EAI Endorsed Transactions
on Pervasive Health and Technology
Research Article EAI.EU

Research on the Home and Community-Based Elderly Care Service Ecosystem Driven by Digital-Intelligence Empowerment

Jiao Xu[1*], Liping Fu[1], Xinyan Xu[2], Yonggang Wang[2], Ying Xu[3] and Zizhu Liu[4]

[1]College of Management and Economics, Tianjin University, Tianjin, China
[2]Phytium Technology Co., Ltd., Tianjin, China
[3]School of Software Technology, Zhejiang University, Ningbo, China
[4]Binhai Industrial Technology Research Institute of Zhejiang University, Tianjin, China

Abstract

INTRODUCTION: Fragmented demand records, invisible provider capacity, and weak closure verification reduce the responsiveness of home and community-based elderly care.
OBJECTIVES: This paper specifies and evaluates a lightweight digital-intelligence workflow system rather than a predictive medical-diagnosis tool. The system links multi-channel demand intake, rule-based priority scoring, provider eligibility filtering, work-order state tracking, delivery verification, exception logging, and feedback closure. The architecture retains a core-provider layer, a beneficiary layer, and a four-module support system, but implements them through minimum data fields, explicit state transitions, and auditable scoring rules.
METHODS: An eight-week AB/BA pilot was conducted at two community centers with 42 adults aged 65–82 and 386 valid service requests.
RESULTS: Compared with the routine workflow, the supported workflow reduced mean demand-to-confirmation time from 58.4 to 36.9 min and staff coordination time from 8.9 to 6.2 min per request. On-time completion increased from 79.2% to 89.1%, while matching accuracy increased from 83.8% to 91.6%.
CONCLUSION: The configuration uses ordinary tablets, office computers, spreadsheet-compatible records, role-based access, and human fallback channels, providing an implementable coordination mechanism for community elderly care.

Keywords: home and community-based elderly care, digital-intelligence, service ecosystem, demand-service matching, coordinated care

Received on 29 July 2026, accepted on 29 September 2026, published on 30 October 2026

Copyright © 2026 Jiao Xu *et al.*, licensed to EAI. This is an open access article distributed under the terms of the CC BY-NC-SA 4.0, which permits copying, redistributing, remixing, transformation, and building upon the material in any medium so long as the original work is properly cited.

doi: 10.4108/eetpht.11.14232

*Corresponding author. Email: xujiao@phytium.com.cn

1. Introduction

Population ageing is increasing the operational load on home and community-based elderly care. China's Seventh National Population Census reported 264 million people aged 60 years or above, representing 18.7% of the population [1].

Community services must therefore coordinate meals, housekeeping, health consultation, rehabilitation, social participation, and emergency contact across users whose needs change over time. The engineering problem is not simply a shortage of facilities. It is the delay and information loss that occur when requests, providers, schedules, and outcomes are recorded in separate notebooks, telephone groups, and institutional systems.

Age-friendly policy emphasizes access to community support, information, participation, and health services [2]. China's national elderly-care plan also calls for stronger home and community services and for appropriate use of information technology [3]. However, digitization can create another barrier when a smartphone account becomes the only entrance to care. An elderly-care platform must therefore improve back-office coordination while preserving telephone, paper, family, and staff-assisted channels. It should also minimize sensitive data and keep automated recommendations subordinate to professional judgement.

The proposed design connects six operational stages: request intake, priority calculation, provider eligibility filtering, candidate ranking, delivery verification, and feedback closure. The target problem is a workflow coordination problem rather than a predictive diagnosis problem. The contributions are: (1) a field-level architecture that defines the minimum records needed to move a request from registration to closure; (2) two transparent scoring rules that can be implemented in spreadsheet software and audited by staff; and (3) an eight-week small-sample evaluation using service logs, timestamped work orders, manual override records, and user ratings.

2. Related Work

Service-dominant logic describes service ecosystems as networks of resource-integrating actors governed by shared institutional arrangements [4]. Service ecosystem design extends this view by treating roles, rules, and physical enactments as design materials and by emphasizing collective, continuing adaptation [5]. These ideas fit community elderly care because no single organization owns the complete service journey. Government sets rules and funding, communities coordinate local resources, providers deliver services, families supply context, and older adults define whether value has been realized. The limitation of a purely conceptual ecosystem is that it does not specify the minimum records, state transitions, or timing rules needed for daily operation.

Digital support for older adults must be evaluated in the setting where it is used. Airola's review found that access to assistance, usability, and fit with daily routines strongly affect home-based eHealth use [6]. An umbrella review by Kunonga et al. reported limited evidence on digital technologies for first-contact access to health and social care and warned that digital exclusion can worsen inequity [7]. These findings support a multi-channel design in which staff may enter a request received by telephone or in person and the older adult is not required to operate a personal device.

Measurement is another challenge. A systematic review of digital-literacy instruments found that many tools cover only one or two competence domains and may not be age appropriate [8]. Electronic health literacy is associated more consistently with behavioral and cognitive outcomes than with physical outcomes [9]. Device-specific evidence also remains mixed; for example, reviews of GPS safety alarms identify acceptable pilots but insufficient outcome evidence [10]. Consequently, the present study evaluates service-process measures rather than medical effects: confirmation time, completion, matching accuracy, coordination time, family notification, and perceived service clarity.

Training and social support are practical components of implementation. A 2023 meta-analysis reported improvements in digital health literacy, knowledge, and self-efficacy after structured interventions for older adults [11]. Digital communication can also support social contact, although effects depend on intervention design and user context [12]. At the infrastructure level, smart-city data governance requires explicit purpose, access control, accountability, and retention rules [13]. The remaining technical gap is therefore a low-cost, auditable mechanism that integrates service demand and capacity without assuming continuous sensing, large-scale artificial intelligence, or exclusive digital access.

3. Methodology and System Design

3.1. Engineering Requirements

The system requirements were derived from the operational failure points observed in routine community service coordination: incomplete or duplicated demand records, limited visibility of provider capacity, delayed confirmation, unverifiable closure, and uneven access for older adults who do not independently use smartphones. Table 1 translates these needs into functional and non-functional requirements.

Table 1. Functional and Non-Functional Requirements of the Digital-Intelligence Workflow System

Requirement type	Requirement	Engineering control
Functional	Multi-channel request intake	Tablet, telephone, paper, and staff-assisted entries use the same request form
Functional	Priority scoring	Urgency, safety risk, waiting pressure, and alternative assistance are converted to a 0–1 score
Functional	Provider matching	Unqualified or unavailable providers are filtered before candidate ranking
Functional	Work-order tracking	Each request moves through explicit states with timestamps and an accountable owner
Functional	Exception and feedback closure	Late, reassigned, unclear, or disputed services are logged and reopened when needed
Non-functional	Low-cost deployment	Ordinary tablets, office computers, and CSV exports are sufficient for the pilot
Non-functional	Data minimization and auditability	Anonymous IDs, role-based access, retention limits, and override reason codes are required
Non-functional	Human fallback	Staff can override recommendations and can enter requests for users through assisted channels

3.2. Ecosystem and Information Architecture

Figure 1 shows the ecosystem framework. The core layer contains government, community organizations, service institutions, and service personnel. The beneficiary layer contains older adults living at home and their families. The support system combines policy, technology and information, social participation, and digital-intelligence support. The implementation maps this structure to four technical layers: a data layer for standardized records, a service layer for reusable service items, an application layer for requests and work orders, and a rule layer for priority and matching. The rule layer does not diagnose health conditions; it orders routine service work and alerts staff when a request needs professional review. In this design, the ecosystem framework specifies the actor roles and institutional relationships that the system must support, whereas the workflow system operationalizes that framework: it converts the framework's roles and support functions into minimum data fields, explicit state transitions, and auditable rules that a community center can operate with ordinary equipment. The framework therefore remains the conceptual anchor of the architecture, and the workflow system is its executable form rather than a competing model.

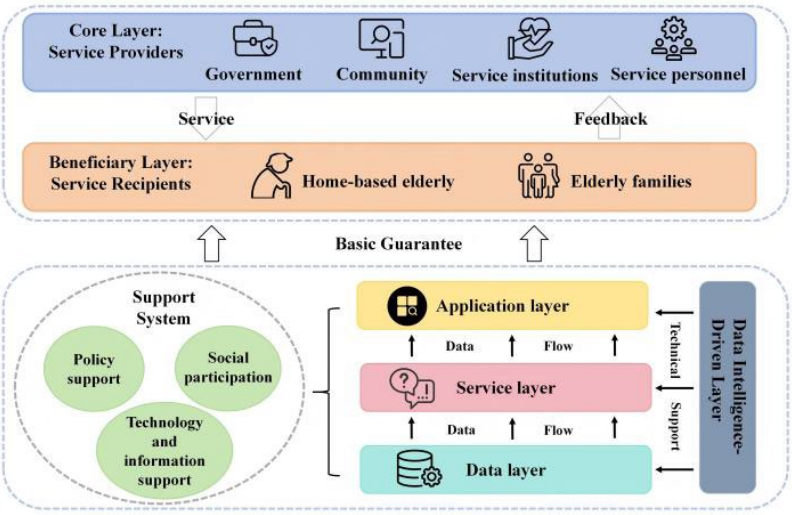


Figure 1. Theoretical framework of the home and community-based elderly care service ecosystem

Six linked record types are used: user, need, service, provider, work order, and feedback. The user record contains an anonymous identifier, age band, contact channel, mobility assistance flag, and consent status. The need record stores category, requested time, urgency, recurrence, and caller role. The service record defines duration, qualification, cost class, capacity, and verification method. The provider record stores service area, available slots, qualification expiry, and current workload. Work orders store assignment, timestamps, exceptions, and closure evidence. Feedback contains a five-point clarity rating, a problem code, and the follow-up action. Diagnoses, continuous location traces, and unrestricted free-text medical notes are excluded. Names and telephone numbers are visible only to authorized coordinators during active service handling and are removed from exported evaluation files (see Table 2).

Table 2. Minimum Data Fields and Control Rules

Record	Required fields	Control rule
User	anonymous ID, channel, assistance, consent	annual consent review
Need	category, time window, urgency, recurrence	urgent request checked by staff
Service	duration, skill, capacity, verification	versioned service definition expired
Provider	area, slots, qualification, workload	qualification blocks assignment
Work order	owner, state, timestamps, exception	closure requires evidence
Feedback	five-point clarity rating, problem code, follow-up	unresolved issue reopened in 24 h

Table 3. Workflow States and Control Points

State	Entry trigger	Required control
Registered	Request received through tablet, telephone, paper, or staff entry	Consent and contact channel recorded
Scored	Minimum need fields completed	Priority score calculated and high-risk requests flagged
Matched	Eligible providers available	Qualification, time window, and service area checked
Confirmed	Coordinator accepts candidate or records override	Provider confirmation timestamp stored
Delivered	Service worker completes task	Closure evidence or exception code required
Verified	Coordinator checks completion record	Late, reassigned, or disputed work orders reviewed
Closed/Reopened	Feedback captured or unresolved problem detected	Unresolved issue reopened within 24 h

3.3. Priority and Matching Model

Rather than treating every incoming request as first-come-first-served, the system triages using a priority score Pi that combines four factors coordinators already consider informally: urgency, safety risk, waiting pressure, and lack of alternative assistance. Staff rate each factor on a 0–0.5–1 scale using predefined examples, which reduces ambiguous free-text judgement while keeping the input understandable. Operationally, each scale point was anchored by written request examples defined before the pilot; staff were instructed to assign the example closest to the observed request and to escalate borderline cases rather than improvise a score. The full rating instructions and anchor examples are available from the corresponding author upon reasonable request as a supplementary instrument. The weights were set as operational parameters before the pilot after two coordinator workshops; they were not trained coefficients and should be recalibrated before deployment in a different service setting. The resulting formula is:

$$P_i = 0.35U_i + 0.30R_i + 0.20D_i + 0.15A_i \quad (1)$$

The score triggers one of three workflows: above 0.75, the request joins a same-day review queue (this threshold was set so that only requests scoring high on at least two factors, such as urgency and safety, would jump the line); between 0.45 and 0.75, it enters the next regular scheduling cycle; below 0.45, it is handled within the user's originally requested time window. These bands reflect the capacity of the pilot centers and can be adjusted as part of routine management.

For provider matching, the system first filters out anyone lacking the required qualification, then ranks the remaining candidates by how well their service category, available time, and travel zone match the request, with a small boost for historical quality and a penalty for current workload. The matching score is:

$$M_{ij} = 0.40C_{ij} + 0.25T_{ij} + 0.20L_{ij} + 0.15Q_j - 0.20B_{ij} \quad (2)$$

Here the workload penalty is deliberately modest: a provider who is excellent but busy should not be excluded outright, only moved lower in the list. The top three candidates are shown to a coordinator, who can accept the ranking or override it with a reason code. This keeps the algorithm in a supporting role: it narrows the search space, exposes the basis for a recommendation, and records the moment when professional discretion takes over. Table 4 defines each variable and its source.

Table 4. Variable Definitions for Priority and Matching Scores

Variable	Range	Source and interpretation
Ui	0–1	Urgency score entered by staff from predefined request examples
Ri	0–1	Safety-risk score requiring same-day staff review when high
Di	0–1	Delay pressure based on elapsed waiting time against the requested service window
Ai	0–1	Lack of alternative assistance from family, neighbor, or existing provider
Cij	0–1	Fit between requested service category i and provider j's authorized service type
Tij	0–1	Compatibility between requested time window and provider availability
Lij	0–1	Travel-zone or service-area fit
Qj	0–1	Historical quality score from recent verified work orders
Bij	0–1	Current workload burden used as a ranking penalty

3.4. Interaction and Deployment Configuration

Figure 2 shows the interaction mechanism among roles, goals, value activities, value objects, processes, and services. In the implementation, a role performs a value activity by changing a work-order state; the resulting record becomes a value object available to authorized actors. Government and community supervisors see aggregate demand and unresolved exceptions. Providers see assigned tasks and necessary contact details. Families receive an optional completion message. Older adults can use a large-button tablet at the center, call staff, or submit a paper request. Human-centered interaction requirements were applied to label size, visible system status, recovery, and staff assistance [14].

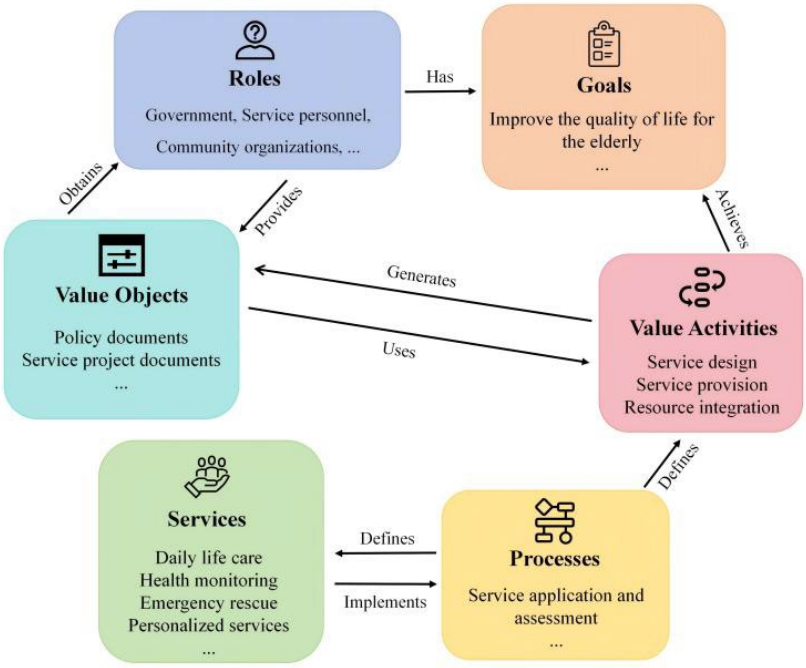


Figure 2. Interaction mechanism among the key elements of the elderly care service ecosystem

The pilot used two 10.1-in Android tablets, two office computers, a local wireless router, and a spreadsheet-compatible database exported daily as CSV. The four tablet actions were request service, check status, call staff, and provide feedback. Buttons were at least 12 mm high, body text was 18 pt, and no gesture was required. When a tablet was unavailable or a participant preferred not to use it, staff entered the same request form on an office computer or paper register before daily closure. The system used role-based accounts, daily encrypted backup, access logs, automatic logout after 10 min, and a 90-day retention period for identifiable pilot records. These controls follow information-security management principles in ISO/IEC 27001 [15] and software-quality characteristics in ISO/IEC 25010 [16]. The national smart health and elderly-care action plan informed the choice of interoperable, affordable components [17].

Shanghai's embedded community model and Japan's integrated home-care arrangements were used as configuration references. The Shanghai case supports a community hub that coordinates nearby services, whereas the Japan case emphasizes integration of home visits, day care, health support, and family preferences. A conjoint study of Japanese home-care preferences shows that service content, monitoring, and provider-related attributes affect choice [18]. These cases were not treated as equivalent outcome datasets; they were used to check whether the same data model could represent different institutional arrangements.

4. Experiments and Results

4.1. Validation Objectives

The pilot was designed as a direct validation of the architecture and rules specified in Section 3. The first objective was to test whether the layered data architecture and minimum-field rules could represent a complete request from registration to verified closure without duplicate entry. The second objective was to test whether the priority score in (1) improved demand-to-confirmation time by making urgency, safety risk, waiting pressure, and alternative-service availability explicit. The third objective was to test whether the matching score in (2) improved matching accuracy and reduced coordinator time by ranking qualified providers against time, location, quality, and workload conditions.

The two community centers were selected to exercise the stakeholder coverage of the framework rather than to represent a single provider. Older adults and family members formed the beneficiary layer and initiated or confirmed requests. Community coordinators represented the core layer's orchestration role, service workers represented delivery providers, and center supervisors performed the governance and aggregate-monitoring role normally associated with government or municipal oversight. Government agencies were not assigned individual requests; their role was simulated through the supervisor dashboard, policy thresholds, retention rules, and weekly exception review. Telephone, paper, and tablet requests entered the same data and scoring path, allowing the experiment to test both digital and assisted access.

4.2. Pilot Design and Data Collection

An eight-week AB/BA pilot was conducted at two urban community centers. Site A used the supported workflow for weeks 1–4 and the routine workflow for weeks 5–8; Site B used the reverse order. The same coordinators, service categories, intake channels, and closure definitions were used in both conditions to reduce operational heterogeneity. Forty-two community-dwelling adults aged 65–82 participated, including 25 women and 17 men. Twelve used a walking aid and nine reported that they did not independently use a smartphone. Four community coordinators and eleven service workers operated both workflows after a 90-min training session. Routine operation used telephone, paper registers, and an existing messaging group. The supported condition added structured records, scoring, candidate ranking, timestamps, access logs, and family notification.

The dataset contained 386 valid requests: 187 under routine operation and 199 under digital-intelligence support. Requests included meal delivery (92), housekeeping (71), accompanied visits (54), health consultation scheduling (68), home maintenance (43), and community activities (58). Test records and cancellations before assignment were excluded. Twenty percent of completed work orders were independently checked by a second coordinator; agreement on completion and reassignment status was 92.3%, with Cohen's kappa of 0.81. Tablet and telephone requests were merged under the same rules, so channel choice did not change priority.

Participant-level weekly means were the primary analysis unit. Paired permutation tests with 10,000 sign swaps compared conditions; mean differences, 95% confidence intervals, and Cohen's dz are reported. Completion proportions were also checked with a mixed-effects logistic model containing condition and period as fixed effects and participant and site as random intercepts. The direction of the model estimates matched the paired analysis. Missing satisfaction responses accounted for 13 of 386 requests and were not imputed. Confirmation time was measured from request registration to provider confirmation; coordination time captured active staff minutes before assignment; on-time completion meant closure within the agreed service window; matching accuracy meant no category, qualification, or reassignment error; family notification meant that a completion message or call was logged; service clarity was the five-point rating collected after closure.

4.3. Service Performance

Table 5. Pilot Outcomes by Workflow Condition (N = 42)

Outcome	Routine	Supported	Difference (95% CI)
Confirmation time	58.4 ± 21.7 min	36.9 ± 18.5 min	-21.5 (-28.1, -14.9)
On-time completion	79.2 ± 12.6%	89.1 ± 9.8%	+9.9 (5.9, 13.9)
Matching accuracy	83.8 ± 10.4%	91.6 ± 7.9%	+7.8 (4.6, 11.0)
Coordination time	8.9 ± 2.1 min	6.2 ± 1.8 min	-2.7 (-3.4, -2.0)
Family notification	69.4%	91.1%	+21.7 percentage points
Service clarity	3.46 ± 0.64 / 5	4.09 ± 0.58 / 5	+0.63 (0.42, 0.84)

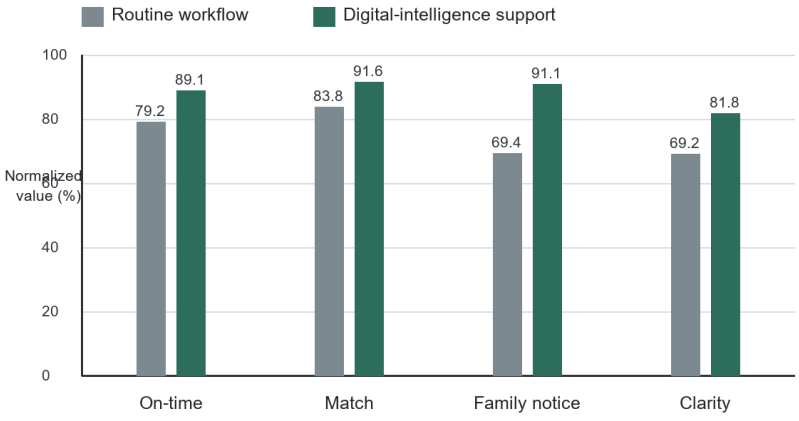


Figure 3. Normalized service outcomes under routine and digital-intelligence-supported workflows

Mean demand-to-confirmation time decreased by 21.5 min ($p < 0.001$; $dz = 1.03$). The reduction was largest for meal delivery and accompanied-visit requests, which had several eligible providers and therefore benefited from visible availability. The reduction was smaller for health consultation scheduling because only two qualified providers were available. Staff coordination time decreased by 2.7 min per request ($p < 0.001$; $dz = 0.91$), primarily because coordinators no longer searched three separate records before contacting a provider.

On-time completion increased by 9.9 percentage points ($p < 0.001$; $dz = 0.76$), and matching accuracy increased by 7.8 points ($p = 0.002$; $dz = 0.71$). Eleven supported assignments were manually overridden: five for user preference, three for provider continuity, two for language compatibility, and one for a temporary mobility constraint. The override rate shows that rule-based ranking supported rather than replaced local knowledge. During routine operation, 23 requests required reassignment; the supported workflow required 13. The period-adjusted model estimated an odds ratio of 2.08 for on-time completion.

Family notification completeness rose from 69.4% to 91.1%. Service clarity increased from 3.46 to 4.09 on the five-point scale ($p < 0.001$; $dz = 0.84$). Nine participants used only telephone or staff-assisted entry throughout the pilot, but their confirmation and completion outcomes improved because the back-office workflow was shared across channels. Three planned services remained late under the supported condition because provider capacity was unavailable, demonstrating that data coordination cannot substitute for workforce capacity. No urgent request was automatically assigned without coordinator review (see Table 5 and Figure 3)

5. Analysis and Discussion

5.1. Interpretation of Key Findings

The 21.5-minute drop in demand-to-confirmation time can largely be traced to a shift in how requests moved through the system. Under the routine workflow, registration, review, and provider acceptance were scattered across separate notebooks, messaging groups, and verbal handoffs. Once these steps were captured as explicit, visible states in the digital-intelligence workflow, coordinators no longer had to reconstruct the conversation history before acting. Formula (1) added another layer of efficiency: by forcing urgency, safety risk, waiting pressure, and alternative-service availability onto the same 0–1 scale, it removed the need for ad-hoc triage discussions. The effect was most pronounced for meal delivery and accompanied visits, where multiple eligible providers existed and could be compared at a glance. Health consultation scheduling, by contrast, improved far less—a reminder that when the qualified-provider pool is tiny, no scoring rule can manufacture capacity. This asymmetry suggests that the system's value lies in making existing resources more visible, not in somehow compensating for their absence.

The gains in on-time completion (+9.9 points) and matching accuracy (+7.8 points) follow a similar logic. Formula (2) pre-filtered out providers lacking the required qualification or a compatible time window, then ranked the remainder by category fit, location, quality, and current workload. This sequence reduced the cognitive load of matching but did not eliminate the need for human judgement. In fact, the 11 manual overrides—five for user preference, three for provider continuity, two for language compatibility, and one for a temporary mobility constraint—are among the most informative results of the pilot. They show that local knowledge and relational continuity still matter, and that an interpretable algorithmic recommendation can actually surface the exact moment where professional discretion should take over, rather than hiding it behind a black-box score.

Coordination time also fell, but the reduction came with an important caveat. Staff spent less time reconciling fragmented records and more time assisting users who preferred telephone or paper channels—a welcome rebalancing of effort. Yet three planned services still missed their targets under the supported workflow simply because no qualified provider was available. The system, in other words, is a coordination tool, not a capacity-creation tool. Confusing the two would lead to unrealistic expectations about what digital-intelligence support can deliver in resource-constrained community settings.

5.2. Comparison with Related Work

These findings speak directly to Airola's review on eHealth use among older adults [6]. Airola identified access to assistance, usability, and fit with daily routines as critical enablers—factors that are often assumed away in technology-centric deployments. Our design took this seriously: support was not a one-off training session but an ongoing capability. Coordinators could enter telephone or paper requests on behalf of users, and those requests flowed through the same priority and matching rules as tablet-based ones. Nine participants who never used a smartphone independently still benefited from the same back-office improvements. This channel-neutral approach moves the field beyond treating digital competence as a prerequisite for service access and instead treats it as something that can be supported through design.

The pilot also addresses a concern raised by Kunonga et al. [7] about digital first-contact interventions potentially widening inequity. Rather than replacing face-to-face contact with a portal, we treated first contact as a service event that could originate from a tablet, a phone call, a paper form, or a staff conversation. The measurable results—family notification completeness up 21.7 points, service clarity up 0.63 points—do not, of course, prove universal equity. Within the boundaries of this two-site pilot, they do show that equity-related requirements—such as channel neutrality and assisted access—can be engineered into a system as testable requirements rather than left as abstract aspirations; whether

these effects generalize to other settings requires larger-scale replication.

Vink et al.'s service ecosystem design model [5] provided the conceptual scaffolding for this work, but the pilot pushed it in a more operational direction. Where Vink et al. describe ecosystem outcomes as emergent and only loosely controllable, our contribution was to make that emergence legible: field definitions, state transitions, threshold rules, and override codes turned institutional and collective logic into executable records. The theoretical perspective explains why multiple actors and arrangements matter; the architecture specifies how a community center can actually record and evaluate those interactions. This is a complementary, rather than competitive, relationship. Compared with existing digital care coordination systems, which typically assume a single institutional owner, a stable provider pool, and a dedicated platform, the advance of the present work is architectural and empirical rather than algorithmic: it derives the workflow from ecosystem-level roles and rules, reduces that workflow to minimum data fields and auditable scoring rules executable on spreadsheet-compatible records and ordinary tablets, and evaluates those rules in a two-site crossover pilot using service-process measures rather than design arguments alone. The same spirit animates Oh et al.'s call for age-appropriate digital literacy measurement [8] and Dong et al.'s evidence on structured interventions for older adults [11]: both point toward assisted interfaces and measurable comprehension rather than assuming uniform technology skill.

5.3. Limitations and Future Work

Several limitations should temper interpretation. The sample—42 older adults across two urban community centers—was adequate for detecting process-level feasibility signals but far too small for subgroup analysis by age, disability, income, or digital literacy. The present report also does not provide a full account of the two centers' characteristics, the participant recruitment and allocation procedure, or an a priori sample-size justification; these details should be documented in future trials to support full reproducibility and comparability. Urban centers also have advantages that rural or dispersed settings lack: denser provider networks, shorter travel distances, and more stable staffing. Extending the same field schema to rural areas with weaker broadband and fewer providers would be a much stronger test. The AB/BA crossover design helped control for period effects, but staff inevitably knew which workflow was active, so learning and awareness biases cannot be ruled out. In particular, familiarity with procedures or habits formed during the first condition could carry over into the second condition at each site; the period-adjusted mixed-effects model mitigates period-related drift but cannot fully separate such learning or carryover effects from the workflow contrast in a two-site crossover. A parallel-arm or stepped-wedge design would be needed to estimate them independently.

We also measured service-process outcomes, not health outcomes, caregiver burden, or cost savings. The coordination-time reduction is promising, but it is not a net economic return until device depreciation, training, ongoing support, provider travel, and data-governance costs are factored in. Satisfaction and clarity were self-reported, and family notification was recorded as a completion event, not as an independently confirmed receipt. These were reasonable choices for a low-cost feasibility study, but they narrow the claims we can make. To support reproducibility, the implementation artifacts described above are available from the corresponding author upon reasonable request; the underlying de-identified records were not included in this article to protect participant privacy.

Future work should therefore go in several directions at once. First, deploy the same schema in both rural and urban sites with varying provider density, and follow requests for at least six months—long enough to catch seasonal and capacity fluctuations. A stepped-wedge or parallel-site design would separate period effects from workflow effects more cleanly than our AB/BA arrangement. Second, a proper cost analysis is needed, combining staff minutes saved, avoided duplicate contacts, travel distance, equipment replacement cycles, and exception-handling overhead. Third, the priority weights in Formula (1) should be validated against observed safety outcomes, not just process timings. Finally, governance questions—deletion requests, access logs, supplier exit, and the consequences of incorrect or incomplete data—deserve their own investigation. These are not afterthoughts; they are the conditions under which a system like this could be responsibly scaled.

6. Conclusion

This paper presents an implementable digital-intelligence workflow system for home and community-based elderly care. The system links records across service providers, beneficiaries, and support agencies, and embeds transparent priority and matching formulas within a controlled work-order state machine accessible through tablet, telephone, paper, and staff-assisted channels. In an eight-week pilot involving 42 older adults and 386 service requests, process-level improvements were observed: confirmation time fell by 21.5 minutes, coordination time fell by 2.7 minutes per request, on-time completion increased by 9.9 percentage points, and matching accuracy increased by 7.8 percentage points. These results demonstrate operational feasibility rather than universal effectiveness. Larger multi-site trials, longer follow-up, and cost analysis are required before the system can be responsibly scaled. Its practical value lies in rendering responsibilities, capacity constraints, and exceptions visible while preserving staff review, human override, telephone access, and data minimization.

Acknowledgements

This work was supported by the Large Model Foundation and Application Based on Domestic Computing Power under Grant No. ZZY20251114, and by the Tianjin Science and Technology Plan Project-Research on Key Technologies and Industrial Application

Demonstration of General-Purpose Large Models for Autonomous Intelligent Computing Power under Grant No. 24ZGZNGX00020.

References

[1] National Bureau of Statistics of China, Communique of the Seventh National Population Census (No. 5): Age Composition of the Population, Beijing, China, 2021.

[2] World Health Organization, National Programmes for Age-Friendly Cities and Communities: A Guide. Geneva, Switzerland: WHO, 2023.

[3] State Council of the People's Republic of China, The 14th Five-Year Plan for National Aging Development and Elderly Care Services, Beijing, China, 2022.

[4] Vargo SL, Lusch RF. Institutions and axioms: an extension and update of service-dominant logic. Journal of the Academy of marketing Science. 2016 Jan;44(1):5-23. https://doi.org/10.1007/s11747-015-0456-3

[5] Vink J, Koskela-Huotari K, Tronvoll B, Edvardsson B, Wetter-Edman K. Service ecosystem design: Propositions, process model, and future research agenda. Journal of Service Research. 2021 May;24(2):168-86.

[6] Airola E. Learning and use of eHealth among older adults living at home in rural and nonrural settings: systematic review. Journal of medical Internet research. 2021 Dec 2;23(12):e23804. https://doi.org/10.2196/23804

[7] Kunonga TP, Spiers GF, Beyer FR, Hanratty B, Boulton E, Hall A, Bower P, Todd C, Craig D. Effects of digital technologies on older people's access to health and social care: umbrella review. Journal of medical Internet research. 2021 Nov 24;23(11):e25887. https://doi.org/10.2196/25887

[8] Oh SS, Kim KA, Kim M, Oh J, Chu SH, Choi J. Measurement of digital literacy among older adults: systematic review. Journal of medical Internet research. 2021 Feb 3;23(2):e26145. https://doi.org/10.2196/26145

[9] Xie L, Zhang S, Xin M, Zhu M, Lu W, Mo PK. Electronic health literacy and health-related outcomes among older adults: a systematic review. Preventive medicine. 2022 Apr 1;157:106997. https://doi.org/10.1016/j.ypmed.2022.106997

[10] Ehn M, Richardson MX, Landerdahl Stridsberg S, Redekop K, Wamala-Andersson S. Mobile safety alarms based on GPS technology in the care of older adults: systematic review of evidence based on a general evidence framework for digital health technologies. Journal of medical Internet research. 2021 Oct 11;23(10):e27267. https://doi.org/10.2196/27267

[11] Dong Q, Liu T, Liu R, Yang H, Liu C. Effectiveness of digital health literacy interventions in older adults: single-arm meta-analysis. Journal of Medical Internet Research. 2023 Jun 28;25:e48166. https://doi.org/10.2196/48166

[12] Shah SG, Nogueras D, van Woerden HC, Kiparoglou V. Evaluation of the effectiveness of digital technology interventions to reduce loneliness in older adults: systematic review and meta-analysis. Journal of medical Internet research. 2021 Jun 4;23(6):e24712. https://doi.org/10.2196/24712

[13] Governance OS. Challenges and the Way Forward. Organisation for Economic Co-Operation and Development: Paris, France. 2023.

[14] International Organization for Standardization, ISO 9241-210:2019, Ergonomics of Human-System Interaction—Part 210: Human-Centred Design for Interactive Systems. Geneva, Switzerland: ISO, 2019.

[15] International Organization for Standardization, ISO/IEC 27001:2022, Information Security Management Systems—Requirements. Geneva, Switzerland: ISO, 2022.

[16] International Organization for Standardization, ISO/IEC 25010:2023, Systems and Software Engineering—Systems and Software Quality Requirements and Evaluation. Geneva, Switzerland: ISO, 2023.

[17] Ministry of Industry and Information Technology, Ministry of Civil Affairs, and National Health Commission of China, Action Plan for the Development of the Smart Health and Elderly Care Industry (2021–2025), Beijing, China, 2021.

[18] Kaneko S. Estimating Family Preference for Home Elderly-care Services: Large-scale Conjoint Survey Experiment in Japan. RePEc: Research Papers in Economics. 2019 Jan 1.