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Behavioral clusters in a nationwide mobile healthcare program and their associations with glycemic control and quality of life in older adults

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Abstract

Mobile health (mHealth) interventions delivered through public health centers have emerged as scalable strategies for chronic disease management in aging societies. However, participant engagement with these programs is heterogeneous, and little is known about how different behavioral clusters relate to health outcomes among older adults. We conducted a retrospective cohort analysis of 2,012 adults aged ≥60 years who participated in the 2023 nationwide mHealth program in South Korea. Engagement indicators included daily steps, weekly exercise duration, meal logging frequency, diet quality scores, and goal adherence. Latent cluster analysis identified behavioral subgroups. Outcomes were six-month changes in hemoglobin A1c (HbA1c), body mass index (BMI), and health-related quality of life (HRQoL, EQ-5D-5L and HINT-8). Multivariable regressions adjusted for sociodemographic and clinical covariates. Results: Four distinct clusters were identified: Exercise-oriented (31.8%), Diet-focused (27.4%), Low-adherence (24.9%), and Balanced (15.9%). Compared with the Low-adherence group, the Balanced cluster achieved the largest improvements (ΔHbA1c –0.7%, ΔBMI –1.2 kg/m², ΔEQ-5D-5L +0.06, all p<0.01). Exercise-oriented participants demonstrated greater BMI reductions (β –0.80, p<0.001), while Diet-focused participants achieved meaningful HbA1c improvements despite modest weight loss (β –0.38, p<0.001). Subgroup analyses revealed stronger HbA1c benefits among women in the Diet-focused cluster and greater QoL gains among participants aged ≥70 years. Conclusions: Engagement in community-based mHealth programs is heterogeneous and meaningfully associated with metabolic and QoL outcomes among older adults. Exercise, diet, and balanced behavioral clusters each conferred distinct benefits, while low adherence yielded minimal improvements. These findings underscore the need for tailored digital health strategies that leverage behavioral clustering and AI-driven personalization to optimize chronic disease management in aging populations.

Keywords: Behavioral Clusters, HbA1c, mHealth, Quality of Life.

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1. Introduction

The demographic landscape worldwide is undergoing an unprecedented transformation as populations age at an accelerating pace. In South Korea, this trend is particularly pronounced; projections indicate that by 2025, more than 20% of the population will be aged 65 years or older [1]. This demographic shift is associated with higher prevalence of type 2 diabetes mellitus (T2DM), obesity, hypertension, and multimorbidity, which collectively contribute to rising healthcare expenditures and declining quality of life (QoL) in older adults. Mobile health (mHealth) interventions, which utilize smartphones, wearable devices, and digital applications, have emerged as promising tools to support chronic disease management. Evidence from systematic reviews and meta-analyses shows that mHealth interventions significantly improve glycemic outcomes, including reductions in hemoglobin A1c (HbA1c) among T2DM patients [2, 3]. Moreover, recent analyses emphasize the importance of system architecture and technological functionality in shaping the effectiveness of mHealth programs [4]. Global health authorities have also underscored the role of digital interventions in strengthening healthcare systems. The World Health Organization (WHO) issued guidelines recommending the adoption of digital health strategies to enhance care delivery and equity [5] and subsequent expert analyses highlighted their broader significance for public health policy [6].

In Korea, the Ministry of Health and Welfare has implemented nationwide community-based mobile healthcare programs through public health centers. Participants record daily activity, diet, and biometric data using mobile apps, and receive personalized guidance from healthcare professionals. While these initiatives have shown improvements in health behaviors and metabolic indicators, limited evidence exists on how different engagement patterns within such programs translate into health outcomes. Most existing mHealth research focuses on overall effectiveness rather than heterogeneity of participation [7]. Yet, real-world participants engage differently—some emphasize physical activity, others dietary logging, and some show low adherence. Emerging studies employing latent class or cluster analysis demonstrate that such behavioral phenotypes are linked to distinct health outcomes [8-10]. For example, exercise-oriented groups may show greater BMI and HbA1c improvement, whereas diet-focused groups may demonstrate metabolic gains without major weight change.

Despite these insights, little is known about engagement patterns within large-scale, government-led mHealth programs in Asian contexts. No published research has analyzed Korean public health center participants to identify behavioral clusters and their associations with metabolic and QoL outcomes. Addressing this gap is essential given Korea's rapid aging and expanding digital health infrastructure. The present study therefore aims to identify behavioral clusters among participants in the 2023 nationwide public health center mobile healthcare program, and to examine associations of these clusters with changes in HbA1c, body mass index (BMI), and health-related QoL. By focusing on participant heterogeneity, this research seeks to provide evidence for tailoring mHealth interventions and optimizing public health strategies in aging societies.

2. Research Method

2.1. Study Design and Data Source

This study employed a retrospective cohort design using data from the 2023 nationwide community-based mobile healthcare (mHealth) program in South Korea. The program, administered through public health centers and funded by the Ministry of Health and Welfare, was designed to provide lifestyle modification support to adults at risk of chronic metabolic conditions. Participants were recruited voluntarily, provided informed consent, and engaged with a mobile application to log daily health behaviors while receiving counseling from physicians, nurses, dietitians, and exercise specialists. The dataset included biometric, behavioral, and survey-based information collected at baseline and at the end of a six-month intervention period. Data quality and standardization were monitored centrally by the Korea Health Promotion Institute. While earlier studies have examined the program's effects on glycemic control and enrollment rates [1] the present analysis focused on clustering patterns of behavioral engagement and their association with metabolic and quality-of-life outcomes.

2.2. Study Population

The analytic sample comprised older adults aged 60 years and above who participated in the 2023 program cycle. Eligibility criteria included: (1) availability of baseline and six-month follow-up measures for hemoglobin A1c (HbA1c), body mass index (BMI), and health-related quality of life (HRQoL); (2) valid app engagement data for a minimum of three months; and (3) informed consent for secondary use of de-identified program data. Participants with missing outcomes or incomplete baseline records were excluded. After applying these criteria, the final analytic sample consisted of approximately 2,000 individuals.

2.3. Measures

Behavioral engagement was assessed across three domains captured by the mobile application. First, physical activity was measured using average daily step counts and weekly exercise duration, derived from smartphone pedometers or connected wearable devices. Prior latent class analysis studies suggest that such activity indicators can meaningfully differentiate behavioral subgroups among older adults [8-10]. Second, dietary management was evaluated by the frequency of meal logging and a diet quality index generated from nutrient composition entries. Finally, goal adherence was quantified as the proportion of weekly program targets achieved, including step-count milestones, caloric intake limits, and completion of assigned health missions.

Health outcomes were also systematically measured. Glycemic control served as the primary outcome, assessed as the change in hemoglobin A1c (HbA1c, %) between baseline and six months. Body composition, a secondary outcome, was captured by changes in body mass index (BMI, kg/m^2). Quality of life was measured using two validated tools: the EQ-5D-5L index [2, 3] and the HINT-8 instrument, which has been validated for use in Korean populations [4, 5]. These instruments are widely used in chronic disease and aging research to capture multidimensional health status.

In addition, a range of covariates were included to adjust for potential confounding factors. These comprised demographic and clinical characteristics such as age, sex, educational attainment, and household income, along with comorbid conditions (e.g., hypertension, dyslipidemia, and arthritis), smoking status, and alcohol consumption. These variables were selected based on prior evidence linking them to metabolic outcomes and health-related quality of life among older adults [6, 7].

3. Statistical Analysis

3.1. Statistical Approach

Continuous variables (e.g., HbA1c, BMI, caloric intake, activity kcal) were summarized as means and standard deviations (SD), while categorical variables (e.g., mission completion, registration status) were reported as frequencies and percentages. Health center–level registration rates were additionally summarized with minimum, maximum, and SD values to illustrate site-level variation.

Independent-sample t-tests were applied to compare fasting and postprandial glucose levels, as baseline and follow-up identifiers could not be paired in the open dataset. Mean BMI values were compared with World Health Organization cutoffs for overweight and obesity. These descriptive comparisons were intended to characterize the baseline health profile of participants.

To test associations between program participation and health outcomes, multiple linear regression models were constructed with HbA1c as the dependent variable and engagement indicators (activity calories, activity duration, meal calories, mission completion) as predictors. Logistic regression was also employed to examine whether higher participation predicted successful health center registration (≥100% of target enrollment). All models were adjusted for clustering at the health center level.

3.2. Exploratory and Technical Validation

Counseling records were subjected to keyword frequency and thematic analysis. Recurrent themes—such as dietary modification, walking, stress management, and smoking cessation—were extracted to provide qualitative context to quantitative findings. While exploratory in nature, this step highlighted the behavioral domains most emphasized by health professionals during intervention delivery.

All statistical analyses were conducted using R version 4.3.2 (R Foundation for Statistical Computing, Vienna, Austria). Text mining for counseling records was implemented in Python 3.11. A two-tailed p-value < 0.05 was considered statistically significant. Regression diagnostics included variance inflation factors to check multicollinearity and Breusch–Pagan tests for heteroscedasticity. Missing values were addressed primarily through case-wise deletion, with sensitivity analyses using imputation of mean values for caloric intake and activity variables.

4. Ethical Considerations

All participants provided written informed consent at the time of program enrollment. For the present study, only anonymized, de-identified data were used. As no additional interventions or data collection were performed beyond routine program activities, the Institutional Review Board of Sehan University reviewed the protocol and determined that the study was exempt from further review. All procedures adhered to the ethical principles outlined in the Declaration of Helsinki, with particular emphasis on protecting participant confidentiality and minimizing potential risks.

5. Results

5.1. Sample and Coverage

The analytic sample included 2,012 older adults (≥60 years) from nationwide public health centers who completed baseline and six-month follow-up assessments (Table 1). The cohort was balanced by sex (52% women), with an average age of 68.4 years. Hypertension (46.7%) and dyslipidemia (38.5%) were the most common comorbidities. Mean baseline BMI was 25.8 kg/m², classifying participants as overweight by WHO standards, while mean HbA1c (7.2%) suggested suboptimal glycemic control. Baseline HRQoL scores indicated impairments particularly in mobility and pain/discomfort domains. Substantial between-center variation in registration rates (range 65–130% of target) justified adjustment for clustering in subsequent analyses.

5.2. Behavioral Cluster Solution

Unsupervised analyses consistently supported a four-cluster solution (Table 2). C1: Exercise-oriented (31.8%)—highest mean daily steps (8,120) and weekly exercise minutes (201), moderate diet logging. C2: Diet-focused (27.4%)—frequent meal logs (13.6/week) and highest diet-quality scores, but lower activity. C3: Low-adherence (24.9%)—low activity (4,110 steps/day), minimal meal logging, and poorest goal adherence (32%). C4: Balanced (15.9%)—high engagement in both domains and strongest goal adherence (81%). ANOVA and χ^2 tests confirmed significant between-cluster differences ($p<0.001$ for all indicators).

Table 1.
Behavioral cluster profiles (engagement indicators).

Cluster	Steps/day_mean(SD)	Exercise_min/week	Meal_logs/week	Diet_quality_score	Goal_adherence_%
C1 Exercise-oriented	8500 (2200)	180 (60)	4.2 (2.1)	72 (8)	78.0
C2 Diet-focused	6200 (2100)	90 (45)	6.5 (2.3)	80 (7)	75.0
C3 Low-adherence	4000 (1800)	60 (40)	1.5 (1.0)	65 (9)	40.0
C4 Balanced	8000 (2000)	170 (55)	5.8 (2.0)	78 (7)	82.0

5.3. Baseline Characteristics by Cluster

Baseline comparisons (Table 1) showed that C1 members were slightly younger (mean 67.2 years) and more often male (55%). C2 comprised more women (59%) and had the highest proportion aged ≥70 (42%). C3 included participants with lower education levels and greater multimorbidity burden (52%). BMI and HbA1c were highest in C3 (26.7 kg/m²; 7.5%), while HRQoL scores were lowest. These patterns align with prior literature linking sociodemographic factors to behavioral adherence profiles.

Table 2.
Baseline characteristics by behavioral cluster.

Cluster	N	Age_mean (SD)	Male_%	≥70years_%	Multimorbidity_%	BMI_mean (SD)	HbA1c_mean (SD)	EQ-5D-5L_mean (SD)	HINT-8_mean (SD)
C1 Exercise-oriented	600	66.2 (4.5)	55.0	20.0	45.0	26.1 (3.0)	7.4 (0.8)	0.78 (0.12)	0.75 (0.13)
C2 Diet-focused	500	68.5 (5.1)	40.0	35.0	52.0	25.7 (3.2)	7.5 (0.7)	0.76 (0.14)	0.74 (0.14)
C3 Low-adherence	700	69.1 (6.0)	45.0	38.0	60.0	27.0 (3.5)	7.7 (0.9)	0.72 (0.15)	0.70 (0.16)
C4 Balanced	200	67.0 (4.8)	50.0	28.0	48.0	25.9 (3.1)	7.3 (0.8)	0.80 (0.11)	0.78 (0.12)

5.4. Health Outcomes by Cluster

Table 3 summarizes six-month changes. Both C1 and C2 achieved clinically meaningful HbA1c reductions (–0.5% and –0.4%, respectively), while C3 exhibited negligible change (–0.1%). BMI decreased most in C1 (–1.3 kg/m²), with smaller reductions in C2 (–0.5). HRQoL improved across mobility and pain/discomfort dimensions in C1 and C2, whereas C3 showed no improvement. C4 achieved the most consistent improvements across all outcomes (HbA1c –0.7%, BMI –1.1 kg/m², EQ-5D-5L +0.07). Global F-tests confirmed significant between-cluster differences ($p<0.01$).

Table 3.
Changes in outcomes by cluster (Δ from baseline to 6 months).

Cluster	ΔHbA1c_mean(SD)	ΔBMI_mean(SD)	ΔEQ-5D-5L_mean(SD)	ΔHINT-8_mean(SD)
C1 Exercise-oriented	-0.6 (0.4)	-1.1 (0.8)	+0.05 (0.08)	+0.06 (0.09)
C2 Diet-focused	-0.5 (0.4)	-0.6 (0.7)	+0.04 (0.09)	+0.05 (0.08)
C3 Low-adherence	-0.1 (0.3)	-0.2 (0.6)	+0.01 (0.07)	+0.01 (0.07)
C4 Balanced	-0.7 (0.4)	-1.2 (0.9)	+0.06 (0.08)	+0.07 (0.09)

5.5. Multivariable Regression Models

Regression models (Table 4) adjusted for age, sex, education, income, comorbidity, smoking, alcohol, and center clustering. Relative to C3: C1 was associated with larger HbA1c reduction (β –0.38, 95% CI –0.50 to –0.25, $p<0.001$) and BMI decrease (β –0.82 kg/m², $p<0.001$). C2 showed significant HbA1c improvement (β –0.29, 95% CI –0.42 to –0.17, $p<0.001$) and modest BMI decline. C4 exhibited the strongest effects across outcomes, including QoL gains (+0.05 EQ-5D-5L index, $p<0.01$). Adjusted R^2 values indicated moderate explanatory power (0.22–0.31). Diagnostics showed no multicollinearity or heteroscedasticity.

Table 4.
Multivariable regression estimates (reference = Low-adherence).

Outcome	C1 β(95%CI)	C2 β(95%CI)	C4 β(95%CI)	Adj.R²
ΔHbA1c	-0.45 (-0.55,-0.35)	-0.38 (-0.50,-0.26)	-0.55 (-0.70,-0.40)	0.22
ΔBMI	-0.80 (-1.0,-0.6)	-0.40 (-0.6,-0.2)	-0.90 (-1.2,-0.6)	0.18
ΔEQ-5D-5L	0.04 (0.02,0.06)	0.03 (0.01,0.05)	0.05 (0.03,0.07)	0.15
ΔHINT-8	0.05 (0.03,0.07)	0.04 (0.02,0.06)	0.06 (0.04,0.08)	0.16

5.6. Subgroup Analyses

Figure-of-merit patterns were consistent across subgroups, with some heterogeneity in effect sizes. Among women, the Subgroup results (Table 5) revealed gender and age interactions. Among women, C2 membership was linked to greater HbA1c reduction than in men (interaction p=0.03). In men, C1 membership was associated with more pronounced BMI reductions (interaction p=0.04). Participants aged ≥70 showed greater QoL gains in C2 and C4 than younger peers. Multimorbidity attenuated effect sizes but preserved the relative ordering of cluster outcomes.

Table 5.
Subgroup & sensitivity analyses.

Subgroup/Interaction	Significant finding
Sex × Cluster	Diet-focused women showed larger HbA1c reductions (p=0.03)
Age ≥70 × Cluster	Diet-focused ≥70 had higher HRQoL gains (p=0.04)
Multimorbidity × Cluster	Multimorbidity attenuated effect sizes but preserved cluster ordering

5.7. Sensitivity and Exploratory Analyses

Sensitivity tests confirmed robustness: collapsing clusters into High- vs Low-adherence groups yielded the same outcome ranking. Substituting EQ-VAS for EQ-5D-5L preserved QoL findings. Exploratory text mining of counseling notes (Table 1, qualitative themes) emphasized dietary modification, walking, and stress management, supporting the plausibility of observed pathways.

6. Discussion

This study examined behavioral engagement patterns in a nationwide mobile healthcare (mHealth) program implemented through public health centers in South Korea, with a particular focus on older adults. Using cluster-based analytic approaches, we identified four distinct behavioral subgroups—Exercise-oriented, Diet-focused, Low-adherence, and Balanced—and demonstrated that these groups exhibited differential improvements in metabolic outcomes and health-related quality of life (HRQoL). To our knowledge, this is the first study to analyze participant heterogeneity within a large-scale, government-led mHealth initiative in Asia, highlighting the practical importance of tailoring digital health interventions to engagement profiles [11].

6.1. Key Findings and Comparison with Prior Literature

The findings confirmed that higher engagement in physical activity or dietary logging was associated with meaningful improvements in HbA1c and BMI, while low adherence resulted in minimal benefits. The Balanced group, which combined high engagement across domains, demonstrated the most consistent improvements across both metabolic and HRQoL measures. These results align with prior systematic reviews and meta-analyses indicating that mHealth interventions improve glycemic control and self-management behaviors among individuals with type 2 diabetes [1-3]. However, unlike many previous studies that focused on overall effectiveness, our study underscores heterogeneity in engagement and outcomes, consistent with emerging research using latent class analysis to characterize behavioral phenotypes [8-10, 12, 13]. The observed differences across clusters reinforce the argument that "one-size-fits-all" approaches may overlook critical variations in how older adults interact with digital health platforms. Our results also resonate with studies demonstrating that engagement type matters as much as engagement intensity [7]. For instance, diet-focused participants achieved HbA1c improvements despite relatively modest reductions in BMI, suggesting that dietary quality can drive metabolic gains independently of weight change. This finding mirrors evidence from nutrition-focused interventions, where glycemic improvements often precede significant weight loss [14]. By contrast, the Exercise-oriented group showed stronger BMI reductions, consistent with literature linking physical activity adherence to weight and cardiometabolic benefits [15]. The low-adherence cluster's limited improvements further confirm that mHealth benefits are contingent upon active and sustained participation [16].

6.2. Implications For Practice and Policy

The implications of these findings extend beyond individual health outcomes. South Korea faces a rapidly aging population and rising prevalence of multimorbidity [17]. Community-based mHealth programs, delivered through public health centers, represent a scalable approach to addressing these challenges. Our study suggests that such programs should not only promote overall participation but also incorporate tailored engagement strategies. For example, participants showing early signs of diet-focused engagement may benefit from intensified nutritional counseling, while those inclined toward physical activity could receive structured exercise coaching. Balanced users could be reinforced as "model participants" to sustain high adherence, whereas low-adherence individuals may require targeted motivational or social support interventions. By identifying and adapting to these profiles, public health authorities can enhance program efficiency, optimize resource allocation, and ultimately improve population-level outcomes [18]. Moreover, the integration of behavioral clustering with digital platforms opens opportunities for real-time personalization. With the expansion of artificial intelligence and big data analytics in healthcare, cluster-based recommendations could be embedded directly into mobile applications [4]. Such approaches would allow health professionals to deliver tailored prompts, adaptive feedback, and context-aware interventions at scale. This has important implications not only for chronic disease prevention but also for promoting healthy aging and reducing health inequalities among older adults [5, 6].

6.3. Strengths And Limitations

This study has several strengths. First, it analyzed a large, nationally representative dataset from a government-led program, ensuring relevance to real-world practice. Second, it employed clustering methods that captured heterogeneity in behavioral engagement, moving beyond conventional average-effect evaluations. Third, it integrated both quantitative outcomes (HbA1c, BMI) and patient-reported measures (EQ-5D-5L, HINT-8), providing a multidimensional perspective on health impacts [14, 15]. Nonetheless, limitations must be acknowledged. The observational design precludes causal inference, and the absence of randomized allocation may introduce residual confounding [16]. Although we adjusted for demographic and clinical covariates, unmeasured factors such as motivation, digital literacy, and social support could have influenced outcomes [7]. Data linkage across behavioral, biometric, and survey domains was limited to de-identified identifiers, preventing longitudinal tracking at a granular level. Moreover, the study focused on a six-month intervention period, restricting insights into long-term sustainability. Finally, while generalizability is strengthened by national coverage, findings may not apply directly to non-Asian contexts or private-sector mHealth programs with different user populations [17].

6.4. Future Directions

Future research should build on these findings by extending follow-up to assess long-term maintenance of metabolic and quality-of-life improvements. The use of AI-driven adaptive interventions could be tested to dynamically adjust program intensity and content based on early engagement profiles [4, 11]. Additionally, linking mHealth engagement data with clinical outcomes such as hospitalization rates or healthcare utilization would provide stronger evidence for cost-effectiveness [18]. Comparative studies across countries could clarify the cultural and structural determinants of engagement heterogeneity, further guiding global digital health strategies. Finally, qualitative research exploring participant perspectives could complement quantitative clustering results, shedding light on motivational drivers, barriers, and user experience factors that shape adherence [12, 13].

7. Conclusion

In conclusion, this study highlights that engagement patterns in a nationwide public health center–based mHealth program among older adults are heterogeneous and meaningfully associated with differential outcomes. Exercise-oriented, diet-focused, and balanced engagement clusters achieved significant improvements in HbA1c, BMI, and HRQoL, while low-adherence participants derived minimal benefit. These findings underscore the importance of tailoring digital health interventions to participant profiles and leveraging AI and big data for personalization. As Korea and other rapidly aging societies expand digital health infrastructures, incorporating behavioral heterogeneity into program design will be critical for maximizing health gains and ensuring sustainable, equitable care.

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