
- Fund development of open-source benchmarking datasets and evaluation toolkits that include geriatric and LTPAC populations.

#### *Professional Credentialing*

- Support professional associations, societies, and professional educational programs in developing AI competency standards and credentialing programs for clinicians and health IT professionals.
- Incentivize AI literacy training through continuing education requirements and Medicare payment bonuses for providers who complete AI training programs.

#### *Market Transparency*

- Establish a public registry of AI tools used in clinical care, including information on their intended use, validation evidence, and performance metrics. This would function similarly to FDA's medical device databases but for non-medical device AI tools.
- Require AI vendors to publish model cards and performance reports that enable informed purchasing decisions by healthcare organizations.

### **Question 6: Where have AI tools deployed in clinical care met or exceeded expectations, and where have they fallen short? What novel AI tools would have the greatest potential?**

**Example feedback from our frontline AHCA/NCAL member providers includes:**

*“AI has fallen short in Managed Care approvals; need more reliable audit tools that are not human dependent; a good AI tool can also be a trainer as it points out opportunities; a good AI tool can also pick up subtle changes so intervention can occur early; however the downside is if these are noticed and nothing happens, then it puts the organization at risk.”*

## Specific AI tools deployed in LTPAC settings and opportunities to improve include the following:

### *AI Tools Meeting or Exceeding Expectations*

While robust evidence specific to LTPAC settings remains limited, emerging applications show promise:

- Fall Risk Prediction: In-person and remote patient monitoring (RPM) AI tools analyzing gait patterns, functional status, medication profiles, and environmental factors show potential for identifying high-risk individuals and triggering preventive interventions.
- Sepsis and Acute Illness Detection: Early warning systems primarily studies in acute care hospital settings analyzing vital signs and laboratory trends may enable earlier identification of acute changes in condition, particularly valuable in nursing home settings where physician presence is intermittent.
- Documentation Automation: Ambient AI documentation tools that transcribe and structure clinical encounters reduce documentation burden and allow clinicians to focus on patient interaction.
- Medication Management: AI-powered polypharmacy optimization tools that flag drug-drug interactions, inappropriate medications for older adults (Beers Criteria), and opportunities for deprescribing show promise for improving medication safety.
- Telehealth: AI technology integrated with telehealth visits facilitate person-centered connectedness between the telehealth clinician and patient while also optimizing usefulness of EHR documentation and sensor technology.
- Virtual Reality: AI-driven virtual reality (VR) tools have been successfully deployed in AHCA/NCAL member communities for treatment interventions, patient education, facilitating movement, and enhancing resident quality of life.
  - VR used in physical therapy (PT): VR assessments include gait and movement analysis while VR supported treatments include neurological rehabilitation, balance & posture training, and pain reduction.
  - VR used in occupational therapy (OT): VR assessments include daily living task performance using sensors while VR supported treatments include neurological rehabilitation, functional stability and balance, and activities of daily living (ADL) task simulation.
  - VR used in speech-language pathology (SLP): VR assessments include speech-recognition and feedback and swallowing performance while VR supported treatments include VR speech stimulation with virtual partners for pronunciation, articulation, and expressive/receptive language activities.
  - VR used to enhance resident quality of life: Older adult-focused VR platforms used in AHCA/NCAL member communities have enhanced physical and psychological needs and desires including reminiscence therapy, social experiences that reduce isolation, exercise and mobility programs (i.e. virtual tennis, bowling), dementia care engagement, virtual tours of cities and landmarks, virtual concerts, stress/anxiety reductions, pain management, cognitive stimulation, and more.
- Staff Training: Intuitive and adaptive AI and VR technologies can assess and track staff competencies and target training materials and staff comprehension in real-world simulations, which can be more effective and less time-consuming than traditional training methods, and can be provided at more convenient time periods for the staff member.

### *AI Tools Falling Short of Expectations*

- Biased Algorithms: Multiple studies have documented racial, age, and socioeconomic bias in AI tools for risk prediction, resource allocation, clinical decision support, and care planning. Tools validated on non-representative populations perform poorly when deployed in diverse real-world settings.

- Alert Fatigue: Some AI-powered clinical decision support systems generate excessive alerts, leading to override behavior and diminished effectiveness.
- Lack of Integration: AI tools that function as standalone systems rather than integrating with existing EHR workflows create additional burden rather than reducing it.
- Cost Without Demonstrated Value: High-cost AI tools that lack rigorous evidence of improved outcomes or cost savings fail to deliver promised return on investment.

### *Novel AI Tools with Greatest Potential for LTPAC Settings*

- Multimorbidity Management: AI tools that synthesize complex patient data (functional status, cognitive status, social determinants, multiple chronic conditions) to generate holistic care plans tailored to individual goals and preferences.
- Caregiver Support Tools: AI-powered virtual assistants (robots) that guide family and facility caregivers in medication administration, food delivery, symptom monitoring, and care coordination for older adults.
- Chatbots & Virtual Assistants: AI-powered technologies in facilities can be used to improve communication and save staff time. Chatbots & virtual assistants are often used for answering resident/family questions, providing medication or appointment reminders, and supporting staff with routine inquiries. Companion chatbots for residents have been successfully used for isolation reduction, reminders, cognitive stimulation, and other quality of life engagement purposes.
- Delirium Detection: Continuous monitoring systems using wearables or ambient sensors to detect early signs of delirium, enabling rapid intervention to prevent adverse outcomes.
- Pain Detection: AI-driven facial or other biometric analysis to detect pain levels—particularly helpful for residents with dementia or communication difficulties.
- Bedsore Risk Monitoring and Interventions: AI leveraging modern bed sensors and other patient biometric monitoring activity can detect increased risk for skin breakdown, can alert recommended interventions, and document effectiveness of staff repositioning activities.
- Functional Decline Prediction: AI tools analyzing longitudinal functional status data to predict risk of hospitalization, nursing home placement, or mortality, enabling proactive care plan adjustments.
- Social Determinants Screening and Intervention: AI tools that screen for social needs (food insecurity, transportation barriers, housing instability) and connect patients with community resources.
- Quality Measure Automation: AI tools that extract quality measure data from clinical documentation and automate reporting to CMS, reducing administrative burden.

### **Examples of Types of AI Technology Used in Nursing Homes and Assisted Living Residences and Recent Research Findings**

While the use of AI-based technologies in nursing homes and assisted living residences is growing rapidly, there is a dearth of scientific research in the appropriateness or effectiveness of these tools specific to the resident populations of these settings. Most research involving using AI-based technologies in United States healthcare settings has been with ambulatory care and hospital patient populations which have quite different clinical characteristics and care needs than LTPAC provider settings. Additionally, most research in long-term care settings has been conducted outside of the United States. The following list highlights some of the recent research we identified relevant to AI-based technologies used in those nursing homes and assisted living residents our members serve.

#### *Predictive Analytics & Early Warning Systems*

Salehinejad, Hojjat, Anne M. Meehan, Parvez A. Rahman, Marcia A. Core, Bijan J. Borah, and Pedro J. Caraballo. 2023. “Novel Machine Learning Model to Improve Performance of an Early Warning System in

Hospitalized Patients: A Retrospective Multisite Cross-Validation Study.” *eClinicalMedicine* 66: 102312. <https://doi.org/10.1016/j.eclinm.2023.102312>.

Seaman, Karla, Kristiana Ludlow, Nasir Wabe, et al. 2022. “The Use of Predictive Fall Models for Older Adults Receiving Aged Care, Using Routinely Collected Electronic Health Record Data: A Systematic Review.” *BMC Geriatrics* 22: 210. <https://doi.org/10.1186/s12877-022-02901-2>.

Quintana, Mereya. 2025. “Harnessing Predictive Analytics and AI in Infection Prevention: A Next Generation Approach to Combat Healthcare Associated Infections.” *American Journal of Infection Control* 53 (6S): S9. [https://www.ajicjournal.org/article/S0196-6553\(25\)00144-0/fulltext](https://www.ajicjournal.org/article/S0196-6553(25)00144-0/fulltext).

### ***Remote Patient Monitoring (RPM) & Biometric Sensors***

Reed, Americus II, Charles Herman, Amit Sawant, Lori Sun, and David Futoran. 2022. “Effectiveness of AI Powered Passive Remote Patient Monitoring on Senior Living Outcomes: A Pilot Study.” *Clinics in Medicine* 4 (2): 1046. <https://www.medtextpublications.com/open-access/effectiveness-of-ai-powered-passive-remote-patient-monitoring-rpm-on-1222.pdf>.

Shaik, Mohmmad Arif, et al. 2025. “Advancing Remote Monitoring for Patients With Alzheimer Disease and Related Dementias: Systematic Review.” *JMIR Aging* 8. <https://aging.jmir.org/2025/1/e69175>.

Tsvetanov, Filip. 2024. “Integrating AI Technologies into Remote Monitoring Patient Systems.” *Engineering Proceedings* 70 (1): 54. <https://doi.org/10.3390/engproc2024070054>.

### ***Fall Detection***

Feng, Xiang, Zhengliang Shan, Zhanfeng Zhao, Zirui Xu, Tianpeng Zhang, Zihe Zhou, Bo Deng, and Zirui Guan. “Millimeter-Wave Radar Monitoring for Elder’s Fall Based on Multi-View Parameter Fusion Estimation and Recognition.” *Remote Sensing* 15, no. 8 (2023): 2101. <https://doi.org/10.3390/rs15082101>.

Gorce, Philippe, and Julien Jacquier-Bret. “Fall Detection in Elderly People: A Systematic Review of Ambient Assisted Living and Smart Home-Related Technology Performance.” *Sensors* 25, no. 21 (2025): 6540. <https://doi.org/10.3390/s25216540>.

Jansi, R., and R. Amutha. “Detection of Fall for the Elderly in an Indoor Environment Using a Tri-Axial Accelerometer and Kinect Depth Data.” *Multidimensional Systems and Signal Processing* 31 (2020): 1207–1225. <https://doi.org/10.1007/s11045-020-00705-4>.

Kramer, Josh Brown, Lucas Sabalka, Ben Rush, Katherine Jones, and Tegan Nolte. “Automated Depth Video Monitoring for Fall Reduction: A Case Study.” In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)* (2020). <https://www.computer.org/csdl/proceedings-article/cvprw/2020/09150602/11PH6bM1nRS>.

Mudiyanselage, Sriyani Padmalatha Konara, Ching Teng Yao, Sujeewa Dilhani Maithreepala, and Bih O. Lee. “Emerging Digital Technologies Used for Fall Detection in Older Adults in Aged Care: A Scoping Review.” *Journal of the American Medical Directors Association* 26, no. 1 (January 2025): 105330. <https://www.jamda.com/article/S1525-8610%2824%2900752-7/abstract>.

Xiong, Glen L., Eleonore Bayen, Shirley Nickels, Raghav Subramaniam, Pulkit Agrawal, Julien Jacquemot, Alexandre M. Bayen, Bruce Miller, and George Netscher. “Real-Time Video Detection of Falls in Dementia Care Facility and Reduced Emergency Care.” *The American Journal of Managed Care* 25, no. 7 (July 2019): 314–315. <https://www.ajmc.com/view/realtime-video-detection-of-falls-in-dementia-care-facility-and-reduced-emergency-care>.

### ***Computer Vision for Pain Recognition***

Babicova, Ivana, Ainslea Cross, Dawn Forman, Jeffery Hughes, and Kreshnik Hoti. 2021. "Evaluation of the Psychometric Properties of PainChek® in UK Aged Care Residents With Advanced Dementia." *BMC Geriatrics* 21: 337. <https://doi.org/10.1186/s12877-021-02280-0>.

ClinicalTrials.gov. 2024. "PainChek® US Validation Nursing Home Study (NCT06049732)." <https://clinicaltrials.gov/study/NCT06049732>.

Sampson, Elizabeth L., Nathan Davies, and Victoria Vickerstaff. 2025. "Evaluation of the Psychometric Properties of PainChek in Older General Hospital Patients With Dementia." *Age and Ageing* 54 (2). <https://doi.org/10.1093/ageing/afaf027>.

### ***Clinical Documentation & Decision Support***

Brydges, Garry. 2025. "Artificial Intelligence in Nursing Practice: Decisional Support, Clinical Integration, and Future Directions." *OJIN: The Online Journal of Issues in Nursing* 30 (2). <https://ojin.nursingworld.org/table-of-contents/volume-30-2025/number-2-may-2025/artificial-intelligence-in-nursing-practice-decisional-support-clinical-integration-and-future-directions/>.

Cato, Kenrick D., and Victoria L. Tiase. 2025. "Can AI Relieve Nursing Documentation Burden?" *American Nurse Journal*. <https://www.myamericannurse.com/can-ai-relieve-nursing-documentation-burden/>.

Marselas, Kimberly. 2025. "Nursing Homes and AI: What's in Use, What's Not and How to Decide." *McKnight's Long Term Care News*. <https://www.mcknights.com/news/nursing-homes-and-ai-whats-in-use-whats-not-and-how-to-decide/>.

### ***Medication Management Systems***

Akyon, Seyma Handan, Fatih Cagatay Akyon, and Tarik Eren Yılmaz. 2023. "Artificial Intelligence–Supported Web Application ... for Reducing Polypharmacy Side Effects and Supporting Rational Drug Use in Geriatric Patients." *Frontiers in Medicine* 10: 1029198. <https://doi.org/10.3389/fmed.2023.1029198>.

Martins, Andreia, João Vitorino, Eva Maia, and Isabel Praça. 2024. "PharmiTech: Addressing Polypharmacy Challenges Through AI Driven Solutions." *Applied Sciences* 14 (19): 8838. <https://www.mdpi.com/2076-3417/14/19/8838>.

Mass General Brigham. 2024. "Study Finds ChatGPT Shows Promise as Medication Management Tool, Could Help Improve Geriatric Health Care." <https://www.massgeneralbrigham.org/en/about/newsroom/articles/study-finds-chatgpt-shows-promise-as-medication-management-tool-could-help-improve-geriatric-health-care>.

### ***Chatbots & Virtual Assistants***

Wolfe, Brooke H., Yoo Jung Oh, Hyesun Choung, et al. 2025. "Caregiving AI Chatbot for Older Adults and Their Preferences, Well Being, and Social Connectivity: Mixed Method Study." *Journal of Medical Internet Research* 27. <https://www.jmir.org/2025/1/e65776>.

Yu, Shulan, and Tianyue Chen. 2024. "Understanding Older Adults' Acceptance of Chatbots in Healthcare Delivery: An Extended UTAUT Model." *Frontiers in Public Health* 12: 1435329. <https://doi.org/10.3389/fpubh.2024.1435329>.

Zhang, Qian, Arkers K. C. Wong, and Jonathan Bayuo. 2024. "The Role of Chatbots in Enhancing Health Care for Older Adults: A Scoping Review." *Journal of the American Medical Directors Association* 25 (9): 105108. <https://doi.org/10.1016/j.jamda.2024.105108>.

### ***Personalized Care Planning***

Aljohani, Abeer. 2025. "AI Driven Decision Making for Personalized Elderly Care: A Fuzzy MCDM Based Framework." *BMC Medical Informatics and Decision Making* 25: 119. <https://doi.org/10.1186/s12911-025-02953-5>.

Centers for Medicare & Medicaid Services (CMS). 2025. Minimum Data Set (MDS) 3.0 Resident Assessment Instrument (RAI) Manual, v1.20.1. <https://www.cms.gov/medicare/quality/nursing-home-improvement/resident-assessment-instrument-manual>.

### ***Robotics & Companion Technologies***

Lim, JunSeo. 2023. "Effects of a Cognitive Based Intervention Program Using Social Robot PIO ..." *Frontiers in Public Health* 11: 1097485. <https://doi.org/10.3389/fpubh.2023.1097485>.

Mehrabi, Fahimeh, and Akram Ghezlbash. 2025. "Wired for Companionship: A Meta Analysis on Social Robots Filling the Void of Loneliness in Later Life." *The Gerontologist* 65 (12). <https://doi.org/10.1093/geront/gnaf219>.

Robinson, Hayley, Bruce MacDonald, Ngaire Kerse, and Elizabeth Broadbent. 2013. "The Psychosocial Effects of a Companion Robot: A Randomized Controlled Trial." *Journal of the American Medical Directors Association* 14 (9): 661–667. <https://doi.org/10.1016/j.jamda.2013.02.007>.

### ***Cognitive & Behavioral Monitoring***

Abedi, Ali, Charlene H. Chu, and Shehroz S. Khan. 2025. "Early Prediction of Agitation in Community Dwelling People With Dementia Using Multimodal Sensors and Machine Learning." In *AI for Aging Rehabilitation and Intelligent Assisted Living (IJCAI 2025)*. [https://link.springer.com/chapter/10.1007/978-981-95-0568-5\\_1](https://link.springer.com/chapter/10.1007/978-981-95-0568-5_1).

Badawi, Abeer, Somayya Elmoghazy, Samira Choudhury, et al. 2025. "Multimodal Detection of Agitation in People With Dementia in Clinical Settings: Observational Pilot Study." *JMIR Aging* 8. <https://aging.jmir.org/2025/1/e68156>.

Fritz, Roschelle, and Diane Cook. "Detecting Older Adults' Behavior Changes During Adverse External Events Using Ambient Sensing: Longitudinal Observational Study." *JMIR Nursing* 8 (2025): e69052. <https://nursing.jmir.org/2025/1/e69052>.

Kleine Deters, Jan, Sarah Janus, Jair A. L. Silva, Heinrich J. Wörtche, and Sytse U. Zuidema. 2024. "Sensor Based Agitation Prediction in Institutionalized People With Dementia: A Systematic Review." *Pervasive and Mobile Computing* 98: 101876. <https://doi.org/10.1016/j.pmcj.2024.101876>.

Kleine Deters, Jan, Rinesh Baidjnath Misier, Sarah Janus, Huib Burger, Heinrich Wörtche, and Sytse Zuidema. "Sensortechnology for Monitoring Challenging Behavior in Nursing Home Residents with Dementia." *International Psychogeriatrics* 35, suppl. (December 2023): 145–46. <https://www.intpsychogeriatrics.org/article/S1041-6102%2824%2905905-2/fulltext>.

Kolakowski, Marcin, and Bartosz Blachucki. "Monitoring Wandering Behavior of Persons Suffering from Dementia Using BLE Based Localization System." *arXiv* (March 22, 2024). <https://doi.org/10.48550/arXiv.2403.19704>.

Ullah, Rahmat, Ikram Asghar, Saeed Akbar, Gareth Evans, Justus Vermaak, Abdulaziz Alblwi, and Amna Bamaqa. "Vision-Based Activity Recognition for Unobtrusive Monitoring of the Elderly in Care Settings." *Technologies* 13, no. 5 (2025): 184. <https://doi.org/10.3390/technologies13050184>.

### ***Telehealth Integration & Virtual Care***

Shaik, Mohmmad Arif, et al. 2025. "Advancing Remote Monitoring for Patients With Alzheimer Disease and Related Dementias: Systematic Review." *JMIR Aging* 8. <https://aging.jmir.org/2025/1/e69175>.

Tana, Claudio, Carmine Siniscalchi, Nicoletta Cerundolo, et al. 2025. "Smart Aging: Integrating AI Into Elderly Healthcare." *BMC Geriatrics* 25: 1024. <https://doi.org/10.1186/s12877-025-06723-w>.

### ***Privacy Preserving Movement/Video Monitoring (blurred or silhouette outputs)***

Badawi, Abeer, et al. 2025. "Multimodal Detection of Agitation ..." *JMIR Aging* 8. (Includes privacy preserving masking in the video pipeline.) <https://aging.jmir.org/2025/1/e68156>.

Farooq, Bashar, Abdellatif Hussine, Ali Al Majid, and Iqra Yakub. 2025. "Privacy Preserving Elderly Activity Monitoring Using Pose Estimation." Undergraduate Research Scholars Thesis, Texas A&M University. <https://oaktrust.library.tamu.edu/bitstreams/9f977b6e-ba78-419a-9900-9b0d7642e3de/download>.

Li, Jiachen, Bingrui Zong, Tingyu Cheng, et al. 2023. "Privacy vs. Awareness: Relieving the Tension Between Older Adults and Adult Children When Sharing In Home Activity Data." *Proceedings of the ACM on Human-Computer Interaction* 7 (CSCW2): 353. <https://doi.org/10.1145/3610202>.

### ***Mattress/Bed Sensors for Pain or Discomfort & (Reframed) Bedsore/Pressure Injury Risk Monitoring***

Pickham, David, Nicole Berte, Marlene Pihulic, et al. 2018. "Effect of a Wearable Patient Sensor on Care Delivery for Preventing Pressure Injuries in Acutely Ill Adults: A Pragmatic Randomized Clinical Trial (LS HAPI)." *International Journal of Nursing Studies* 80: 12–19. (Summarized by manufacturer evidence page.) <https://www.sn-leaf.com/study-summaries>.

Smith+Nephew. 2023. Evidence in Focus: Compendium of Clinical Evidence for the LEAF Patient Monitoring System. <https://journals.lww.com/sensortechnology-resourcecenter/PublishingImages/37700%20LEAF%20Evidence%20in%20Focus%20Compendium%20of%20Evidence%200123.pdf>.

USC Alfred E. Mann School of Pharmacy. 2024. "USC Led Study Leverages Artificial Intelligence to Predict Risk of Bedsores in Hospitalized Patients." (BMJ Open report). <https://mann.usc.edu/news/usc-led-study-leverages-artificial-intelligence-to-predict-risk-of-bedsores-in-hospitalized-patients/>.

### ***Virtual Reality Technologies Used in SNF and AL for Older Adults Recreation and Quality of Life***

Kubota, Kazumi, et al. "Immersive Virtual Reality for Older Adults with Mild Cognitive Impairment..." *BMC Geriatrics* (2026). <https://link.springer.com/article/10.1186/s12877-025-06957-8>.

Li, Xiaohan, et al. "Effects of VR-based Interventions on Cognitive Function, Emotional State, and Quality of Life ..." *Frontiers in Neurology* 16 (2025). <https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2025.1496382/full>.

Makmee, Patrawadee, and Peera Wongupparaj. "VR Cognitive-based Intervention for Enhancing Cognitive Functions and Well-being in Older Adults..." *Psychosocial Intervention* 34, no. 1 (2025). <https://journals.copmadrid.org/pi/art/pi2025a4>.

Moore, Ryan C., Jeffrey T. Hancock, and Jeremy N. Bailenson. "From 65 to 103, Older Adults Experience Virtual Reality Differently Depending on Their Age: Evidence from a Large-Scale Field Porras-Garcia, Bruno, et al. "Immersive Virtual Reality Cognitive Training for Improving Cognition ..." *Cyberpsychology, Behavior, and Social Networking* 27, no. 10 (2024). <https://journals.sagepub.com/doi/pdf/10.1089/cyber.2024.0090>.

Study in Nursing Homes and Assisted Living Facilities.” *Cyberpsychology, Behavior, and Social Networking* 26, no. 12 (2023). <https://vhil.stanford.edu/sites/g/files/sbiybj29011/files/media/file/moore-et-al-2023-from-65-to-103-older-adults-experience-virtual-reality-differently-depending-on-their-age-evidence.pdf>.

Walden, Allison, et al. “Immersive Virtual Reality Interventions for Older Adults: A Series of Meta-Analyses.” *Innovation in Aging* 7, Supplement 1 (2023). [https://academic.oup.com/innovateage/article/7/Supplement\\_1/875/7490571](https://academic.oup.com/innovateage/article/7/Supplement_1/875/7490571).

Yang, Qin, et al. “Virtual Reality Interventions for Older Adults With Mild Cognitive Impairment: Systematic Review and Meta-Analysis.” *Journal of Medical Internet Research* 27 (2025). <https://www.jmir.org/2025/1/e59195>.

### ***AI technologies used in Physical Therapy, Occupational Therapy, and Speech-Language Pathology***

Adikari, Achini, Nelson Hernandez, Daminda Alahakoon, Miranda L. Rose, and John E. Pierce. “From Concept to Practice: A Scoping Review of the Application of Artificial Intelligence to Aphasia Diagnosis and Management.” *Disability and Rehabilitation* 46, no. 7 (2024): 1288–1297. <https://doi.org/10.1080/09638288.2023.2199463>.

American Physical Therapy Association. “Digital Health in Practice.” <https://www.apta.org/your-practice/practice-models-and-settings/digital-health-in-practice>.

Andreev, Daniel. “VR in Occupational Therapy: Usage & Effectiveness.” *PsyTechVR Blog*. December 19, 2025. <https://psytechvr.com/vr-in-occupational-therapy>. Georgiou, Georgios P. “Transforming Speech-Language Pathology with AI: Opportunities, Challenges, and Ethical Guidelines.” *Healthcare* 13, no. 19 (2025): 2460. <https://doi.org/10.3390/healthcare13192460>.

Archer, Kristin R., and Theresa D. Ellis. “Advances in Rehabilitation Technology to Transform Health.” *Physical Therapy* 104, no. 2 (February 2024): pzae008. <https://doi.org/10.1093/ptj/pzae008>.

Green, Jordan R. “The Role of Artificial Intelligence in Speech Disorders.” *ASHA Journals Academy* (November 12, 2024). <https://academy.pubs.asha.org/2024/11/the-role-of-artificial-intelligence-in-speech-disorders/>.

Hodge, Brianna. “Empowering PTs, OTs, and SLPs With Breakthrough Virtual Reality.” *Neuro Rehab VR Blog*. Accessed February 2026. <https://neurorehabvr.com/blog/pt-ot-slp-breakthrough>.

Kokkotis, Christos, Ioannis Kansizoglou, Theodoros Stampoulis, Erasmia Giannakou, Panagiotis Siaperas, Stavros Kallidis, Maria Koutra, Christina Koutra, Anastasia Beneka, and Evangelos Bebetos. “Artificial Intelligence as Assessment Tool in Occupational Therapy: A Scoping Review.” *BioMedInformatics* 5, no. 2 (2025): 22. <https://doi.org/10.3390/biomedinformatics5020022>.

Merler, Michele, Carla Agurto, Julian Peller, Esteban Roitberg, Alan Taitz, Marcos A. Trevisan, Indu Navar, James D. Berry, Ernest Fraenkel, Lyle W. Ostrow, Guillermo A. Cecchi, and Raquel Norel. “Clinical Assessment and Interpretation of Dysarthria in ALS Using Attention Based Deep Learning AI Models.” *npj Digital Medicine* (2025). <https://doi.org/10.1038/s41746-025-01654-7>.

Morelli, Nathan. “Seeing Past the Event Horizon: A Framework for Integrating Artificial Intelligence and Machine Learning Into Physical Therapy.” *Physical Therapy* 105, no. 2 (February 2025): pzae137. <https://doi.org/10.1093/ptj/pzae137>.

Nicora, Giovanna, Samuele Pe, Gabriele Santangelo, Lucia Billeci, Irene Giovanna Aprile, Marco Germanotta, Riccardo Bellazzi, Enea Parimbelli, and Silvana Quaglini. “Systematic Review of AI/ML Applications in Multi-Domain Robotic Rehabilitation: Trends, Gaps, and Future Directions.” *Journal of NeuroEngineering and Rehabilitation* 22 (2025): 79. <https://doi.org/10.1186/s12984-025-01605-z>.

Qian, Zhaopeng, and Kejing Xiao. “A Survey of Automatic Speech Recognition for Dysarthric Speech.” *Electronics* 12, no. 20 (2023): 4278. <https://doi.org/10.3390/electronics12204278>.

Rekant, Julie, et al. “Wearable-Sensor-Instrumented Assessment of Prolonged Walking Identifies Performance Deficits in Older Adults With Normal Clinical Presentation.” *Journal of Geriatric Physical Therapy* 48, no. 3 (2025): 146–152. <https://doi.org/10.1519/jpt.000000000000458>.

Shah, Dipti. “Revolutionizing Rehab: The Impact of Virtual Reality in Physical Therapy.” *JOSPT Blog*. August 12, 2024. <https://www.jospt.org/do/10.2519/jospt.blog.20240812/full/>.

“Virtual Reality and Physical Therapy: 10 Questions Answered.” *E3 Diagnostics Blog*. March 2, 2025. <https://e3diagnostics.com/blog/virtual-reality-and-physical-therapy>.

Waller, Zachary et al. “OTs’ Experiences With and Perceptions of the Use of Virtual Reality Technology During Treatment.” *American Journal of Occupational Therapy* 76, no. Supplement 1 (2022): 7610505109p1. <https://doi.org/10.5014/ajot.2022.76S1-PO109>.

Wei, Suyao, and Zhihui Wu. “The Application of Wearable Sensors and Machine Learning Algorithms in Rehabilitation Training: A Systematic Review.” *Sensors* 23, no. 18 (2023): 7667. <https://doi.org/10.3390/s23187667>.

Zhou, Yafeng, Fadilla ’Atyka Nor Rashid, Marizuana Mat Daud, Mohammad Kamrul Hasan, and Wangmei Chen. “Machine Learning-Based Computer Vision for Depth Camera-Based Physiotherapy Movement Assessment: A Systematic Review.” *Sensors* 25, no. 5 (2025): 1586. <https://doi.org/10.3390/s25051586>.

**Question 7: Which roles or governing bodies have the most influence on AI adoption in clinical care? What are the primary administrative hurdles?**

**Example feedback from our frontline AHCA/NCAL member providers includes:**

*“Influencer is Nurse Executives; the hurdles are cost and having an IT set up/team to facilitate the adoption.”*

**Specific LTPAC provider governing bodies and decision makers and administrative barriers that influence AI adoption include:**

***Influential Decision Makers***

In LTPAC settings, the following roles and bodies significantly influence AI adoption:

- **Facility Administrators:** Nursing home administrators generally determine operational technology priorities within resource constraints.
- **Clinical Champions:** Medical directors, directors of nursing, and other clinician leaders who advocate for specific AI tools and support staff adoption.
- **Corporate Ownership:** For provider organizations owned by larger health systems or private equity firms, corporate-level IT and innovation teams often dictate technology choices.
- **Health System Leadership:** Chief Information Officers (CIOs), Chief Medical Information Officers (CMIOs), and Chief Nursing Information Officers (CNIOs) make strategic technology investment decisions. However, enterprise AI governance models led by CIOs, CMIOs, or centralized steering committees are uncommon in LTPAC, reinforcing the need for policy expectations aligned with administrator and nursing led decision structures.
- **Payers:** Medicare Advantage plans, Medicaid managed care organizations, and commercial payers influence adoption through coverage decisions and value-based contract requirements.

- Legislative/Regulatory Bodies: State legislatures and health departments, Congress, CMS, and accrediting organizations (Joint Commission, ACHC) shape adoption through regulatory requirements and survey processes.

### ***Primary Administrative Hurdles***

- Resource Constraints: Limited capital budgets, IT staff, and technical expertise in LTPAC organizations constrain ability to evaluate, purchase, implement, and maintain AI tools.
- Workforce Capacity/Stability: AHCA/NCAL members face significant workforce challenges that may make it unfeasible to implement new AI technology. As of December 2025, per the Bureau of Labor Statistics, the nursing home sector alone would need 26,000 additional care provider staff just to return to pre-pandemic levels at a time when the population of persons in the United States over ages 65 and over ages 85 is expected to expand rapidly. Staff burnout, turnover, and training and AI change management challenges are exacerbated when workforce capacity/stability is not optimal.
- Competing Priorities: LTPAC providers face numerous regulatory requirements, quality reporting mandates, and operational challenges that compete with AI adoption for attention and resources.
- Vendor Fragmentation: Lack of standardization across AI vendors requires providers to navigate multiple contracts, integration requirements, and training programs.
- Interoperability Barriers: Difficulty obtaining necessary patient data from hospitals, clinics, and other providers limits AI tools' effectiveness in LTPAC settings.
- Staff Resistance: Concerns about job displacement, skepticism about AI accuracy, and technology anxiety among frontline staff create adoption barriers.
- Unclear Return on Investment: Lack of robust evidence demonstrating cost savings or outcome improvements makes it difficult to justify AI investments, particularly in fee-for-service payment environments.
- Procurement Processes: Complex procurement requirements, particularly for government-funded providers, slow adoption cycles. For example, accreditation or certification of AI tools is meaningful for LTPAC providers only if it is linked to coverage decisions, payment incentives, or survey recognition, rather than functioning solely as a market-based quality signal.
- Training and Change Management: Insufficient time and resources for staff training, workflow redesign, and change management undermine successful implementation.

### ***Special Focus Needed to Address Medicare Advantage AI-Driven Prior Authorization and Claim Review Algorithms***

A key opportunity for AI deployment lies in strengthening compliance in the Medicare Advantage (MA) program. According to statute, MA organizations are required to make coverage determinations that are fully aligned with Medicare coverage criteria, including National Coverage Determinations (NCDs), Local Coverage Determinations (LCDs), and other applicable regulations. However, recent oversight findings have demonstrated persistent issues with MA plans applying coverage rules and AI-driven prior authorization and claim review algorithms more restrictively than Traditional Medicare permits.

To address this, CMS should consider leveraging AI tools internally to systematically assess whether MA plans' internal coverage criteria – and the algorithms or decision-support tools that encode them – are compliant with Medicare requirements. Applying AI in this targeted compliance function would:

- Support CMS' statutory role in ensuring MA enrollees receive the same access to medically necessary services as Traditional Medicare beneficiaries.
- Provide scalable, proactive oversight as MA plans increasingly integrate their own AI-based decision mechanisms.

- Enhance transparency by flagging where plan-developed coverage logic diverges from CMS policy or nationally recognized clinical standards.
- Promote responsible AI use by setting expectations that algorithmic decision tools used by plans must reflect Medicare’s coverage framework – not proprietary or overly restrictive criteria.

Importantly, this type of CMS-led AI oversight aligns with HHS’ broader goals of ensuring efficient and accountable AI use. As CMS shifts away from direct payer functions toward a regulatory and oversight-oriented, adopting AI for compliance activities is both timely and appropriate. It allows CMS to modernize program integrity functions while ensuring that beneficiaries are protected by inappropriate denials or delays in care that any be amplified by automated systems.

AHCA/NCAL encourages CMS to explicitly include this oversight function in future AI strategy and implementation guidance, as it represents a high-impact, low-burden approach to improving beneficiary protections and reinforcing the integrity of the MA program.

**Question 8: Where would enhanced interoperability widen market opportunities, fuel research, and accelerate AI development for clinical care?**

**Example feedback from our frontline AHCA/NCAL member providers includes:**

*“Medical record review: we have all the data, but we are not pulling information to look at clinical outcomes; use to point out clinical training needs; possible research opportunities;”*

**Specific LTPAC provider comments on enhancing interoperability, and facilitating research to accelerate AI adoption include the following:**

***Critical Data Types Requiring Enhanced Interoperability***

- Overarching Need to Adapt to LTPAC Needs: Although AI tools have demonstrated success in certain acute care domains, those results cannot be assumed to translate to LTPAC settings without validation against geriatric populations, nursing driven workflows, and long- stay resident care models.
- Functional Status: Activities of Daily Living (ADLs), Instrumental Activities of Daily Living (IADLs), mobility assessments, and functional trajectories over time.
- Cognitive and Mental Health: Cognitive assessments (Mini-Mental State Exam, Montreal Cognitive Assessment), delirium screening (Confusion Assessment Method), depression screening (PHQ-9), and behavioral health diagnoses.
- Social Determinants of Health: Living situation, caregiver support, food security, transportation access, housing stability, social isolation, and community resources.
- Care Goals and Preferences: Advance directives, goals of care conversations, patient values and preferences, and care plan goals.
- Medications: Complete medication lists including over-the-counter medications, supplements, and medication administration records with adherence data.
- Care Transitions: Transition of care summaries, discharge instructions, pending tests and follow-up needs, and communication between sending and receiving providers.
- Quality and Outcome Measures: Patient-reported outcome measures (PROMs), clinician-reported outcomes, adverse events, and quality metric data.
- Remote Monitoring Data: Wearable device data, home monitoring data, continuous vital sign monitoring, and consumer-generated health data.

### ***Data Standards Requiring Broader Adoption***

- Overarching Need to Adapt to LTPAC Needs: LTPAC focused AI priorities center on functional status, cognitive assessments, medication management, care goals, and care transition data, rather than genomics or precision medicine use cases that are largely inapplicable to most SNF and assisted living settings.
- PACIO Project FHIR Implementation Guides: HL7 FHIR profiles for functional status (PACIO Functional Status), cognitive status (PACIO Cognitive Status), advance directives (PACIO Advance Directives), care transitions, and other geriatric-specific data elements.
- USCDI Expansion: Incorporation of PACIO-developed data elements into the United States Core Data for Interoperability (USCDI) to ensure widespread adoption.
- FHIR Clinical Reasoning Module: HL7 FHIR Clinical Reasoning module for representing clinical decision support logic in a transparent, interoperable format.
- FHIR Subscription and Notification: Real-time event notification standards to enable timely care coordination and early warning system alerts.
- SMART on FHIR: Application programming interface (API) standards that enable third-party AI applications to access EHR data with patient consent.

### ***Benchmarking Tools and Infrastructure***

- Standardized Performance Metrics: Industry-wide agreement on how to measure AI tool performance, including sensitivity, specificity, positive predictive value, negative predictive value, and calibration across demographic subgroups.
- Open Benchmarking Datasets: Publicly available, de-identified datasets representative of diverse populations (including geriatric and LTPAC patients) for AI developers to test and benchmark their tools.
- Federated Learning Infrastructure: Privacy-preserving federated learning networks that enable AI training on distributed datasets without centralizing sensitive patient data.
- QHIN Connectivity: Universal connectivity to Qualified Health Information Networks (QHINs) under TEFCA to enable seamless data exchange across all care settings.

### ***Market Opportunities Created by Enhanced Interoperability***

Enhanced interoperability would create market opportunities for:

- AI tools focused on care transitions and post-acute care optimization,
- Predictive analytics for high-risk, complex patients across care settings,
- Population health management platforms serving integrated delivery networks,
- Real-time clinical decision support tools that leverage longitudinal patient data,
- Patient-facing applications that aggregate data from multiple providers and consumer devices,
- Quality measurement and reporting automation tools, and
- Research platforms supporting pragmatic clinical trials and real-world evidence generation.

## Question 9: What challenges do patients and caregivers wish to see addressed by AI adoption? What concerns do they have?

Example feedback from our frontline AHCA/NCAL member providers includes:

*“Access to specialists, therapists, and other medical care when there are not providers available. Equally, what concerns do patients and caregivers have related to the adoption and use of AI in clinical care? Not person-centered care.”*

Specific LTPAC provider comments on AI adoption opportunities and concerns from provider staff and residents and their families include the following:

### *Challenges Patients and Caregivers Want AI to Address*

- **Care Coordination:** Patients and caregivers struggle with fragmented care across multiple providers, specialists, and care settings. They desire AI tools that facilitate seamless information sharing, reduce redundant testing, and ensure all providers have access to complete patient information.
- **Medication Management:** Managing complex medication regimens is challenging for older adults and caregivers. AI tools that identify drug interactions, simplify medication schedules, and provide reminders would be valuable.
- **Early Problem Detection:** Patients and caregivers want systems that detect early signs of health decline (infections, falls, cognitive changes) before they become emergencies, enabling timely intervention.
- **Caregiver Support and Guidance:** Family caregivers often lack medical training but are responsible for complex care tasks. AI-powered guidance tools, educational resources, and decision support would help caregivers provide better care and reduce anxiety.
- **Reducing Hospital Readmissions:** Patients and caregivers fear repeated hospitalizations and desire tools that help manage conditions effectively at home or in LTPAC settings.
- **Transparent Communication:** Patients want clear, understandable explanations of their conditions, treatment options, and prognoses. AI tools that translate medical jargon into plain language and provide personalized education materials would be valuable.
- **Access to Specialists:** In rural and under-resourced communities, access to specialists is limited. AI tools that provide specialized expertise or triage patients for teleconsultation could improve access.
- **Quality of Life:** Patients prioritize maintaining independence, function, and quality of life. AI tools that support aging in place, prevent functional decline, and align care with patient goals and preferences are desired.

### *Concerns Patients and Caregivers Have About AI*

- **Privacy and Data Security:** Patients worry about who has access to their health data, how it will be used, and whether it will be protected from breaches or misuse. Concerns are heightened regarding data from consumer devices and wearables that may not be HIPAA-protected.
- **Algorithmic Bias and Discrimination:** Patients fear that AI tools may perpetuate or worsen health disparities, particularly for underrepresented or marginalized populations. Concerns about age-based bias are particularly relevant for older adults.
- **Loss of Human Connection:** Patients value relationships with their clinicians and worry that AI will replace human interaction, empathy, and personalized care. Concerns about "dehumanizing" healthcare are common.
- **Accuracy and Reliability:** Patients and caregivers question whether AI tools are accurate and reliable, particularly when recommendations conflict with clinician judgment or seem counterintuitive.

- Lack of Transparency: Patients want to understand how AI tools reach conclusions and recommendations. Black-box algorithms that cannot explain their reasoning are concerning, particularly when they influence important treatment decisions.
- Reduced Clinician Autonomy: Patients worry that clinicians will blindly follow AI recommendations without exercising clinical judgment, or conversely, that clinicians will ignore valid AI alerts due to alert fatigue.
- Access and Parity: Patients in under-resourced settings worry that AI tools will only be available to wealthy health systems, widening rather than narrowing health disparities.
- Consent and Control: Patients want meaningful control over whether AI tools are used in their care and how their data is used to train AI systems. Concerns about informed consent processes that are difficult to understand are common.
- Job Displacement: Patients and communities worry about whether AI will displace healthcare workers, particularly in communities where healthcare facilities are major employers.

## **Key AI Barriers and Facilitators in Healthcare Research**

### ***Published Findings on Openness to Adopt Artificial Intelligence Technology in Healthcare***

Angus, Derek C., Rohan Khera, Tracy Lieu, et al. “AI, Health, and Health Care Today and Tomorrow: The JAMA Summit Report on Artificial Intelligence.” *JAMA* 334, no. 18 (2025).  
<https://jamanetwork.com/journals/jama/fullarticle/2840175>.

Barrett, Meredith A., Angier Allen, Vy T. Vuong, et al. “Impact of an Artificial Intelligence and Machine Learning Enhanced Electronic Health Record System on Quality Measures in Nursing Homes: A Difference in Differences Analysis.” *Journal of the American Medical Directors Association* 26, no. 7 (2025).  
[https://www.jamda.com/article/S1525-8610\(25\)00197-5/fulltext](https://www.jamda.com/article/S1525-8610(25)00197-5/fulltext).

Bevilacqua, Roberta, Elvira Maranesi, Elisa Felici, et al. “Social Robotics to Support Older People with Dementia: A Study Protocol with Paro Seal Robot in an Italian Alzheimer’s Day Center.” *Frontiers in Public Health* 11 (2023). <https://doi.org/10.3389/fpubh.2023.1141460>.

Boudouraki, Andriana, Maria Waheed, Rafael Mestre, et al. “Responsible and Adaptive Robots in Care Home Settings: An Implementation Framework Analysis of a Workshop with Public and Professionals.” *Frontiers in Robotics and AI* 12 (2025). <https://www.frontiersin.org/journals/robotics-and-ai/articles/10.3389/frobt.2025.1610329/full>.

Chen, Shu Chuan, Mei Feng Lin, Cindy Jones, et al. “Effect of a Group Based Personal Assistive RObot (PARO) Robot Intervention on Cognitive Function, Autonomic Nervous System Function, and Mental Well Being in Older Adults with Mild Dementia: A Randomized Controlled Trial.” *Journal of the American Medical Directors Association* 25, no. 11 (2024). [https://www.jamda.com/article/S1525-8610\(24\)00650-9/fulltext](https://www.jamda.com/article/S1525-8610(24)00650-9/fulltext).

ClinicalTrials.gov. “Effectiveness and Cost Effectiveness of Robot Therapy With the Paro Robot in People Living With Dementia (NCT05884424).” Updated November 18, 2023.  
<https://clinicaltrials.gov/study/NCT05884424>.

El Arab, Rabie Adel, Alya H. Alshakihs, Sarah H. Alabdulwahab, et al. “Artificial Intelligence in Nursing: A Systematic Review of Attitudes, Literacy, Readiness, and Adoption Intentions among Nursing Students and Practicing Nurses.” *Frontiers in Digital Health* 7 (2025). <https://www.frontiersin.org/journals/digital-health/articles/10.3389/fdgth.2025.1666005/full>.

Guleria, Shan, Janet Guptill, Ishmeet Kumar, Mia McClintic, and Juan C. Rojas. “Artificial Intelligence Integration in Healthcare: Perspectives and Trends in a Survey of U.S. Health System Leaders.” *BMC Digital Health* 2 (2024). <https://link.springer.com/article/10.1186/s44247-024-00135-3>.

- Grigorovich, Alisa, Ashley Ann Marcotte, Romeo Colobong, et al. "Using Voice Activated Technologies to Enhance Well Being of Older Adults in Long Term Care Homes." *Innovation in Aging* 8, no. 12 (2024): ig ae102. <https://doi.org/10.1093/geroni/igae102>.
- Jain, Sakshi, and Caitlin Burke. "Falls Prevention Using AI and Remote Surveillance in Nursing Homes." *Journal of the American Medical Directors Association* 25, no. 8 (2024). [https://www.jamda.com/article/S1525-8610\(24\)00504-8/fulltext](https://www.jamda.com/article/S1525-8610(24)00504-8/fulltext).
- Liu, Jing, Xingang Wang, and Jiaqi Zhang. "Investigating Elderly Individuals' Acceptance of AI Powered Companion Robots: The Influence of Individual Characteristics." *Behavioral Sciences* 15, no. 5 (2025). <https://www.mdpi.com/2076-328X/15/5/697>.
- Liu, Sai, Yanchao Xiao, Manhua Nie, et al. "Nurses' Attitudes toward Artificial Intelligence: AI Literacy as a Predictor and the Mediating Effect of AI Anxiety." *BMC Nursing* 24 (2025). <https://link.springer.com/article/10.1186/s12912-025-04142-1>.
- Loveys, Kate, Matthew Prina, Chloe Axford, et al. "Artificial Intelligence for Older People Receiving Long Term Care: A Systematic Review of Acceptability and Effectiveness Studies." *The Lancet Healthy Longevity* 3, no. 4 (2022): e286–e297. [https://www.thelancet.com/journals/lanhl/article/PIIS26667568\(22\)00034-4/fulltext](https://www.thelancet.com/journals/lanhl/article/PIIS26667568(22)00034-4/fulltext).
- Lukkien, Dirk R. M., Nathalie E. Stolwijk, Sima Ipakchian Askari, et al. "AI Assisted Decision Making in Long Term Care: Qualitative Study on Prerequisites for Responsible Innovation." *JMIR Nursing* 7 (2024). <https://nursing.jmir.org/2024/1/e55962>.
- Oewel, Bruna, Tawfiq Ammari, and Robin Brewer. "Voice Assistant Use in Long Term Care." Working paper, 2018. <https://robinbrewer.com/papers/valogs.pdf>.
- Poon, Eric G., Christy Harris Lemak, Juan C. Rojas, et al. "Adoption of Artificial Intelligence in Healthcare: Survey of Health System Priorities, Successes, and Challenges." *Journal of the American Medical Informatics Association* 32, no. 7 (2025): 1093–1100. <https://academic.oup.com/jamia/article/32/7/1093/8125015>.
- Sandanasamy, Stephanie, Philip McFarlane, Yu Okamoto, and Alannah L. Couper. "Nurses' Knowledge and Attitudes towards Artificial Intelligence and Related Factors: A Systematic Review." *Journal of Nursing Reports in Clinical Practice* 3, no. 5 (2025): 486–93. [https://www.jnursrcp.com/article\\_217752\\_7b8d522fa477dfc9ae5f60f03d31ec27.pdf](https://www.jnursrcp.com/article_217752_7b8d522fa477dfc9ae5f60f03d31ec27.pdf).
- Schoenborn, Nancy L., Kacey Chae, Jacqueline Massare, et al. "Perspectives on AI and Novel Technologies Among Older Adults, Clinicians, Payers, Investors, and Developers." *JAMA Network Open* 8, no. 4 (2025): e253316. <https://jamanetwork.com/journals/jamanetworkopen/fullarticle/2832211>.
- University of Waterloo / CBC News. "New AI Safety System Tracks Seniors in Care Homes While Giving Them More Privacy." April 9, 2023. <https://www.cbc.ca/news/canada/kitchener-waterloo/ai-monitoring-system-long-term-care-homes-university-waterloo-1.6800965>.
- Ventura Silva, João, Maria Manuela Martins, Leticia de Lima Trindade, et al. "Artificial Intelligence in the Organization of Nursing Care: A Scoping Review." *Nursing Reports* 14, no. 4 (2024): 2733–45. <https://www.mdpi.com/2039-4403/14/4/202>.
- Zheng, Jia, and Wubin He. "Predictors and Perceptions of mHealth App Engagement in Older Adults: A Mixed Methods Study on Nurse Supported Interventions." *Journal of the American Medical Directors Association* (Articles in Press, 2026). [https://www.jamda.com/article/S1525-8610\(25\)00618-8/fulltext](https://www.jamda.com/article/S1525-8610(25)00618-8/fulltext).

## ***AI Human Training Needs Barriers in Healthcare***

Forbes. 2026. Jones, Rebecca. “How To Build Trust in AI Driven Healthcare Experiences.” Forbes Technology Council. <https://www.forbes.com/councils/forbestechcouncil/2026/02/03/how-to-build-trust-in-ai-driven-healthcare-experiences/>.

Hospitalogy. 2025. Madden, Blake. “Why Healthcare Teams Need Practical AI Skills.” Hospitalogy. <https://hospitalogy.com/articles/2025-08-25/why-healthcare-teams-need-practical-ai-skills/>.

The Lancet Digital Health. 2025. Ning, Yilin, Jasmine Chiat Ling Ong, Haoran Cheng, et al. “How Can Artificial Intelligence Transform the Training of Medical Students and Physicians?” The Lancet Digital Health. <https://www.thelancet.com/journals/landig/article/PIIS2589-7500%2825%2900082-2/fulltext>.

### **Question 10: Are there specific areas of AI research that HHS should prioritize to accelerate AI adoption in clinical care?**

#### **Example feedback from our frontline AHCA/NCAL member providers includes:**

*“Mimic the effort and research prioritization historically offered to acute and primary care but customize to the unique patient population and care needs, and workflow of facility based long-term and post-acute care providers.”*

#### **Specific provider recommendations for HHS to prioritize to accelerate AI adoption in clinical care in LTPAC settings include the following:**

##### ***Priority Research Areas for LTPAC and Geriatric Populations***

- **Inclusion of Aging Populations in AI Research**: Establish requirements that NIH, AHRQ, and other HHS-funded research include adequate representation of older adults, particularly those with multimorbidity, polypharmacy, cognitive impairment, and functional limitations.
- **Multimorbidity and Polypharmacy Optimization**: Develop AI tools that can synthesize evidence across multiple chronic conditions and optimize medication regimens for older adults with complex needs.
- **Functional Status and Trajectories**: Research AI applications for predicting functional decline, targeting interventions to prevent disability, and personalizing rehabilitation approaches.
- **Cognitive Assessment and Dementia Care**: Develop AI tools for early detection of cognitive impairment, monitoring dementia progression, and supporting caregivers of persons with dementia.
- **Fall Prevention**: Research AI applications for fall risk assessment, environmental modification recommendations, and real-time fall detection and response.
- **Delirium Prevention and Management**: Develop AI tools for early delirium detection, identification of modifiable risk factors, and guidance on non-pharmacological interventions.
- **Social Determinants of Health**: Research AI tools that screen for social needs, predict social risk, and connect patients with appropriate community resources.
- **Palliative and End-of-Life Care**: Develop AI tools that facilitate goals-of-care conversations, predict prognosis, and ensure care aligns with patient values and preferences.
- **Bias Detection and Mitigation**: Research methods for detecting and mitigating age-based, racial, and socioeconomic bias in AI algorithms. Develop fairness metrics and bias audit tools specific to vulnerable populations.
- **Explainable AI**: Research techniques for making AI recommendations interpretable and actionable for clinicians and patients, particularly for complex clinical decisions.
- **Implementation Science**: Study effective strategies for implementing AI tools in LTPAC settings, including workflow integration, training approaches, and change management methods.

- Health Disparities: Research on how AI tools can reduce rather than widen health disparities, including studies of AI deployment in under-resourced and rural settings.

### ***Costs, Benefits, and Transfers of AI in Clinical Care***

Critical research gaps remain regarding long-term impact, cost-effectiveness, and patient population appropriateness implications of AI adoption in clinical care, particularly in LTPAC settings. The literature suggests:

- Potential Benefits: Improved diagnostic accuracy, earlier disease detection, reduced medical errors, personalized treatment recommendations, workflow efficiency, reduced clinician burden, and cost savings through prevention of adverse events.
- Potential Costs: High acquisition and implementation costs, ongoing maintenance expenses, training costs, infrastructure requirements, and potential for increased health disparities if access is unequal.
- Transfers: Shifts in labor from routine tasks to oversight and complex decision-making, redistribution of resources from late-stage treatment to prevention, and potential concentration of benefits in well-resourced health systems.

While the literature on AI in LTPAC settings remains limited, growing evidence exists regarding:

- Racial and age bias in clinical risk prediction algorithms.
- Performance degradation of AI models when applied to populations other than used in the training data.
- Alert fatigue and override behavior with clinical decision support systems
- Challenges with AI tool integration into clinical workflows
- Variable evidence quality for commercially available AI tools

AI research in healthcare, particularly related to applications intended for use with the LTPAC population, should consider these more global factors as part of the design, implementation, and reporting of the results of the research.

## **Conclusion**

AHCA/NCAL appreciates the opportunity to provide input on HHS's approach to accelerating the adoption and use of artificial intelligence in clinical care. We emphasize the critical importance of ensuring that AI innovation benefits all people, including the rapidly growing population of older adults served by LTPAC providers.

Key recommendations from this response include:

1. Mandate age-stratified validation and bias testing for AI tools intended for use in Medicare populations.
2. Expand interoperability standards to include geriatric-specific data elements (functional status, cognitive status, social determinants)
3. Align payment policies to incentivize high-value AI adoption in LTPAC settings.
4. Provide infrastructure support and technical assistance to enable AI readiness in under-resourced LTPAC providers.
5. Prioritize research funding for AI applications addressing multimorbidity, functional decline, and other priorities for aging populations.
6. Establish clear regulatory frameworks addressing liability, privacy, and algorithmic transparency for non-medical device AI tools.
7. Create validation testbeds and evaluation frameworks that include LTPAC settings and geriatric populations.

We urge HHS to take a comprehensive, patient population appropriateness-focused approach that ensures AI technologies reduce rather than widen health disparities, protect vulnerable populations from algorithmic bias, and support the complex care needs of older adults across all care settings.

AHCA/NCAL stands ready to collaborate with HHS ASTP/ONC to advance these priorities. We welcome the opportunity for ongoing dialogue and partnership to ensure that AI policy and programs are inclusive of the needs of LTPAC providers and the millions of older adults and people with physical and cognitive disabilities they serve. Please contact Daniel E. Ciolek at AHCA/NCAL at [dciolek@ahca.org](mailto:dciolek@ahca.org) for questions or needed follow-up.