Original Paper

Latent Class Analysis for Identifying Patterns of Digital Device Use and Adaptation Difficulty and Their Associations With Service Needs Among Older Adults: Secondary Data Analysis of a Cross-Sectional Survey Study

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Abstract

Background: In this digital era, digital devices play an increasingly vital role in health management beyond daily convenience. However, age-related physical changes and low digital literacy hinder technology use among older adults, widening the digital divide, with potential implications for health outcomes.

Objective: This study aimed to identify subgroups of older adults based on their digital device use and adaptation difficulty, examine the characteristics of each subgroup, and assess their preferred service needs for digital adaptation.

Methods: This is a cross-sectional secondary data analysis study. Data were drawn from 7470 older adults participating in the 2023 National Survey of Older Koreans. Digital device use and adaptation difficulty were assessed using 13 binary items and one 5-point Likert-scale item. Latent class analysis was conducted to identify subgroups of older adults based on these patterns. Service needs for digital adaptation were categorized as digital accessibility support, digital literacy enhancement, and age-friendly digital solutions. Additionally, bias-adjusted 3-step multinomial logistic regression approaches were used to examine subgroup characteristics and service preferences.

Results: The study sample included older adults aged 65 to 98 (mean 73.78, SD 6.65) years. Among the preferred service needs for digital adaptation, digital accessibility support was selected most frequently (n=2731, 36.6%), followed by digital literacy enhancement (n=2508, 33.6%) and age-friendly digital solutions (n=2231, 29.9%). Four distinct subgroups emerged from the analysis: digitally active (active; n=1112, 14.9%), moderately active (moderate; n=2492, 33.4%), text messages only (text-only; n=2082, 27.9%), and digitally inactive (inactive; n=1784, 23.9%). Compared to the active group, the inactive and text-only groups exhibited lower cognitive functioning (odds ratio [OR] 0.676, 95% CI 0.637-0.717 and OR 0.761, 95% CI 0.720-0.805, respectively). The inactive group required greater assistance in daily living (OR 1.165, 95% CI 1.024-1.326). Additionally, older age, rural residence, lower income, and lower educational attainment were significantly associated with patterns characterized by more limited digital device use. Regarding service needs, compared to the active group, groups reflecting greater digital limitations expressed a significantly stronger preference for age-friendly digital solutions over digital literacy enhancement, with ORs ranging from 1.294 (95% CI 1.051-1.593) to 1.978 (95% CI 1.510-2.591).

Conclusions: This study identified 4 distinct subgroups of digital device use and adaptation difficulty among older adults and examined their sociodemographic and health-related characteristics. Notably, individuals in classes reflecting greater digital limitations demonstrated a stronger preference for age-friendly digital services than for conventional digital literacy

training, indicating that usability and design barriers might be more salient than skill-based limitations for many older adults. By delineating subgroup-specific needs, our findings can provide actionable guidance for developing targeted interventions. Tailored strategies are essential to support older adults in navigating an increasingly digital environment, thereby reducing digital divides and promoting digital inclusion with potential implications for healthy aging.

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Keywords: digital adaptation; digital divide; digital inclusion; latent class analysis; older adults

Introduction

Technology-driven devices have been incorporated into many aspects of daily activities such as information exchange, communication with others, leisure, and, most importantly, health care [1-3]. With the widespread use of smartphones, wearable devices, and health-related apps, both health care professionals and patients have benefited from real-time health monitoring and personalized care, thereby supporting more effective preventive health behaviors [4]. The COVID-19 pandemic further accelerated the adoption of digital health technologies, as the demand for remote health care services surged [5]. Various digital functions used in everyday life, such as digital communication, information searching, video viewing, and application use, are also increasingly applicable in accessing and navigating digital health care services. Digital communication supports remote consultations, while information searching and video viewing provide access to health information and education. Apps are also used to enable engagement with various health care services [1,2]. As digital health care increasingly relies on functions that are similarly used in everyday digital activities, limited experience with these functions or difficulty adapting to digital technologies may pose additional challenges for older adults in accessing digital health care services.

Despite these technological advancements, older adults remain disproportionately affected by the digital divide, limiting their access to devices, internet usage, and overall engagement with technology compared to that observed with the younger generations [6-9]. Their lower digital literacy levels are often attributed to unfamiliarity and limited experience with digital devices [2,10,11]. In addition, age-related sensory impairments, such as diminished vision and hearing loss, present significant physical barriers to effective interactions with digital technologies [2,11-13]. Cognitive aging—manifesting as difficulties with memory, such as recalling passwords or acquiring new information—further compounds these challenges [11,12]. Previous studies have reported differences in digital technology use among older adults according to sociodemographic characteristics, including age, education, and income, as well as health-related factors such as cognitive and functional statuses [12,14,15]. As health care services increasingly rely on digital technologies, these differences in digital device use and adaptation difficulty may translate into unequal access to digital health resources and services, potentially widening existing health inequities [16-20]. In contrast, older adults often encounter barriers from the outset of the health care journey. For instance, since the onset of the COVID-19 pandemic, many hospitals have adopted app-based reservation systems, which have created substantial difficulties for older adults in the scheduling of medical appointments [10]. As digital health care solutions continue to evolve and become established as the standard of service delivery, older adults risk further marginalization in accessing essential health care services, thereby exacerbating existing health inequities.

This issue is particularly salient in Korea, one of the most digitally connected countries, with a smartphone penetration rate of 95% and a household internet penetration rate of 83% as of 2024 [21,22]. Within this highly digitalized context, many public services and welfare benefits have transitioned to exclusively digital formats, offering additional advantages to only online users [13]. However, a substantial proportion of older adults in Korea (50.0%-67.2%) continue to experience difficulties with using digital devices, limiting their ability to benefit from these digital-based services [23,24]. Digital inclusion encompasses multiple dimensions, including access to digital technologies and individuals' ability to use them effectively [2,7]; therefore, it is particularly important in highly digitalized societies such as Korea. This gap between digital infrastructure and older adults' access to and use of digital services highlights the urgent need for more targeted support to ensure equitable access for older adults.

A growing body of research has examined the digital divide among older adults, with particular attention to digital device usage, literacy levels, and influencing factors [12,14,15,18,25]. Some qualitative studies have examined the challenges older adults face in adapting to digital technologies [10,13,26]. Notably, digital skill training and support have frequently been emphasized as strategies to promote digital inclusion among older adults by improving their ability to access and engage with digital technologies [14,18]. Nonetheless, improvements in digital knowledge or skills through training do not necessarily translate into increased digital device use or fewer difficulties in adapting to digital technologies [2,11]. For older adults, challenges in digital technology use may persist even after training, as improved knowledge does not always lead to confident or autonomous use [27]. Digital competency is a broader construct encompassing operational device skills, communication, safety, problem-solving, and attitudes toward technology [28]. Previous studies have identified distinct profiles of older adults primarily based on digital literacy, which focuses on knowledge and skills related to the use of digital technologies [29]. However, digital literacy reflects the knowledge and capabilities of older adults, rather than their engagement with digital devices or related difficulties. Little is known about the patterns of digital device use among older adults and the difficulties they face in adapting to digital

technologies. Understanding this heterogeneity may provide a more nuanced view of digital device use and adaptation difficulty among older adults and inform more tailored digital inclusion strategies.

Therefore, this study aimed to explore heterogeneity in digital device use and adaptation difficulty among older adults and to examine the characteristics and service needs associated with the identified patterns. Specifically, this study addressed the following research questions: (1) What distinct patterns of digital device use and adaptation difficulty exist among older adults? (2) What sociodemographic and health-related factors are associated with the identified patterns? (3) How do service needs for digital adaptation differ across these patterns?

Methods

Study Design and Data

This was a cross-sectional secondary data analysis study using data sourced from the 2023 National Survey of Older Koreans (NSOK). The NSOK, conducted every 3 years since 2008, is administered by the Ministry of Health and Welfare of South Korea and the Korean Institute for Health and Social Affairs under the Welfare of Senior Citizens Act. The survey serves as a foundational resource for policy development aimed at improving the quality of life for older Koreans by examining their diverse characteristics, living conditions, and needs. For the 2023 NSOK, 176 trained survey interviewers administered the survey via tablet-assisted personal interviews conducted face-to-face between September and November 2023.

Study Sample

The 2023 NSOK surveyed older adults aged 65 years and above across the nation. To ensure a representative sample, a proportional 2-stage stratified sampling method was used for the survey, using the 2021 Population and Housing Census of Korea as the primary sampling frame. Among the 10,178 older adults who participated in the survey, individuals with cognitive impairment, those who had a proxy respondent, and those with missing responses to key questions were excluded from the analysis. Consequently, data from a final sample of 7470 older adults were used for this study.

Measures

Patterns of Digital Device Use and Adaptation Difficulty

Patterns of digital device use and adaptation difficulty were assessed using 2 aspects of the 2023 NSOK: digital device activities and difficulty with digital adaptation. Digital device use was measured using 13 items, assessing whether participants used specific functions when they are using their digital devices: text messages, video calls, information searches, taking photos/videos, music, games, watching videos, social networking service (SNS), e-commerce, financial transactions, app search/installation, and machine-based ordering/check-in at service locations. Participants responded to each item with a "yes" or "no." Difficulty in digital adaptation was assessed using a single item on a 5-point Likert scale, ranging from "not difficult at all" (1) to "very difficult" (5).

Service Needs for Digital Adaptation

A single question was used to assess service needs for digital adaptation. Participants were asked to select the most necessary service from six options: provision of smart devices, support for smart device usage fees, expansion of public Wi-Fi, diversification of digital literacy education programs, development of senior-friendly smart devices and applications, and expansion of digital infrastructure to bridge the digital divide (eg, hands-on experience spaces). Previous studies have highlighted the importance of access to digital technologies, education and support for developing digital skills, and the usability of these technologies among older adults [2,6,11]. Based on these considerations, the six service needs were grouped into 3 broader categories according to their primary implementation purpose. Provision of smart devices, support for smart device usage fees, and expansion of public Wi-Fi were grouped as "digital accessibility support," which aims to improve access to digital technology by addressing financial and infrastructural barriers. Diversification of digital literacy education programs and expansion of education-based digital infrastructure were categorized as "digital literacy enhancement," which focuses on improving digital skills among older adults through experiential learning opportunities. Development of senior-friendly smart devices and apps was classified as "age-friendly digital solutions," which aims to make digital technology more tailored to older adults by reducing usability challenges.

Covariates

The covariates included participants' sociodemographic and health factors, identified from the literature [30]. Sociodemographic factors included age, sex, residential area, household type, annual household income, and education level [6,9,25]. Health factors comprised chronic diseases, cognitive function, and functional status, which have been directly linked to digital device use and adaptation difficulty [8,12,15], as well as smoking status, drinking, exercise, and self-rated health [14]. Chronic diseases were assessed as the number of physician-diagnosed chronic diseases. Cognitive function and functional status were evaluated using the Korean-Mini Mental State Examination, 2nd Edition (K-MMSE-2) and the Korean Instrumental Activities of Daily Living (K-IADL), respectively [31,32]. Questions on smoking, drinking, and exercise were answered with yes or no, while self-rated health was categorized as healthy, moderate, or unhealthy.

Statistical Analysis

To identify patterns of digital device use and adaptation difficulty among older adults, a latent class analysis (LCA) was conducted. LCA estimates the probability of individual responses to questions about digital device activities and difficulties in adapting to the digital society. The LCA model included 14 indicators: 13 binary items assessing digital device activities (yes/no) and 1 ordinal item assessing

adaptation difficulty, measured on the original 5-point Likert scale ("not difficult at all" to "very difficult"). All the 14 indicators, including the 5-category difficulty item, were modeled according to the standard categorical LCA procedures, in which indicator variables—including those with more than 2 ordered response categories—are treated as categorical variables with class-specific response probabilities estimated for each category [33]. Multiple latent class models with an increasing number of classes were compared to optimize model fit and determine the most appropriate number of classes. Several statistical indicators, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), sample size–adjusted BIC (aBIC), entropy, Lo-Mendell-Rubin (LMR) adjusted likelihood ratio test, bootstrapped likelihood ratio test (BLRT), and smallest estimated class proportions, were used to evaluate the model fit [33-35]. The preferred model was selected based on the lower AIC, BIC, or aBIC values, as lower values indicate better model fit [36]. Entropy was used to assess classification accuracy, with values above 0.80 generally considered acceptable [35,37]. The LMR and BLRT tests were conducted to compare models with k and k-1 classes, with a statistically significant difference (P<.05) indicating that a model with k classes provided a better fit than a model with k-1 classes [38]. The smallest estimated class proportion was set at 5% of the total sample size to ensure meaningful class sizes [39]. In addition to the statistical criteria, the interpretability and parsimony of the identified classes were considered in selecting the final model [39-42]. Once the optimal latent class model was identified, latent class membership was incorporated into subsequent analyses using bias-adjusted 3-step approaches, which account for classification uncertainty rather than treating class assignment as an error-free observed variable [43]. Specifically, the 3-step approach with covariates (R3STEP) [44] was used to relate covariates to latent class membership, and the Bolck-Croon-Hagenaars (BCH) method [43,45] was used to derive classification-error-adjusted weights for examining differences in a distal outcome across latent classes.

Using the R3STEP method, multinomial logistic regression was performed to compare the sociodemographic and health characteristics of the identified latent classes. The odds ratio (OR) and corresponding 95% CIs were estimated to assess the likelihood of belonging to a specific class compared to the reference group. Finally, differences in service needs across the identified latent classes were examined using a BCH-weighted multinomial logistic regression model. Statistical significance was determined at a P value of <.05, and all multinomial logistic regression analyses were conducted after adjusting for covariates. The LCA was conducted in Mplus (version 8; Muthén & Muthén). R3STEP-based multinomial logistic regression and BCH-weighted multinomial logistic regression were also performed in Mplus. Descriptive statistical analyses were conducted in SPSS (version 27.0; IBM Corp).

Because the analyses in this study were conducted on a restricted subsample defined by specific inclusion criteria, survey weights calibrated for the whole NSOK population were not applied. Although omitting survey weights in analyses of nationally representative samples can lead to biased estimates and distorted statistical inference [46], using the original weights for a subsample without recalibration may itself introduce bias and increase estimation error [47]. Given that the analytic sample was no longer representative of the broader population, using the original weights could have led to misleading parameter estimates and incorrect variance estimates. Therefore, unweighted analyses were deemed more appropriate; this analytic approach was adopted in consultation with an experienced biostatistician to ensure sound analytic practice.

Ethical Considerations

Permission to use the data was granted by the Korea Institute for Health and Social Affairs, and this study was exempted from ethics approval by the institutional review board of the university affiliated with the research team (number 4-2025-0085).

Results

Sample Characteristics

Table 1 presents the sociodemographic and health-related characteristics of 7470 older adults aged 65 to 98 (mean 73.78, SD 6.65) years. More than half were female (n=4462, 59.7%) and lived with a spouse (n=4183, 56.0%). The majority resided in urban areas (n=5357, 71.7%). Regarding health factors, participants had an average of 2.11 (SD 1.57) chronic diseases (range 0-13), scored an average of 26.25 (SD 3.16) on the K-MMSE-2 (range 10-30), and reported a mean K-IADL score of 10.53 (SD 1.91; range 10-33). Only 8.4% (n=625) of the participants were current smokers, 35.0% (n=2611) consumed alcohol, and 43.7% (n=3266) reported not engaging in regular exercise. Additionally, 45.0% (n=3363) of the participants rated their overall health as healthy.

Table 1. Sociodemographic and health-related characteristics (N=7470).

Variables	Values
Sociodemographic factors	
Age (y), mean (SD; range)	73.78 (6.65; 65-98)
Sex, n (%)	
Male	3008 (40.3)
Female	4462 (59.7)
Residential area, n (%)	
Urban	5357 (71.7)
Rural	2113 (28.3)
Household type, n (%)	
Living alone	2450 (32.8)
Living with spouse	4183 (56.0)
Multigenerational	837 (11.2)
Annual household income, n (%)	
1st quintile (low)	1541 (20.6)
2nd quintile	1553 (20.8)
3rd quintile	1524 (20.4)
4th quintile	1480 (19.8)
5th quintile (high)	1372 (18.4)
Education level, n (%)	
Elementary or less	3137 (42.0)
Middle-high	3823 (51.2)
College or above	510 (6.8)
Health factors	
Number of chronic diseases, mean (SD; range)	2.11 (1.57; 0-13)
K-MMSE-2[a], mean (SD; range)	26.25 (3.16; 10-30)
K-IADL[b], mean (SD; range)	10.53 (1.91; 10-33)
Smoking, n (%)	
Yes	625 (8.4)
No	6845 (91.6)
Drinking, n (%)	
Yes	2611 (35.0)
No	4859 (65.0)
Exercise, n (%)	
Yes	4204 (56.3)
No	3266 (43.7)
Self-rated health status, n (%)	
Healthy	3363 (45.0)
Moderate	2553 (34.2)
Unhealthy	1554 (20.8)

[a]K-MMSE-2: Korean-Mini-Mental State Examination, 2nd Edition.
[b]K-IADL: Korean Instrumental Activities of Daily Living.

Table 2 presents digital device use, adaptation difficulty, and perceived service needs for digital adaptation among older adults. Regarding overall participation in 13 digital device activities, approximately 80% of the participants could send and receive text messages, whereas more than 80% could not play games, use SNS, engage in e-commerce or financial transactions, search for or install apps, or use machines for ordering/check-in. Most participants reported either “difficult” (n=3116, 41.7%) or “very difficult” (n=1868, 25.0%) in their digital adaptation. In contrast, only a small proportion of participants found digital adaptation as “not difficult” (n=556, 7.4%) or “not difficult at all” (n=57, 0.8%). Regarding the preferred service needs for digital adaptation, the most frequently selected support area was digital accessibility support (n=2731, 36.6%), followed closely by digital literacy enhancement (n=2508, 33.6%) and age-friendly digital solutions (n=2231, 29.9%).

Table 2. Digital device use, adaptation difficulty, and service needs for digital adaptation (N=7470).

Variables	Participants, n (%)
Digital device use	
Receiving text messages	
Yes	6306 (84.4)
No	1164 (15.6)
Sending text messages	
Yes	5548 (74.3)
No	1922 (25.7)
Video calls	
Yes	3294 (44.1)
No	4176 (55.9)
Information search and browsing	
Yes	3759 (50.3)
No	3711 (49.7)
Taking photos/videos	
Yes	3925 (52.5)
No	3545 (47.5)
Listening to music	
Yes	2009 (26.9)
No	5461 (73.1)
Playing games	
Yes	1058 (14.2)
No	6412 (85.8)
Watching videos	
Yes	3308 (44.3)
No	4162 (55.7)
SNS[a]	
Yes	662 (8.9)
No	6808 (91.1)
E-commerce	
Yes	894 (12.0)
No	6576 (88.0)
Financial transactions	
Yes	1479 (19.8)
No	5991 (80.2)
Searching for and installing apps	
Yes	973 (13.0)
No	6497 (87.0)
Machine-based ordering and check-in at service locations	
Yes	1211 (16.2)
No	6259 (83.8)
Adaptation difficulty	
Not difficult at all	57 (0.8)
Not difficult	556 (7.4)
Moderate	1873 (25.1)
Difficult	3116 (41.7)
Very difficult	1868 (25.0)
Service needs for digital adaptation	
Digital accessibility support	2731 (36.6)
Digital literacy enhancement	2508 (33.6)
Age-friendly digital solutions	2231 (29.9)

[a]SNS: social networking service.

Patterns of Digital Device Use and Adaptation Difficulty

Table 3 shows the model fit indices for the LCA, comparing models with 2 to 5 classes, to identify patterns of digital device use and adaptation difficulty among older adults. The optimal number of latent classes was determined to be 4 based on multiple criteria, including model fit statistics, interpretability, parsimony, and the elbow pattern observed in Figure 1. Although the AIC, BIC, and aBIC values consistently decreased as additional classes were added, the rate of improvement diminished beyond the 4-class model. Entropy values exceeded 0.8 for the 2-, 3-, and 4-class models, indicating acceptable classification accuracy, whereas the 5-class model fell below this threshold. Both the 3- and 4-class models demonstrated adequate statistical fit; nevertheless, the 4-class model offered superior interpretability by distinguishing a text-only group from the moderately active and inactive groups, thereby allowing for a more nuanced characterization of patterns of digital device use and adaptation difficulty. Additionally, the elbow plot exhibited an inflection at the 4-class point, with minimal information loss when moving from 4 to 5 classes, further supporting its selection. Furthermore, its smallest class accounted for 14.9% (n=1112) of the sample, indicating that all classes were reasonably sized. Accordingly, the 4-class model was retained for subsequent analysis.

Table 3. Model fit indices for latent class analysis.

Class	AIC[a]	BIC[b]	aBIC[c]	Entropy	LMR[d] *P* value	BLRT[e] *P* value	Smallest class size (%)
2	91,769.431	92,011.584	91,900.361	.91	<.001	<.001	49.3
3	85,215.300	85,581.988	85,413.565	0.887	<.001	<.001	19.0
4	82,669.662	83,160.886	82,935.263	0.874	<.001	<.001	14.9
5	82,250.775	82,866.535	82,583.712	0.799	.009	<.001	12.6

[a]AIC: Akaike information criterion.
[b]BIC: Bayesian information criterion.
[c]aBIC: sample size–adjusted BIC.
[d]LMR: Lo-Mendell-Rubin.
[e]BLRT: bootstrapped likelihood ratio test.

Figure 1. Elbow plot. aBIC: sample size–adjusted Bayesian information criterion; AIC: Akaike information criterion; BIC: Bayesian information criterion.

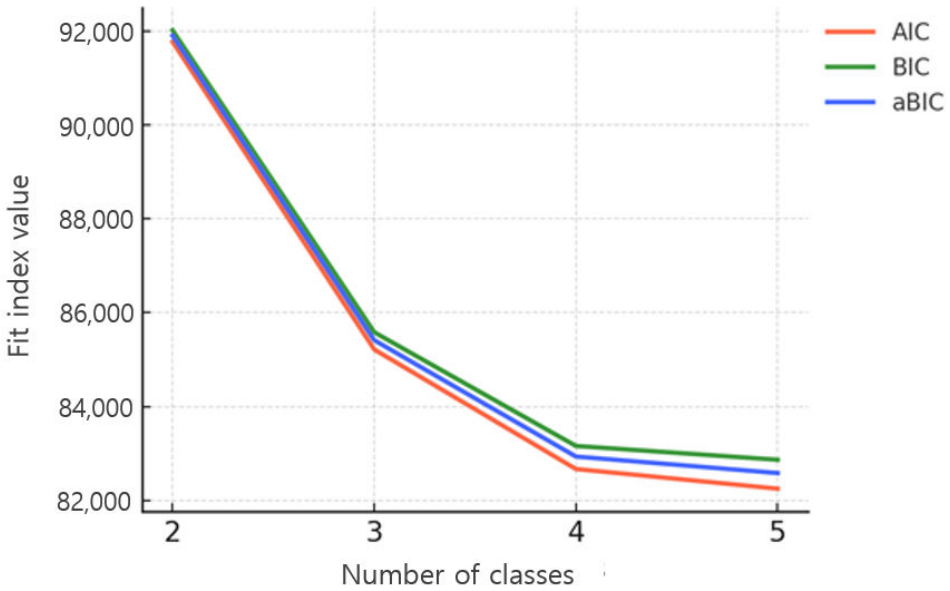


Figure 2 displays the latent class of digital device use and adaptation difficulty, along with estimated probabilities for each activity, and Multimedia Appendix 1 provides detailed characteristics by latent class. Participants were classified into to 4 classes based on their patterns of digital device use and adaptation difficulty. Class 1 (n=1112, 14.9%), labeled "digitally active with lower difficulty (active)," represented individuals with the broadest digital device use and the least difficulty, although it was the smallest group in size. Most participants in this class could perform nearly all digital activities. The least performed digital activities were playing games and using SNS, which were used by approximately half of the group. Regarding perceived difficulty, 45.0% (n=500) of the participants reported digital adaptation

as moderate, and 25.9% (n=288) as not difficult. Class 2 (n=2492, 33.4%), the largest group, was labeled "moderately active (moderate)" and exhibited mid-range probabilities across all activities. The least performed tasks in this group were e-commerce and app search/installation. Most participants could engage in approximately half of the digital activities. However, approximately 60% (n=1469) reported difficulties with digital adaptation. Class 3 (n=2082, 27.9%), labeled "text messages only (text-only)," was characterized by a high probability of only sending and receiving text messages, with over 90% being able to perform these 2 tasks. A smaller subset (approximately 20%) could perform 4 activities—video calls, information searches, taking photos/videos, and watching videos. The remaining digital device activities were rarely performed. Only 4.2% (n=92) of the participants in this class reported no difficulty in digital adaptation, while 74.2% (n=1546) reported it as difficult. Class 4 (n=1784, 23.9%), labeled "digitally inactive with difficulty (inactive)," was characterized by the most limited digital device use and the greatest difficulty in digital adaptation. Nearly all digital activities were reported as unperformable, except for sending text messages, which 35.6% (n=635) of the participants could perform. A striking 92.2% (n=1645) of this group reported digital adaptation as difficult or very difficult. The estimated proportions of participants reporting digital adaptation as difficult or very difficult were 29.2% (n=324), 59% (n=1469), 74.2% (n=1546), and 92.2% (n=1645) across classes 1 (active) through 4 (inactive), respectively.

Figure 2. Four latent classes of digital device use and adaptation difficulty.

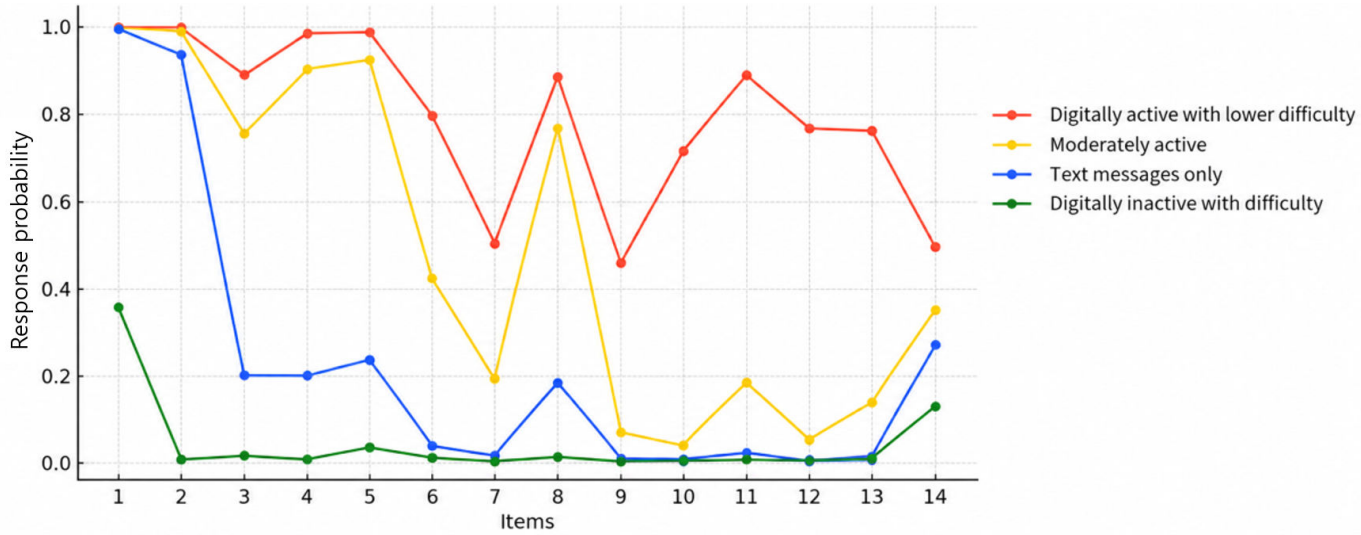


Table 4 presents the results of an R3STEP-based multinomial logistic regression analysis of sociodemographic and health-related factors associated with the identified latent classes, using the "active" class as the reference group. Older age was significantly associated with greater odds of belonging to classes characterized by more limited digital device use and greater adaptation difficulty across all comparisons, with ORs ranging from 1.136 (95% CI 1.110-1.162) to 1.335 (95% CI 1.301-1.370). Conversely, younger age was associated with a greater likelihood of membership in the active class. Living in urban areas was associated with a lower likelihood of being in the "inactive" class (OR 0.675, 95% CI 0.525-0.867). Regarding income, participants in lower-income quintiles, especially the first to third quintiles, were significantly more likely to be in the "inactive," "text-only," or "moderate" classes compared with that observed with those in the highest quintile. Similarly, individuals with lower educational attainment—particularly those with only elementary education—had substantially higher odds of belonging to classes characterized by more limited digital device use and greater adaptation difficulty (OR 22.956 for "inactive" vs "active").

Table 4. R3STEP (3-step approach with covariates)–based multinomial logistic regression of latent class membership by sociodemographic and health characteristics of older adults.

Variables	Inactive vs active (ref), OR[a] (95% CI)	Text-only vs active (ref), OR (95% CI)	Moderate vs active (ref), OR (95% CI)
Sociodemographic factors			
Age (y)	1.335 (1.301-1.370)	1.222 (1.192-1.253)	1.136 (1.110-1.162)
Sex			
Male	0.851 (0.656-1.104)	0.907 (0.727-1.132)	0.883 (0.725-1.076)
Female	—[b]	—	—
Residential area			

Variables	Inactive vs active (ref), OR[a] (95% CI)	Text-only vs active (ref), OR (95% CI)	Moderate vs active (ref), OR (95% CI)
Urban	0.675 (0.525-0.867)	1.182 (0.938-1.491)	0.983 (0.794-1.218)
Rural	—	—	—
Household type			
Living alone	0.774 (0.516-1.161)	1.009 (0.714-1.427)	0.986 (0.722-1.347)
Living with spouse	0.813 (0.568-1.164)	1.017 (0.755-1.369)	1.181 (0.914-1.527)
Multigenerational	—	—	—
Annual household income			
1st quintile (low)	2.996 (1.968-4.563)	2.787 (1.980-3.922)	1.458 (1.072-1.981)
2nd quintile	4.391 (2.841-6.786)	4.051 (2.833-5.793)	2.586 (1.840-3.634)
3rd quintile	2.019 (1.368-2.980)	2.201 (1.627-2.979)	1.609 (1.238-2.091)
4th quintile	1.063 (0.725-1.560)	1.448 (1.100-1.907)	1.333 (1.076-1.650)
5th quintile (high)	—	—	—
Education level			
Elementary or less	22.956 (12.773-41.258)	15.370 (9.773-24.174)	5.074 (3.366-7.650)
Middle–high	2.549 (1.523-4.265)	2.894 (2.006-4.174)	1.962 (1.524-2.525)
College or above	—	—	—
Health factors			
Number of chronic diseases	1.081 (0.995-1.175)	1.067 (0.988-1.151)	1.086 (1.013-1.165)
K-MMSE-2[c]	0.676 (0.637-0.717)	0.761 (0.720-0.805)	0.837 (0.796-0.879)
K-IADL[d]	1.165 (1.024-1.326)	1.138 (1.000-1.294)	1.014 (0.894-1.150)
Smoking			
Yes	1.687 (1.118-2.546)	1.367 (0.982-1.903)	1.236 (0.924-1.654)
No	—	—	—.
Drinking			
Yes	0.469 (0.362-0.608)	0.548 (0.444-0.677)	0.822 (0.684-0.987)
No	—	—	—
Exercise			
Yes	0.386 (0.307-0.485)	0.413 (0.339-0.503)	0.700 (0.587-0.835)
No	—	—	—
Self-rated health status			
Healthy	0.182 (0.120-0.276)	0.325 (0.219-0.481)	0.466 (0.319-0.682)
Moderate	0.439 (0.288-0.668)	0.747 (0.496, 1.125)	0.680 (0.454-1.020)
Unhealthy	—	—	—

[a]OR: odds ratio.
[b]Not applicable.
[c]K-MMSE-2: Korean-Mini Mental State Examination, 2nd Edition.
[d]K-IADL: Korean Instrumental Activities of Daily Living.

Regarding health factors, a higher number of chronic diseases was associated with increased odds of belonging to the "moderate" class (OR 1.086, 95% CI 1.013-1.165). Older adults with lower cognitive function compared with the others, as measured by the K-MMSE-2, were significantly more likely to be digitally less active, with ORs of 0.676 (95% CI 0.637-0.717), 0.761 (95% CI 0.720-0.805), and 0.837 (95% CI 0.796-0.879) for the "inactive," "text-only," and "moderate" classes, respectively. Greater dependence in instrumental activities of daily living, as indicated by higher K-IADL scores, also increased the likelihood of being classified into the "inactive" class. Additionally, current smokers were more likely to belong to the "inactive" class (OR 1.687, 95% CI 1.118-2.546). Individuals who consumed alcohol or engaged in regular exercise had lower odds of belonging to classes characterized by more limited digital device use and greater adaptation difficulty than those who did not. Compared with participants who rated their health as unhealthy, those who perceived their health as healthy were significantly less likely to belong to the inactive (OR 0.182, 95% CI 0.120-0.276), text-only (OR 0.325, 95% CI 0.219-0.481), or "moderate" (OR 0.466, 95% CI 0.319-0.682) classes.

Service Needs for Digital Adaptation

Multimedia Appendix 1 presents tables that provide the descriptive analysis of sociodemographic characteristics, digital device use and adaptation difficulty, and preferred service needs for digital adaptation across the 4 latent

classes. Among participants in the "inactive" class, the most frequently selected service need was age-friendly digital solutions (n=727, 40.8%), followed by digital accessibility support (n=544, 30.5%) and digital literacy enhancement (n=513, 28.7%). In the "text-only" class, a shift in preference was observed, with digital accessibility support emerging as the most selected option (n=787, 37.8%), slightly ahead of digital literacy enhancement (n=657, 31.6%) and age-friendly solutions (n=638, 30.6%). The "moderate" class expressed the highest preference for digital accessibility support (n=987, 39.6%), followed by digital literacy enhancement (n=870, 34.9%). Finally, participants in the "active" class demonstrated a clear preference for digital literacy enhancement (n=468, 42.1%), with digital accessibility support (n=413, 37.1%) also rated as high. Only 20.8% (n=231) of this class selected age-friendly solutions.

Table 5 presents the results of the BCH-weighted multinomial logistic regression examining the associations between the identified latent classes and preferred service needs for digital adaptation, with "digital literacy enhancement" used as the reference category for service needs. After adjusting for sociodemographic and health-related covariates, participants in the "inactive" class compared with the "active" class were significantly more likely to prefer age-friendly digital solutions over digital literacy enhancement (OR 1.978, 95% CI 1.510-2.591) but showed no significant difference in preference for digital accessibility support (OR 1.012, 95% CI 0.787-1.302). Similarly, members of the "text-only" class were also more likely to prefer age-friendly solutions (OR 1.536, 95% CI 1.218-1.937), with no significant difference observed for accessibility support (OR 1.158, 95% CI 0.938-1.429). The "moderate" class demonstrated significantly higher odds of preferring both digital accessibility support (OR 1.236, 95% CI 1.029-1.485) and age-friendly digital solutions (OR 1.294, 95% CI 1.051-1.593) compared to digital literacy enhancement.

Table 5. Bolck-Croon-Hagenaars (BCH)–weighted multinomial logistic regression of service needs for digital adaptation across identified latent classes.[a]

Class	Digital accessibility support vs digital literacy enhancement (ref), OR[b] (95% CI)	Age-friendly digital solutions vs digital literacy enhancement (ref), OR (95% CI)
Inactive	1.012 (0.787, 1.302)	1.978 (1.510-2.591)
Text-only	1.158 (0.938-1.429)	1.536 (1.218-1.937)
Moderate	1.236 (1.029-1.485)	1.294 (1.051-1.593)
Active	—[c]	—

[a]Analyses were adjusted for the following covariates: age, sex, residential area, household type, annual household income, education level, number of chronic diseases, Korean-Mini Mental State Examination-2, Korean Instrumental Activities of Daily Living, smoking, drinking, exercise, and self-rated health status.
[b]OR: odds ratio.
[c]Not applicable.

Discussion

Principal Findings

To the best of our knowledge, this study is the first to assess preferred service needs for digital adaptation across distinct patterns of digital device use and adaptation difficulty among older adults. Using LCA and multinomial logistic regression, we identified 4 distinct classes, examined the characteristics associated with each class, and evaluated their corresponding service preferences. The LCA revealed 4 distinct classes: the "active" class, characterized by the broadest digital device use and minimal difficulty in digital adaptation; the "moderate" class, with mid-range probabilities across most digital activities; the "text-only" class, defined by high engagement in only sending and receiving text messages; and the "inactive" class, which exhibited the lowest digital activities and the greatest difficulty in digital adaptation. The results from the multinomial logistic regression indicated that older age, rural residence, lower household income, and lower educational attainment were consistently associated with classes characterized by more limited digital device use and greater adaptation difficulty. Regarding health factors, individuals with reduced cognitive functioning, greater dependence in daily living activities, and poorer self-rated health were significantly more likely to belong to the "inactive" or "text-only" classes. Finally, analysis of preferred service needs by latent class revealed that individuals in the "inactive" and "text-only" classes expressed a significantly greater preference for age-friendly digital solutions over digital literacy enhancement, while those with more active digital device users prioritized literacy and accessibility support.

Among the sociodemographic characteristics, age and education have long been recognized as key determinants of the digital divide among older adults. Prior research has consistently shown that older age is associated with lower levels of digital literacy, competency, and proficiency [48-50]. Similarly, higher educational attainment has been linked to more frequent use of e-services and digital technologies [14,48,50]. Our findings align with these established patterns. In our study, participants with older age and lower levels of education were significantly associated with membership in classes with lower levels of digital device use and greater adaptation difficulty. Notably, participants with only elementary-level education had the highest likelihood of belonging to the "inactive group" across all comparisons. These findings underscore the importance of targeted digital inclusion strategies that address educational disparities among

older populations. Furthermore, our analysis revealed that older adults with higher household income levels and those living in urban areas were more likely to be members of the "active" class. This suggests that socioeconomic resources, including financial capacity and geographic location, might play an important role in shaping digital device use and adaptation among older adults [51-53]. Enhancing digital inclusion among older adults, therefore, requires addressing both individual-level factors and the broader structural and financial barriers that systematically create a digital disadvantage in increasingly digital societies. Specifically, improving the affordability of digital devices and internet service fees, alongside reducing disparities in rural digital infrastructure, might help to address structural barriers to digital access [7]. Expanding access to digital literacy education through community-based educators might further support skill development among vulnerable older adults [51]. Finally, addressing the adaptation and usage barriers among older adults when they are engaging with increasingly digitized public and health services might help to reduce their exclusion from these services [11,54].

Health factors were significantly associated with patterns of digital device use and adaptation difficulty among older adults. Previous research has shown that cognitive impairments mostly lead to functional limitations over time, further complicating digital engagement [55,56]. In particular, cognitive decline has been identified as a major barrier to digital engagement, as it can impair older adults' ability to learn new technologies, understand technical terminology, and comprehend or remember digital procedures [2,57]. On the other hand, emerging evidence has suggested that smartphone and tablet use may be associated with cognitive benefits among older adults, including those with and without cognitive impairment [58], suggesting a potential association between engagement and cognitive outcomes. Given that individuals with severe cognitive impairment or those requiring proxy respondents were excluded, the associations observed in this study likely reflect a relatively higher-functioning subset of older adults. Nonetheless, cognitive function may be an important consideration when tailoring digital support for this population. In addition, previous research has suggested that, among adults with chronic disease, older adults are generally less likely than younger adults to use telemedicine, often due to difficulties navigating telehealth platforms or adapting to small screens and text [11,59,60]. Consistent with these findings, our study revealed that individuals with more chronic diseases, reduced cognitive function, and higher levels of dependence in instrumental activities of daily living were significantly more likely to belong to classes reflecting greater digital limitations [14,61,62]. This disproportionate use of digital devices may be associated with a compounded burden on older adults—particularly those with cognitive and physical impairments—who often have the greatest health care needs. This pattern may suggest potential limitations in their access to digitally delivered health services.

Furthermore, our study found that self-rated health and health behaviors were closely associated with patterns of digital device use and adaptation difficulty. Participants who perceived themselves as unhealthy were significantly more likely to be classified as digitally inactive. Self-rated health, one of the most commonly used indicators in health and social research, serves as a comprehensive measure of overall health status—capturing aspects of health that may extend beyond clinical diagnoses [63]. Consistent with other health-related factors, poor self-rated health may be linked to a dual burden of health-related vulnerability and technological exclusion, which may reflect greater disparities in access to digital health resources, services, and information. Moreover, health behaviors, including smoking, alcohol consumption, and physical exercise, were also significantly associated with latent class membership. While these findings suggest that certain health behaviors may align with greater digital technology use and adaptation, the associations remain underexplored and, in some cases, inconsistent in the existing literature [14]. Further research is needed to clarify these relationships and determine whether the observed associations reflect health behaviors themselves or broader differences in health and functional status.

Analysis of service needs revealed that older adults in the "inactive" and "text-only" classes expressed a significantly greater preference for age-friendly digital solutions over digital literacy enhancement. Notably, members of the "inactive" class were nearly twice as likely as those in the "active" class to prioritize age-friendly features, suggesting that their barriers extend beyond knowledge gaps or lack of training. This is consistent with recent studies that have identified challenges such as difficulties navigating digital technologies, poor website usability, lack of adaptive features, and poorly designed user interfaces as key obstacles to technology use among older adults [2,55]. Conversely, simple and customizable technologies aligned with older adults' abilities and preferences are considered facilitators of digital adoption—supporting our findings that older adults require more than training alone.

Although our survey did not assess preferences for specific design features, participants in the inactive and text-only classes were significantly more likely to prefer age-friendly digital solutions to digital literacy enhancement. These findings suggest that improving the usability of digital services may be as important as providing additional digital literacy education for older adults in these groups. In response to these limitations, the concept of an "age-friendly lens" has gained attention in recent literature. This approach moves beyond standardized assumptions of the "average" user and embraces the full spectrum of aging and diversity [64]. While traditional interventions have emphasized raising awareness, enhancing self-efficacy, and providing digital literacy training [65-67], age-friendly technology incorporates both the biological realities of aging and the broader values, aspirations, and lived experiences of older adults. It emphasizes inclusive, human-centered design rather than merely modifying existing technologies. Emerging technologies, including care robots, demonstrate this paradigm shift; older adults should be engaged from the outset through participatory or co-design processes rather than being

treated as secondary end users [64,68]. Potential examples include simplified navigation, voice-controlled interfaces, and extended screen timeouts, which may reduce usability barriers for older adults with physical or cognitive limitations [64]. However, the specific design features required might differ according to the digital task. For example, booking a medical appointment, using a telehealth application, completing a financial transaction, and interacting with a self-service kiosk involve different interaction demands; therefore, they might require different age-friendly design strategies [64]. Importantly, these examples are illustrative rather than directly evaluated in the present study, and our findings do not indicate the design features that should be prioritized for specific digital tasks.

Age-friendly usability also spans domains such as providing access to a variety of services, simple and intuitive use, and security that ensures privacy and authenticity [69]. Collectively, these design principles highlight the practical implications of our findings and may inform the design of public services and health care platforms that better support digital inclusion and healthy aging. Although traditional alternatives, such as in-person services and telephone support, are available, they are increasingly becoming limited as public services and health care shift toward digital platforms. Consequently, the efficiency of digitalization might not be experienced by older adults who cannot use digital systems, further excluding them from the benefits of digitization. Improving digital inclusion is therefore essential to enable older adults to benefit from convenient access to public services, health information, and health care. These features should be carefully considered and implemented in public services to promote digital inclusion among the most digitally inactive older adults, with similar implications for health care platforms supporting healthy aging. Additionally, the "moderate" class exhibited a balanced demand for both digital accessibility and age-friendly support, indicating that their needs span both usability and skill development. These differentiated needs highlight the shortcomings of "one-size-fits-all" digital inclusion strategies and emphasize the importance of tailoring interventions to different patterns of digital technology use and adaptation. Future research should adopt longitudinal designs to examine changes in class membership over time, identify age-friendly design features that best support different digital tasks, and evaluate the effectiveness of tailored digital interventions for each latent class.

Recommendations for Implementation

Taken together, these findings have meaningful implications for advancing digital inclusion among older adults and guiding the development of responsive, subgroup-specific strategies to reduce digital divides. Local governments, health care systems, and welfare organizations could apply these latent classes to segment their programs more effectively, offering tiered digital support rather than relying on one-size-fits-all digital literacy workshops. This approach underscores the need for age-sensitive service design across both public and private sectors, ensuring that interventions are aligned with the specific needs and capabilities of diverse older adult groups. Prior studies provided concrete design examples to operationalize age-sensitive design principles. Specifically, for visual accessibility, larger high-contrast fonts and simplified navigation menus with minimal hierarchical steps can help reduce cognitive and visual load for those with sensory decline [11,70]. Moreover, regarding interaction and input, touch-friendly screens with larger clickable areas, voice-command functions, and audio feedback can enable older adults with reduced dexterity or vision to operate devices more independently [11,70,71]. To support ongoing engagement, tailoring interface complexity to users' abilities and offering clear privacy and security indicators can build confidence and promote sustained use [11]. These design considerations illustrate how digital services can be better aligned with older adults' functional needs. Building on these principles, subgroup-specific intervention strategies can be further refined. For the "inactive" group, individualized instruction or small group training sessions, supplemented with real-time technical assistance, may help address multifaceted barriers and support sustained digital engagement. For the "text-only" group, a stepwise introduction to more diverse digital tasks, such as video communication, mobile apps, and online services, can gradually expand their digital participation beyond messaging. Additionally, policy initiatives should focus on reducing structural barriers by increasing access to digital devices and strengthening infrastructure, particularly in socioeconomically disadvantaged or rural areas. Aligning intervention content, delivery approaches, and broader policy supports with the distinct needs of each subgroup will enable digital inclusion efforts to improve both digital literacy and practical device-use skills among older adults.

Limitations and Strengths

This study has some limitations. First, because this study used secondary data, the available measures were limited to 13 binary items assessing digital device use and one 5-point Likert item assessing digital adaptation difficulty. As these items were from the secondary data rather than a validated digital competency scale, the identified patterns should be interpreted as an exploratory classification of digital device use and adaptation difficulty. Future studies using validated, multidimensional measures are needed to confirm and extend these patterns. Second, the 6 service-need options were grouped into 3 categories based on dimensions identified in the previous literature rather than on a validated classification framework. In particular, "expansion of digital infrastructure to bridge the digital divide (eg, hands-on experience spaces)" could plausibly be classified as either literacy- or access-related; this categorization involves interpretive judgment, and alternative classifications could yield different patterns in the analysis of service-preference findings. Third, because the measure relied on self-report, responses may be subject to social desirability bias, with some participants potentially overstating or understating their actual digital device use and adaptation difficulty in line with perceived expectations in the digital era. Fourth, individuals with severe cognitive impairment or those requiring proxy responses were excluded

due to the self-reported nature of the measures. Consequently, our findings may understate the digital exclusion and needs of the most vulnerable older adults, and associations involving cognitive function should be interpreted within this narrower range. Finally, the cross-sectional design limits the ability to infer causal relationships. A longitudinal approach would be necessary to capture intra-individual change in digital device use and adaptation difficulty, particularly given that older adults' health conditions are likely to change over time. Such an approach would allow for the analysis of how patterns of digital device use and adaptation evolve with aging. Despite these limitations, this study has important strengths. Its primary contribution lies in its focus on older adults, who are at the highest risk of digital exclusion. By identifying heterogeneity within the older population and examining the corresponding service needs, the study provides meaningful insights for developing tailored digital inclusion strategies. These findings are particularly relevant for supporting the most vulnerable subgroup, that is, the digitally inactive group, by informing interventions that address specific barriers to digital inclusion.

Conclusions

This study identified 4 distinct latent classes of the patterns of digital device use and adaptation difficulty among older adults and examined the sociodemographic and health-related factors associated with digital inclusion. Notably, digitally inactive older adults were more likely to be older, less educated, and had lower incomes and reduced cognitive and functional abilities compared with their digitally active counterparts. Additionally, those in classes reflecting greater digital limitations expressed a stronger preference for age-friendly digital services over conventional digital literacy training, suggesting that usability and design-related barriers may be more relevant than skill-based limitations for many participants in this group. These findings underscore the need for differentiated and targeted digital inclusion strategies that go beyond basic skills training to address cognitive, educational, and usability challenges. Tailoring digital support to diverse patterns of digital use and adaptation difficulty may help policymakers and service providers to develop more responsive digital inclusion strategies and facilitate older adults' access to essential digital services, including health care services. Future studies should build on these findings to deepen the understanding of digital behavior trajectories among aging populations and inform evidence-based policies and practices that promote digital inclusion and support healthy aging.

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Data Availability

The data used in this study are publicly available.

Authors' Contributions

Conceptualization: SL
Data curation: SL
Formal analysis: SL, MY
Funding acquisition: EC
Methodology: SL
Supervision: EC
Writing – original draft: SL, MY, JC, JK, EC
Writing – review & editing: SL, MY, JC, JK, EC
All the authors read and approved the final version of the manuscript.

Conflicts of Interest

None declared.

Multimedia Appendix 1

Sociodemographic characteristics, digital device use, adaptation difficulty, and service needs by the identified latent classes.
[DOCX File (Microsoft Word File), 30 KB-Multimedia Appendix 1]

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Abbreviations

aBIC: sample size–adjusted Bayesian information criterion
AIC: Akaike information criterion
BCH: Bolck-Croon-Hagenaars
BIC: Bayesian information criterion
BLRT: bootstrapped likelihood ratio test
K-IADL: Korean Instrumental Activities of Daily Living
K-MMSE-2: Korean-Mini Mental State Examination, 2nd Edition
LCA: latent class analysis
LMR: Lo-Mendell-Rubin
NSOK: National Survey of Older Koreans
OR: odds ratio
R3STEP: 3-step approach with covariates
SNS: social networking service

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