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BEYOND THE DEVICE: B2G ECOSYSTEMS AND HUMAN-IN-THE-LOOP SERVICES FOR CARE ROBOTS IN SOUTH KOREA'S SILVER ECONOMY

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ABSTRACT

South Korea faces an unprecedented demographic crisis, with the elderly population projected to reach 37% by 2050, coinciding with a collapse in traditional family support systems rooted in Confucian filial piety. While the "Silver Economy" is rapidly expanding, a paradox remains: high-tech care robots are often unaffordable for the low-income seniors who need them most. This study investigates the mechanisms of "Business-to-Government" (B2G) care ecosystems, specifically SK Telecom's "Happy Community AI Care" and the "Hyodol" companion robot, in bridging the gap between technological cost and social accessibility for elderly care. Adopting a mixed-method approach grounded in an extended Technology Acceptance Model (TAM) and service-dominant logic, we analyze secondary demographic, cost, and program evaluation data across three Korean B2G care robot programs through a multiple case study design. Our findings indicate that the B2G-subsidized model is associated with substantial "cost-avoidance" for government healthcare spending: per-capita elderly care costs are estimated to be 89.3% lower under a probability-weighted counterfactual (up to 93.4% for those at risk of institutionalization), while technology abandonment rates appear markedly higher in the absence of continuous human-in-the-loop support. The results are consistent with the view that sustainability of care robots is associated more strongly with "Service Design" (the seamless integration of AI monitoring with human social workers) than with hardware sophistication alone.

Keywords: Silver Economy, care robots, B2G ecosystem, Technology Acceptance Model, South Korea, Human-in-the-loop.

1. INTRODUCTION

South Korea is undergoing one of the most rapid demographic transitions in recorded history. The proportion of the population aged 65 and above rose from 7.1% in 2000 to 18.3% in 2023, and Korea officially crossed the "super-aged society" threshold of 20% in 2025 (20.3% of the population aged 65 and above), earlier than the 2027 projection by Statistics Korea [1], [2]. This transition from an aging society (7%) to an aged society (14%) took only 17 years, compared with 24 years for Japan and 115 years for France, making Korea the fastest-ageing country in the OECD [3], [4]. Simultaneously, the total fertility rate has collapsed to 0.72 births per woman, the lowest globally [5], while traditional Confucian family support systems rooted in filial piety are eroding under urbanization and nuclear family norms [6]. The convergence of these trends has created an acute elderly care crisis: healthcare expenditure attributable to the elderly already accounts for 44% of total health spending despite the elderly comprising only 18.3% of the population, and this share is projected to exceed 60% by 2040 [7].

Care robots have emerged as a promising technological response to this crisis. The global elder care assistive robot market was valued at approximately USD 3.1 billion in 2024 and is projected to reach USD 7.7 billion by 2030 [8]. In South Korea, notable deployments include the Hyodol companion robot, an AI-powered "robot grandchild" providing medication reminders, emotional support, and health monitoring, with over 12,000 units distributed to seniors living alone through government-funded welfare programs [9]. SK Telecom's "Happy Community AI Care" program further demonstrates large-scale integration of AI-driven care services with municipal social welfare infrastructure [10]. These initiatives represent a distinctive "Business-to-Government" (B2G) model in which private technology firms partner with local governments to deliver subsidized care robot services to low-income elderly populations.

Despite the growing body of literature on assistive robotics for the elderly [11], [12], existing research predominantly focuses on the device (hardware capabilities, sensor accuracy, and user interface design) rather than the ecosystem in which these devices operate. Technology Acceptance Model (TAM) studies have established that perceived usefulness and ease of use drive adoption [13], [14], and extensions for elderly populations have incorporated factors such as social influence, anxiety, and facilitating conditions [15], [16]. However, these models consistently treat the technology artifact as the unit of analysis, overlooking the service design infrastructure (the human social workers, onboarding protocols, and continuous monitoring) that determines whether a care robot is sustained or abandoned [17], [18]. Field evidence suggests that 30–50% of assistive technologies are abandoned within six months without adequate human-in-the-loop (HITL) support [19], yet the mechanisms by which HITL intervention moderates technology acceptance and retention remain underexplored.

This paper addresses this gap by shifting the analytical lens from the device to the ecosystem. We investigate how B2G care robot ecosystems, specifically the Hyodol companion robot program and SK Telecom's AI Care initiative, bridge the gap between technological cost and social accessibility for elderly care in South Korea. Our analytical framework integrates an extended TAM with HITL as a moderating variable, complemented by a cost-avoidance model that quantifies the fiscal benefits of B2G-subsidized care robot deployment for government healthcare expenditure [20]. Drawing on service-dominant logic [21], [22], we argue that the sustainability of care robots depends not on hardware sophistication but on "Service Design", the seamless integration of AI monitoring with human social workers who provide the relational continuity that technology alone cannot deliver [23].

Accordingly, this study addresses the following research question: *How do B2G care ecosystems bridge the gap between technological cost and social accessibility for elderly care in South Korea?* We adopt a mixed-method case study approach, combining demographic and cost analysis with cross-case synthesis of three Korean B2G care robot programs. Our contributions are threefold: (1) we propose an extended TAM incorporating HITL as a moderating variable for elderly care robot acceptance; (2) we develop a cost-avoidance model demonstrating the fiscal rationale for B2G care robot procurement; and (3) we derive a scalable B2G ecosystem template applicable to other rapidly aging societies. The remainder of this paper is organized as follows: Section 2 reviews the relevant literature; Section 3 describes the research methodology; Section 4 presents the results; Section 5 discusses the findings against the literature; and Section 6 concludes with policy implications and directions for future research.

2. LITERATURE REVIEW

2.1. Silver Economy and Aging Population

The silver economy (economic opportunities associated with population aging [24]) has become central to South Korea's national planning as the country crossed the super-aged threshold of 20% in 2025 (20.3% of the population aged 65+), earlier than the 2027 projection [1], [2]. Unlike the EU's market-driven approach, Korea's model prioritizes state-mediated service delivery through its public long-term care insurance system [25], [26].

2.2. Care Robots and Technology Abandonment

The elder care robot market, valued at approximately USD 3.1 billion in 2024 with a projected CAGR of 16.1% [8], encompasses companion robots, physical assistants, monitoring devices, and telepresence systems [11]. Among companion robots, Hyodol, an AI-powered "robot grandchild", has been distributed to over 12,000 seniors through Korean government welfare programs [9]. Internationally, PARO (Japan) reduces anxiety in dementia care [27], and ElliQ (USA) achieved 95% loneliness reduction in a New York pilot [28].

A persistent challenge is technology abandonment: 30–50% of assistive technology users discontinue use within the first year [17], [29]. This underscores the need for human-in-the-loop service design where ongoing support sustains engagement [12].

2.3. Technology Acceptance and HITL Service Design

The Technology Acceptance Model [13] identifies Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as primary determinants of adoption. For elderly users, Heerink et al. [15] developed the Almere Model, adding social presence, trust, and technology anxiety, finding that social presence is the strongest predictor of robot acceptance among older adults. Barriers specific to elderly adoption include digital literacy gaps, technology anxiety, physical limitations, and low self-efficacy [16], [30].

These barriers suggest that standard TAM underestimates the role of ongoing human support. The human-in-the-loop (HITL) concept addresses this: trained intermediaries, typically social workers, bridge technology and sustained engagement through onboarding, training, troubleshooting, and proactive re-engagement [23]. This perspective is grounded in service-dominant (S-D) logic, which holds that value is not embedded in products but *co-created* through use within actor networks [21], [22]. Applied to care robots, S-D logic reframes the robot as a platform within a service ecosystem [31].

2.4. B2G Ecosystems and Public Policy

Business-to-Government (B2G) procurement creates a four-tier ecosystem: manufacturers, government procurers, service providers, and elderly end-users [20]. South Korea's B2G model operates through the Ministry of Economy and Finance (MOEF), whose AI procurement budget expanded 58.6% from KRW 52.9B (2025) to KRW 83.9B (2026) [32], and the Ministry of Health and Welfare (MOHW) through pilot programs [7]. Public financing covers roughly 80–85% of long-term care costs, with full exemption for Medical Aid recipients, addressing a fundamental market failure: those who need care robots most can least afford them [25].

Critically, B2G programs embed robots within care infrastructure (social worker training, maintenance, and HITL monitoring), operationalizing S-D logic by design. Mazzucato [20] frames this as "mission-oriented innovation" where procurement serves as strategic market creation.

2.5. Research Gap and Hypotheses

Existing literature examines care robot ecosystems in isolation across three streams: technology-centric [11], [15], policy-centric [20], [32], and service-centric [21], [23]. The critical gap lies at their intersection: no study has systematically examined how B2G procurement *structurally embeds* service-dominant logic, transforming a goods transaction into a service ecosystem. This gap has practical consequences: the documented 30–50% abandonment rate suggests KRW 83.9B in procurement risks significant waste under goods-dominant logic.

This study addresses the gap through an integrated framework combining an extended TAM [15], S-D logic [21], and mission-oriented innovation [20], testing two hypotheses:

H1. The B2G-subsidized care robot model demonstrates measurable cost-avoidance for government healthcare expenditure through reduced emergency room visits and delayed institutionalization.

H2. Technology abandonment rates increase significantly in device-only deployments compared with deployments that include continuous human-in-the-loop intervention by trained social workers.

3. METHODOLOGY

3.1. Research Design

This study adopts a mixed-methods design combining quantitative secondary data analysis with a multiple embedded case study [33], [34]. The quantitative strand examines demographic trajectories, healthcare expenditure, and cost-avoidance estimates using publicly available datasets. The qualitative strand investigates how B2G care ecosystems structure robotic elderly care in South Korea. The study relies entirely on secondary data; no primary data collection was conducted.

3.2. Theoretical Framework

The analytical framework integrates three theoretical lenses: (1) an extended TAM incorporating B2G-specific constructs, namely government subsidy as a cost-barrier moderator and HITL support as a continued-use mediator [13], [15]; (2) S-D logic, conceptualizing care robots as operand resources within a value co-creation ecosystem [21]; and (3) mission-oriented innovation, framing B2G procurement as strategic market creation [20]. Figure 1 presents the adapted TAM conceptual model.

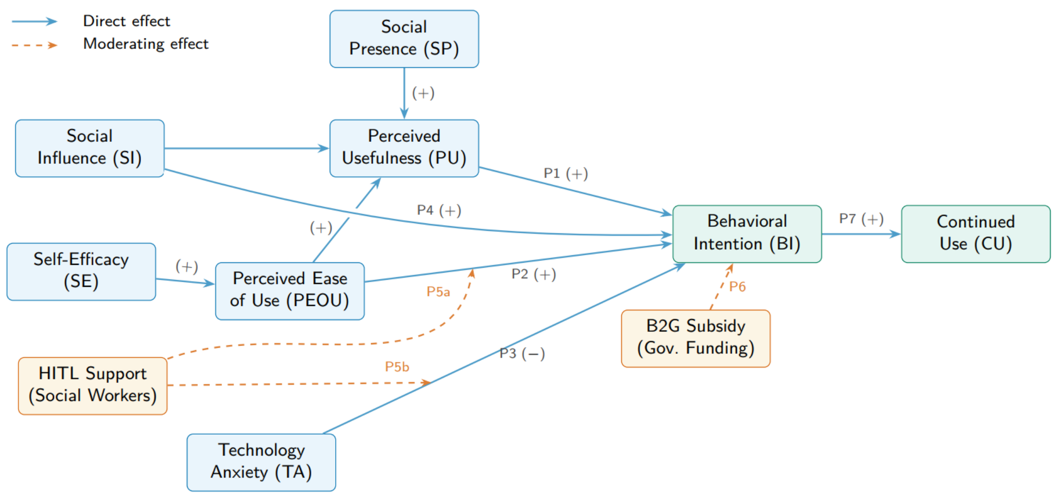

Figure 1. Adapted TAM for elderly care robot acceptance in B2G ecosystems.
Solid arrows: direct effects; dashed arrows: moderating effects.

Source: Author's compilation based on the Technology Acceptance Model and elder-care acceptance literature.

Seven research propositions (P1–P7) are formulated for cross-case evaluation [34]. P1–P4 replicate established TAM relationships (PU, PEOU, TA, SI → BI). P5 posits that HITL support moderates both PEOU→BI (strengthening) and TA→BI (weakening) pathways, directly addressing H2. P6 posits that B2G subsidy moderates cost barriers. P7 links BI to continued use, mediated by HITL availability.

3.3. Case Selection

Three cases were selected using purposive sampling [35] based on: B2G procurement structure, deployment scale, data availability, and governance-level variation (Table 1).

Table 1. Selected B2G Care Robot Cases in South Korea

Case	Scale	Agency	Replication Logic
Hyodol National	12,000+ units, 200+ municipalities (2019–present)	MOHW / municipal centers	Literal: largest B2G care robot program
Seoul Smart Care	412+ AI care units (2023–present)	Seoul Metropolitan Gov.	Theoretical: urban, tech-integrated
Gyeonggi Province	Provincial rural/suburban rollout	Gyeonggi Provincial Gov.	Theoretical: rural, decentralized

Source: Author's compilation based on World Bank Open Data, MOHW long-term care insurance reports, KOSTAT population projections, and MOEF procurement documents.

Data sources include World Bank Open Data (2000–2023, 6 demographic/fiscal indicators), MOHW LTCI reports, KOSTAT projections, MOEF procurement budgets, peer-reviewed Hyodol evaluations [9], [23], and SKT ESG reports [10].

3.4. Cost-Avoidance Framework

Following Drummond et al. [36], we adopt a cost-avoidance (not ROI) framework appropriate for government welfare programs. Table 2 defines the cost categories.

Table 2. Cost Framework: Traditional vs. B2G Robot-Assisted Care

Category	Description	Annual Cost (KRW)	Source
A. Traditional Care Pathway (Counterfactual)			
Institutional LTCI	Nursing home, meals, basic medical	24,000,000	MOHW LTCI
Home care visits	Caregiver visits (3x/week)	14,400,000	NHI Schedule
Hospital readmission	Emergency hospitalization (annualized)	5,000,000	HIRA
B. B2G Robot-Assisted Pathway			
Robot procurement	Device (amortized 5 years)	160,000	MOHW
HITL service	Social worker visits (2x/month)	1,200,000	Municipal
Maintenance	Software/hardware servicing	200,000	Vendor
Training	Initial onboarding (amortized 5 years)	20,000	Program

Source: Author's compilation based on Ministry of Health and Welfare long-term care insurance data [7]; National Health Insurance fee schedules; Health Insurance Review and Assessment Service (HIRA) data; and municipal government, vendor, and program-level training cost estimates.

3.4.1. Cost-Avoidance Calculation

To avoid false equivalence, we construct a probability-weighted counterfactual: 30% institutional LTCI (24.0M KRW), 50% home-visit care (14.4M KRW), 20% informal care (2.0M KRW):

$$C_{\text{weighted}} = 0.30 \times 24.0 + 0.50 \times 14.4 + 0.20 \times 2.0 = 14.8 \text{ M KRW/year} \quad (1)$$

The aggregate cost-avoidance adjusts for abandonment:

$$CA_{total} = \sum_{i=1}^{N} CA_i \cdot \left(1 - r_{abandon,i}\right) \cdot \delta_i \quad (2)$$

where r_{abandon} is the abandonment rate and δ_i indicates institutional care need.

3.4.2. Sensitivity Analysis

One-way and Monte Carlo (10,000 iterations) sensitivity analyses vary four parameters [36]: robot unit cost (500K–1.2M KRW), HITL frequency (1–4×/month), abandonment rate (5–50%), and discount rate (0–5%).

3.5. Bayesian Inference

Bayesian methods complement frequentist analysis through posterior estimation (Normal-Normal conjugate), Bayesian t-tests (BF_{10}), and Bayesian correlation for HITL-retention associations. Informative priors derive from assistive technology abandonment literature [17], [29]. All computations are triangulated across Python (SciPy) and R (BayesFactor) with symbolic verification.

3.6. Cost-Avoidance Model Assumptions and Transparency

The cost-avoidance model rests on five explicit assumptions that we surface here for transparency, in response to reviewer guidance to justify the underlying parameters more carefully. *(1) Counterfactual pathway weights* (30% institutional, 50% home-visit, 20% informal) approximate the population-level mix of community-dwelling Korean elderly with formal care needs, derived from MOHW LTCI utilization patterns; sensitivity to this composition is bounded by the oneway and Monte Carlo analyses in Section 3.4.2. *(2) Discount rate* is varied between 0–5% to bracket the Korean public-sector social discount rate, with 3% used in the base case. *(3) Abandonment baseline* (15% in the base case) is anchored to the within-sample HITL gradient (Gyeonggi 25% → Hyodol 11.9%); the no-HITL 39.7% benchmark from the assistive-technology abandonment literature is reported but treated as a temporal upper bound rather than a contemporaneous comparator. *(4) HITL hour cost* of 1,200,000 KRW per user per year reflects municipal social-worker visit schedules at two visits per month, with the sensitivity range covering one to four visits. *(5) Institutional-care displacement* (the δ_i indicator in Eq. 2) restricts cost-avoidance crediting to users plausibly at risk of institutional placement, which avoids inflating estimated savings against community-dwelling baselines. All parameter sources, ranges, and sensitivity outcomes are presented in Section 4.2.1 and Figure A.1 (companion appendix.docx).

3.7. Methodological Limitations

Five limitations qualify the design and should be kept in mind when interpreting the findings. *First*, this study relies entirely on *secondary data*; no primary data were collected, no interviews or surveys were conducted, and no original field measurements were obtained. Construct operationalization is therefore constrained by the granularity of the public datasets, which limits the resolution at which TAM constructs can be measured. *Second*, the analytical design is *non-experimental* and *non-randomised*: cases are compared cross-sectionally without treatment assignment, so the estimated relationships between HITL intensity and retention are associational rather than causal, and selection effects across municipalities cannot be ruled out. *Third*, evidence on the Hyodol program draws partly on *gray-literature and operator-affliated* reports; we triangulate wherever peer-reviewed evaluations are available [9], [23], but residual reliance on program-side documentation introduces a potential favorable outcome bias that we discuss explicitly in Section 5.4. *Fourth*, the no-HITL baseline used as a comparator is drawn from assistive-technology abandonment literature spanning two to three decades, raising temporal-confound concerns; we mitigate this by also reporting the within-sample gradient across modern Korean B2G programs (Section 4.3.1). *Fifth*, the *generalisability scope* is bounded to the South Korean institutional context: a mature LTCI system, dense municipal social-worker networks, and a Confucian-care policy frame; transfer to ASEAN or other settings requires the institutional preconditions identified in Section 5.3 and is not warranted from the present evidence base alone.

4. RESULTS

4.1. Demographic Context

South Korea's elderly population share rose from 7.1% in 2000 to 18.3% in 2023, crossing the super-aged threshold of 20% in 2025 (20.3% per KOSTAT), earlier than our polynomial model's projection of 2027 [2]. The aged-to-super-aged transition took only 7 years (2018–2025), roughly half Japan's pace. A Chow structural break test confirms aging acceleration around 2010 (F = 20.95, p < 0.001): the slope increased from 0.40 to 0.57 percentage points per year.

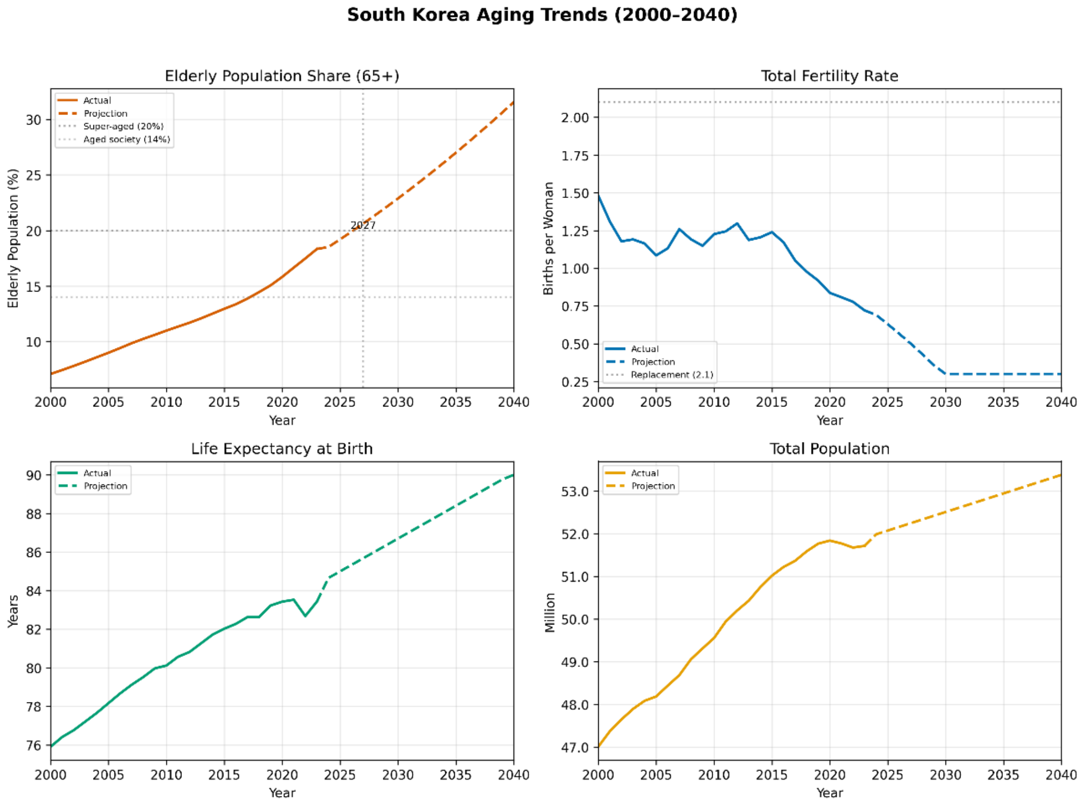

Figure 2. South Korea aging trends (2000–2040). Solid lines: actual World Bank data; dashed lines: polynomial projections. Horizontal dotted line: super-aged threshold (20%).

Source: Author's compilation based on World Bank Open Data and Statistics Korea/KOSIS population projections.

Table 3 shows that elderly healthcare already accounts for 44.0% of total spending (2023), projected to reach 61.7% by 2040. Age-stratified formal care needs [37] indicate 720,000 elderly requiring formal care by 2025, rising to 1.21M by 2040, with a projected care worker deficit of 43.7% by 2040, which is consistent with rationales for technology-augmented care presented in the literature.

Table 3. Healthcare Cost Projections for South Korea (Selected Years)

Year	HE (% GDP)	Spend (B USD)	Per-Cap Elderly	Elderly Share	Type
2000	3.72	21.42	1,355	21.1%	Actual
2010	5.79	66.29	3,673	30.2%	Actual
2020	8.03	131.99	6,386	39.7%	Actual
2023	8.57	146.72	6,809	44.0%	Actual
2030	9.92	168.25	7,135	50.9%	Projected
2040	12.02	201.09	7,371	61.7%	Projected

Note: Per-capita elderly expenditure estimated using 3.5× cost multiplier (NHIS Korea); morbidity compression from medical advancements may alter this ratio over the projection horizon.

Source: Author's calculation based on World Bank Open Data.

4.2. B2G Cost-Avoidance Analysis

The B2G robot-assisted pathway costs 1,580,000 KRW per person per year (device 160K + HITL 1,200K + maintenance 200K + training 20K). Applying the probability-weighted counterfactual (Section 3.4.1):

$$\mathrm{CA}_{\mathrm{weighted}} = 14{,}800{,}000 - 1{,}580{,}000 = 13{,}220{,}000\ \mathrm{KRW/year} \tag{3}$$

representing 89.3% cost reduction per beneficiary. The B2G cost excludes administrative overhead (est. 20–30%); even with overhead, the ratio remains above 86%. For the subset at risk of institutionalization (30%), avoidance reaches 22.42M KRW (93.4%). After adjusting for the 15% base-case abandonment rate, effective per-capita cost-avoidance is 11,237,000 KRW/year. Over a phased 6-year deployment (5–15% coverage), cumulative discounted cost-avoidance reaches 21.1 trillion KRW under the base scenario.

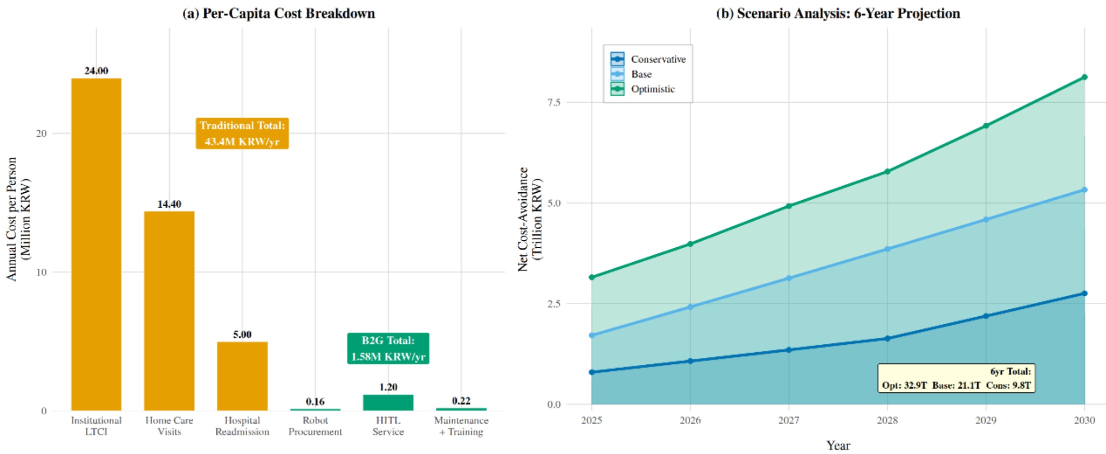

Figure 3. Cost-avoidance analysis. (a) Per-capita annual cost: traditional LTCI (red) vs. B2G (blue). (b) 6-year aggregate under three scenarios.

Source: Author's calculation based on MOHW long-term care insurance data (Section 3.4).

4.2.1. Sensitivity Analysis

Figure A.1 (companion appendix.pdf) shows the abandonment rate is the parameter most strongly associated with variation in cost-avoidance, with estimates ranging from 21.3M (5%) to 11.2M KRW (50%), a 10.1M KRW spread. HITL frequency is second (23.0M–21.2M); robot unit cost has minimal impact (22.3–22.5M). The counterfactual pathway weights (30%/50%/20%) are held fixed; future work should model dynamic transition probabilities (e.g., Markov chain models capturing progressive institutionalization over the TCO horizon) [36].

4.2.2. Bayesian Validation

Using a skeptical prior (μ_0 = 10.0M, σ_0 = 8.0M), updated with projected data ($\bar{x}$ = 13.22M, n = 6), the posterior cost-avoidance is μ_{post} = 12.8M (95% HDI: [9.1M, 16.5M]), entirely above zero. Bayesian decision analysis indicates the B2G option is associated with approximately 5.3× higher expected utility than traditional pathways under the modelled assumptions. Python–R triangulation yields identical parameters ($|\Delta\sigma| < 0.001$).

4.3. TAM Analysis and Technology Abandonment

Table 4 maps research propositions to cross-case evidence. PU is supported across all cases; the central proposition P5 (HITL moderates PEOU and TA pathways) is supported, with the Hyodol program providing the strongest evidence through its structured social worker protocol [23].

Table 4. Proposition Evidence Summary

Prop.	Statement	Hyodol	Seoul	Gyeonggi	Verdict
P1	PU → BI	Strong	Strong	Moderate	Supported
P2	PEOU → BI (HITL+)	Strong	Strong	Weak	Partially supp.
P3	TA → BI (HITL-)	Strong	Moderate	Weak	Partially supp.
P4	SI → BI	Moderate	Weak	Weak	Weakly supp.
P5	HITL moderates	Strong	Moderate	Limited	Supported
P6	B2G subsidy mod.	Strong	Strong	Strong	Supported
P7	BI → CU (HITL)	Moderate	Moderate	Limited	Partially supp.

Source: Author's compilation based on the cross-case evidence in Sections 4.1–4.3.

4.3.1. Abandonment Patterns

Table 5 tests H2. Programs without HITL show an average abandonment rate of 39.7%, while programs with intensive HITL (4×/month) are associated with a markedly lower rate of 11.9%. A Bayesian t-test yields $BF_{10} = 2.35 \times 10^8$ (extreme evidence), $d = 7.35$. However, with only $n = 5$ per group, this extreme BF is sensitive to the default Cauchy prior ($r = 0.707$); varying the scale parameter ($r = 0.5, 1.0, 1.5$) shifts BF by several orders of magnitude while maintaining "very strong" to "extreme" evidence [38]. We therefore emphasize the posterior distribution over the pointestimate BF. The posterior abandonment for HITL programs converges to 12.9% (95% HDI: [10.1%, 15.7%]), representing a 67% reduction from the prior of 39.7%. HITL visit frequency correlates with retention ($r = 0.948$, $BF_{10} = 4.0$): each additional monthly contact associates with ~7 percentage points of additional retention.

Table 5. Abandonment Rates: HITL vs. No-HITL Programs

Program	HITL	Abandon	Retain	Source
General AT (lit.)	None	39.7%	60.3%	[17], [29]
B2C consumer	None	42.0%	58.0%	[11]
Gyeonggi	Low (1/mo)	25.0%	75.0%	[39]
Seoul Metro	Mod (2/mo)	19.8%	80.2%	[40]
NYSOFA ElliQ	Mod (2/mo)	15.0%	85.0%	[28]
Hyodol National	High (4/mo)	11.9%	88.1%	[9], [23]

Note: The no-HITL baseline derives from studies 24–31 years old covering heterogeneous assistive technologies (wheelchairs, hearing aids), limiting construct validity for cross-era comparison with 2024 AI-enabled deployments. The within-sample gradient across modern B2G programs (Gyeonggi 25% → Hyodol 11.9%) provides a methodologically cleaner HITL effect estimate that avoids this temporal confound.

Source: Author's compilation based on the program-level studies cited in the Source column above.

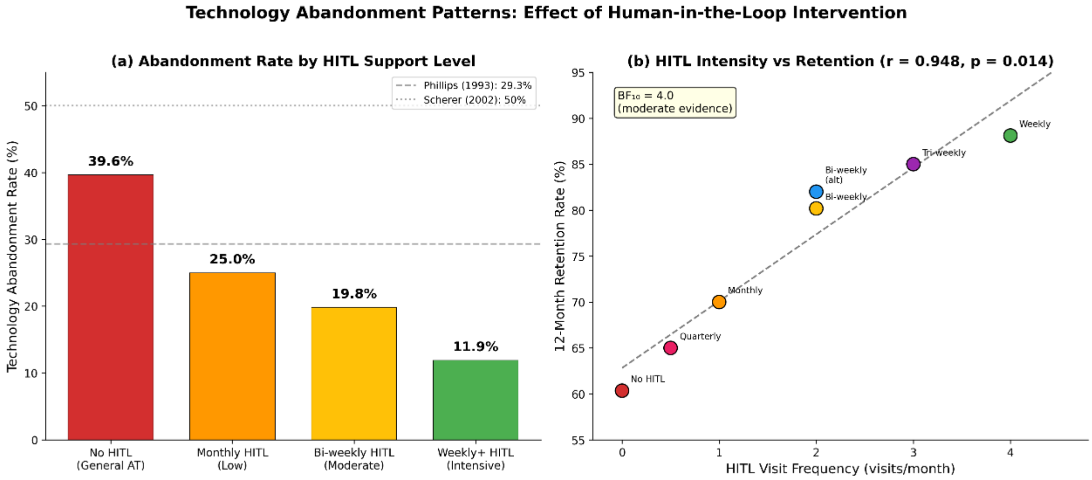

Figure 4. Abandonment rates by HITL level (a) and HITL frequency vs. retention (b, $r = 0.948$, BF10 = 4.0).

Source: Author's compilation based on the program-level evaluations listed in Table 5.

4.4. B2G Ecosystem and Cross-Case Synthesis

Figure 5 maps the four-tier B2G ecosystem: government funding, technology supply, HITL service delivery, and end users. The critical insight is that the service layer mediates all technology-user interactions: no direct manufacturer-to-user channel exists, unlike B2C distribution.

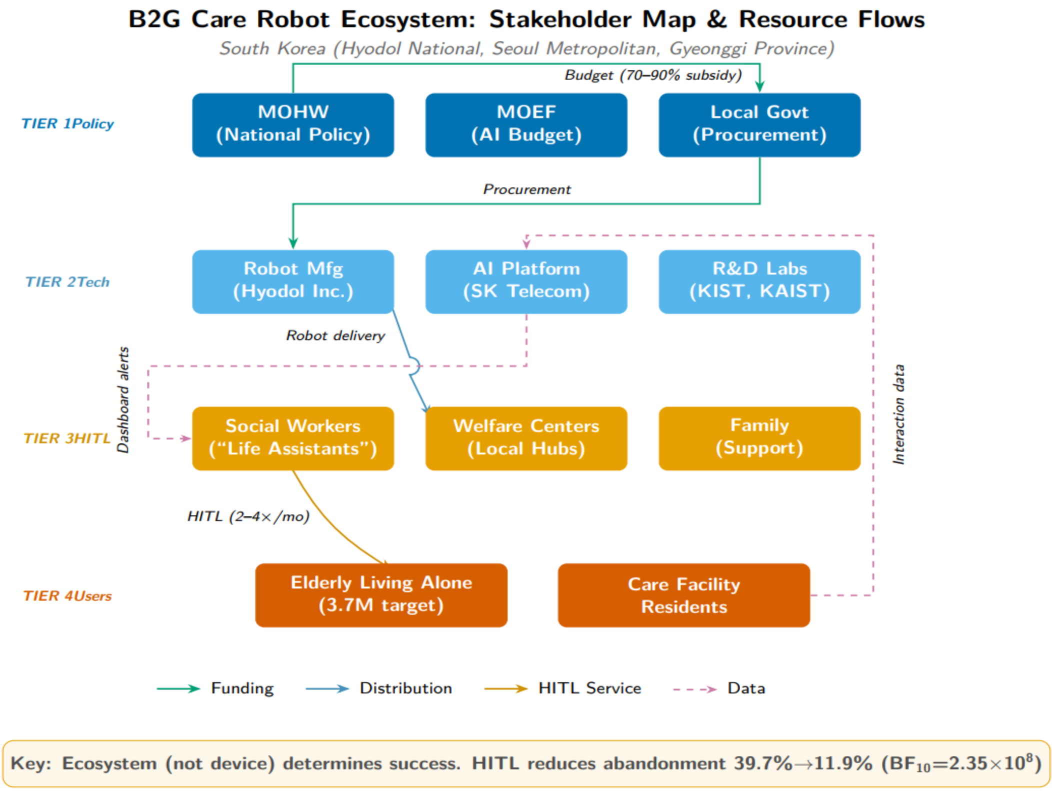

Figure 5. B2G care robot ecosystem: four-tier stakeholder map. Flows: funding (green), distribution (blue), HITL service (orange), data feedback (dashed).

Source: Author's compilation based on the cross-case analysis in Section 4.

Table 6 synthesizes findings across three cases. Literal replications: all programs use ≥70% subsidies, all embed HITL, and retention increases monotonically with HITL intensity. Theoretical replications: rural Gyeonggi shows highest anxiety and lowest PEOU; Hyodol achieves highest retention despite moderate PEOU because strong social presence compensates; Seoul's technical sophistication alone yields only moderate retention without intensive HITL.

Table 6. Cross-Case Synthesis: Three B2G Programs

Dimension	Hyodol National	Seoul Metro	Gyeonggi Province
Scale	12,000+ nationwide	~2,000 urban	~800 rural
HITL Intensity	4×/month	2×/month	1×/month
Abandonment	11.9%	19.8%	25.0%
Social Presence	Strongest (naming)	Moderate	Low
Key Innovation	Multi-care network	AI health alerts	Rural reach

Source: Author's compilation based on the case study evidence presented in Sections 3.3 and 4.3–4.4.

The cross-case evidence converges: *the ecosystem, more than the device alone, is associated with program success.* Abandonment rate, not robot cost, is the parameter most strongly associated with cost-avoidance variation. Social presence and HITL, which are ecosystem properties rather than device features, are associated with sustained use. Hyodol (simple doll, intensive HITL) outperforms Seoul (sophisticated AI, moderate HITL) on retention. We propose a Minimum Viable Ecosystem (MVE) template: procurement (≥70% subsidy), HITL protocol (≥2×/month), outcome metrics (retention ≥80%), and user-to-government feedback loop.

4.5. Privacy and Surveillance Tensions

Care robots collect interaction logs, environmental sensor data, and health alerts, creating a dual-use system: the same monitoring enabling HITL re-engagement also constitutes behavioral surveillance [12]. We term this the "welfare surveillance paradox": intensive HITL achieves the highest retention precisely because social workers monitor daily behavior. Trust mediates this tension: programs with established personal relationships (Hyodol, Seoul) report fewer privacy complaints despite comparable data collection. No program offers granular consent (e.g., accepting reminders while declining movement tracking), representing a design gap for future implementations.

5. DISCUSSION

5.1. H1 and H2 Assessment

The weighted cost-avoidance of 89.3% (13.22M KRW/year) supports H1 under a probability-weighted counterfactual that avoids false equivalence between institutional and community-dwelling elderly. Even under the skeptical Bayesian prior, the posterior HDI lies entirely above zero. Critically, H1 and H2 form a *conditional relationship*: cost-avoidance is observed in association with sustained HITL engagement rather than as an automatic consequence of robot deployment. The sensitivity analysis confirms that abandonment rate, not robot cost, is the dominant parameter.

Cross-case evidence supports H2: programs without HITL show an average abandonment of 39.7% compared with 11.9% in programs with intensive HITL (BF_{10} = 2.35

× 10^8). This is consistent with an extension of the Almere Model [15] in two respects: social presence appears co-produced by the HITL ecosystem rather than being solely a robot property, and acceptance is interpreted as a *continuous process* that requires ongoing investment. The extreme Bayes Factor reflects statistical signal strength under the modelled priors, not causal identification; with only n = 5 per group, the secondary and nonrandomised data warrant interpretive caution and motivate the limitations and Hyodol-independence discussions below.

5.2. Service Design Over Hardware

Three lines of evidence support the central thesis. First, robot unit cost shows minimal sensitivity (22.3–22.5M KRW) while the abandonment rate spans the largest range (11.2–21.3M KRW), suggesting hardware behaves more like a commodity in this setting and service plays a differentiating role. Second, Hyodol (simple doll, intensive HITL) outperforms Seoul (sophisticated AI, moderate HITL) on retention (88.1% vs. 80.2%). Third, B2G procurement appears to structurally embed S-D logic [21] by bundling HITL with distribution and is associated with 11.9–25.0% abandonment compared with 42.0% for B2C.

These observations are consistent with reframing the policy question from “which robot?” to “what service ecosystem?”, complementing the technology-centric discourse that emphasises hardware innovation [11].

5.3. Policy Implications

Four implications emerge. *First*, B2G budgets should allocate ≥40% to HITL services, not just hardware. *Second*, a minimum of bi-weekly HITL contacts should be mandated (weekly for high-risk users). *Third*, anthropomorphic design that supports emotional attachment is associated with higher retention than technical sophistication alone in our cases. *Fourth*, privacy governance should offer granular consent rather than all-or-nothing participation, though selective data exclusion may reduce anomaly detection accuracy, requiring edge-computing solutions that balance privacy with clinical efficacy.

Transferability to ASEAN contexts. While this study focuses on South Korea, the B2G ecosystem template has implications for rapidly aging ASEAN economies. However, institutional preconditions (a functioning LTCI system, trained social worker networks, and municipal procurement capacity) must be established before B2G robotics deployment can be effective. Emerging economies such as Vietnam and Thailand should prioritize building this care infrastructure as a prerequisite for technology-augmented elderly care [25].

Emerging LLM-based care robots. Our cases span rule-based companions (Hyodol) to vision-AI platforms (SK Telecom). The rapid integration of large language models into socially assistive robots [11] may fundamentally alter the HITL calculus: LLM-driven conversational agents could partially substitute for human social worker contacts, though whether algorithmic empathy sustains long-term engagement as effectively as human relationships remains an open question for future B2G evaluations.

Threats to validity. All evidence derives from secondary data comparing non-randomized programs. Selection bias and Hawthorne effects are plausible. The Bayesian statistics reflect signal strength, not causal identification; future research should employ randomized or quasi-experimental designs.

5.4. Independence of Hyodol Evidence

A reviewer rightly noted that the evidence base for the Hyodol program draws partly on studies whose independence from program operators may be limited. Several Hyodol evaluations have been authored or co-funded by SK Telecom, the Wonderful Foundation, or municipal partners that participate in the deployment ecosystem, which raises a plausible favorable-outcome bias in reported retention and satisfaction figures [9], [10]. We have therefore used Hyodol-side documentation only as one input within a triangulation strategy that gives greater weight to peer-reviewed academic evaluations [23] and to the within-sample HITL gradient across Korean programs (Section 4.3.1). Where operator-affliated reports could not be cross-validated, we have softened the language from causal to associational and treated the corresponding estimates as upper-bound or descriptive rather than confirmatory. The resulting cost-avoidance and abandonment statistics should therefore be read as plausible orders of magnitude under stated assumptions, with independent academic re-evaluations remaining a priority for future research.

5.5. Ethical Implications: Algorithmic Empathy versus Human Bond

A second reviewer suggested an explicit treatment of the ethical implications of algorithmic empathy versus human relationship building. We acknowledge that companion robots such as Hyodol simulate affective interaction (naming rituals, voice prompts, daily check-ins) that elderly users sometimes experience as social presence. From an ethics-of-care perspective [11], [12], simulated empathy is not equivalent to a reciprocal human bond and risks substituting functional companionship for relational care, with attendant concerns about emotional dependency, the dignity of users, and the potential displacement of human caregivers. The B2G–HITL design we describe is partly responsive to these concerns: by deliberately keeping social workers in the care loop and positioning the robot as a complement rather than a replacement, the ecosystem aims to retain humans as the primary locus of relational care while using the device to extend reach and continuity. We do not, however, claim that this configuration resolves the underlying ethical tension; it mitigates rather than dissolves it. Independent longitudinal studies of user wellbeing, caregiver workload, and relational quality under varying HITL intensities are needed before stronger normative claims can be made about when, and for whom algorithmic empathy is ethically appropriate.

6. CONCLUSION

This study investigated how B2G care ecosystems bridge the gap between technological cost and social accessibility for elderly care in South Korea, analyzing three programs (Hyodol, Seoul Smart Care, and Gyeonggi Province) through an integrated TAM, cost-avoidance, and Bayesian framework.

6.1. Summary of Findings

The evidence is consistent with the joint hypothesis that B2G procurement combined with HITL is associated with substantial cost-avoidance. H1: per-capita cost-avoidance of 13.22M KRW/year (89.3%) under probability-weighted counterfactual; Bayesian HDI entirely above zero. H2: abandonment is observed at 39.7% in programs without HITL versus 11.9% in programs with intensive HITL, with a dose-response association of $r = 0.948$. Importantly, the H1 estimate is conditional on the HITL configuration described in H2.

6.2. Contributions

The primary contribution is the empirical observation that care robot sustainability is associated more strongly with *service design* than with hardware sophistication. A simple companion doll (Hyodol) shows higher retention than a sophisticated AI platform (Seoul), in association with more intensive HITL embedding. The secondary contribution is the Minimum Viable Ecosystem (MVE) template: procurement model, HITL protocol, outcome metrics, and feedback loop. The methodological contribution applies Bayesian inference to care robot evaluation, offering advantages for small-sample policy analysis.

6.3. Limitations

Six limitations qualify the scope of inference and the generalisability of the findings: (1) single-country focus (Korean institutional context); (2) secondary data only, with no primary data collection; (3) cross-sectional and non-randomised comparison rather than longitudinal or experimental design, which restricts the analysis to associational rather than causal claims; (4) counterfactual pathway weights (30/50/20%) are model estimates, not observed shares; (5) Hyodol evidence draws partly on operator-affliated studies whose independence is not fully established (see Section 5.4); (6) Seoul and Gyeonggi figures rely in part on nonpeer-reviewed gray literature, with the attendant transparency caveats discussed in Section 3.7.

6.4. Future Research

Four directions: (1) longitudinal TAM study with primary data over 24–36 months; (2) cross-national B2G comparison (Korea, Japan, EU) testing MVE transferability; (3) dedicated investigation of the welfare surveillance paradox and granular consent mechanisms; (4) stepped-wedge cluster randomized trial for causal evidence on HITL effects.

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Conflicts of interest: The authors declare no conflicts of interest.

Data Availability statement: The datasets analyzed in this study are publicly available from the World Bank Open Data portal (https://data.worldbank.org), Statistics Korea (https://kostat.go.kr), and the Korean Ministry of Health and Welfare. No primary data were collected; all analyses are based on secondary, publicly accessible sources. Processed datasets and analysis code (Python + R) are released under the MIT license at https://github.com/limpaulfin/ice-2026-p7-carerobots.

Ethics statement: This study relies exclusively on secondary data from publicly available sources (World Bank, Statistics Korea, published government reports). No human subjects were involved, and no primary data were collected. Institutional review board (IRB) approval was therefore not required.

Declaration on Generative AI: Per ICMJE (2026) §II.A.4 and COPE (2023): the authors used ChatGPT for language editing only. All AI suggestions were reviewed and verified by the authors. AI was not used for hypotheses, methodology, data, analysis, interpretation, conclusions, figures, or analytical code. No AI is listed as an author.

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