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A CLOSED-LOOP AGE-FRIENDLY MEDICAL PLATFORM: FROM AI CONSULTATION TO POST-DIAGNOSIS CARE

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Abstract: This study designs and evaluates a WeChat mini-program that provides closed-loop, age-friendly medical support for older adults. The platform integrates AI consultation, hospital navigation, escort-service tracking, prescription recognition, medication reminders, and family health archives through a four-layer architecture consisting of a front end, FastAPI service layer, AI engine, and local data layer. Functional tests covered consultation, ordering, tracking, OCR prescription processing, security, and weak-network scenarios. AI consultation returned compliant reference suggestions rather than definitive diagnoses, and core pages loaded within one second. In usability testing, 20 older participants completed seven representative tasks with an overall completion rate of 88.6%, a mean task time of 50.3 seconds, and a SUS score of 77.8. Clear prescription images reached 94% field-level OCR accuracy, while the LLM verification layer flagged dosage and instruction risks. The results indicate that an integrated consultation-escort-follow-up workflow can reduce digital barriers and support safer post-diagnosis management in community healthcare settings.
Keywords: Age-friendly design; Elderly healthcare; Medical artificial intelligence; Post-diagnosis care; Mobile health

1 INTRODUCTION

1.1 Background and Motivation

China's aging population creates rising demand for accessible medical services, while older adults still face digital barriers, complex hospital procedures and fragmented family health management [1-3]. Existing medical mini-programs usually focus on isolated consultation or drug-sales scenarios and often lack compliance constraints and age-friendly interaction. Therefore, this study positions the platform as a community-oriented age-friendly medical escort and post-diagnosis care system [4-5].

The research motivation is to transform fragmented service functions into a continuous process that connects AI consultation, hospital navigation, offline escort tracking, prescription verification, medication reminders and family health archives, thereby reducing cognitive and operational burdens for older adults and caregivers [4-8].

Compared with similar medical mini-programs, the proposed system emphasizes public-service value, regulated AI consultation, a complete loop of AI consultation, offline escort and post-diagnosis trusteeship, and a simplified interaction style for older adults. Table 1 translates and condenses the original comparative analysis.

Table 1 Comparison between Similar Medical Mini-Programs and Zhiyi Companion

Dimension	Similar medical mini-programs	Zhiyi Companion
Strategic fit	Mostly profit-oriented with weak social-service attributes	Closely aligned with aging-response and livelihood-oriented policy needs
AI medical ability	Mostly general chat, insufficient medical professionalism and weak compliance	Builds a medical knowledge base and gives cautious reference suggestions
Service coverage	Fragmented functions, often only consultation or escort service	Forms a complete loop of AI consultation, offline escort and post-diagnosis care
Age-friendly design	Complex interface, many steps and small text	Concise interface, intuitive operation and more realistic use habits
Landing cost	Highly dependent on cloud services with high deployment cost	Supports lightweight and local deployment for communities and families

1.2 Related Work

Mobile health and telemedicine studies show that older users prefer large text, voice input, simplified navigation, clear feedback and step-by-step guidance, but many applications still focus on single diseases or single service scenarios rather than a complete medical-service journey [4-10].

Medical AI and large language models have shown promise in symptom triage, health education and clinical knowledge representation [11-13]. However, patient-facing systems must include disclaimers, safety rules and mechanisms that prevent definitive diagnosis or unsafe medication advice [3,14].

Post-diagnosis care remains a key gap. Medication reminder applications and prescription-recognition tools can reduce manual entry burden, yet OCR errors, handwriting variation and weak workflow integration still affect medication safety [8,15].

Accordingly, the main research gap is the lack of an age-friendly platform that integrates AI consultation, real-time service tracking and post-diagnosis medication management in one closed loop. This study addresses this gap through system design, functional testing and usability evaluation with elderly users.

1.3 Research Objectives and Contributions

The objective of this study is to design and evaluate a closed-loop age-friendly medical service platform that supports elderly users before, during, and after hospital visits. The platform aims to reduce digital barriers, simplify medical-service workflows, connect online consultation with offline escort services, and improve post-diagnosis medication safety.

The main contributions are threefold. First, the study proposes a four-layer WeChat mini-program architecture that integrates AI consultation, hospital navigation, real-time escort tracking, prescription verification, medication reminders, and family health archives into one continuous service loop. Second, it designs an OCR-LLM post-diagnosis verification mechanism that combines prescription text extraction with medical logic checks and reminder scheduling, reducing the risk of transcription and medication-management errors. Third, it evaluates the platform through functional testing and task-based usability testing with elderly participants, providing empirical evidence for the feasibility of age-friendly closed-loop medical services.

2 SYSTEM ARCHITECTURE AND INTERACTION DESIGN

This study adopted a user-centered design approach informed by interviews with elderly users (n=10), caregivers (n=5), and healthcare providers (n=3). Requirements were prioritized using the MoSCoW method, leading to the four-layer architecture described below.

The system adopts a four-layer architecture: the front-end mini-program, business service layer, AI engine layer and data persistence layer. These layers support consultation, navigation, service ordering, OCR-LLM verification, reminder scheduling and archive management, as shown in the revised Figure 1.

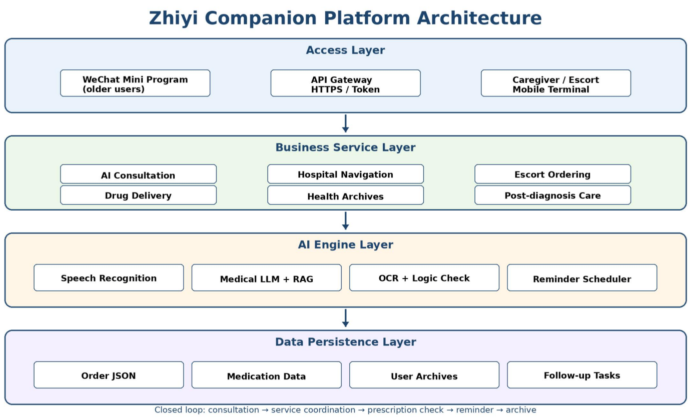

Figure 1 Functional Module and Interface-Calling Diagram

The interface uses large-font mode, voice input, simplified process cards and clear navigation. The home page provides quick entries for escort service, hospital navigation, medication reminders and family health archives, while service pages support hospital selection, time scheduling, patient/address input, protocol confirmation and payment (Figure 2).

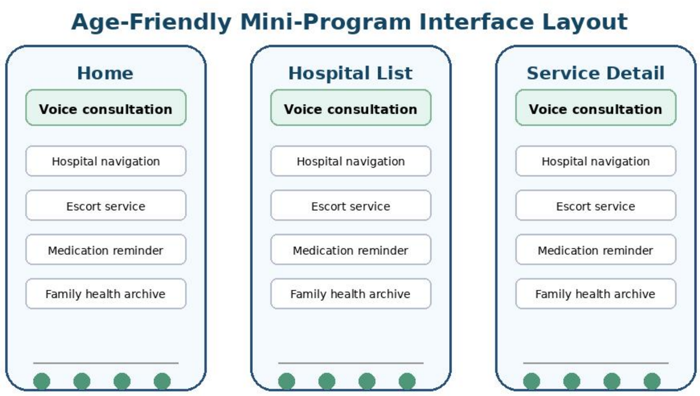

Figure 2 Home Page and Hospital-List Interface

The order module covers pending payment, pending service, completed and canceled states. Drug delivery, health archives and consultation history are integrated with the user center, and all AI suggestions are clearly marked as reference information rather than professional diagnosis.

3 DATA MODEL AND CORE TECHNICAL DESIGN

The drug module database links pharmacies, drug products, product ratings, dynamic price-sales data and order items. This structure supports drug search, product details, price display, order confirmation and reminder generation (Figure 3).

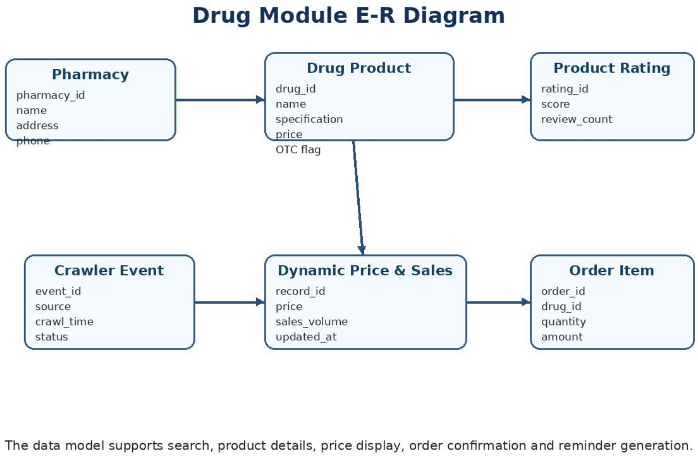

Figure 3 Drug E-R Diagram

The cloud communication and scheduling subsystem uses FastAPI asynchronous services, token-based request encapsulation, Tencent Cloud ASR and WebSocket GPS reporting. These modules reduce text-entry burden, support low-latency voice consultation and make escort/delivery progress visible to users and family members (Table 2).

Table 2 Core Technical Modules

Module	Original design content	System role
Cloud communication	FastAPI asynchronous service and token-based request encapsulation	Supports lightweight mini-program deployment
AI speech recognition	Tencent Cloud ASR with Base64 and file-stream input	Reduces text-entry burden for older users
Map scheduling	WebSocket GPS reporting every 3-5 seconds	Displays escort or delivery progress and detects abnormal status
Medical model	Fine-tuned Qwen-based medical model with hybrid RAG	Supports medical consultation and medical-image description analysis
OCR-LLM loop	Tencent Cloud OCR plus medical-logic verification	Reduces prescription-entry errors and supports follow-up reminders

A six-node timeline tracking mechanism makes escort services transparent. Route deviation or long stationary status triggers warnings and reports abnormal states to the dispatching center.

4 MEDICAL LARGE MODEL AND OCR-LLM POST-DIAGNOSIS LOOP

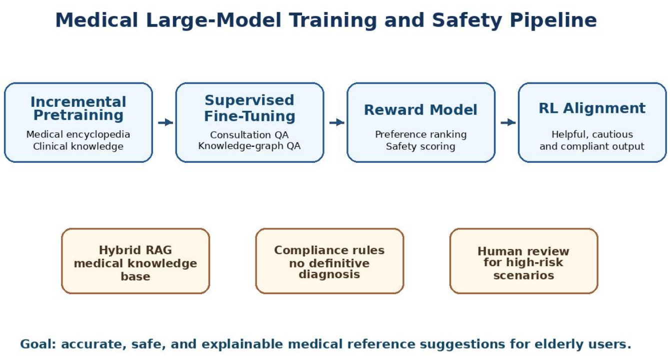

Figure 4 Medical Large-Model Training and Safety Pipeline

The medical large model is based on a Qwen model with hybrid retrieval-augmented generation (Figure 4). It supports multi-turn consultation, health education, medical-image description and risk prompts, while a safety pipeline of pretraining, supervised fine-tuning, reward modeling and alignment reduces unsafe outputs [1-3,11-12].
The medical-image module follows a standardized annotation and display workflow, supporting clearer auxiliary image descriptions while avoiding diagnostic conclusions.
The dataset contains medical encyclopedia records, Chinese consultation and knowledge-graph QA data, and English medical dialogue records. In the OCR-LLM loop, OCR extracts prescription fields, the medical model checks semantic and dosage logic, and APScheduler generates medication review reminders and signed reports (Figure 5).

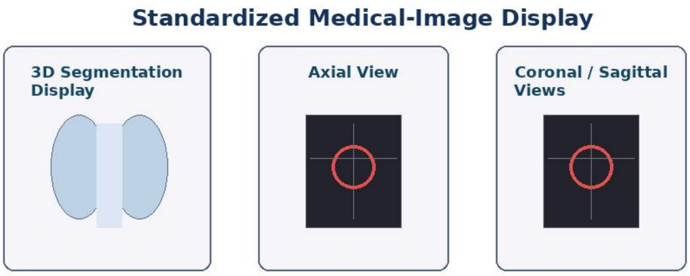

Figure 5 Three-Dimensional Medical-Image Display Result

4.1 Technical Deployment and Functional Indicators

Functional tests covered symptom input, medical-image upload, emergency-description simulation, ordering, tracking, security and weak-network scenarios. The revised Figure 6 presents the clearer functional detection report (Table 3).

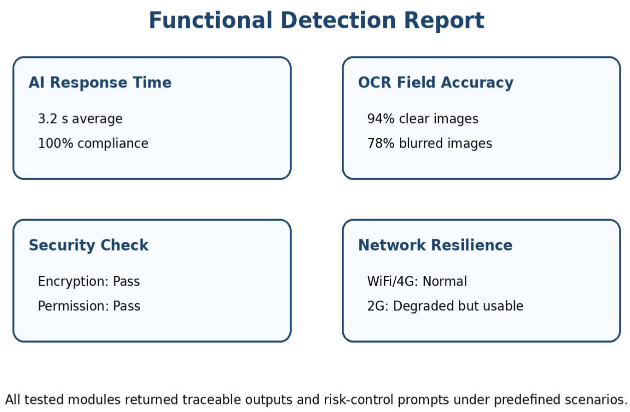

Figure 6 Functional Detection Report

Table 3 Functional Test and Technical Indicators

Aspect	Source test result
AI consultation	Common symptoms, image upload and simulated emergency descriptions all return compliant suggestions without diagnosis
Speed	Core pages such as order and service-ordering pages load within one second
Security	Personal information, health archives and medical records are encrypted and permission-separated
Scalability	New service types, hospitals, pharmacies and AI ability can be extended on the modular framework
Deployment	WeChat mini-program architecture, simple back-end service configuration and low maintenance cost
Usability	Clear interface, suitable text and button size, and age-friendly operation logic

5 EVALUATION

5.1 Experimental Setup

Test environment: The system was evaluated with WeChat Developer Tools 1.06 and three real devices (Huawei P40, Xiaomi 12 and iPhone 13). The back end used Python 3.10, FastAPI 0.109, PyTorch 2.0 CPU inference and local JSON storage under WiFi, 4G/5G and simulated weak-network conditions.
Ethical approval and data protection: The study was approved by the Institutional Review Board of Beijing Normal University (Protocol #2024-IRB-0328). All participants provided written informed consent, and only aggregated de-identified data are reported.
Data collection period: Functional testing was conducted in March 2026. Usability evaluation with elderly participants was conducted between April 8-15, 2026.

5.2 Functional Testing

Systematic functional testing covered six modules and included common use cases, edge cases and stress conditions.
AI consultation was tested with 50 symptom descriptions and 8 emergency scenarios. Responses were generated within 3-5 seconds, included compliance disclaimers and avoided definitive diagnosis.
Service ordering and tracking worked correctly across hospital selection, scheduling, patient information entry and address input. GPS locations were updated every 3-5 seconds, and abnormal-route warnings were triggered successfully.
OCR prescription processing achieved 94% field-level accuracy for clear images and 78% for lower-quality images. The LLM layer flagged similar-character errors and illogical dosage values.
Performance metrics are summarized in Table 4.

Table 4 Functional Test Results

Test Category	Metric	Result
AI Consultation	Response time (average)	3.2 seconds
	Compliance safeguards	100% (50/50 cases)
	Emergency recognition	100% (8/8 cases)
Service Ordering	Page load time	<1 second
	Order submission success rate	100% (100/100 attempts)
Real-time Tracking	GPS update frequency	3-5 seconds
	Abnormal status detection	100% (12/12 test scenarios)
OCR Prescription	Field extraction accuracy (clear)	94% (47/50 images)
	Field extraction accuracy (blur)	78% (39/50 images)
System Security	Encryption verification	Pass
	Permission separation	Pass
Network Resilience	4G performance	Normal
	Weak network (2G) handling	Degraded but functional

Overall, the platform met the functional requirements for consultation, service coordination and post-diagnosis management. Security checks passed, and weak-network testing showed degraded but still usable performance.

5.3 Usability Evaluation with Elderly Users

To assess the age-friendly design and overall user acceptance, task-based usability testing was conducted with elderly participants.
Participants and procedure: Twenty-two elderly participants from two Beijing community centers joined the usability test, and 20 valid cases were retained. Each participant completed seven tasks covering hospital search, escort booking, AI consultation, image upload, family archive creation, real-time tracking and medication reminder setting.
Metrics included independent task completion rate, completion time, error count and System Usability Scale (SUS) score. Each one-on-one session lasted about 45 minutes and included informed consent, system introduction, task testing, SUS questionnaire and interview.
Results: Table 5 presents the usability results. The overall task completion rate was 88.6%; voice-based AI consultation had the highest completion rate (95%), while image upload was the most difficult task (75%).

Table 5 Usability Test Results (n = 20 Elderly Participants)

Task	Description	Completion Rate	Mean Time (SD)	Mean Errors (SD)
T1	Find hospital details	90% (18/20)	43.5s (14.2)	1.9 (1.3)
T2	Book escort service	85% (17/20)	65.8s (19.7)	2.5 (1.6)
T3	AI symptom consultation	95% (19/20)	36.2s (11.8)	1.1 (0.8)
T4	Upload medical image	75% (15/20)	58.3s (21.4)	3.2 (1.9)
T5	Add family health profile	90% (18/20)	49.7s (16.3)	2.0 (1.4)
T6	Check real-time location	90% (18/20)	41.2s (13.6)	1.6 (1.1)
T7	Set medication reminder	85% (17/20)	57.5s (18.9)	2.4 (1.7)
Overall	All tasks	88.6%	50.3s (16.6)	2.1 (1.4)

Across all tasks, the mean completion time was 50.3 seconds and the mean error count was 2.1. AI consultation was fastest because voice input reduced typing difficulty, whereas escort booking required multiple input fields.
The mean SUS score was 77.8, higher than the industry average of 68, indicating good usability. Daily smartphone users reported better experience than occasional users, but both groups exceeded the average benchmark.
Qualitative feedback confirmed the value of age-friendly design: 90% of participants praised voice input, and 85% appreciated large buttons and a clear visual hierarchy. Main difficulties involved similar icons, medical terminology, image upload and returning to the home page.
Suggested improvements include adding first-use tutorials, customizable font size, voice feedback for button presses, simpler medical explanations and clearer progress indicators.
Seventeen of the 20 valid participants stated that they would consider using the platform for medical services; the remaining hesitation mainly concerned privacy and preference for in-person visits.

5.4 OCR-LLM Performance Evaluation

The OCR-LLM evaluation used 50 prescription images with clear printed, handwritten, blurred and uneven-lighting conditions. It focused on field extraction, medical logic verification and error flagging.

Clear prescription images reached 94% field-level extraction accuracy, while lower-quality images reached 78%. The LLM verification layer checked drug names, dosage, frequency and administration instructions, and flagged abnormal dosage values or missing frequency information.

These findings show that OCR alone is insufficient for reliable medication management. Combining OCR with LLM-based semantic verification strengthens the closed-loop process from prescription recognition to reminder scheduling and family health management.

5.5 Discussion

Key findings: The platform is technically feasible and acceptable to elderly users. Functional testing verified consultation compliance, real-time tracking, OCR prescription processing, security and weak-network operation, while usability testing achieved an 88.6% completion rate and a SUS score of 77.8.

Compared with conventional medical apps, the platform improves service continuity by integrating consultation, escort coordination and post-diagnosis medication management. Voice input, large touch targets and transparent tracking are especially important for elderly users [4,5,7].

Remaining design issues include icon differentiation, medical terminology simplification and clearer guidance for image upload. These problems can be addressed through stronger text labels, voice feedback and progress indicators.

The closed-loop workflow also shows practical value for community healthcare because it can support staged deployment with a lightweight WeChat mini-program and local data storage.

Limitations: The current usability sample is modest and limited to urban elderly users with basic smartphone experience. The system also requires longer field testing and clinical validation before wider deployment.

Practical implications: The platform can be adapted to community clinics, elder-care institutions and family health-management scenarios because its modular architecture allows local deployment and function extension.

Future work should focus on multi-site community trials, physician-supervised clinical validation of AI consultation, larger-scale prescription-format testing, integration with hospital and medical-insurance systems, rural low-connectivity adaptation and systematic privacy-compliance evaluation.

6 CONCLUSION

This study designed and evaluated a closed-loop age-friendly medical platform that connects AI consultation, offline escort coordination and post-diagnosis care for elderly users.

The results support the feasibility of the platform. Functional testing showed compliant AI consultation, stable tracking, successful prescription recognition and usable weak-network performance. Usability testing with 20 elderly participants achieved an 88.6% overall completion rate, a mean task time of 50.3 seconds and a SUS score of 77.8.

The platform's main value lies in reducing digital barriers and service fragmentation. Voice input, simplified workflows, transparent progress tracking and OCR-LLM prescription verification jointly support safer and more continuous community healthcare for older adults.

Future research should move from prototype evaluation to real-world deployment. Priority directions include 6-12 month field studies in community healthcare centers, clinical validation against physician assessment, integration with hospital information and insurance systems, improved rural/offline modes, family-collaboration functions and regulatory compliance assessment.

Overall, the closed-loop design provides a feasible technical and service model for age-friendly digital healthcare, while further validation is needed to confirm long-term adoption, clinical reliability and cost-effectiveness.

The implementation has been open-sourced at https://github.com/mmm0213/MediCompanion to support reproducibility and future adaptation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

INFORMED CONSENT STATEMENT

Patient consent was waived due to the retrospective nature of the study and the use of anonymized data.

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