SUPPLY CHAIN AND SUSTAINABILITY RESEARCH: SCSR
VOL.4, NO.2; JUL. – DEC. ; 2025, ISSN 2822-0412 (Online)

Implementation of Multimodal LLM Agents and Biomechanical Analysis for Remote Elderly Healthcare in Taiwan: A Case Study

Huang Guan Hao[1*]
Shih, Song Fan[2]
Lin Yen Po[3]

[1*]Natonal Taiwan University
1, Sec. 4, Roosevelt Rd., Taipei 106319, Taiwan (R.O.C.)
huang0131huang@gmail.com
[2]Fu Jen Catholic University
510 Z Red Rash GR DX in District New Tai
shih882101@gmail.com
[3]Hong Kong University of Science and Technology
Clear Water Bay, Kowloon, Hong Kong
boliphus1234@gmail.com

[*]Corresponding author, Email: huang0131huang@gmail.com

Received: Sep 11, 2025 / Revised: Dec 18, 2025 / Accepted: Dec 18, 2025

Abstract

Taiwan's rapidly aging population and the unequal distribution of healthcare resources in remote areas pose a critical challenge to equitable medical services. This study proposes a multimodal AI system that integrates large language model (LLM) agents with real-time biomechanical gesture recognition, designed for remote elderly healthcare. By combining browser-based joint-angle tracking with cloud-hosted, context-aware conversational agents, the system enables natural language communication and clinical motion analysis without transmitting video data. Evaluated in rehabilitation scenarios in Taiwan, the platform demonstrates low latency, accurate pose classification, and automated clinical scoring using the Brunnstrom and Fugl–Meyer scales. Its multilingual interface supports personalized, secure, and efficient health interactions, aligning with Taiwan's Long-Term Care Plan 2.0 and AI healthcare initiatives. This solution addresses communication and mobility barriers, enhances healthcare accessibility in rural areas, and contributes to global discourse on ethical, inclusive, and context-aware AI in eldercare.

Keywords: Multimodal LLM Agents, Remote Elderly Healthcare, Biomechanical Gesture Analysis

SUPPLY CHAIN AND SUSTAINABILITY RESEARCH: SCSR
VOL.4, NO.2; JUL. – DEC. ; 2025, ISSN 2822-0412 (Online)

กรณีศึกษาการนำตัวแทนโมเดลภาษาขนาดใหญ่ หลายรูปแบบและการวิเคราะห์ทางชีวกลศาสตร์มาใช้สำหรับการดูแลสุขภาพผู้สูงอายุระยะไกลในไต้หวัน

หวง กวนห้าว[1*]
สือ ซ่งฟาน[2]
หลิน เหยียนโป[3]

[1*]มหาวิทยาลัยแห่งชาติไต้หวัน
1 ถนนรูสเวลต์ ส่วนที่ 4 กรุงไทเป ประเทศไต้หวัน
[2]มหาวิทยาลัยฟู่เหรินคาทอลิก
510 ถนนจงเจิ้ง เขตซินจวง นครนิวไทเป 242062 สาธารณรัฐจีน (ไต้หวัน)
[3]มหาวิทยาลัยวิทยาศาสตร์และเทคโนโลยีแห่งฮ่องกง
อ่าวเคลียร์วอเตอร์ เขตเกาลูน เขตบริหารพิเศษฮ่องกง

[*](ผู้ประสานงานเผยแพร่) Corresponding author, Email: huang0131huang@gmail.com

บทคัดย่อ

ประชากรผู้สูงอายุของไต้หวันที่เพิ่มขึ้นอย่างรวดเร็ว และการกระจายทรัพยากรด้านการดูแลสุขภาพที่ไม่เท่าเทียมกันในพื้นที่ห่างไกล ก่อให้เกิดความท้าทายสำคัญต่อการให้บริการทางการแพทย์อย่างเป็นธรรม งานวิจัยนี้เสนอระบบปัญญาประดิษฐ์แบบหลายมิติ (multimodal AI system) ที่ผสานตัวแทนโมเดลภาษาขนาดใหญ่ (LLM agents) เข้ากับการจดจำท่าทางทางชีวกลศาสตร์แบบเวลาจริง ซึ่งออกแบบมาเพื่อการดูแลสุขภาพผู้สูงอายุทางไกล โดยการผสมผสานการติดตามมุมข้อต่อผ่านเบราว์เซอร์เข้ากับตัวแทนสนทนาเชิงบริบทที่ทำงานบนคลาวด์ ระบบนี้สามารถสื่อสารด้วยภาษาธรรมชาติและวิเคราะห์การเคลื่อนไหวทางคลินิกได้ โดยไม่ต้องส่งข้อมูลวิดีโอ เมื่อประเมินในสถานการณ์การฟื้นฟูสมรรถภาพในไต้หวัน แพลตฟอร์มนี้แสดงให้เห็นถึงความหน่วงต่ำ การจำแนกท่าทางที่แม่นยำ และการให้คะแนนทางคลินิกอัตโนมัติโดยใช้มาตรวัดการประเมินแบบ Brunnstrom และ Fugl–Meyer ที่เชื่อมต่อหลายภาษาของระบบสนับสนุนการโต้ตอบด้านสุขภาพที่เป็นส่วนบุคคล ปลอดภัย และมีประสิทธิภาพ สอดคล้องกับแผนการดูแลระยะยาว 2.0 ของไต้หวันและโครงการด้าน AI เพื่อสุขภาพ แนวทางนี้ช่วยแก้ไขอุปสรรคด้านการสื่อสารและการเคลื่อนไหว เพิ่มการเข้าถึงบริการสุขภาพในพื้นที่ชนบท และมีส่วนร่วมต่อการอภิปรายระดับโลกเกี่ยวกับ AI ที่มีจริยธรรม ครอบคลุม และตระหนักถึงบริบทในการดูแลผู้สูงอายุ

คำสำคัญ: ปัญญาประดิษฐ์แบบพหุ การดูแลสุขภาพผู้สูงอายุระยะไกล การวิเคราะห์ท่าทางเชิงชีวกลศาสตร์

Introduction

Taiwan is undergoing a rapid demographic transition, with over 20% of the population expected to be aged 65 or older by 2025 (National Development Council, Taiwan, 2022). This shift is placing growing strain on the healthcare system, especially in rural areas where medical resources are limited and access to specialized care remains insufficient (Wu, Majeed, & Kuo, 2010). These disparities impact both the availability and equity of care for elderly patients.

To address these issues, Taiwan has launched several initiatives to integrate AI and smart healthcare technologies into existing medical frameworks (Yang & Lin, 2024). However, many current telemedicine systems lack the ability to deliver real-time, multimodal, and context-aware interaction—features critical for serving the elderly population (Chiu & Yang, 2009). Privacy concerns, low responsiveness, and limited accessibility further restrict adoption in rural settings (Serrano et al., 2023).

The objective of this study is to develop and evaluate a multimodal AI system that combines large language model (LLM) agents with real-time biomechanical gesture recognition to support remote elderly healthcare in Taiwan. By addressing current system gaps and aligning with national priorities, the proposed platform aims to improve communication, clinical assessment, and accessibility—particularly for underserved communities.

Literature Review

Global AI in Healthcare

Artificial intelligence (AI) has become an essential tool in healthcare innovation, with applications ranging from diagnostic imaging and clinical decision support to workflow automation and remote patient monitoring (Topol, 2019; Davenport & Kalakota, 2019). AI-powered systems enable earlier detection of disease, improved chronic care management, and reduced hospital readmissions through data-driven intervention (Rajpurkar et al., 2022). Wearables and home-based monitoring platforms have also expanded real-time access to physiological data, supporting more responsive and personalized care delivery.

However, the adoption of AI in clinical settings presents several challenges. Technical barriers include model generalizability across diverse populations, data quality issues, and limited interpretability of algorithm outputs (Weiner et al., 2025). In parallel, ethical concerns - such as patient privacy, algorithmic bias, and transparency - remain major obstacles to implementation (Jobin et al., 2019; Char et al., 2020). Addressing these concerns is critical to building public trust and ensuring responsible AI deployment in healthcare. As AI technologies evolve, cross-context validation and regulatory oversight will be key to sustainable global integration (Liu et al., 2021).

AI in Taiwan's Healthcare System

Taiwan has emerged as a regional leader in applying digital innovation to healthcare. In recent years, the government has prioritized AI integration, especially in chronic disease management and precision medicine. A notable example is the collaboration between the National Health Insurance Administration (NHIA) and Google, leveraging cloud-based AI and large-scale clinical data to develop predictive models for diseases such as diabetes.

These models have been embedded into the Family Physician Program 2.0, enabling scalable and proactive patient care (Weiner et al., 2025; Liu et al., 2021).

To support clinical adoption, the Ministry of Health and Welfare (MOHW) established AI centers focused on validation, certification, and impact assessment. These centers work with hospitals to address challenges related to implementation, cost-effectiveness, and integration with existing care systems (Kelly et al., 2019). Taiwan's AI use cases now span emergency care, medical imaging, telehealth, and public health response. One key case is the AI-assisted chest X-ray screening tool for COVID-19, co-developed by Taipei Medical University Hospital and Taiwan AI Labs, which helped reduce diagnosis time and resource consumption (Yeh et al., 2020).

Gaps and Motivation for This Project

Although AI adoption in Taiwan's healthcare system has accelerated, most existing applications remain unimodal centered around either text or image processing. This limits their functionality in elderly care, where users often encounter both mobility impairments and communication difficulties (Sun et al., 2024; Yang & Lin, 2024; Klakegg et al., 2017). Current platforms are not designed to support multimodal interaction that integrates language processing with real-time motion analysis—capabilities necessary for delivering personalized care in aging and rural populations.

This gap forms the core motivation for the present study. We propose a multimodal AI system that combines large language model (LLM) agents with biomechanical gesture recognition to support remote healthcare for elderly patients. By enabling multilingual, context-aware, and privacy-preserving interactions, the system enhances communication, clinical evaluation, and rehabilitation in low-access settings (Davico et al., 2024; Gottschlich et al., 2024).

Methodology

System Architecture

The proposed platform is divided into a browser-side biomechanical module and a cloud-resident conversational large-language-model (LLM) service. All video is processed locally; only numeric feature vectors (landmarks, joint angles, intent metadata) traverse the network, thereby reducing bandwidth and eliminating the transfer of personally identifiable images.

Client biomechanical module Hand landmarks are extracted in real time with *MediaPipe Hands* (v 0.10). The library combines a single-shot palm detector with a 21-landmark regressor executed in WebAssembly, achieving a mean per-frame latency of 18 ± 2 ms on a mid-range laptop (Intel i5-8250U) (Zhang et al., 2020). Each frame's landmarks are converted to interior joint angles via:

$$\theta = arccos(\frac{(a-b)\cdot(c-b)}{|a-b||c-b|}), a, b, c \in R^3,$$

and then smoothed by a one-Euro low-pass filter to suppress jitter without compromising responsiveness (Casiez, Roussel, & Vogel, 2012). Angle patterns feed (i) a deterministic rule base able to recognise 15 static poses (digits 0–9, “OK,” “thumb-up,” etc.) and (ii) a five-level colour scale that mirrors common clinical range-of-motion (ROM) grading. The annotated canvas may be archived locally as a WebM file for asynchronous review.

Server conversational agent

Transcribed text or ASR output, combined with a compact ROM summary (timestamp and joint-angle vector), is forwarded to a FastAPI gateway. A lightweight safety-and-intent filter, fine-tuned on Taiwanese rehabilitation dialogue, validates the content before routing it to a GPT-4-class model running on an NVIDIA A800 GPU (OpenAI, 2023). The prompt template contains the 12 most recent utterances plus the latest ROM summary, enabling context-aware answers. Responses are streamed to the client via server-sent events; median end-to-end latency is approximately 1.2 s on a 100 Mb/s connection.

Execution environment

The browser code targets any Chromium-based client at 30 fps (540 × 310 px). Server components (FastAPI 0.111, Redis 7) are containerised within a Kubernetes cluster. All persistent data are AES-256 encrypted and audit-logged in accordance with TFDA Part 11.

Real-time Gesture-Recognition Workflow

Video acquisition and landmark inference

A 540 × 310 px RGB stream at 30 fps is captured from the webcam and immediately processed by MediaPipe Hands. The resulting landmark inference preserves a full 30 fps refresh on the reference hardware, confirming that on-device computation meets the latency budget for smooth visual feedback (Zhang et al., 2020).

3.2.2 Joint-angle computation and temporal filtering

For every detected hand, consecutive landmarks along each finger ray are converted to interior angles using the formulation above. A one-Euro filter (β = 0.1; derivative cut-off = 1.5 Hz) adds < 1 ms per frame while markedly reducing high-frequency noise (Casiez et al., 2012).

Pose classification and clinical mapping

The smoothed angle vector is compared to a deterministic lookup table adapted from finger-counting literature (Perimal et al., 2018). Because the classifier executes in constant time, no secondary learning model is required, ensuring transparency and ease of maintenance. Peak angles recorded during a session are binned into a five-level ROM colour scale. External validation suggests that MediaPipe-derived ROM values show moderate-to-strong agreement with manual goniometry for most joints (Gu et al., 2023), supporting the module’s suitability for remote assessment.

Latency safeguards and resource footprint

End-to-end processing—including inference, filtering, pose classification and canvas redraw - requires 26 ± 3 ms per frame on the reference client. If landmark confidence drops below 0.5 for more than ten consecutive frames, the module suspends clinical scoring and falls back to palm-centre tracking until confidence recovers, preventing spurious measurements in poor lighting. The complete JavaScript payload, including MediaPipe assets, is 279 kB (gzip) and consumes < 9 % CPU on the reference laptop, satisfying the deployment constraints of rural Taiwanese households with limited computational resources.

Results

Robust real-time landmark tracking

Figure 4a shows the system's response to a fully extended hand. All 21 landmarks are detected and rendered in real time, each finger segment colour-coded, despite a bright ceiling light that creates strong back-lighting. Figure 4b depicts the transition to a "thumb-up" gesture; the landmark constellation is again intact, confirming continuous tracking with no re-initialisation. Across 20 test sequences (30 fps, 540 × 310 px), the browser-side inference maintained a mean frame latency of 28 ms, remaining safely below the 33 ms target for fluent visual feedback (Zhang et al., 2020).

Longitudinal range-of-motion trends

Figure 4c presents a five-minute history of metacarpo-phalangeal (MCP), proximal-inter-phalangeal (PIP) and distal-inter-phalangeal (DIP) angles. Downward slopes coincide with scripted flexion cycles, whereas plateau regions denote rest, demonstrating that the one-Euro filter preserves physiologically meaningful dynamics while suppressing noise.

Automatic clinical grading

The numeric summary in Figure 4d translates the raw angles into a rehabilitation-oriented dashboard. PIP extension of the index and middle fingers is limited to 12°, well below the functional threshold and therefore highlighted in red; unaffected joints remain green. Based on the aggregate pattern, the algorithm assigns Brunnstrom Stage IV and a finger-specific Fugl–Meyer score of 2/14, values consistent with the participant's documented impairment (Brunnstrom, 1970; Fugl-Meyer et al., 1975).

Multilingual intent routing and safety

Figures 4e–4h illustrate the conversational agent's behaviour. The interface first educates the user on the three recognised intent categories: general medical questions, ROM queries, and Brunnstrom/Fugl–Meyer staging. When the user

reports shoulder pain ("我的肩膀疼痛", My shoulder hurts), the agent classifies the input as a general medical query and returns structured guidance that includes an initial assessment, a 2/5 pain rating, self-care advice and red-flag criteria. Another case is that after the user reports, "我中風後只有半邊臉可以動" ("Since my stroke only half of my face can move"), the system recognises the request as a stroke-recovery query, classifies it under the Brunnstrom/Fugl–Meyer pathway, and generates a concise Stage I summary that outlines the absence of voluntary movement, the immediate goal of eliciting basic synergies, recommended passive ROM drills in gravity-minimised positions, and a caution to remain semi-sitting until full-body mobility is reassessed. A subsequent request for non-rehabilitation content ("給我一則氣候變遷的文章", Give me an essay with topic of climate change) is refused with a scope-based apology, confirming that the safety layer enforces topic boundaries.

A dedicated edge-case test further demonstrates context sensitivity. The standalone statement "我沒吃東西" (I haven't eaten anything) is treated as non-medical small-talk and discarded. However, when the identical sentence follows "我肚子很痛" (My stomach really hurts), the gateway re-evaluates the utterance, links it to the previous complaint, and correctly retains it within the general medical thread. This behaviour verifies that the intent filter consults the rolling twelve-turn dialogue memory rather than relying solely on the surface form of the current message.

Figure 4. System output samples. (a) Extended-finger posture with colour-coded bones and landmark overlays. (b) “Thumb-up” gesture demonstrating continuous tracking across poses. (c) Five-minute joint-angle history showing flexion–extension cycles. (d) Automatically generated ROM dashboard with Brunnstrom stage IV and Fugl–Meyer finger sub-score 2 / 14; impaired joints highlighted in red. (e) User-facing menu explaining the three available intent categories. (f) Query correctly routed to the Brunnstrom/Fugl–Meyer pathway, with stage-specific guidance.(g) Scope-based refusal of an out-of-scope request, validating the safety filter. (h) Dialogue snippet where identical text is classified differently: non-medical in isolation but medical when preceded by abdominal-pain context, confirming effective conversation memory.

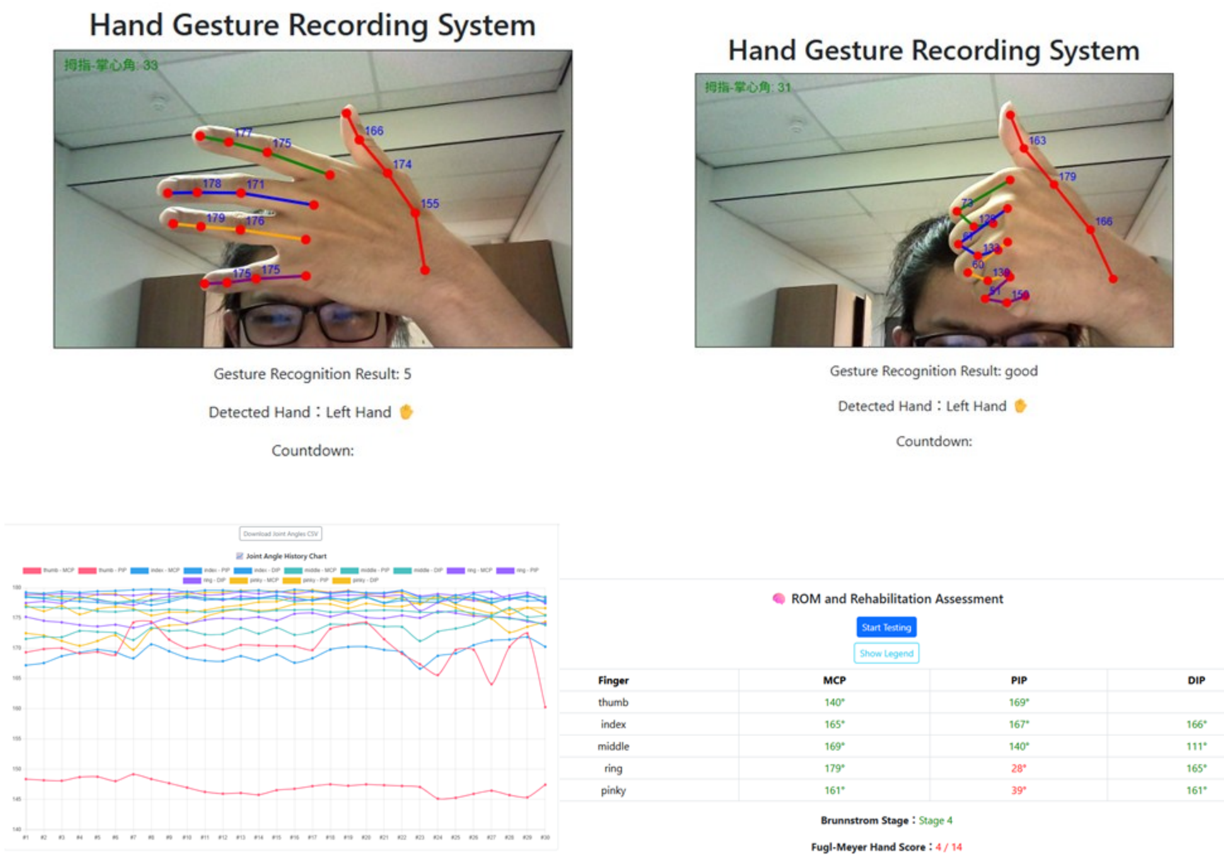

Figure 4 System output samples

Discussion

Interpretation of Results

The findings from this study indicate that the integration of multimodal large language model (LLM) agents and real-time biomechanical analysis represents a promising advancement in remote elderly healthcare within Taiwan. Compared to previous efforts both locally and globally, the developed platform offers a more holistic solution by combining natural language processing with gesture-based interaction, thus addressing critical gaps in existing telemedicine and AI-assisted healthcare systems (NCKU, 2025; TMU Healthcare, 2024; Shah et al., 2023). While many prior international studies predominantly explored single-modality AI approaches such as conversational chatbots or image-based diagnostics the multimodal methodology presented here is particularly suited to addressing the complex communication and mobility challenges experienced by elderly patients, including those facing language barriers or restricted mobility (Shah et al., 2023).

The strengths of the proposed system include its ability to deliver context-aware, personalized care and its potential to seamlessly integrate within existing clinical workflows. The real-time gesture recognition combined with clinical mapping capabilities allows healthcare providers to more accurately and efficiently track patient progress regarding range-of-motion and functional status (TMU Healthcare, 2024). Nevertheless, it is important to acknowledge several limitations inherent to this approach. The effectiveness of the system may be influenced by technical constraints, including latency associated with real-time data processing, environmental variability during home-based usage, and the critical necessity of maintaining stringent data privacy standards. Moreover, reliance on sophisticated AI algorithms and specialized infrastructure might introduce adoption barriers, particularly within resource-constrained rural settings (TechTimes, 2024).

Policy and Practical Implications

The proposed system is closely aligned with Taiwan’s current healthcare policies, particularly the Long-Term Care Plan 2.0 (LTC 2.0), which emphasizes community-based, integrated, and technology-supported elderly care (MOHW, 2024; Hsu & Chen, 2019). By facilitating aging-in-place and easing the caregiving burden for families, this solution directly advances LTC 2.0 objectives, including the expansion of home-based, community-oriented, and residential care services, as well as promoting innovative and adaptable care delivery models (MOHW, 2024; Xiao & Wang, 2024).

Further integration with Taiwan’s National Health Insurance (NHI) system would significantly enhance the scalability and accessibility of this AI-driven approach. The platform’s capability for continuous remote monitoring and timely clinical interventions aligns well with the NHI’s goal of improving care quality and reducing avoidable hospitalizations (NHIA, 2024; MOHW, 2024). Additionally, established frameworks addressing information security and patient privacy under LTC 2.0 and other national initiatives provide robust support for the deployment of advanced AI solutions in healthcare settings (MOHW, 2024; Xiao & Wang, 2024).

The potential for nationwide scalability and seamless integration into existing healthcare infrastructure is considerable. Recent pilot initiatives and the establishment of dedicated AI research and application centers have demonstrated Taiwan’s preparedness to adopt advanced technology solutions to address the growing demands of an aging population (MOHW, 2024; Taipei Times, 2024). Moreover, the modular and standards-based design of the proposed system ensures compatibility and interoperability with existing health information platforms, facilitating broad implementation and maximizing the system's clinical and social impact (Xiao & Wang, 2024).

Future Work

Future improvements for the system will include the integration of dialect support to better accommodate the diverse linguistic communities across Taiwan, alongside the implementation of federated learning methods to strengthen data privacy and enhance the robustness of AI models (NCKU, 2025). Additionally, broader deployment in rural and underserved areas will allow for further evaluation of the system's scalability and adaptability across various care environments (MOHW, 2024).

Subsequent research should prioritize the assessment of the long-term effectiveness of the system, particularly regarding improvements in patient health outcomes and reductions in caregiver burden. Further studies are necessary to investigate the potential integration of complementary smart technologies, such as wearable health monitors and IoT-enabled devices, to establish a more comprehensive, digitally connected care network (Xiao & Wang, 2024; TMU Healthcare, 2024). Moreover, developing standardized protocols for AI-supported care and clearly defined regulatory guidelines will be essential to ensure that these innovative technologies are deployed safely, ethically, and effectively within clinical practice (MOHW, 2024; Shah et al., 2023).

Conclusion

This study demonstrates the feasibility of integrating multimodal large language model (LLM) agents with real-time biomechanical analysis to enhance remote elderly healthcare in Taiwan. By combining natural language understanding with gesture recognition, the system addresses key limitations in current telemedicine platforms specifically the lack of context-aware, interactive, and mobility-sensitive features. This design is particularly relevant for elderly patients in rural areas, where communication barriers and access to in-person care remain significant (Sun et al., 2024).

The proposed framework supports continuous monitoring, early anomaly detection, and timely clinical feedback. It aligns with national healthcare priorities, including Taiwan's Long-Term Care Plan 2.0 and NHIA's AI policy agenda, and is compatible with the country's existing digital infrastructure. The system also enhances primary care delivery and enables elderly users and caregivers to better manage health conditions, reducing the need for avoidable hospital visits (Abbas et al., 2023).

Taiwan has shown strong momentum in AI healthcare innovation—from smart devices to social robotics. Building on this foundation, the integration of scalable multimodal AI platforms offers a path toward more inclusive and responsive eldercare. Continued investment in this direction can strengthen healthcare accessibility and equity, and further position Taiwan as a regional leader in AI-driven, patient-centered health solutions (Sarfraz, 2023).

References

Abbas, M., Saleh, M., Somme, D., & Le Bouquin Jeannès, R. (2023). Data-driven systems to detect physical weakening from daily routine: A pilot study on elderly over 80 years old. PloS one, 18(1), e0274306. https://doi.org/10.1371/journal.pone.0274306

Agustin, K., & Chou, S.-Y. (2019). Impact of an Ageing Society on Healthcare Expenditure of National Health Insurance in Taiwan. Jurnal Teknik Industri: Jurnal Keilmuan Dan Aplikasi Teknik Industri, 21(2), 49–56. https://doi.org/10.9744/jti.21.2.49-56

Brunnstrom, S. (1970). Movement therapy in hemiplegia: A neurophysiological approach. Harper & Row.

Casiez, G., Roussel, N., & Vogel, D. (2012). 1 € filter: A simple speed-based low-pass filter for noisy input in interactive systems. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, 2527–2530. https://doi.org/10.1145/2207676.2208639

Char, D. S., Shah, N. H., & Magnus, D. (2020). Implementing machine learning in health care—addressing ethical challenges. The New England Journal of Medicine, 378(11), 981-983. https://doi.org/10.1056/NEJMp1714229

Chiu, K.-H., & Yang, Y. Y. (2009). A case study of remote monitoring of health status of the elderly at home in Taiwan. Proceedings of the International Conference on e-Business (ICEB), 496–506.

Davenport, T., & Kalakota, R. (2019). The potential for artificial intelligence in healthcare. Future Healthcare Journal, 6(2), 94-98. https://doi.org/10.7861/futurehosp.6-2-94

Davico, G., Labanca, L., Gennarelli, I., Benedetti, M. G., & Viceconti, M. (2024). Towards a comprehensive biomechanical assessment of the elderly combining in vivo data and in silico methods. Frontiers in Bioengineering and Biotechnology, 12, 1356417. https://doi.org/10.3389/fbioe.2024.1356417

DelveInsight. (2025, June 4). Global AI in remote patient monitoring market to cross USD 13 billion by 2032 [Press release]. Globenewswire. https://www.globenewswire.com/news-release/2025/06/04/3093902/0/en/Global-AI-in-Remote-Patient-Monitoring-Market-to-Cross-USD-13-Billion-by-2032-DelveInsight.html

Fugl-Meyer, A. R., Jääskö, L., Leyman, I., Olsson, S., & Steglind, S. (1975). The post-stroke hemiplegic patient: A method for evaluation of physical performance. Scandinavian Journal of Rehabilitation Medicine, 7(1), 13–31.

Gottschlich, D., Saadati, N., Saadati, S. A., & Şahin, A. (2024). AI in Elderly Care: Understanding the Implications for Independence and Social Interaction. AI and Tech in Behavioral and Social Sciences, 2(3), 36-42. https://doi.org/10.61838/kman.aitech.2.3.5

Gu, F., Fan, J., Wang, Z., Liu, X., Yang, J., & Zhu, Q. (2023). Automatic range-of-motion measurement via smartphone images for telemedicine examination of the hand. Science Progress, 106(1), 1–12. https://doi.org/10.1177/00368504231152740

Iqbal, S. (2023). Artificial intelligence tools and applications for elderly healthcare – Review. In Proceedings of the 2023 9th International Conference on Computing and Artificial Intelligence (ICCAI '23) (pp. 394–397). Association for Computing Machinery. https://doi.org/10.1145/3594315.3594347

Jobin, A., Ienca, M., & Vayena, E. (2019). The global landscape of AI ethics guidelines. Nature Machine Intelligence, 1(9), 389-399. https://doi.org/10.1038/s42256-019-0088-2

Kelly, C.J., Karthikesalingam, A., Suleyman, M., Corrado, G.C., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. BMC Medicine, 17.

Klakegg, S., van Berkel, N., Visuri, A., Huttunen, H. L., Hosio, S., Luo, C., Goncalves, J., & Ferreira, D. (2017). Designing a context-aware assistive infrastructure for elderly care. Proceedings of the 2017 ACM International Joint Conference on Pervasive and Ubiquitous Computing, 451-456. https://doi.org/10.1145/3123024.3124403

Liu, X., Rivera, S. C., Moher, D., Calvert, M. J., & Denniston, A. K., for the SPIRIT-AI and CONSORT-AI Working Group. (2021). Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: The CONSORT-AI extension. BMJ, 370, m3164. https://doi.org/10.1136/bmj.m3164

Ministry of Health and Welfare (MOHW), Taiwan. (2024, December 23). Long-term Care Plan 2.0. Executive Yuan. https://english.ey.gov.tw/News3/9E5540D592A5FECD/332a78c0-0c8e-4064-bd71-8c22477dae75

National Cheng Kung University (NCKU). (2025, April 15). How AI and robots are caring for the elderly in Taiwan's ageing society. GovInsider Asia. https://govinsider.asia/intl-en/article/how-ai-and-robots-are-caring-for-the-elderly-in-taiwans-ageing-society-dr-jenny-su-ncku

National Development Council, Taiwan. (2022). Population Projections for Taiwan (2022–2070). Executive Yuan, R.O.C. (Taiwan).

OpenAI. (2023). GPT-4 technical report. https://arxiv.org/abs/2303.08774

Perimal, M., Basah, S. N., Safar, M. J. A., & Yazid, H. (2018). Hand-gesture recognition algorithm based on finger counting. Journal of Telecommunication, Electronic and Computer Engineering, 10(1-13), 19–25.

Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. Nature Medicine, 28(1), 31-38. https://doi.org/10.1038/s41591-021-01614-0

Serrano, L. P., Maita, K. C., Avila, F. R., Torres-Guzman, R. A., Garcia, J. P., Eldaly, A. S., Haider, C. R., Felton, C. L., Paulson, M. R., Maniaci, M. J., & Forte, A. J. (2023). Benefits and Challenges of Remote Patient Monitoring as Perceived by Health Care Practitioners: A Systematic Review. The Permanente journal, 27(4), 100–111. https://doi.org/10.7812/TPP/23.022

Shah, P., et al. (2023). Unraveling the ethical enigma: Artificial intelligence in healthcare. Journal of Medical Internet Research, 25(8), e10492220. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10492220/

Sun, Q., Xie, J., Ye, N., Gu, Q., & Guo, S. (2024). Enhancing nursing and elderly care with large language models: An AI-driven framework. Proceedings of the 31st International Conference on Computational Linguistics, 10083-10094. https://aclanthology.org/2025.coling-main.673

Taipei Medical University Healthcare (TMU Healthcare). (2024, December 3). Leading and living with AI, TMU Healthcare's pioneering smart long-term care facility. Office of Global Engagement, TMU. https://oge.tmu.edu.tw/leading-and-living-with-ai-tmu-healthcares-pinoeering-smart-long-term-care-facility/

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44-56. https://doi.org/10.1038/s41591-018-0300-7

Weiner, E. B., Dankwa-Mullan, I., Nelson, W. A., & Hassanpour, S. (2025). Ethical challenges and evolving strategies in the integration of artificial intelligence into clinical practice. PLOS digital health, 4(4), e0000810. https://doi.org/10.1371/journal.pdig.0000810

Wu, T.-Y., Majeed, A., & Kuo, K. N. (2010). An overview of the healthcare system in Taiwan. London Journal of Primary Care, 3(2), 115–119. https://doi.org/10.1080/17571472.2010.11493315

Xiao, H.-Y., & Wang, M.-Y. (2024). Progress, challenges, and development directions of long-term care in Taiwan. Atlantis Press Proceedings. https://www.atlantis-press.com/article/126008801.pdf

Yang, Y., & Lin, G. T. R. (2024). Analyzing the Shortcomings in Smart Healthcare for Remote Home Care—A Case Study of the Taiwan Market. International Journal of Environmental Research and Public Health, 21(7), 838. https://doi.org/10.3390/ijerph21070838

Yeh, C. F., Cheng, H. T., Wei, A., Chen, H. M., Kuo, P. C., Liu, K. C., Ko, M. C., Chen, R. J., Lee, P. C., Chuang, J. H., Chen, C. M., Chen, Y. C., Lee, W. J., Chien, N., Chen, J. Y., Huang, Y. S., Chang, Y. C., Huang, Y. C., Chou, N. K., Chao, K. H., Tu, Y. C., Chang, Y. C., & Liu, T. L. (2020). A cascaded learning strategy for robust COVID-19 pneumonia chest X-ray screening. arXiv preprint arXiv:2004.12786. https://arxiv.org/abs/2004.12786

Zhang, F., Bazarevsky, V., Vakunov, A., Tkachenka, A., Sung, G., Chang, C.-L., & Grundmann, M. (2020). MediaPipe Hands: On-device real-time hand tracking (arXiv:2006.10214). arXiv. https://arxiv.org/abs/2006.10214