Demonstrating the effectiveness of evidence-based Chronic Disease Self-Management Education (CDSME) programs.

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1. Abstract

OBJECTIVES: Chronic diseases such as heart disease, diabetes, arthritis, and depression represent a growing public health crisis in the United States with over 70% of older adults living with multiple chronic conditions. The demand for effective strategies to manage chronic diseases is more urgent than ever with one in five Americans projected to be aged 65 years or older by 2030. Evidence-based Chronic Disease Self-Management Education (CDSME) programs equip older adults to better manage health, reducing healthcare costs and improving quality of life. This research aims to explore the effectiveness of CDSME programs in improving self-efficacy to manage chronic disease, improving self-reported general health, and reducing self-reported loneliness among older adults.

METHODS: Data were drawn from the Healthy Aging Programs Integrated Database (HAPID ®), which includes participants enrolled in ACL-funded CDSME programs between 2010 and 2025. Analyses were restricted to participants with complete pre-and post-program survey data on outcomes of interest, yielding outcomes-specific analytic samples. We employed analysis of covariance (ANCOVA) models to estimate program-related changes in self-reported self-efficacy and self-reported general health and loneliness, while adjusting for participant characteristics and potential selection bias using a Heckman-style correction technique.

RESULTS: Baseline self-efficacy was the strongest predictor of post-program participation self-efficacy scores (0.30, p=0.000). After adjusting for baseline status, demographics, chronic disease burden, disability burden, and selection bias, CDSME program completion was associated with an 11.7 percentage-point increase in the likelihood of reporting high self-efficacy at post survey completion (p=0.000). Higher chronic disease and disability burden were associated with reduced self-efficacy, while education showed a positive effect. The inverse Mills ratio (IMR) was large and significant, indicating meaningful selection bias and supporting our use of the Heckman correction technique. Secondary models for self-reported general health and loneliness also showed similar results.

CONCLUSIONS: CDSME participation was significantly associated with improved self-efficacy among older adults to manage chronic disease in daily life, even after adjusting for baseline characteristics, health burden and selection bias. Program completion emerged as a key predictor of improvement, in key outcomes – self-efficacy, general health and loneliness, highlighting the importance of engagement and retention strategies in maximizing the impact of CDSME programs.

2. Background

Chronic diseases such as heart disease, diabetes, arthritis, and depression represent a persistent and growing public health challenge in the United States, particularly among older adults. Approximately 60–75% of adults aged 65 years and older live with two or more chronic conditions, a pattern that substantially increases clinical complexity, healthcare utilization, and costs.[1,2] As the U.S. population continues to age, with one in five Americans projected to be aged 65 years or older by 2030, the burden associated with chronic disease management is expected to intensify.[3] Chronic conditions now account for more than three-quarters of total healthcare expenditures, driven largely by preventable emergency department visits, hospitalizations, and complications related to inadequate self-management.[4]

Beyond direct medical costs, chronic illness is associated with diminished quality of life, functional decline, and loss of independence.[5] Mental health conditions such as anxiety and depression are common comorbidities among older adults with chronic disease and further exacerbate healthcare utilization and costs.[6,7,8] Social factors including loneliness and social isolation, have also emerged as important determinants of health in later life, with well-documented associations with depression, cognitive decline, poorer health behaviors, and increased mortality.[9,10,11] Together, these clinical, psychological, and social challenges underscore the need for scalable, cost-effective interventions that address not only disease symptoms but also individuals' capacity to manage their health.

Chronic Disease Self-Management Education (CDSME) programs were developed to address these challenges by strengthening individuals' self-efficacy - the confidence and skills needed to manage chronic conditions in daily life.[12] CDSME programs are structured, evidence-based interventions delivered through peer-led group workshops, typically over six weeks, and emphasize action planning, problem-solving, goal setting, symptom management, and effective communication with healthcare providers.[13,14] The theoretical foundation of CDSME draws heavily on social cognitive theory, particularly the role of self-efficacy as a key mechanism linking behavioral skills to sustained health behavior change.[15]

A substantial body of literature has documented the benefits of CDSME participation across multiple outcome domains. Prior studies have demonstrated improvements in self-reported self-efficacy, general health, fatigue, health distress, and functional limitations.[16,17] These gains are often sustained beyond program completion and are frequently observed across diverse populations and delivery modalities, including in-person and online formats.[18,19] Improvements in self-efficacy have been shown to mediate broader health outcomes, reinforcing the central role of confidence and perceived control in chronic disease management.[20,21]

CDSME programs have also demonstrated positive effects on psychosocial outcomes, including loneliness and social isolation. The group-based, peer-led structure fosters social connection, shared problem-solving, and mutual support, which can counteract isolation commonly experienced by older adults with chronic illness.[22,23] Reduced loneliness has been linked to improved mental health outcomes and may indirectly support better health behaviors and healthcare engagement.[24,25,26] These social benefits are particularly salient given growing recognition of loneliness as a public health risk factor among older adults.[27]

Importantly, CDSME participation has been associated with reductions in healthcare utilization, including fewer emergency department visits and hospitalizations within six to twelve months following program completion.[28,29,30] Several national and state-level evaluations have documented corresponding healthcare cost savings that persist even after accounting for program delivery costs.[31,32] When extrapolated to the population level, these utilization reductions suggest that CDSME programs may generate substantial savings for Medicare, Medicaid, and other public payers, while simultaneously improving patient-reported outcomes.[33]

Despite this evidence base, gaps remain in understanding the magnitude of CDSME's effects when evaluated using large-scale, participant-level data and rigorous analytic approaches that account for baseline differences and selection mechanisms into CDSME programs. Many prior studies rely on smaller observational samples, while fewer have examined real-world program implementation at scale or explicitly addressed potential selection bias in observed outcomes.

To address these gaps, the present study evaluates the effectiveness of CDSME programs in improving self-efficacy using participant-level data from a large national database of program participants. The analysis focuses on changes in self-efficacy, general health, and loneliness, while employing statistical methods designed to adjust for baseline characteristics, chronic disease burden, and non-random selection of program participants. By doing so, this study aims to provide robust evidence using real-world program data on the effectiveness of CDSME programs in improving self-management capacity among older adults and to inform ongoing efforts to sustain and scale evidence-based interventions that reduce the burden of chronic disease on individuals and the healthcare system.

3. Methods

3.1 Data Source and Study Population

This study draws on participant-level data from the Healthy Aging Programs Integrated Database (HAPID), a national data system maintained by the National Council on Aging (NCOA) to support implementation of evidence-based programs delivered through community-based organizations across the United States. HAPID includes participant-level program data for over 532,000 individuals who enrolled in Administration for Community Living (ACL)–funded Chronic Disease Self-Management Education (CDSME) programs between 2010 and 2025. For the present analysis, the analytic sample was restricted to 19,491 participants with complete baseline and post-program data for at least one of the primary outcomes: self-efficacy, general health, and loneliness/isolation outcomes. Figure 1 shows the breakdown of the sample.

Table 1: Demographic information of CDSME participants in the analytical sample

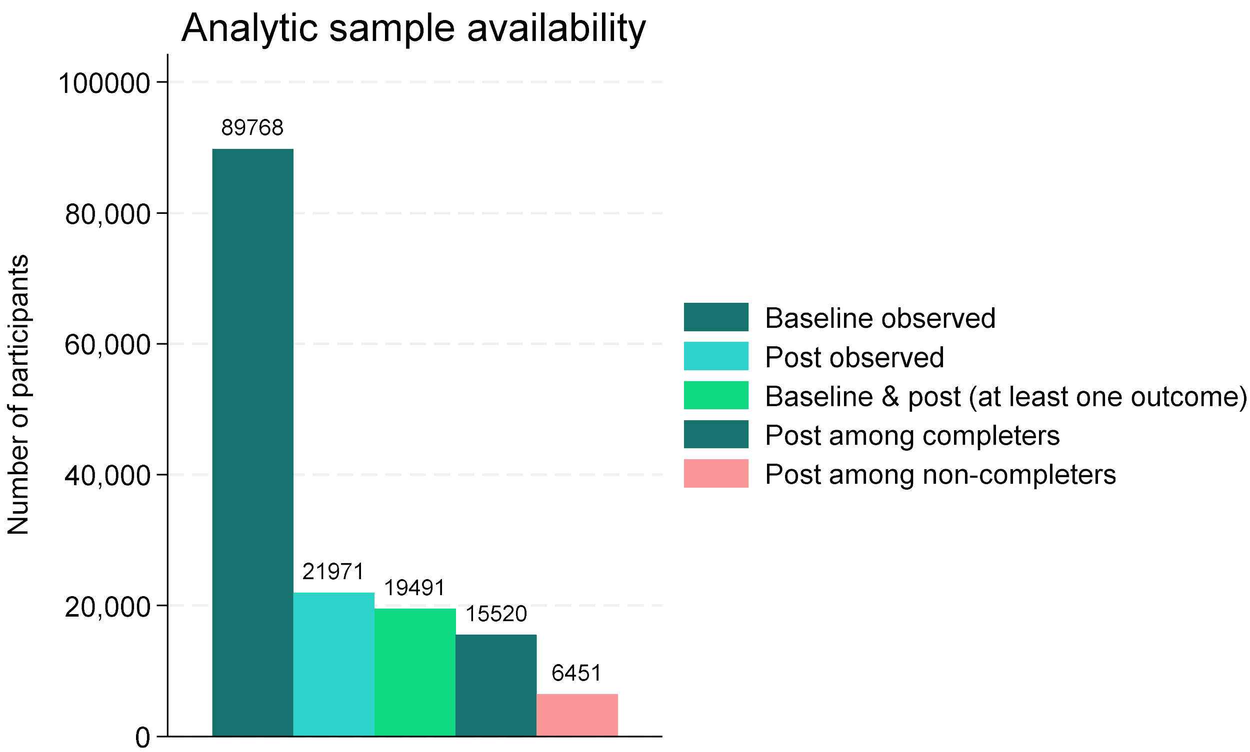
Variable	Has Pre - Mean (sd)	Has Post - Mean (sd)	N
Age	70.59 (9.81)	71.62 (9.62)	89,920

Number of Chronic Conditions	3.84 (2.21)	4.01 (2.41)	84,557
Number of Disability	0.74 (1.03)	0.89 (1.28)	85,858
Race	**Percentage of Participants (Pre-)**	**Percentage of Participants (Post-)**	**N**
American Indian or Alaska Native	1.5%	1.2%	1,664
Asian American	6.2%	10.6%	7,887
Black/African American	19.9%	18.2%	21,857
Hispanic/Latino	17.9%	24.7%	81,915
Multi-Racial	1.3%	1.3%	1,473
Native Hawaiian or Pacific Islander	0.5%	0.3%	504
Unknown	9.2%	10.4%	10,565
White	61.4%	58.0%	67,977
Education Level			
Some elementary, middle, or high school	15.1%	18.1%	16,504
High school graduate or GED	25.5%	23.1%	26,314
Some college or technical school	32.4%	28.8%	33,300
College (4 years or more)	27.0%	30.1%	29,006
Sex			
Male	21.4%	18.8%	22,959
Female	78.5%	81.0%	86,877
Prefer not to say	0.1%	0.2%	96
Disability Type			
Seeing Difficulty	12.5%	11.0%	75,330
Hearing Difficulty	15.0%	12.9%	75,273
Physical Limitations	37.0%	25.5%	49,433
Concentration Difficulty	18.9%	18.0%	28,270
Errand Difficulty	18.7%	17.6%	27,932
Dressing Difficulty	12.4%	11.5%	28,282
Walking Difficulty	35.2%	34.1%	29,223

Source: HAPID (2010-2025)

The database captures a broad range of participant information, including demographic and socioeconomic characteristics, chronic condition burden, disability status, and self-reported health and psychosocial outcomes using validated measures. Participants were predominantly older adults aged 60 years and older, though adults under age 60 with chronic conditions or disabilities are also eligible. Programs were implemented across diverse settings, including senior and tribal centers, aging services agencies, healthcare organizations, community-based nonprofits, and educational institutions.

Figure 1: Analytical sample description



3.2 Study Design

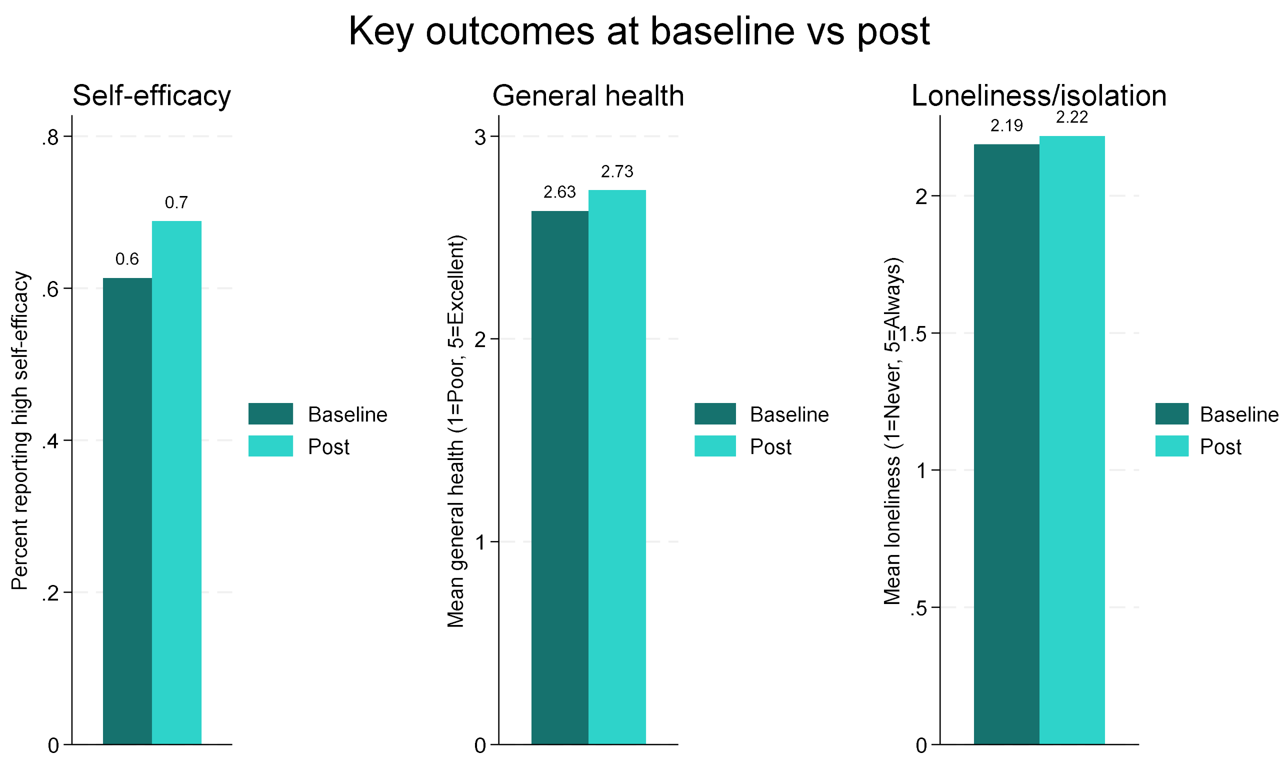
The study employs a pre–post observational design using participant-reported outcomes collected immediately before program enrollment and upon program completion. Because CDSME participation occurs in real-world community settings, program completion is voluntary. CDSME is an umbrella term encompassing a variety of evidence-based programs, and specific interventions may differ in duration, delivery format, and topical focus. Importantly, eligibility for CDSME programs explicitly requires the presence of at least one chronic condition, and participants with greater chronic disease burden may differ systematically from those with fewer conditions in both baseline outcomes and likelihood of completing the program. These eligibility criteria and participation dynamics motivate an analytic approach that adjusts for both baseline outcome levels and potential selection bias.

3.2.1 Outcomes and Covariates

The primary outcome is self-efficacy, measured on a validated 10-point scale capturing confidence in managing chronic conditions and health-related tasks. Secondary outcomes include self-rated general health, measured on a five-point ordinal scale, and psychosocial well-being, assessed using validated ordinal measures of loneliness and social isolation. For econometric analysis, outcomes were modeled both as continuous measures and as binary indicators reflecting clinically meaningful thresholds (e.g., high self-efficacy defined as ≥8). The ≥8 threshold corresponds to the sample mean, allowing classification of participants with above-average self-efficacy while preserving statistical power and interpretability. Binary outcomes facilitate interpretation in terms of probabilities of achieving favorable health states while remaining consistent with the ANCOVA and selection-correction framework.

All models were adjusted for baseline participant characteristics measured at program entry, including age, age squared, sex, race/ethnicity, educational attainment, number of chronic conditions, and number of reported disabilities. Figure 2 shows a description of key outcome variables.

Figure 2: Summary statistics for key outcomes



3.2.2 Econometric Strategy

ANCOVA Framework: Program effects were estimated using an analysis of covariance (ANCOVA) specification, in which post-program outcomes are modeled as a function of baseline outcome values, program completion, and participant characteristics. This approach improves efficiency and reduces bias relative to simple change-score models, particularly in non-randomized pre–post designs.[34]

The baseline ANCOVA specification is given by:

$$Y_{i1} = \alpha + \beta Y_{i0} + \gamma C_i + \mathbf{X}_i' \boldsymbol{\delta} + \varepsilon_i$$

where Y_{i1} denotes the post-program outcome for individual i, Y_{i0} is the corresponding baseline outcome, C_i is an indicator for program completion, $\mathbf{X}_i$ is a vector of baseline covariates (including age, age squared, chronic condition count, disability count, education, race/ethnicity, and sex), and ε_i is an idiosyncratic error term. The coefficient γcaptures the association between program completion and post-program outcomes, conditional on baseline status and covariates.

Although ANCOVA controls for observed baseline differences, it does not address selection on unobservables that may influence both program completion and outcomes.[35] In the CDSME context, selection bias is particularly salient for two reasons. First, eligibility for participation requires the presence of chronic disease, implying that the analytic sample is already selected on health status. Second, individuals with higher chronic disease or disability burden may face greater barriers to program completion while simultaneously having different potential for outcome improvement.[36] As a result, completion status may be endogenous to post-program outcomes.

To address this concern, we implement a Heckman-style two-step selection correction, allowing for correlation between unobserved determinants of program completion and unobserved determinants of outcomes.[37]

Heckman Selection Model: In the first stage, program completion is modeled using a probit specification:

$$C_i^* = \mathbf{Z}_i'\boldsymbol{\pi} + u_i, C_i = 1[C_i^* > 0]$$

where $C_i^*$is a latent propensity to complete the program, $\mathbf{Z}_i$includes baseline demographics, education, disability burden, chronic condition burden, and baseline outcome measures, and $u_i$is a normally distributed error term.

When the selection process is modeled using a probit specification, then the expected value of the outcome error conditional on being selected has a closed form solution. This conditional expectation gives rise to the inverse Mills ratio (IMR) defined as:

$$\lambda_i = \frac{\phi(\mathbf{Z}_i'\boldsymbol{\pi})}{\Phi(\mathbf{Z}_i'\boldsymbol{\pi})}$$

where $\phi(\cdot)$and $\Phi(\cdot)$denote the standard normal probability density and cumulative distribution functions, respectively. The IMR provides a continuous measure of the degree to which an observation is selected into the analytic sample, capturing the likelihood that a participant completes the program and is observed at follow up. Including the IMR in the outcome equation serves two key purposes. First, it explicitly accounts for the component of the outcome that is attributable to non random selection into program completion. Second, it allows the estimated association between program participation and outcomes to be distinguished from differences driven by selective retention of participants who remain engaged long enough to be measured. This approach is well established in applied health economics and program evaluation research, particularly in evaluations of voluntary, community based interventions such as CDSME.[38]

In the second stage, the IMR is included in the ANCOVA outcome equation:

$$Y_{i1} = \alpha + \beta Y_{i0} + \gamma C_i + \mathbf{X}_i'\boldsymbol{\delta} + \rho\lambda_i + \varepsilon_i$$

A statistically significant coefficient ρindicates the presence of selection bias due to correlation between unobserved determinants of completion and outcomes. All primary results are reported from models including the IMR.

Model Estimation and Robustness: Binary outcomes were primarily estimated using a probit model, with results reported as average marginal effects for ease of interpretation. As a sensitivity check, the same ANCOVA specification was re-estimated using a linear probability model to assess robustness to functional form assumptions. Additional sensitivity analyses examined alternative outcome thresholds, exclusion of baseline outcome controls, and estimation without selection correction. Across specifications, the direction and relative magnitude of program-associated effects remained stable, supporting the robustness of the findings.

Method limitation: Identification of the two step Heckman selection model ideally relies on the inclusion of at least one exclusion restriction, an observed factor that influences program completion but does not directly affect post program outcomes, conditional on covariates. In the present analysis, the variables used to model program completion largely overlap with those included in the outcome equations, reflecting the limited availability of credible exclusion restrictions in real world evaluations of voluntary community based programs. As a result, identification is achieved primarily through the functional form assumptions of the probit selection model and the nonlinearity of the inverse Mills ratio. While this approach is common in applied health economics and program evaluation research, it relies on distributional assumptions and therefore represents a weaker source of identification than designs that incorporate exclusion restrictions.

4. Results

4.1 Self-efficacy

Table 2 reports estimates from the ANCOVA specifications with selection correction for the binary indicator of high self-efficacy at post-program completion (defined as a score ≥8 on a 1–10 scale). The model conditions on baseline self-efficacy status, program completion, demographic characteristics, health burden, and an inverse Mills ratio derived from a first-stage participation equation. Model 1 uses a probit estimator while Model 2 uses a linear probability model as a sensitivity check, with similar results across both models. Baseline self-efficacy is the strongest predictor of post-program outcomes. Participants who entered the program with high self-efficacy are associated with a 30.3 percentage points higher likelihood of reporting high self-efficacy at follow-up ($p<0.001$), highlighting substantial state dependence in self-management confidence. Program completion is independently associated with a statistically and economically meaningful increase in self-efficacy: completers were 11.7 percentage points more likely to achieve high post-program self-efficacy relative to non-completers, conditional on baseline status and covariates ($p<0.001$).

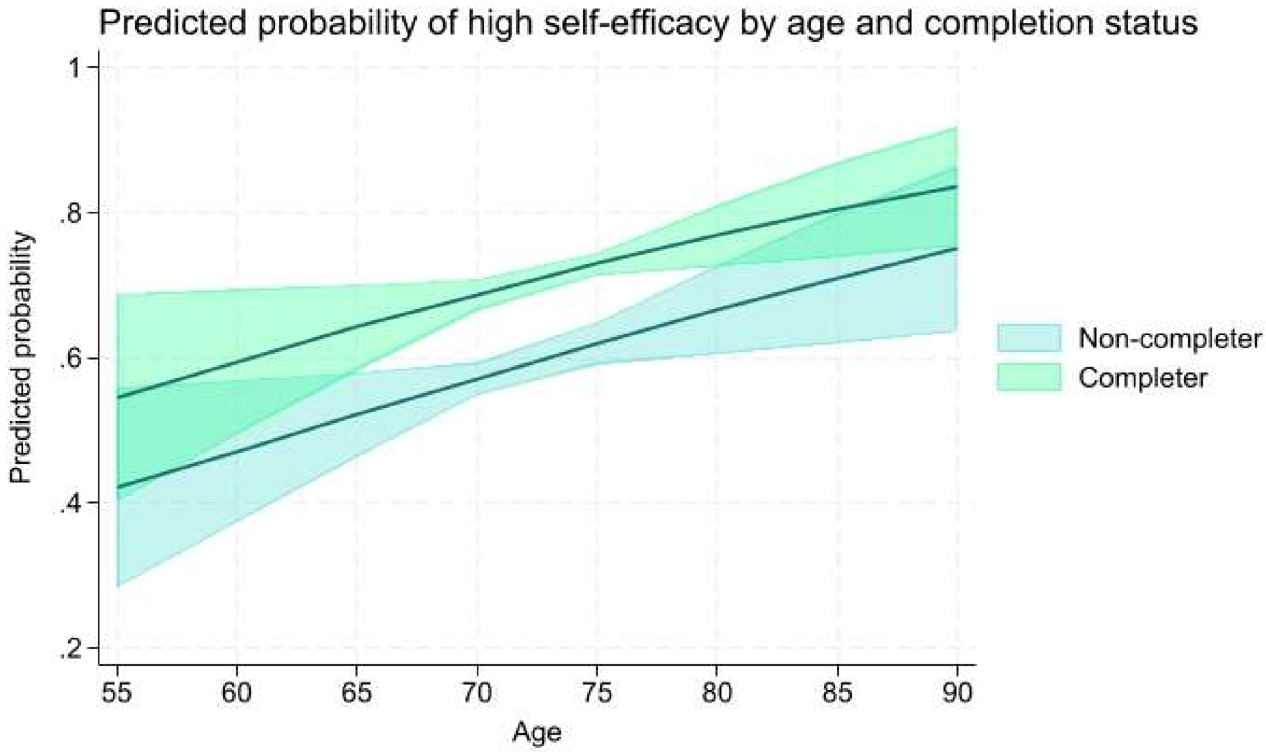
Table 2: Results of ANCOVA Models for Self-efficacy of CDSME participants

ANCOVA Models for Self-efficacy		
	Model 1 (Main Model)	**Model 2 (Sensitivity)**
Baseline self-efficacy	0.303*** (0.011)	0.318*** (0.011)
Completer	0.117*** (0.012)	0.114*** (0.012)

Age	0.009*	(0.004)	0.010*	(0.004)
Age squared	-0.000*	(0.000)	-0.000**	(0.000)
Chronic Conditions Count	-0.015***	(0.002)	-0.016***	(0.002)
Disability Count	0.010	(0.008)	0.003	(0.009)
Education	0.012**	(0.004)	0.011**	(0.009)
Race (Base=Black)				
American Indian or Alaska Native	-0.164***	(0.034)	-0.160***	(0.038)
Asian American	-0.219***	(0.023)	-0.214***	(0.022)
Multi-Racial	0.032	(0.028)	0.035	(0.031)
Native Hawaiian or Pacific Islander	-0.254**	(0.081)	-0.237**	(0.074)
Unknown	-0.106***	(0.018)	-0.102***	(0.018)
White	-0.030**	(0.009)	-0.032**	(0.010)
Hispanic/Latino	-0.065***	(0.009)	-0.066***	(0.009)
Sex (Base=Male)				
Female	0.042***	(0.012)	0.0399**	(0.012)
Prefer not to say	-0.196*	(0.098)	-0.1733*	(0.085)
Selection Correction				
IMR	1.024***	(0.154)	0.991***	(0.163)
Constant			-0.010	(0.160)
Observations	13,812		13,812	
Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001				

Age exhibits a nonlinear relationship with self-efficacy gains. The linear age term is positive, while the quadratic term is negative, indicating diminishing returns to self-efficacy levels at older ages as illustrated in Figure 3. Greater chronic disease burden was found to be associated with lower probabilities of achieving high self-efficacy post-program, consistent with more complex self-management challenges among participants with higher health needs. Higher educational attainment is positively associated with self-efficacy improvements. The coefficient on the inverse Mills ratio is positive and statistically significant (p<0.001), indicating the presence of non-random selection of participants into CDSME programs. This result supports the use of a Heckman-style correction, consistent with the program's eligibility criteria that prioritize individuals with existing chronic disease burden.

Figure 3: Predicted probability of high self-efficacy by age and completion status



4.2 General health

We next examine changes in self-rated general health, measured on an ordinal scale from 1 (poor) to 5 (excellent). Model 1 in Table 3, uses a probit estimator for an indicator equal to one if post-program health is reported as good, very good, or excellent (≥3), conditioning on baseline health status and covariates. Model 2 uses a linear probability model as a sensitivity check, with similar results across both models. Baseline general health is a strong predictor of post-program health status: participants reporting good or better health at baseline were 45 percentage points more likely to report good or better health at follow-up ($p<0.001$). Program completion is associated with a modest but statistically significant improvement in general health, increasing the probability of reporting good or better health by 3 percentage points ($p<0.001$).

Table 3: Results of ANCOVA Models for General Health of CDSME participants

ANCOVA Models for General Health				
	Model 1 (Main Model)		**Model 2 (Sensitivity)**	
Baseline general health	0.450***	(0.015)	0.483***	(0.011)
Completer	0.034***	(0.009)	0.031***	(0.008)
Age	0.005	(0.004)	0.004	(0.004)
Age squared	-0.000	(0.000)	-0.000	(0.000)
Chronic Conditions Count	-0.012***	(0.002)	-0.012***	(0.002)
Disability Count	-0.003	(0.004)	0.012**	(0.004)

Education	0.029***	(0.004)	0.025***	(0.004)
Race (Base=Black)				
American Indian or Alaska Native	-0.083*	(0.033)	-0.075	(0.039)
Asian American	-0.178***	(0.019)	-0.152***	(0.015)
Multi-Racial	0.010	(0.032)	0.006	(0.036)
Native Hawaiian or Pacific Islander	-0.020	(0.074)	-0.009	(0.064)
Unknown	-0.064***	(0.017)	-0.051**	(0.018)
White	-0.024*	(0.011)	-0.024*	(0.010)
Hispanic/Latino	-0.015***	(0.010)	-0.017	(0.011)
Sex (Base=Male)				
Female	0.017	(0.012)	0.006**	(0.010)
Prefer not to say	0.225	(0.098)	-0.172*	(0.075)
Selection Correction				
IMR	0.447***	(0.086)	0.272***	(0.049)
Constant			0.184	(0.159)
Observations	11,489		11,489	
Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001				

Higher chronic disease burden and disability burden are both negatively associated with post-program general health and statistically significant in the linear probability model, Model 2. Education is positively associated with general health improvement post program participation. As with self-efficacy, the inverse Mills ratio is positive and statistically significant (p<0.01), again indicating selection of participants into CDSME programs based on unobserved characteristics correlated with health outcomes.

4.3 Loneliness and social isolation

We estimate models for a combined loneliness and social isolation outcome, measured on a five-point scale where higher values indicate greater frequency (1=never, 5=always). The primary outcome is a binary indicator equal to one if respondents report loneliness or isolation sometimes or more frequently (≥3). As reported in Table 4, Baseline loneliness and isolation strongly predict post-program status: participants reporting loneliness or isolation at baseline were 46.7 percentage points more likely to report loneliness or isolation at follow-up (p<0.001). Program completion is associated with a statistically significant reduction in loneliness and isolation, lowering the probability of reporting loneliness or isolation by 8 percentage points (p<0.001).

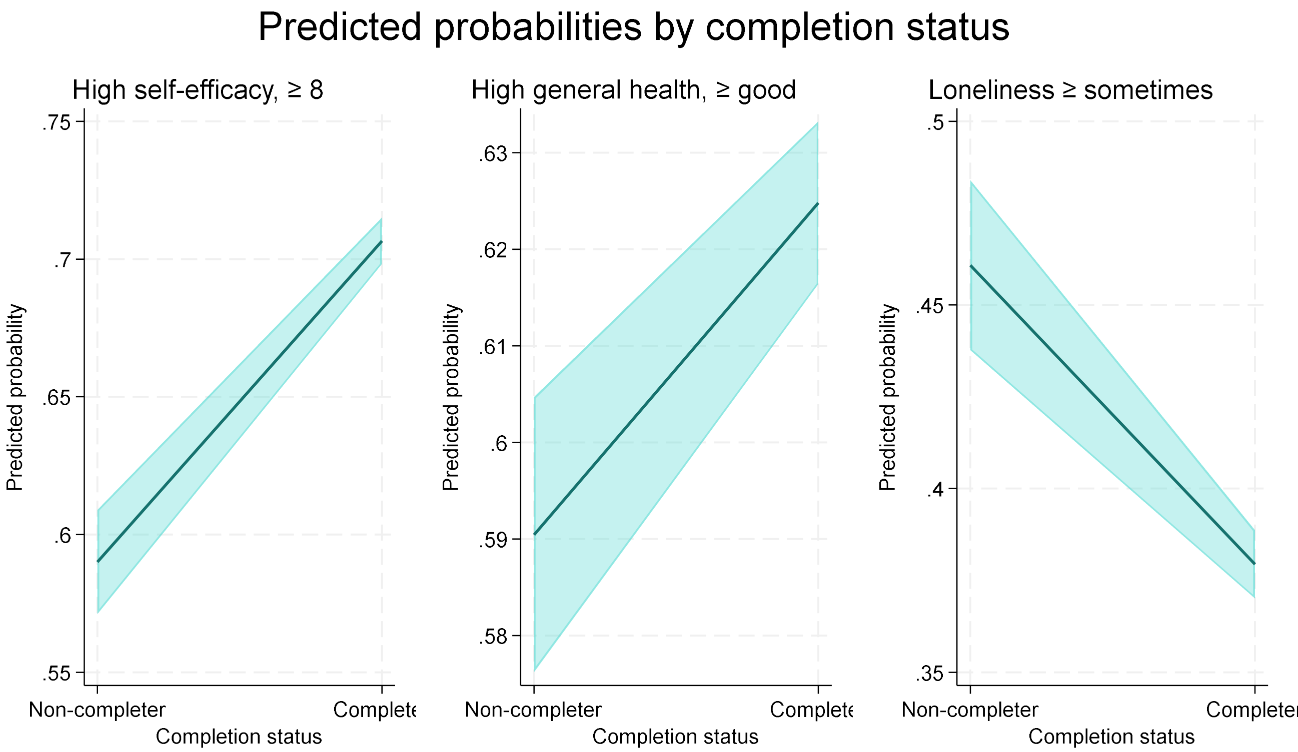
Table 4: Results of ANCOVA Models for Loneliness of CDSME participants

ANCOVA Models for Loneliness and Isolation				
	Model 1 (Main Model)		**Model 2 (Sensitivity)**	
Baseline loneliness and isolation	0.457***	(0.017)	0.462***	(0.014)
Completer	-0.081***	(0.014)	-0.075***	(0.014)
Age	-0.004	(0.005)	-0.004	(0.005)
Age squared	0.000	(0.000)	0.000	(0.000)
Chronic Conditions Count	0.005**	(0.002)	0.005**	(0.002)
Disability Count	-0.046***	(0.008)	-0.040***	(0.008)

Education	-0.001	(0.004)	-0.001	(0.004)
Race (Base=Black)				
American Indian or Alaska Native	0.074*	(0.037)	0.070	(0.044)
Asian American	0.295***	(0.029)	0.267***	(0.027)
Multi-Racial	-0.096**	(0.030)	-0.097	(0.041)
Native Hawaiian or Pacific Islander	0.230**	(0.085)	0.205	(0.086)
Unknown	0.144***	(0.022)	0.137***	(0.023)
White	-0.016	(0.011)	-0.017	(0.011)
Hispanic/Latino	0.052***	(0.012)	0.056***	(0.012)
Sex (Base=Male)				
Female	-0.029*	(0.012)	-0.027*	(0.011)
Selection Correction				
IMR	-1.583***	(0.160)	-1.450***	(0.148)
Constant			0.812***	(0.186)
Observations	8,952		8,952	
Standard errors in parentheses * p<0.05, ** p<0.01, *** p<0.001				

Disability burden is negatively associated with improvements, while chronic disease burden shows a small positive association with loneliness persistence, suggesting that health complexity may constrain psychosocial gains even in supportive group settings. Female participants exhibit slightly lower loneliness at follow-up relative to males. Notably, the inverse Mills ratio is large and negative (p<0.001), indicating substantial negative selection: individuals more likely to complete the program, conditional on observables, also exhibit unobserved characteristics associated with lower loneliness. This reinforces the importance of accounting for selection when interpreting psychosocial outcomes.

Figure 4: Summary of predicted probabilities of key outcomes by completion status



Across specifications as summarized in Figure 4, CDSME program completion is robustly associated with improvements in self-efficacy and self-rated health after adjusting for baseline status, health burden, and non-random selection of participants into CDSME programs. The strong and significant selection terms across outcomes underscore the importance of accounting for non-random participation when evaluating community-based chronic disease interventions.

5. Discussion

5.1 Interpretation and mechanisms

This study provides new evidence on the effectiveness of Chronic Disease Self-Management Education (CDSME) programs using a large, national, real-world dataset and an econometric framework that explicitly accounts for baseline outcome persistence and non-random participant selection. Three main findings emerge. First, CDSME participation is robustly associated with improvements in self-efficacy, even after adjusting for baseline status, health burden, and selection bias. Second, program completion is associated with modest but statistically significant improvements in self-rated general health. Third, evidence for reductions in self-reported loneliness and social isolation is present in selection-adjusted models as results showed lower likelihood of loneliness for completers relative to non-completers post program participation.[39]

A central contribution of this study is the demonstration of substantial state dependence in self-efficacy and general health among older adults with chronic conditions. Baseline outcomes are the strongest predictors of post-program status across all specifications, underscoring the importance of conditioning on baseline levels when evaluating community-based interventions.[40] This finding aligns with, and extends, prior experimental and quasi-experimental evidence by quantifying post-program gains in self-management confidence and health status at scale, in routine program delivery settings rather than controlled trial environments. Beyond documenting persistence, the results show that CDSME completion is associated with economically meaningful improvements in self-efficacy. An 11.7 percentage-point increase in the probability of achieving high self-efficacy is substantial in magnitude relative to baseline levels and compares favorably with effects reported in smaller randomized studies.

The general health results are more modest in magnitude but consistent in direction. Improvements in self-rated health remain statistically significant after adjustment, suggesting that gains in self-management confidence may contribute to, at least partially, perceived improvements in overall health. Importantly, these effects are detected despite the relatively short pre–post window typical of CDSME evaluations, indicating that self-rated health may be responsive to changes in self-management capacity even in the near term.

5.2 Selection, eligibility, and methodological implications

A key methodological contribution of this study is its explicit treatment of health-related selection. CDSME eligibility criteria require the presence of chronic disease, and participants with higher disease or disability burden may differ systematically in both their likelihood of completing the program and their potential for improvement. The statistically significant inverse Mills ratios across outcomes provide clear empirical evidence that selection on unobservables is present and relevant in this context.

Notably, the direction and magnitude of the selection terms differ across outcomes. For self-efficacy and general health, positive selection implies that individuals more likely to complete the program also possess unobserved characteristics associated with better outcomes. For loneliness and social isolation, the large negative selection term suggests the opposite pattern: individuals more likely to complete the program may already have unobserved characteristics associated with lower loneliness.

From a methodological standpoint, these findings reinforce the importance of incorporating selection correction or alternative identification strategies when evaluating voluntary, non-randomized programs targeting populations defined by health status. Evaluations that do not address such selection bias may either overstate or understate program-associated effects, depending on the outcome under consideration.

5.3 Policy implications for U.S. health policy

From a U.S. health policy standpoint, these findings are salient because CDSME sits at the intersection of 1) aging population and rising chronic disease burden, 2) pressure on Medicare and Medicaid to support “whole-person” care, and 3) growing recognition that community-based infrastructure can complement clinical care by strengthening patients’ self-management capacity. In this context, the magnitude of self-efficacy gains associated with completion is policy-relevant: self-efficacy is a well-established mediator of adherence, self-care behavior, and effective use of healthcare services, and is frequently the pathway through which self-management interventions are theorized to influence downstream outcomes.[41]

For funders the results lend empirical support for continued investment in CDSME as an evidence-based strategy to improve self-management capacity among older adults and adults with disabilities. Two actionable implications for future funders to consider:

1. **Shift performance management toward engagement and completion, not only enrollment.** With completion as a key predictor of improvement, then implementation strategies that reduce barriers to attendance (transportation supports, flexible scheduling, hybrid delivery, and referral pathways from healthcare systems) become central to maximizing program impact.

2. **Target "high-burden" participants with tailored supports.** The negative associations between chronic disease/disability burden and improvements indicate that individuals with the greatest needs may require additional accommodations, coaching, or linkages (e.g., care coordination, caregiver supports, or wraparound services) to fully benefit from standard CDSME curricula.

More broadly, these results strengthen the rationale for positioning CDSME as part of U.S. strategies to expand access to evidence-based, community-delivered interventions, particularly as federal and state systems increasingly promote integration between healthcare and community-based organizations. Increased federal investment in evidence-based CDSME programs can bring programs to scale so every American who is managing a chronic condition has access to low cost- high yield information and skill building to better manage their condition and decrease healthcare utilization. They also motivate more rigorous implementation-focused research on what increases completion among high-need populations and whether adaptations (e.g., digital/hybrid delivery) can preserve effectiveness while improving reach and retention.

5.4 Limitations and future research

Several limitations merit acknowledgment. Although the analytic approach addresses baseline differences and selection bias, the observational design precludes strong causal claims. Measurement relies on self-reported outcomes, which may be subject to reporting bias. In addition, the short pre–post interval limits assessment of longer-term effects, particularly for psychosocial outcomes.

Future research should explore heterogeneity in effects by program modality, delivery setting, and participant risk profiles, as well as longer-term follow-up to assess durability. Linking CDSME participation to administrative utilization data and coordination across diagnostic assessment, clinical interventions, and healthcare resource use would further strengthen understanding of how improvements in self-efficacy translate into downstream health system outcomes.

6. Conclusion

In sum, this study provides rigorous, large-scale evidence that CDSME participation is associated with meaningful improvements in self-efficacy and modest improvements in self-rated health among older adults with chronic conditions, even after accounting for baseline status and non-random participant selection. The results highlight both the promise of CDSME as a core component of U.S. aging policy and the importance of careful econometric evaluation in real-world program settings.

As the U.S. population ages and the burden of chronic disease intensifies, scalable, evidence-based interventions like CDSME will be essential to sustaining the health and financial viability of our healthcare system. Continued investment, policy integration, and targeted expansion of CDSME can strengthen individual self-management capacity, improve population health, and generate cost savings that benefit individuals, communities, and federal health programs alike.

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