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# The Impact of AI-Powered Alexa Assistant on Loneliness in Homebound Older Adults: A Pilot Study

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## ABSTRACT

*Background*: Loneliness and social isolation are significant public health concerns among homebound older adults, often exacerbated by limited mobility and chronic health conditions. This study evaluates the impact of Artificial intelligence (AI))-powered Alexa voice assistant Echo Show on loneliness in this vulnerable population.

*Methods*: An observational study was conducted with 105 homebound older adults receiving home care services. Participants were provided with Amazon Alexa devices and followed for six months. Loneliness was measured using the UCLA Loneliness Scale-20. Descriptive statistics and multivariate regression models were used to analyze changes in the loneliness score.

*Results*: The mean age of 105 participants was 73.14 years (SD ± 6.56), with 78.1% female and 78.1% White. At baseline, 88.57% of participants reported moderate to severe loneliness, and 93.34% had mild to moderate depression. At six-month follow-up, significant improvements were observed: loneliness scores decreased from 47.343 to 36.474 ($p < 0.001$). Regression analysis confirmed the intervention's significant positive effect on reducing loneliness (coefficient = −9.27, $p < 0.001$), even after controlling for demographic and health-related variables. Participants with congestive heart failure (CHF) reported lower loneliness scores than those without CHF (coefficient = −4.877, $p = 0.022$), an unexpected finding warranting further investigation.

*Conclusion*: AI-powered voice assistants like Alexa Echo Show significantly reduce loneliness in homebound older adults. These findings highlight the potential of technology-based interventions to address social isolation and enhance the well-being of this population. Policymakers and healthcare providers should consider integrating voice assistants into Medicare and Medicaid home care services to improve outcomes and reduce healthcare costs. Further research is needed to explore long-term effects and mechanisms of action.

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**KEYWORDS:** loneliness; homebound; older adult; voice assistant; Alexa Echo Show

## INTRODUCTION

Loneliness among older adults is a pervasive and growing public health issue, which is defined as the subjective feeling of social isolation or lack of meaningful connections. Loneliness has been linked to a range of adverse health outcomes, including depression, cognitive decline, cardiovascular disease, and even increased mortality [1,2]. Loneliness among homebound older adults, a longstanding public health issue, was observed by the COVID-19 pandemic's social distancing measures and reduced access to community services have left many older adults feeling even more isolated [3].

Homebound elderly individuals are particularly vulnerable to loneliness due to their limited mobility, reduced social interactions, and higher prevalence of chronic health conditions [4]. Traditional interventions to combat loneliness, such as in-person social activities or community programs, often face significant barriers, including accessibility, scalability, and the physical limitations of the elderly population [5]. As a result, there is a pressing need for innovative, accessible solutions to effectively address this population's loneliness.

Emerging technologies, particularly AI-powered voice assistants like Amazon Alexa, offer a promising avenue for mitigating loneliness among homebound elderly. These devices can provide companionship, facilitate communication with family and friends, and offer reminders for medications or appointments, enhancing social engagement and improving overall well-being [6]. Preliminary studies have shown that voice assistants can reduce feelings of loneliness and improve mental health outcomes in older adults. However, more rigorous research is needed to understand their potential fully [7].

This study aimed to assess the potential impact of using Amazon Alexa Echo Show on loneliness in homebound older adults receiving home care. We hypothesize that the intervention will significantly reduce the overall loneliness score. By leveraging the capabilities of AI-powered voice assistants, this research seeks to provide a scalable and accessible solution to a critical public health issue.

## MATERIALS AND METHODS

### Study Design and Population

This observational study, conducted from December 2023 to August 2024, employed a pre-post intervention design to evaluate the impact of an AI-powered voice assistant (Amazon Alexa Echo Show) on loneliness, depression, and health-related quality of life (HRQL) in homebound older adults. The study population comprised eligible105 participants recruited from home care services in primarily rural locations across eastern Kansas. Inclusion criteria were: (1) age 65 years or older, (2) homebound status (defined as rarely or never leaving home without assistance), and (3) ability to provide informed consent. Exclusion criteria included severe cognitive impairment or inability to use the device due to physical or sensory limitations.

All eligible participants provided written informed consent after being informed the study evaluated Alexa's impact on well-being, without emphasizing loneliness to minimize response bias.

**Intervention**

Participants were provided with an Amazon Alexa Echo Show device and trained on its essential functionalities, including voice commands for setting reminders, playing music, making phone calls, and accessing news or weather updates. Reminders (e.g., for medications) were set manually by participants or caregivers during training or follow-up visits, as Alexa requires user-initiated commands to set up routines. All participants were encouraged to use the Echo Show daily for over six months for companionship and practical support, though usage frequency and specific functions were not systematically tracked due to the confidentiality and privacy.

The intervention lasted six months, during which participants were encouraged to use the device daily. Technical support was available throughout the study to address any issues.

**Data Collection**

Data were collected at two-time points: baseline (pre-intervention) and six-month follow-up (post-intervention). Trained research assistants conducted in-home visits to administer surveys and ensure proper device setup. The following measures were used:

(1) Loneliness: It was measured using the UCLA Loneliness Scale Version 3 (UCLA-20), a 20-item self-report questionnaire [8]. We chose the UCLA-20 because it is a verified, established reliability (Cronbach's α = 0.94), and most widely used instrument in loneliness research.

Participants respond to each of the 20 items on a 4-point Likert scale, ranging from 1 (Never) to 4 (Often). with scores ranging from 20 to 80 [8]. It is a widely used instrument for measuring subjective feelings of loneliness and social isolation [1,2]. To accurately capture the multifaceted nature of loneliness, the ULS-20 employs a mix of positively and negatively worded items. Higher scores indicate greater loneliness.

(2) Depression: assessed using the Geriatric Depression Scale (GDS-15), a 15-item self-report scale designed for older adults [9]. Scores range from 0 to 15, with higher scores indicating more severe depressive symptoms. The GDS-15 has shown good reliability (Cronbach's α = 0.89) and validity in older adults.

(3) Health-Related Quality of Life (HRQL): evaluated using the EQ-5D-5L, a standardized measure of health status that includes five dimensions (mobility, self-care, usual activities, pain/discomfort, and anxiety/depression). Scores are converted into a single index value ranging from −0.109 (worst health) to 1.000 (best health). The EQ-5D-5L has been validated in elderly populations and demonstrates high reliability (Cronbach's $\alpha$ = 0.87) [10].

(4) Demographic and health information: collected including age, gender, race, and comorbidities (e.g., diabetes, hypertension, chronic obstructive pulmonary disease, yes/no).

**Statistical Analysis**

Calculating total loneliness score: Certain items on the UCLA Loneliness Scale-20 are framed positively. These items, including 1, 4, 5, 6, 9, 10, 15, 16, 19, and 20, require reverse scoring before calculating the total score. Reverse scoring was achieved by subtracting the original score from 5. Once the positively worded items were reverse scored, all 20 item scores were summed to obtain the total loneliness score [8].

Descriptive statistics were calculated for demographic and health-related variables, including means and standard deviations (SD) for continuous variables and percentages for categorical variables. The t-test was used for continuous variables. The Chi square test was used for categorical variables. Baseline and follow-up loneliness scores were compared using paired t-tests to assess changes over time. The two-sided *p*-value were reported at 0.05 or 0.01 level.

To examine the intervention's impact on loneliness while controlling for potential confounders, a random-effects maximum likelihood (ML) regression model was employed. This model was chosen to account for the data's hierarchical structure, where multiple observations (baseline and follow-up) were nested within individuals [11]. The dependent variable was the UCLA Loneliness Scale score, and independent variables included: post-intervention status (post), a dummy variable (0 = baseline, 1 = follow-up); demographic variables including gender (Female = 1, Male = 0), age (continuous), and race (White = 1, Non-White = 0); and comorbidity measured by dummy variables (e.g., diabetes, hypertension, dementia).

The model was estimated using Stata's 'xtreg' procedure, and results were reported as unstandardized coefficients with standard errors, z-values, and *p*-values to reflect the raw change in the overall UCLA-20 scores per unit change in predictors. A likelihood ratio (LR) test was conducted to assess the significance of the random-effects component. All analyses were performed using Stata 18.0 [12].

The local Institutional Review Board (IRB) approved the study protocol.

## RESULTS

### Descriptive Analysis of Characteristics of Study Participants

The study population at baseline consisted of 105 homebound older adults with a mean age of 73.14 years (SD ± 6.56), as shown in Table 1. Most participants were female (78.1%) and White (78.1%), with African American and other racial groups comprising 18.1% and 3.8%, respectively. The prevalence of comorbidities was high, with hypertension (85.71%) and diabetes mellitus (54.29%) being the most common. Other prevalent conditions included chronic obstructive pulmonary disease (COPD, 53.33%), chronic kidney disease (CKD, 38.1%), and congestive heart failure (CHF, 31.43%).

**Table 1.** Baseline characteristics of the study participants (*N* = 105).

| Variable | Mean (%) | *p*-value |
|---|---|---|
| Age (Mean, SD) | 73.14 (± 6.56) | |
| Gender (%) | | <0.01 |
| Female | 78.10 | |
| Male | 21.90 | |
| Race (%) | | <0.01 |
| White | 78.10 | |
| AA | 18.10 | |
| Other | 3.80 | |
| Comorbidity (%, 1/0) | | |
| DM | 54.29 | NS |
| HTN | 85.71 | <0.01 |
| COPD | 53.33 | NS |
| Asthma | 19.05 | <0.01 |
| CKD | 38.10 | <0.05 |
| CHF | 31.43 | <0.01 |
| AFIB | 17.14 | <0.01 |
| Dementia | 5.71 | <0.05 |
| PTSD | 1.90 | <0.01 |
| Cancer | 3.81 | <0.01 |

Note: (a) AA: African American; DM: diabetes mellitus; HTN: hypertension; COPD: chronic obstructive pulmonary disease; CKD: chronic kidney disease; CHF: congestive heart failure; AFIB: atrial fibrillation; PTSD: post-traumatic stress disorder. (b) NS: non-significant.

Outcome Measures at Baseline: At baseline as shown in Table 2, the mean loneliness score, as measured by the UCLA Loneliness Scale (UCLA-20), was 47.343 (SD ± 11.938). The distribution of loneliness levels indicated that 88.57% of participants experienced moderate to severe loneliness, with 45.71% reporting moderate loneliness, 35.24% moderately high loneliness, and 7.62% severe loneliness. Only 0.95% of participants reported normal levels of loneliness.

**Table 2.** Pre- and post- intervention on loneliness mean score and level.

| Loneliness | | Baseline | Follow-up | Difference | *p*-value |
|---|---|---|---|---|---|
| In-complete Case (*N* = 105) | Mean | 47.34 | 36.47 | 10.87 | <0.01 |
| | SD | (±11.94) | (±10.62) | | |
| Complete Case (*N* = 78) | Mean | 46.89 | 36.47 | 10.42 | <0.01 |
| | SD | (±11.32) | (±10.62) | | |
| **Loneliness Level (%)** | | **Baseline** | **Follow-up** | ***p*-value** | |
| 0 = Normal | | 0.95 | 1.28 | <0.01 | |
| 1 = Low | | 10.49 | 47.44 | | |
| 2 = Moderate | | 45.71 | 35.90 | | |
| 3 = Moderate High | | 35.24 | 14.10 | | |
| 4 = Severe | | 7.62 | 1.28 | | |

Note: The sensitivity analysis showed that there were no statistical differences in the mean loneliness scores (difference = −0.45) at the baseline between the in-complete and complete follow-up participants.

Outcome Measures at Six-Month Follow-Up: At the six-month follow-up, two died, four was not able to complete the survey due to cognitive decline, and twenty-one withdrew from the study. Therefore, data were available for seventy-eight participants (80% retention rate). Significant improvements were observed in the loneliness outcome. As shown in Table 2, the mean loneliness score decreased to 36.474 (SD ± 6.22), representing a statistically significant reduction from baseline (mean difference = −10.869, $p < 0.001$). The proportion of participants experiencing moderate to severe loneliness decreased from 88.57% to 65.38%. To assess a potential bias of the dropout, we performed a sensitivity analysis by comparison in the mean loneliness scores between the complete and in-complete cases at the baseline. It was found that there was no statistically significant difference in the baseline mean loneliness scores between the complete and in-complete follow-up of the study participants.

### Multivariate Regression Analysis

A random-effects maximum likelihood (ML) regression model was used to assess the impact of the intervention on loneliness scores while controlling for demographic and health-related variables. The results revealed several significant predictors, as shown in Table 3.

**Table 3.** Random-effects ML Regression: effect of Alexa intervention on loneliness.

| Loneliness Score | Coefficient | Standard Error | 95% CI Lower | 95% CI Upper |
|---|---|---|---|---|
| Post Intervention (=1) | −10.70*** | 0.99 | −12.63 | −8.77 |
| Female (=1) | −0.66 | 2.66 | −5.88 | 4.56 |
| Age | −0.14 | 0.18 | −0.49 | 0.20 |
| Race (white = 1) | 4.60* | 2.56 | −0.43 | 9.62 |
| Comorbidity (1=yes; 0=no) | | | | |
| DM (=1) | 1.46 | 2.26 | −2.97 | 5.90 |
| HTN (=1) | 4.73 | 2.97 | −1.09 | 10.55 |
| Dementia (=1) | −3.36 | 5.04 | −13.24 | 6.52 |
| COPD (=1) | 1.91 | 2.27 | −2.54 | 6.35 |
| Asthma (=1) | 0.23 | 2.75 | −5.16 | 5.62 |
| CKD (=1) | −2.65 | 2.24 | −7.05 | 1.74 |
| CHF (=1) | −5.44** | 2.25 | −9.84 | −1.04 |
| AFIB (=1) | 0.36 | 2.75 | −5.03 | 5.75 |
| PTSD (=1) | 1.07 | 7.58 | −13.79 | 15.92 |
| Cancer (=1) | −5.20 | 5.56 | −16.10 | 5.69 |
| Constant | 51.99*** | 14.05 | 24.45 | 79.53 |
| Sigma_u | 8.70*** | 0.85 | 7.04 | 10.37 |
| Sigma_e | 6.25*** | 0.52 | 5.24 | 7.27 |
| Rho | 0.66 | 0.06 | 0.52 | 0.78 |
| Log likelihood | −671.467*** | - | - | - |

Note: (a) UCLA Loneliness Scale (range 20–80). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. (b) CI: Confidence Interval. (c) 0 is the reference.

(1) Post-intervention Status: The coefficient for the post-intervention dummy variable was −9.27 ($p < 0.01$), indicating that participants reported significantly lower loneliness scores after the intervention compared to baseline. This suggests that the use of Amazon Alexa has had a substantial positive effect on reducing loneliness.

(2) Race: The coefficient for race was 4.598 ($p = 0.073$), which approached significance. White participants tended to report higher loneliness scores compared to non-White participants, although this effect was not statistically significant at the conventional 0.05 level.

(3) Congestive Heart Failure: Participants with CHF reported significantly lower loneliness scores (coefficient = −4.877, $p = 0.022$) than those without CHF. This unexpected finding warrants further investigation.

(4) Other covariates: Demographic variables (gender, age) and other health-related conditions (e.g., diabetes, hypertension, dementia) were insignificant predictors of loneliness scores in this model. The random-effects component of the model was significant (log likelihood test of sigma_u = 0: $\chi^2(01) = 29.68$, $p < 0.01$), indicating substantial variability in loneliness scores across individuals that was not explained by the included predictors.

## DISCUSSION

The findings of this study demonstrate that the use of AI-powered voice assistants, such as Amazon Alexa, significantly reduced loneliness while controlling confounding factors among homebound elderly individuals. These results align with emerging evidence on the potential of technology-based interventions to address social isolation and loneliness in older adults, particularly those with limited mobility or access to traditional social activities.

The significant reduction in loneliness scores observed in this study (mean decrease of 10.869 points on the UCLA Loneliness Scale) is consistent with findings from other studies exploring the use of technology to combat loneliness in older adults. For example, a pilot study by Kowalski et al. found that voice-controlled devices like Google Home reduced feelings of loneliness and improved social engagement among older adults [7]. Similarly, Chen et al. reported that AI-powered chatbots significantly decreased loneliness in older adults by providing companionship and facilitating communication with family members [13]. The magnitude of the effect in our study is comparable to these findings, suggesting that voice assistants can be an effective tool for mitigating loneliness in homebound populations. Unlike Chen et al. [13], who noted chatbots enhanced family communication, we lack data on whether Alexa served similar roles. Future studies should examine log usage (e.g., call frequency, reminder use) to clarify mechanisms.

The effectiveness of AI-powered voice assistants in reducing loneliness may be attributed to several mechanisms. First, these devices provide companionship and simulate social interaction, alleviating feelings of isolation. Second, they facilitate communication with family and friends, enhancing social connectedness. Third, voice assistants offer practical support, such as reminders for medications or appointments, which can reduce stress and improve overall well-being. These mechanisms are consistent with the findings of Pradhan et al. [6] and Kowalski et al. [7] who highlighted the role of voice assistants in promoting social engagement and emotional support.

The unexpected finding that participants with congestive heart failure (CHF) reported significantly lower loneliness scores warrants further investigation. This may reflect increased social support or medical attention among individuals with CHF, as suggested by studies showing that chronic illness can sometimes lead to stronger social networks due to frequent interactions with healthcare providers and caregivers [4]. Alternatively, this finding may be influenced by unmeasured confounding factors, such as socioeconomic status or access to care.

### Limitations and Future Research Directions

While this study provides promising evidence on the effectiveness of AI-powered voice assistants in reducing loneliness among homebound older adults, the interpretations should be cautious. Several limitations must be acknowledged. First, this was a pilot study. This pilot study did not collect data on how often or in what ways participants used Alexa (e.g., daily interaction, specific features) due to the privacy, limiting our ability to link usage patterns to loneliness reductions. Future studies should log usage (e.g., call frequency, reminder use) to clarify mechanisms.

The study's sample size, though adequate for initial exploration, was small (*N* = 105), with 78 participants completing the six-month follow-up. This attrition, coupled with the study participants' predominantly female and White composition, may limit the generalizability of the findings to more diverse populations of homebound older adults, including those from different racial, ethnic, and socioeconomic backgrounds [14]. Future studies should aim to recruit larger and more diverse cohorts to ensure broader applicability of the results. Second, the reliance on self-reported measures, such as the UCLA Loneliness Scale, introduces the potential for response bias. Participants may have underreported or overreported their feelings of loneliness due to social desirability or other psychological factors [8]. Incorporating objective measures of social isolation, such as frequency of social interactions or caregiver reports, could provide a more comprehensive assessment of the intervention's impact [15]. In addition, the UCLA-20, while reliable, may not fully capture loneliness reductions due to AI companionship, as it focuses on interpersonal relationships. Post-intervention qualitative interviews were not conducted, limiting contextual insights into participants' experiences with Alexa. Future studies could complement UCLA-20 with qualitative interviews to elucidate how Alexa fosters companionship, building on Chen et al.'s findings with AI chatbots [13].

Third, the absence of a control group in this observational study design limits the ability to draw definitive causal inferences. While the significant reduction in loneliness scores is encouraging, it is possible that other external factors—such as seasonal changes, increased caregiver attention, or participation in other social activities—may have contributed to the observed outcomes [16]. Future research should employ randomized controlled trials (RCTs) with control groups to isolate the specific effects of AI-powered voice assistants on loneliness and social isolation [17]. Fourth, the six-month follow-up period, while sufficient to detect short-term changes, may not capture the long-term sustainability of the intervention's effects. Longitudinal studies with extended follow-up periods (e.g., 12–24 months) are needed to evaluate whether the benefits of voice assistants persist over time or diminish as the novelty of the technology wears off [18]. Fifth, the study did not account for participants' prior experience or comfort with technology, which may have influenced their ability to use the Alexa device effectively. Older adults with limited technological literacy may have difficulty navigating the device, potentially attenuating the impact of the intervention [19]. Future studies should assess participants' baseline technological proficiency and provide tailored training to ensure equitable access and usability [20]. Sixth, Participants' awareness of the study's focus on Alexa may have influenced post-intervention responses (Hawthorne effect), though we mitigated this by framing the study broadly as a well-being assessment.

Finally, while the study controlled for several demographic and health-related variables, other unmeasured confounders—such as the quality of social support networks, frequency of family visits, or participation in community programs—may have influenced the outcomes [21]. Future research should incorporate a broader range of covariates to isolate the effects of the intervention better.

**Implications**

The findings of this study have significant implications for healthcare providers, policymakers, and caregivers, particularly in the context of public health initiatives and Medicare/Medicaid policies aimed at improving the well-being of homebound older adults. Integrating AI-powered voice assistants like Amazon Alexa into home care services offers a scalable, cost-effective solution to address loneliness in this vulnerable population.

(1) Integration into Home Care Services: AI-powered voice assistants can seamlessly integrate into existing home care programs, particularly those funded by Medicare and Medicaid. For example, Medicare's Home Health Benefit and Medicaid's Home and Community-Based Services (HCBS) programs could incorporate voice assistants into their care packages. These devices can complement traditional home health services by providing companionship, facilitating communication with family and caregivers, and offering reminders for medications or appointments. This integration could enhance the overall quality of care and reduce the burden on home health aides and caregivers.

(2) Addressing Social Determinants of Health (SDOH): Loneliness and social isolation are recognized as critical social determinants of health (SDOH) that significantly impact physical and mental health outcomes. The Centers for Medicare & Medicaid Services (CMS) has increasingly emphasized addressing SDOH through innovative interventions. AI-powered voice assistants align with this focus by providing a low-cost, scalable solution to mitigate loneliness. Policymakers should consider incorporating voice assistants into Accountable Care Organization (ACO) models and Medicare Advantage (MA) plans, designed to address SDOH and improve health outcomes for beneficiaries.

(3) Healthcare Utilization and Costs: Loneliness and social isolation are associated with increased healthcare utilization and costs, including hospitalizations, emergency room visits, and long-term care admissions [22]. By reducing loneliness and improving mental health, voice assistants might potentially lower healthcare costs for Medicare and Medicaid beneficiaries. A report by the American Association of Retired Persons (AARP) Public Policy Institute estimated that addressing social isolation

among older adults could save Medicare billions of dollars annually by reducing unnecessary healthcare utilization [23]. Policymakers should explore funding pilot programs to evaluate the cost-effectiveness of voice assistants in reducing healthcare expenditures.

(4) Supporting Caregivers: Caregivers play a critical role in supporting homebound older adults, but they often face significant stress and burnout. Voice assistants might alleviate some of the burden by providing reminders for medication, appointments, and daily tasks and facilitating communication between caregivers and care recipients. The National Family Caregiver Support Program (NFCSP), funded by the Administration for Community Living [24], could incorporate voice assistants as a resource for caregivers, helping them manage their responsibilities more effectively and improving the quality of care for their loved ones.

(5) Expanding Access to Technology: To ensure equitable access to voice assistants, policymakers should consider initiatives to provide these devices to low-income and underserved populations. For example, Medicaid’s 1915(c) Home and Community-Based Services Waivers could be expanded to include funding for voice assistants as part of assistive technology services [25]. Additionally, public-private partnerships could be established to distribute voice assistants to eligible beneficiaries, similar to initiatives like the Federal Communications Commission’s (FCC) Lifeline Program, which provides discounted phone and internet services to low-income individuals [26].

(6) Promoting Digital Literacy: To maximize the benefits of voice assistants, it is essential to promote digital literacy among older adults and caregivers. Public health initiatives, such as the Administration for Community Living’s (ACL) Older Americans Act (OAA) programs, could include training sessions on using voice assistants effectively. These programs could be delivered through senior centers, Area Agencies on Aging (AAAs), and other community-based organizations, ensuring that older adults can use this technology to its full potential.

(7) Enhancing telemedicine and telehealth services: In addition to helping older adults become more comfortable using technologies that may enhance their future use of telehealth, the Alexa device can also be used to deliver actual telehealth consultations through its audio-visual capabilities [20,27,28]. Future studies to determine the most effective healthcare delivery with Alexa are warranted.

## CONCLUSION

Integrating AI-powered voice assistants like Alexa Echo Show into home care services might offer a promising solution in reducing loneliness in homebound elderly individuals though further research with usage data is needed to confirm mechanisms and scalability. By leveraging existing Medicare and Medicaid programs, policymakers can ensure that this technology reaches those who need it most while reducing healthcare costs and supporting caregivers. Public health initiatives should focus on expanding access to voice assistants, promoting digital literacy, and evaluating the impact of these interventions through pilot programs and research. By taking these steps, policymakers can enhance the well-being of homebound elderly individuals and create a more sustainable healthcare system.

## ETHICAL STATEMENT

### Ethics Approval

The local Institutional Review Board (IRB) approved the study protocol (IRB protocol #STUDY00160150, April 4, 2024).

All participants provided written informed consent prior to enrollment. They were also informed of their right to withdraw from the study at any time without affecting their access to home care services.

### Declaration of Helsinki STROBE Reporting Guideline

This study adhered to the Helsinki Declaration. The Strengthening the Reporting of Observational studies in Epidemiology (STROBE) reporting guideline was followed.

## DATA AVAILABILITY

The author's study dataset is available upon request.

## AUTHOR CONTRIBUTIONS

Conceptualization, RS and GC; Methodology, RS and GC; Validation, RS and GS; Investigation, RS and GC; Data Curation, RS and GC; Resources, RS; Formal analysis, GC; Writing Original Draft Preparation, GC; Writing Review & Editing, RS and GC; Funding Acquisition, RS.

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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