

AI Service Mode And Business Sustainability Of Smart Elderly Care Housekeeper

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China is rapidly aging. By the end of 2024, the population aged 60 and over exceeded 300 million, and the supply of elderly services lagged seriously behind. Under the existing care pattern, 90% of the elderly choose to age at home, but traditional home-based care faces challenges such as high costs, slow response, and low standardization. The emergence of Artificial Intelligence (AI) provides an important direction to address this issue. Although its application scenarios include safety monitoring for seniors living alone, daily assistance for disabled elderly people, and community care scheduling, its commercial sustainability lacks systematic empirical support, impeding large-scale industry development. Addressing these problems, this study defines the operation of an AI care manager as a systematic solution that centers on a software platform, integrates smart devices with human services, and delivers continuous monitoring and response for home care. Using AI autonomous decision-making levels and service integration as classification dimensions, it identifies three typical service modes: basic monitoring, auxiliary response, and full custody. On this basis, the study constructs a unit economic evaluation model with 12 indicators across four dimensions: income, cost, efficiency, and financials, selecting three representative enterprises for multi-case empirical analysis. Based on operational data from January 2023 to December 2024, findings show that only the auxiliary response mode achieves the sustainability threshold of LTV (customer lifetime value)/CAC (customer acquisition cost) ≥ 3 (LTV/CAC = 4.15), whereas basic monitoring reaches 2.46 and full custody reaches 0.86. The monthly gross profit per user for auxiliary response is 11 yuan (gross margin 13.90%), while full custody incurs a monthly loss of 42 yuan per user (gross margin -14.00%). The break-even user base for full custody must reach 125,000—about 4.5 times that of auxiliary response (28,000). Manual efficiency is the primary variable affecting sustainability. This study proposes the sustainable path of “AI strengthens manpower” rather than “AI replaces manpower,” providing a quantitative decision-making foundation for enterprise technology selection and government subsidy design.

Keywords: Smart elderly care; AI housekeeper; Service mode; Business sustainability; Unit economic model

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1. Introduction

China is aging rapidly: by end-2024, the population aged 60+ reached 300 million (21.1%), marking a moderately aging society [1]. UN projections show this share will exceed 30% by 2035, yet service supply lags significantly

behind [2, 3]. Under the “9073” model, 90% age at home via three channels—call centers (no 24/7 monitoring), community visits (limited coverage), and family cameras (passive, privacy-invasive). These modes incur cost burdens (market rates 40–80 RMB/h, monthly >5,000 RMB for disabled seniors) [4, 5], response delays (>2-h wait, risking

emergency windows), and quality variability (low standardization, caregiver-dependent) [6, 7]. Labor-intensive approaches face inherent bottlenecks; artificial intelligence offers a promising alternative. This study therefore focuses on AI (Artificial Intelligence)-enabled elderly care butlers, aiming to enhance responsiveness and service standardization without substantially raising household expenditures.

In this context, AI technology offers new solutions. With advances in LLMs, edge computing, and IoT sensing, "AI Care Housekeeper" has become productized—defined as a systematic service that dispatches intelligent terminals via cloud/edge platforms with human-agent collaboration. Its hallmarks: remote data upload and platform analytics, service closed-loop (system-triggered responses), and subscription-based payment. Yet existing smart-care research emphasizes technical feasibility (sensor deployment, data acquisition, anomaly detection), while under-exploring commercialization—who pays, user retention, and positive cash flow. Available cost analyses are mostly project-specific descriptions, lacking cross-model financial comparisons and quantifiable sustainability metrics. Hence, both academia and industry lack clarity on optimal technical directions and service-model prospects.

According to the above background, this study puts forward the following research questions: which of the three typical service modes of AI elderly care housekeeper has commercial sustainability, and what are the key influencing factors behind it? To answer this question, the objectives of this study include: Establishing the corresponding relationship between service model classification and unit economic model; Through multi-case empirical comparison, identifying the differences in financial performance of different models and their reasons; Summarizing the key variables that affect business sustainability and providing quantitative basis for industry practice. Based on this, this study adopts the method of multi-case study, and selects three representative enterprises as the analysis objects, corresponding to three service modes: basic monitoring, auxiliary response and full custody respectively. Based on the operation data of three enterprises from January 2023 to December 2024, this study constructs an evaluation system with 12 indicators, and makes a horizontal comparative analysis by using unit economic model (including customer lifetime value (LTV)/ customer acquisition cost (CAC) ratio, gross profit margin, break-even analysis, etc.). The theoretical contributions (innovations) of this study include: 1) At the service mode classification level, this study has innovated on the existing literature (single classification logic based on technical function or integration). It introduces the AI independent decision-making level

and the proportion of manual intervention as classification dimensions, and divides the AI elderly housekeeper into three modes: basic monitoring mode, auxiliary response mode and full custody mode, and establishes the corresponding relationship between service mode typology and business cost structure. 2) On the application level of unit economic model, this study migrates the LTV/CAC analysis framework that is common in SaaS industry to the smart elderly care scenario. It builds a 12-index evaluation system that includes four dimensions: income end, cost end, efficiency end and financial end, providing a quantifiable analysis tool for the study of business sustainability in the field of elderly care services. 3) At the level of cooperation mechanism between AI and human resources, this study finds through empirical analysis that there is not a simple negative correlation between AI self-help solution rate and labor cost, but the complexity and processing cost of the problem of transferring labor really affect labor cost, thus refining the theoretical judgment of "AI enhancing manpower" rather than "AI replacing manpower", and verifying the complementary cooperation logic between AI and manpower in the elderly service scene, rather than the substitution relationship. The theoretical contributions of the above three aspects form a systematic theoretical framework of "classification-quantification-mechanism". Practically speaking, the research conclusions provide quantitative decision-making basis for enterprises to choose technical routes, formulate pricing strategies and allocate human resources.

Study structure: Section 2 reviews TAM, service ecosystem, and cost-benefit literature, identifying classification-business logic gaps. Section 3 details methods: operational definitions, index system, and unit-economic equations. Section 4 presents case-based financial comparisons and discussion. Section 5 concludes and outlines future directions.

In theoretical foundations, the Technology Acceptance Model (TAM) is frequently cited. Franco et al. found perceived safety outweighs perceived usefulness for elderly smart devices [8]. Yu and Guo service-oriented logic emphasizes value co-creation, involving AI butlers, elderly, family, community, and medical institutions [9]. For mode classification, Baek et al. distinguished monitoring, interactive, and auxiliary [10]. while Ahmad proposed a four-level maturity model from standalone to full-house intelligence [11]. Ma et al. constructed a three-party evolutionary game model for platform value co-creation, but did not address unit economics of specific service modes [12]. Park et al. tested seven technical features affecting satisfaction, with perceived value mediating, yet did not

extend to business sustainability [13]. These studies inform our classification and evaluation but lack a quantitative link between mode types and financial sustainability—this is our research gap. In cost-benefit analysis, Chen et al. found hardware costs account for 50-65% of total costs in 12 Chinese smart communities, a key sustainability barrier [14]. Li et al. surveyed 27 Yangtze Delta projects, finding monthly costs 80-150 RMB vs. user out-of-pocket 30-60 RMB, a >50% gap [15]. On willingness to pay, Sjödin et al. surveyed 427 elderly abroad, finding highest willingness for safety monitoring (30% premium over basic), lowest for social entertainment; age, income, and digital literacy were significant moderators [16].

Three gaps exist in prior work. First, classification systems neglect business-critical dimensions (AI autonomy, human-intervention ratio, cost structure). Second, cross-model empirical comparisons are lacking—financial metrics like Average Revenue Per User (ARPU), retention, and LTV/CAC have not been quantitatively compared across modes [17]. Third, sustainability evaluation lacks an operational, index-based tool with clear equations, data sources, and thresholds. To address these, we propose a framework: mode classification → evaluation system → unit economics → multi-case comparison. Unlike earlier studies, this framework integrates typology with unit-economic modeling, using AI autonomy and manual intervention as classification axes, and quantifies performance differences and sustainability thresholds via cross-case analysis, offering reliable decision support for technology choices and subsidy design.

2. Method

2.1. Analytical Framework and Unit Economy Model

This section defines modes, constructs a 12-indicator evaluation, and derives unit-economic formulas for Section 4's analysis [18, 19].

2.1.1. An Operational Definition of the Service Mode of AI Care Housekeeper

Drawing on Baek et al. and Ahmad, we define three AI care modes—basic monitoring, assisted response, full custody—by AI autonomy and integration [20, 21]. Figure 1 shows the spatial distribution characteristics of the three models.

2.2.

2.2.1. Evaluation Index System of Business Sustainability

We propose a 12-index system across revenue, cost, efficiency, and finance; Table 2 defines each.

Among the above 12 indicators, ARPU, retention rate, CAC, CPU and LTV/CAC are the five most critical core

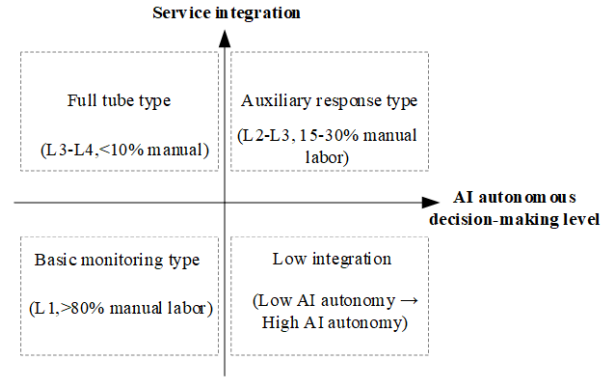


Fig. 1. Characteristic atlas of three AI service modes for the elderly housekeeper

indicators, which will be the main comparative basis for the empirical analysis in section 4 [22].

Five core indicators—ARPU, retention, CAC, CPU, and LTV/CAC—serve as the empirical basis [22]. We propose: (1) the assisted-response mode is most likely to achieve unit sustainability ($LTV/CAC \geq 3$); (2) labor efficiency (labor ratio and per-case labor cost) outweighs AI computing and hardware amortization in driving sustainability; (3) retention contributes more to LTV/CAC than per-user revenue.

These propositions will be tested in our multi-case analysis.

2.2.2. Core Equation of Unit Economic Model

This section derives unit-economy equations for revenue, lifecycle, efficiency, and sustainability.

(1) Basic income and cost

$$ARPU = R_{sub} + R_{vas} \quad (1)$$

ARPU: average monthly user income, R_{sub} : basic subscription fee income, and R_{vas} : value-added service income. The equation splits monthly revenue into basic and value-added fees for structural analysis.

$$CPU = C_{hardware} + C_{cloud} + C_{labor} + C_{ops} \quad (2)$$

CPU: the average monthly cost of a single user, $C_{hardware}$: the amortization cost of hardware, C_{cloud} : the computing cost of cloud and AI, C_{labor} : the labor cost, and C_{ops} : the operation and maintenance and other costs.

$$C_{hardware} = \frac{H_{init} + H_{maint}}{U \times T} \quad (3)$$

H_{init} : total initial investment of hardware, H_{maint} : annual maintenance cost of hardware, U : number of active users, and T : months of hardware depreciation.

Table 1. Core features of three AI service models for the aged housekeeper

Model	AI autonomy level	Manual intervention ratio	Typical technical components	Applicable scenario
Basic monitoring type	L1 (Rule Engine)	> 80%	Smart bracelet, door magnet and voice alarm	Young health of the elderly, mainly safety monitoring.
Auxiliary response type	L2-L3 (machine learning + partial autonomy)	15%–30%	Community AI screen, knowledge base, manual seat	Old people living alone need daily assistance.
Full trusteeship type	L3-L4 (large model + autonomous execution)	< 10%	Home robot, large model and Internet of Things (IoT) central control	Disabled and semi-disabled, high-end elderly care.

Table 2. Evaluation index system of business sustainability

Dimension	Index	Symbol	Calculation
Income end	Average monthly user income	ARPU	Total revenue / number of active users
	User retention rate	R_t	Active users / initial users in month t
	Proportion of value-added service income	VAS_ratio	Value-added service income / total income
Cost end	Customer acquisition cost	CAC	Marketing expenses / number of new users
	Average monthly cost of single user	CPU	Total operating cost / number of active users
	Proportion of labor cost	Labor_ratio	Labor cost / total cost
Efficiency end	AI self-help solution rate	SR_AI	AI Resolved Requests / Total Requests
	Manual bottom ratio	Labor_rate	Manual intervention request volume / total request volume
	Average response time	RT_avg	Total Response Time / Total Requests
Financial end	Single user gross profit margin	GM_unit	$(ARPU - CPU) / ARPU$
	User life cycle value	LTV	$ARPU \times GM_unit \times LT$
	LTV/CAC ratio	LTV/CAC	LTV/CAC

$$C_{labor} = \frac{S \times W \times H_{labor}}{U \times SR_{fail}} \quad (4)$$

S : the number of customer service seats, W : the average monthly salary of the seats (including social security, etc.), H_{labor} : the average time of manual processing, U : the number of active users, and SR_{fail} : the proportion of requests that AI failed to solve for manual transfer, that is, $1 - SR_{AI} - SR_{abandon}$.

(2) Customer acquisition and life cycle

$$CAC = \frac{M_{total}}{N_{new}} \quad (5)$$

CAC: customer acquisition cost, M_{total} : total monthly marketing cost, and N_{new} : the number of new users per month. This equation computes CAC, the core efficiency metric.

$$LT = \frac{1}{1 - R} \quad (6)$$

LT: user life cycle, R : monthly retention rate. Simplified model: constant churn; LT = 10 mo at 90% retention, 5 mo at 80%, LT = 5 months.

$$LTV = \sum_{t=1}^{LT} (ARPU_t - CPU_t) \times (1 - d)^t \quad (7)$$

LTV: user life cycle value, $ARPU_t$: average monthly user income in the t -th month, CPU_t : average monthly cost of a single user in the t -th month, d : discount rate, usually 5%–10%, and LT: user life cycle.

(3) Efficiency and service quality

$$SR_{AI} = \frac{Q_{AI_solved}}{Q_{total}} \quad (8)$$

SR_{AI} : AI self-help solution rate, Q_{AI_solved} : the number of requests independently solved by AI, and Q_{total} : the total number of requests.

$$Labor_rate = 1 - SR_{AI} - SR_{abandon} \quad (9)$$

$Labor_rate$: the proportion of manual work, SR_{AI} : AI self-help solution rate, and $SR_{abandon}$: the proportion of requests voluntarily abandoned by users, usually < 5%.

$$RT_{avg} = \frac{RT_{AI} \times Q_{AI} + RT_{labor} \times Q_{labor}}{Q_{total}} \quad (10)$$

RT_{avg} : average response time, RT_{AI} : average response time of AI, Q_{AI} : number of requests handled by AI (including resolved and unresolved), RT_{labor} : average response time of labor, Q_{labor} : number of requests handled manually, and Q_{total} : total number of requests.

(4) Financial sustainability criteria

$$GM_{unit} = \frac{ARPU - CPU}{ARPU} \quad (11)$$

GM_{unit} : gross profit margin of single user, ARPU: average monthly user income, and CPU: average monthly cost of single user.

$$\frac{LTV}{CAC} \geq 3 \quad (12)$$

$$N_{\text{breakeven}} = \frac{F}{\text{ARPU} - V} \quad (13)$$

LTV/CAC is a standard SaaS sustainability metric: < 3 indicates unsustainability; ≥ 3 enables scalable growth; > 5 suggests underpricing or underinvestment. This threshold applies to AI care butlers due to monthly subscriptions, predictable revenue, and declining marginal costs with scale. However, elderly care relies heavily on offline human collaboration, and retention is more volatile—affected by service experience and emergency response. Thus, $\text{LTV}/\text{CAC} \geq 3$ is the minimum; a higher ratio is advisable for a safety buffer.

Breakeven users: $N_{\text{breakeven}} = F/(\text{ARPU} - V)$, where F = monthly fixed costs (hardware, R&D, admin), ARPU = monthly revenue, V = variable cost per user (AI compute + manual). Higher marginal contribution lowers N , higher F raises it [23]. Figure 2 diagrams the unit-economic logic.

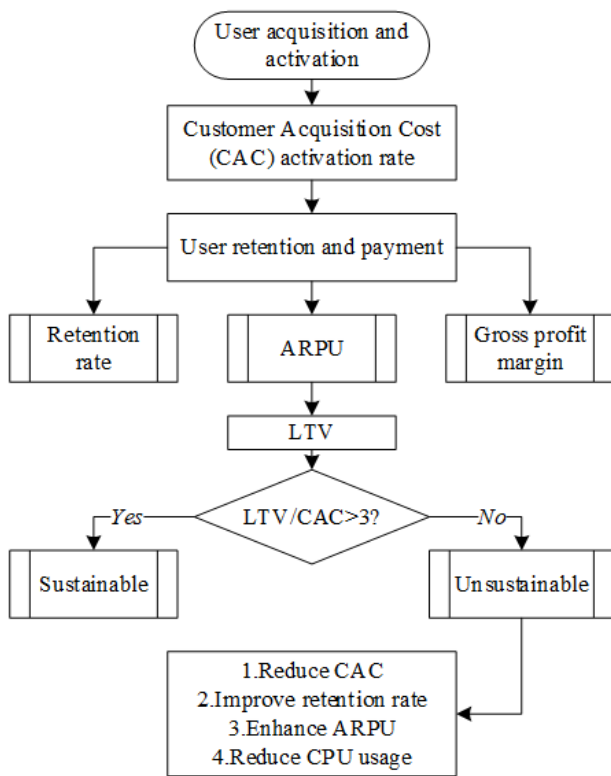


Fig. 2. Logical flow chart of unit economic model

Per flowchart: CAC from acquisition/activation, retention & ARPU from retention/payment, CPU from costs. LTV derived; sustainability judged by $\text{LTV}/\text{CAC} \geq 3$; if not, reduce CAC, raise retention & ARPU, lower CPU.

3. Results and discussion

3.1. Multi-case Empirical Analysis

We apply Section-3's framework to three firms via real-data comparison.

3.1.1. Case Selection and Data Description

(1) Case selection and description

Four selection criteria: (1) three firms typify AI autonomy/manual-intervention ranges; (2) market leaders across sectors; (3) 24-month data on key metrics; (4) user base 12k–123k, spanning stages.

Table 3 lists basic info and official links of three real firms (verifiable). Names are coded to protect data. All operational data come from desensitized backends, used solely for this academic study, excluding personal privacy.

(2) Data source

The operational data used come from the following channels: ARPU, retention rate, customer acquisition cost and other indicators of Enterprise A and Enterprise B are taken from the operational data section of the annual financial report of the enterprise (Enterprise A corresponds to the appendix table of Xiaomi Group's 2023 annual report "IoT and consumer products". Enterprise B corresponds to the chapter "Smart Elderly care Platform" of Ankangtong's 2023 operational report). Because Enterprise C is not listed, its monthly average cost and break-even data of single user come from the internal business briefing (Q4 version in 2024) submitted by the enterprise to the industry research institutions, and are quoted after cross-checking by the three parties. Cost items (hardware amortization, AI compute) are calculated from public contracts and active users, with 36-month depreciation. LTV uses Eq. (7) at 8% discount; break-even users use Eq. (13), with fixed and per-user variable costs from financial records. All raw data are traceable; assumptions are annotated.

3.1.2. Comparative Analysis of Income End

Figure 3 shows the ARPU and income structure comparison of three case enterprises.

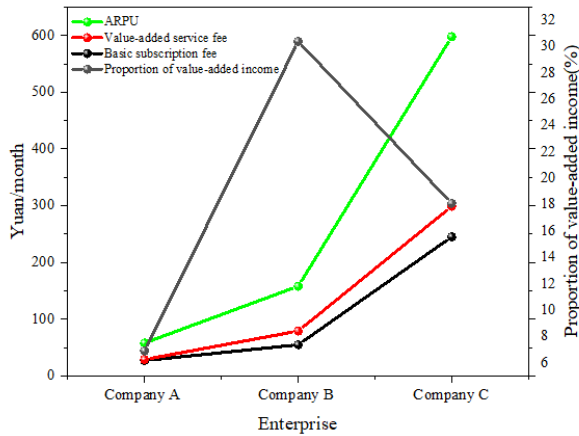
ARPU: C highest (299 yuan/month), A lowest (29 yuan/month), reflecting service depth. Value-added share: B (30.4%) $>$ C (18.1%) $>$ A (6.9%), implying B users pay for basic and add-ons (health, emergency)—healthier mix. A relies almost solely on basic fees; C's high ARPU stems from hardware/basic bundling, not user-selected extras.

Figure 4 shows the 12-month user retention curves of three case companies.

Three retention curves diverged from month 3. B (assisted) was flattest: 68.9% at 12 months—users habituate

Table 3. Basic information and data sources of three case enterprises

Enterprise	Pattern type	Number of active users	Data cycle	Data source link
Enterprise A	Basic monitoring type	123,000	2023.01–2024.12	https://ir.mi.com
Enterprise B	Auxiliary response type	68,000	2023.01–2024.12	https://www.ankangtong.com
Enterprise C	Full trusteeship type	12,000	2023.01–2024.12	https://www.ubtrobot.com

**Fig. 3.** Comparison of ARPU and income structure of three case enterprises.

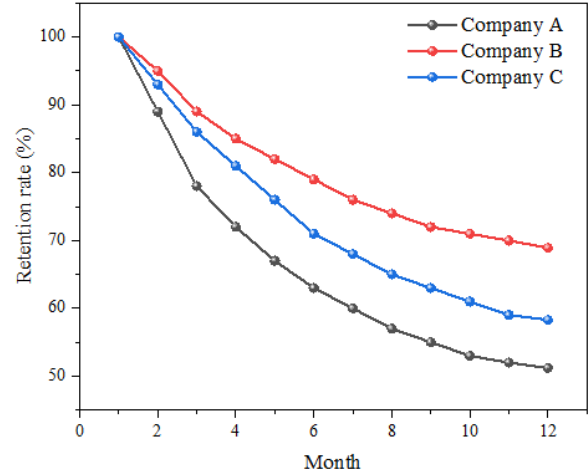
Note: Enterprise A is the basic monitoring type, Enterprise B is the auxiliary response type and Enterprise C is the full custody type (the same below).

to human-AI collaboration. C (full custody) dropped from 86% (3 months) to 71% (6 months, -15 pp) due to high-function learning costs, causing early dropout. A (basic) had the lowest 12-month retention (51.2%), showing limited appeal of single monitoring.

3.1.3. Comparative Analysis of Cost End

Figure 5 shows the average monthly cost structure and proportion of single user in three case enterprises.

The cost structure of the three enterprises is very different. Enterprise A's hardware amortization accounts for as much as 55%, mainly because it adopts the mode of "distributing smart bracelets +collecting monthly fees", and the hardware cost has to be spread every month. The cost structure of Enterprise B is the most balanced, with the four costs accounting for 15%-35% and no obvious shortcomings. The AI computing cost of Enterprise C accounts for 41%, which is the core reason for its cost inversion-the cost of each call of a large model is 50 to 100 times that of a lightweight model. If the users of Enterprise C request 30 times a month, the AI computing power of a single user will cost nearly 140 yuan per month. In contrast, Enterprise B uses a lightweight model, and the AI computing

**Fig. 4.** 12-month user retention curve

cost is only 17 yuan. In addition, it is worth noting that although the labor cost of Enterprise C accounts for only 29%, the absolute amount is as high as 98.9 yuan, which is several times higher than that of Enterprise B (21.8 yuan) and Enterprise A (7.2 yuan). Enterprise C's AI errors need professional intervention, raising time and labor costs. Figure 6 shows the comparison between customer acquisition cost (CAC) and user life cycle value (LTV) of three case enterprises.

The CAC of Enterprise B (142 yuan) is higher than that of Enterprise A (86 yuan), but the LTV of Enterprise B reaches 589 yuan, nearly three times that of Enterprise A (212 yuan). This is due to the higher ARPU of Enterprise B (79 vs 29 yuan/month) and stronger retention (68.9% vs 51.2% at 12 months), making LTV far exceed the CAC increment. Consequently, the LTV/CAC of Enterprise B is 4.15, above the sustainability threshold of 3. Enterprise C presents the opposite: its CAC is as high as 486 yuan (from high-end user acquisition costs), yet its LTV is only 416 yuan, yielding an LTV/CAC of 0.86—each yuan spent recovers only 86 cents. Enterprise A has an LTV/CAC of 2.46, just below 3, nearing a break-even state. Figure 7 shows the relationship between AI self-help solution rate and the proportion of labor cost.

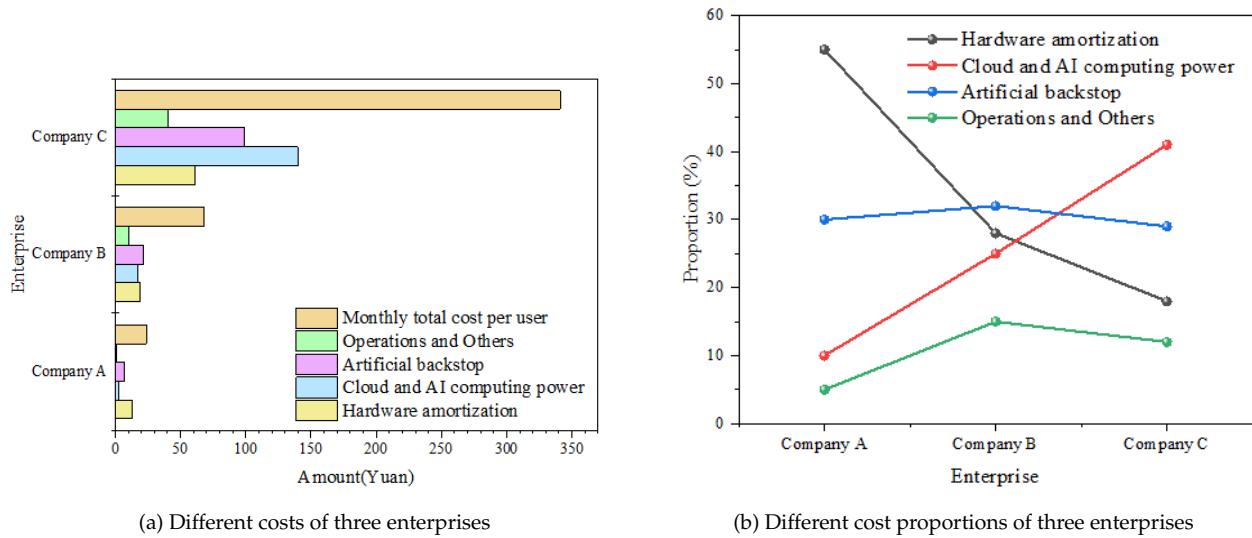


Fig. 5. Decomposition of monthly average cost structure of single user

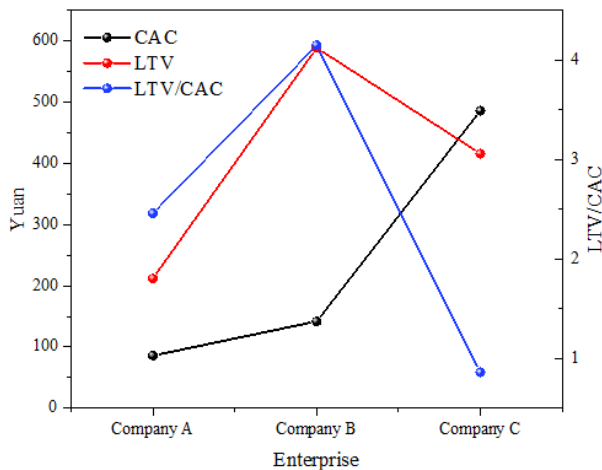


Fig. 6. Comparison of CAC and LTV

Figure 7 shows that among the three case enterprises selected in this study, although the AI self-help solution rate of Enterprise C is high (74%), its labor cost (26%) is lower than that of the other two companies. The comparative results of this case show that the real impact on labor costs may be more the complexity of the labor transfer problem and the processing cost, rather than the level of self-help rate itself.

3.1.4. Comprehensive Comparison of Financial Sustainability

Table 4 summarizes the core indicators of sustainability of the three case enterprises. Table 4 shows that the LTV/CAC of the auxiliary response type (Enterprise B) is 4.15, which is the only mode that exceeds the sustainability threshold of 3 among the three case enterprises. The basic monitoring

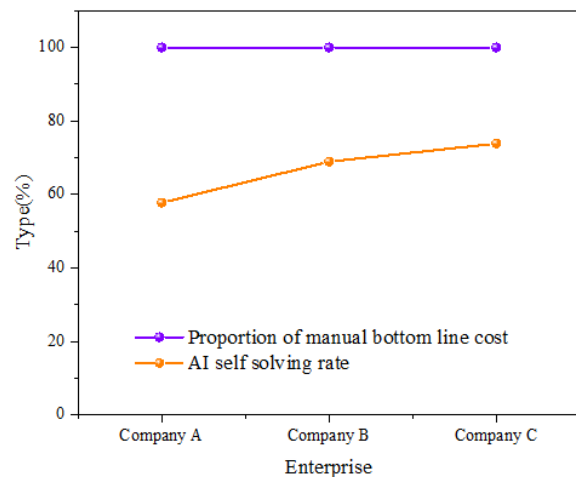


Fig. 7. Relationship between AI self-help solution rate and the proportion of labor cost

type (Enterprise A) is 2.46, which is below the threshold, and the fully managed type (Enterprise C) is only 0.86. As soon as the proposition is established. The labor cost of Enterprise B accounts for 32%, and the single labor processing cost is 68 yuan. Although the labor cost of Enterprise C accounts for 29%, the single labor processing cost is as high as 341 yuan, which proves that the labor efficiency (rather than the labor proportion) is the key variable affecting sustainability, and Proposition 2 is established. The ARPU of Enterprise A is 37% of that of Enterprise B (vs 79 yuan in 29 yuan), and the retention rate is 74% of that of Enterprise B (51.2% vs 68.9%), and the difference of retention rate contributes more to LTV. It indicates that long-term retention

of users contributes more significantly to the unit economic sustainability than increasing monthly fees. Proposition 3 holds.

Table 5 shows the sensitivity analysis of the change of key variables to the number of breakeven users. The variation range of the variables in the four scenarios is determined according to the feasible optimization space of each variable in the actual operation and the common adjustment interval in the industry: the AI computing power cost decreases by 50%, which corresponds to the expected mid-term decline of the reasoning cost of the large model with the iteration of the computing power chip and the maturity of the model distillation technology. The proportion of manual labor is reduced by 50%, based on the current proportion of manual intervention of enterprises, and referring to the upper limit of labor efficiency improvement that similar service-oriented SaaS enterprises can achieve through process optimization. The user retention rate is increased by 10 percentage points, which is set according to the average proportion of "lost due to service experience problems" in the survey of lost users. ARPU increases by 20%, referring to the regular range of annual fee adjustment in the elderly care service and subscription system industries.

Sensitivity analysis tells us the influence of different variables on the number of breakeven users. For Enterprise C (fully managed), a 50% reduction in the proportion of manpower is the most effective optimization path—the number of users with breakeven is reduced from 125,000 to 48,000, a decrease of 62%. This means that what Enterprise C should do now is not to continue to optimize the AI model (although the AI computing power cost can be reduced to 62,000 by 50%, the effect is not as good as the former), but to redesign the "AI+ labor" collaboration process and reduce those high-cost manual intervention scenarios. For Enterprise A (basic monitoring type), all the optimizations can pull it down from the breakeven point of 12,000 yuan, and there is a lot of room for improvement. For Enterprise B (auxiliary response type), the number of breakeven users of 28,000 is far lower than its actual user scale (68,000), and the safety mat is thick enough, so there is no need to worry about survival in the short term.

3.2. Discussion

By constructing an analytical framework and making an empirical analysis of three typical enterprises, this study draws the following findings: The study found that there is an important variable of "safety net perception" in the AI-based housekeeper scenario. The 12-month retention rate of Enterprise B (auxiliary response type) is 68.9%, which is

significantly higher than that of Enterprise C (full custody type) which is 58.3%. Although the AI technology of Enterprise C is more advanced, the proportion of manual intervention is too low ($< 10\%$). When users encounter problems that AI can't solve, they lack all the protection and give up using them because of insecurity. This shows that for the elderly, "accessibility to the bottom" may be more predictive of user retention than "AI intelligence level". This finding is in contrast with the research conclusion of Franco et al. [8] based on TAM model. It is found that elderly users attach more importance to "perceived security" than "perceived usefulness" of smart devices. This study further extends this observation from the device level to the service model level, indicating that users' trust in AI care-givers is related to the reliability of the system itself, and to whether there is an accessible remedy channel when the system goes wrong or fails. This shows that there is a separation between the technical performance of AI system and users' subjective sense of security in the elderly service scenario, and simply improving the AI self-help solution rate is not enough to maintain users' trust. In addition, this study found that there is a phenomenon of "unilateral crowding" in the scene of smart elderly care—the demand-side digital acceptance speed is fast, but the supply-side (nurses and community workers) digital ability is slow to improve. Although Enterprise C has the largest investment in technology, the degree of integration on the supply side is insufficient, which leads to the failure to convert the efficiency of "finding problems" into the ability of "solving problems", which explains the structural reasons why the full-hosting model is difficult to scale up. From the perspective of the digital divide, the plight of Enterprise C actually reflects the general problem that the digitalization ability of the supply side lags behind the demand side in the smart elderly care service. Previous studies have shown that the low coverage of digital training on the supply side of elderly care services and the uneven technical acceptance of front-line personnel are important factors affecting the effective implementation of smart elderly care. In this study, the data of Enterprise C provides a financial proof for this judgment: although the technical input has improved ARPU, the high labor cost of the supply side and the insufficient cooperation efficiency make it difficult for the cost side to optimize synchronously, which leads to the failure of the unit economic model.

Different from Wang et al. [22] that "reducing hardware cost is the priority path", the sensitivity analysis of this study shows that it is more effective for Enterprise C to optimize the efficiency of manual bottom-covering (the number of breakeven users decreases by 62% vs 50%), which may be due to the structural differences of different

Table 4. Summary of core indicators of corporate sustainability in three cases

Indicator	Enterprise A (basic type)	Enterprise B (auxiliary type)	Enterprise C (fully managed)	Sustainability threshold
ARPU (yuan/month)	29	79	299	—
Monthly cost per user (yuan)	24	68	341	—
Monthly gross profit of single user (yuan)	5	11	−42	> 0
Gross profit rate	17.20%	13.90%	−14.00%	> 0%
12 months retention rate	51.20%	68.90%	58.30%	> 60%
LTV/CAC	2.46	4.15	0.86	≥ 3
AI self-help solution rate	41%	71%	82%	> 60%
Manual bottom ratio	30%	32%	29%	< 30%
Breakeven users (ten thousand)	1.2	2.8	12.5 (estimate)	—

Table 5. Sensitivity Analysis — Influence of the change of key variables on the number of breakeven users

Scenario	Variable change	Enterprise A (ten thousand)	Enterprise B (ten thousand)	Enterprise C (ten thousand)
Benchmark scenario	present value	1.2	2.8	12.5
Scenario 1	AI computing power cost drops by 50%	0.9	1.8	6.2
Scenario 2	The proportion of manual bottoming decreased by 50%	0.7	1.4	4.8
Scenario 3	User retention rate increased by 10 percentage points.	0.8	1.6	7.1
Scenario 4	ARPU increased by 20%	0.8	1.9	8.3

elderly care service systems. Unlike Jabeen et al. [23] who found that "the willingness to pay for safety monitoring is the highest", the ARPU of Enterprise A in this study is only 29 yuan/month, which may be due to the age difference of the samples. Compared with the case observation of You and Liang [20] on the business model innovation of China's elderly care service industry, the conclusion of this study is consistent with it in terms of "model adaptability", that is, different regions and service positioning need to match differentiated business models. However, this study further points out the financial feasibility of each model, while the research of You and Liang mainly focuses on the qualitative model induction. This difference is mainly due to the different emphasis of research objectives. The former focuses on typological induction of business models, while this study focuses on quantitative sustainability judgment at the unit economic level.

Looking at the above findings together, a common theoretical direction is summarized: in the scenario of AI elderly care manager, the improvement of technical efficiency does not automatically translate into the creation of service value, and its transformation needs to be based on the accessible manual bottom-up mechanism and the matching digital capability of the supply side. This judgment is different from the popular "technical substitution" in the current research of AI service industry, and the role of AI in the elderly care scene is more in line with "enhancement" than "substitution". In other words, the value of

AI is not reflected in reducing the number of manpower, but in improving the quality and response efficiency of human collaboration. At the same time, the above findings also suggest that the construction of smart elderly service ecology needs the coordinated evolution of supply and demand sides, and it is difficult to produce a sustainable closed-loop business only by relying on the technical penetration of demand side.

According to the results of the above discussion, some suggestions are put forward from the aspects of enterprise technology route selection, service pricing strategy, artificial bottom-up mechanism design and government subsidy policy formulation. At the enterprise level, the technical route should match the service positioning. In the mass market, it can refer to the lightweight AI model adopted by Enterprise B and maintain a moderate proportion of manual intervention to control the cost. In the high-end market, it needs to focus on optimizing the single processing efficiency of manual bottom-up links. In terms of pricing, Enterprise B's 30.4% revenue from value-added services shows that users have a clear willingness to pay for health consultation and emergency rescue, and enterprises can upgrade ARPU through ladder pricing instead of just charging subscription fees. In the mechanism of manual intervention, it is important to reduce the frequency of high-cost manual intervention scenarios, such as diverting complex problems through AI pre-screening. At the level of government subsidies, it is suggested to shift from

"subsidies by number of devices" to performance subsidies based on service effect and user retention rate. In the aspect of community cooperation, community workers can be explored as localization cooperation nodes to undertake equipment training and simple fault handling to alleviate the problem of insufficient supply-side integration.

4. Conclusion

4.1. Main Conclusion

Firstly, there are three typical service modes of AI-basic monitoring, auxiliary response and full custody, and there are systematic differences among them in AI independent decision-making level, service integration and manual intervention ratio. Secondly, business sustainability can be evaluated from four dimensions: revenue end, cost end, efficiency end and financial end, with a total of 12 indicators. Among them, $LTV/CAC \geq 3$ is the core quantization criterion. Furthermore, through empirical analysis, it is found that within the scope of this case study, the auxiliary response type shows stronger commercial sustainability ($LTV/CAC=4.15$, gross profit margin 13.9%). There is a structural cost inversion in the fully managed type (the monthly loss of a single user is 42 yuan, and the gross profit margin is -14.0%), and the scale of breakeven users is 125,000, which is about 4.5 times that of the auxiliary response type of 28,000; The basic monitoring type is in a critical state ($LTV/CAC=2.46$). The order of sustainability is: auxiliary response type > basic monitoring type > full custody type. Finally, the core variables that affect sustainability are ranked as follows: manual efficiency > user retention rate > AI computing cost. High AI self-help solution rate does not necessarily bring low labor costs. "AI to enhance manpower" is more commercially feasible than "AI to replace manpower".

4.2. Research Limitations and Future Research Direction

There are three limitations in this study: the number of cases is limited (3 enterprises), so the conclusion should be popularized cautiously; The data period is 2 years, which does not cover technical iterations such as cost reduction of large models. Government subsidies are not included as variables in the model. Future research can be deepened from four directions: Introduce cases from various countries and rural areas to test the external validity of the conclusions. Track the impact of the decline in the reasoning cost of the large model on the fully managed financial model from 2025 to 2026, and re-evaluate its sustainability inflection point. Incorporate government subsidies into the unit economic model, and study the optimal subsidy intensity and subsidy exit path. Explore the relationship

between AI trust and churn behavior of elderly users, and build a prediction model of user churn. On the theoretical level, this study combines the service mode classification with the unit economic model for the first time and puts forward a quantifiable sustainability evaluation system. At the method level, it provides a cross-mode comparative analysis paradigm based on real operational data. On the practical level, the sustainability thresholds and optimization paths of the three models are defined, which provides quantitative basis for the selection of enterprise technology routes and the design of government subsidy policies.

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