**Three options for the title**

1. **Recursive partitioning analysis of the Canadian Longitudinal Study on Aging (CLSA) to identify potential predictors of formal and informal home care use. A utilization of intersectionality theory (very descriptive and long)**
2. **Older Canadian adults receiving home care – not simply a matter of health and need (not detailed enough)**
3. **Despite (or because of) universal healthcare: variation in receiving home care among Canada's older adults. A recursive partitioning analysis of the Canadian Longitudinal Study on Aging (the best, in my idea, thank you Susan for your insight)**

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**Abstract**

OBJECTIVES*:* To identify factors that predict home care use among Canadian middle-age and older adults.

METHODS: We used data from the Canadian Longitudinal Study on Aging (CLSA) of community-dwelling adults aged 45 to 85. SRH was measured via subjective questions. Multiple Poisson regression identified individual, behavioural, and social factors related to SRH. Intersections between sex, education, wealth, and rural/urban status, and individual and joint cluster effects on SRH were quantified using multilevel models.

RESULTS:

DISCUSSION:

**Keywords:** sex differences, formal carte, informal care , CLSA, intersectionality, social determinants

1. **Introduction:**

**1.1. Issue:**

As populations age the prevalence of chronic diseases and functional limitations increases and subsequently the need for care grows (UN, 2020). Generally, care needs will align with limitations in Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL) and the presence of chronic diseases (Zhang & Sun, 2020). However, patterns of care receiving seem to also be a function of the complex interplay among individual characteristics, social networks, and contextual/policy level factors. The theoretical models referred to in the literature tend to describe patterns of care receiving but not those characteristics that *predict* use of care. Understanding such predictors has implications for modifying healthcare systems to better address the needs of aging populations. No such research exists in Canada despite availability of rich databases such as Canadian Longitudinal Study on Aging (CLSA). The main objective of this study is, therefore, to identify factors that predict home care use among Canadian middle-aged and older adults.

* 1. **Assumed predictors of care use:**

Two theoretical models are frequently referred to in the literature on ‘care’: the Andersen–Newman model (Andersen & Newman, 2005a) and the task-specific model (Messeri et al., 1993). The focus of both models is on how care receivers envision an ‘optimal’ level of receiving care (Bertogg & Strauss, 2020). Drawing on these models, one can group factors explaining use of care into three categories: need, enabling circumstances, and predisposing characteristics.

Needs arising directly from functional, physical and cognitive health limitations represent the most immediate reason for seeking care (Bassetti & Rebba, 2015; Paraponaris et al., 2012; Penkunas et al., 2017; Van Houtven & Norton, 2004). Predisposing factors such as age, sex, and health behaviours are often individual level risks whose existence predates the onset of the impairment that created a need for care. Enabling factors tend to be structural and contextual, and related to care availability. They include income (Bertogg & Strauss, 2020; Rodríguez, 2013; Van Houtven & Norton, 2004), health insurance, local policies (Blomberg et al., 2012; Suanet et al., 2012), and social support networks (Kjær & Siren, 2020; Suanet et al., 2012). This model has been recently criticized because of its failure to account for dynamic trajectories of care use over time (Geerts & Van den Bosch, 2012; Kemp et al., 2013). Enabling and predisposing factors sometimes overlap. For example, sex can be both. Women, in general, have a more established social network to call upon for informal care. On the other hand, female sex is a recognized risk factor for a variety of chronic diseases that precipitate a need for care (Arber & Ginn, 1995). Economic considerations add more complexity as employment status and income affect willingness and ability to provide and receive care (Sarkisian & Gerstel, 2004). The impact of incentives (such as cash-for -care programs offered in some social welfare systems) appears to be gendered as well (Schmidt, 2017). Cultural norms also add complexity to care receiving. The balance of informal and formal care expected and delivered varies across cultures (Bolin et al., 2008).

Current theoretical models (Andersen & Newman, 2005b; Messeri et al., 1993) can identify factors that define *needs* for care use as well as those factors that *predispose* individuals to be in need. Additionally, models can describe factors that *enable* individual to access better care. However, these models, while able to delineate specific determinants of health care utilization, are deficient in explaining the interplay among these, and instead, assume each to function independent of the rest.

* 1. **Definition of formal and informal care use**

There are no standard definitions for formal and informal care. We use the most common definition of formal care, that is ‘paid’ care services provided by a healthcare institution or professional, whereas unpaid care delivered by family, relatives, friends, neighbours, and community members is what we will consider to be informal care (Li & Song, 2019). Whether formal and informal care use are related or distinct provisions is debated (Lyons & Zarit, 1999). The ‘substitution model’ suggests an inverse relationship between formal and informal care use (Greene, 1983), while the ‘complementarity model’ (Chappell & Blandford, 1991) considers formal and informal care to have different structural characteristics.

Although need for informal and formal care are assumed to be similar, these different care use behaviours may be influenced differentially by enabling and predisposing factors. For example, persons with higher socio-economic status (SES) such as those with higher income are more likely than those of lower SES to share or outsource care-giving with a formal service provider, while persons of lower SES are more likely to receive only informal care (Bertogg & Strauss, 2020). In the exploratory analysis that follows we analyze formal and informal care use in separate models to identify specific predictors of each.

* 1. **Intersectional approach and quantitative assessment of intersectionality**

In order to take into account the complexity of care use behaviours, adopting an intersectionality model can be helpful. With roots in the study of social inequalities (Bauer & Scheim, 2019; Crenshaw, 1989) intersectionality theory assumes membership in marginalized social groups generates interlocking systems of oppression (Hankivsky et al., 2010) . These so called “social locations” defined by intersections of various social factors create social power or marginalization (Crenshaw, 1989). In this study we extend the domains of social location not only to those that define access to power but to any social situation that potentially can generate disparities in health or care use.

Several methods have been suggested for quantitative analysis of intersectionality; however, the advantage of one method over others is still debated (Phillips et al., 2020). Recursive partitioning, one such method, separates samples into homogenous subcategories of individuals grouped by distinct social locations to provides direct quantitative information on intersectionality (Bauer & Scheim, 2019; Cairney et al., 2014). This is a special category within more general machine learning techniques (Bi et al., 2019) and provides an easy to understand graphical depiction (in the form of a recursive regression tree) of combinations of factors that define homogenous subgroups in terms of the outcome of interest. One advantage of regression trees is identification of factors that define subgroups with higher risk within groups that are deemed, overall, to be of low risk for an outcome. This contrasts with traditional regression methods that quantify ‘risk’ in high-risk groups. For example, utilizing recursive partitioning one can recognize which factors precipitate receipt of care among those with no limitation in ADL (a generally low risk group).

* 1. **Rationale for our study**

Few studies have considered intersections between limitations in ADL, perception of physical health, and social factors as potential predictors of care use. In other words, whether interplays between real physical needs, perception of need and SES have a role in predicting care use. Guided by, but expanding on intersectionality theory which generally only considers interlocking positions of power and powerlessness, our aim was to identify factors that predict care receiving among Canadian middle-aged and older adults. More specifically, we wished to disentangle the effects of need, and enabling and predisposing factors with a distinction between objective physical needs and perception of care needs. Separate models were constructed for formal and informal care use to differentiate specific predictors for each.

**2. Methods**
**2.1. Settings and participants**

We used data from the baseline (2010 to 2015) Canadian Longitudinal Study on Aging (CLSA) that included a random sample of 30,097 community-dwelling adults aged 45 to 85. Participants sampled resided within a 25- to 50-km radius of 1 of the 11 data collection sites in 7 Canadian provinces (Victoria, Vancouver, Surrey, Calgary, Winnipeg, Hamilton, Ottawa, Montreal, Sherbrooke, Halifax, St. John’s) (Raina et al., 2019). Those living in a First Nations community, an institution or a care facility, full-time members of the Canadian Armed Forces, anyone unable to speak French or English, or with cognitive impairment that made them unable to understand the study or answer basic personal questions were excluded.

**2.2. Sampling strategy and data collection**

CLSA employs two sampling strategies for their Comprehensive Cohort of participants. Recruitment from provincial health registries (14% of the sample) followed random sampling of eligible persons with 86% of the sample recruited through random digit dialing of landline telephone numbers for a given geographic area. After establishing eligibility of the respondent, consent was obtained. To ensure adequate representation of diverse demographic groups, the CLSA sample was stratified within provinces according to age group, sex, and distance from the data collection site (Raina et al., 2019).

Questionnaires were administered by trained interviewers at participants' homes or at a data collection site. Physical examinations were conducted at data collection sites.

**2.3. Assessment of formal and informal home care use**

Use of home care was self-reported via answers to the following questions: " During the past 12 months, did you receive short-term or long-term professional assistance at home, because of a health condition or limitation that affects your daily life, for any of the following activities" and "During the past 12 months, did you receive short-term or long-term assistance from family, friends, or neighbours because of a health condition or limitation that affects your daily life, for any of the following activities?"

**2.4. Assessment of potential predictors**

*2.4.1 Sociodemographic factors:*

Information gathered included sex, highest educational attainment (less than secondary school, secondary school graduation, some post-secondary, post-secondary graduation) and total personal income from all sources, before taxes and deductions, in the past 12 months as a categorical variable (<$20,000, $20,000-$49,999, $50,000-$99,999, $100,000-$149,999, ≥$150,000, Don't know/No answer/Refused). By linking participants’ residence postal codes to dissemination areas, their place of residence was classified into ‘urban core’, ‘other urban’, and ‘rural’, a standard proxy measure for place of residence in Canada as per precedents (Pong et al., 2009). Additional socio-demographic characteristicsincluded age in years, country of birth, and time since immigration (in years).

*2.4.2 Family related variables:*

We included marital status (with partner, widowed, divorced, separated, single) and living arrangement (number of generations that live in the same household) in the analysis as these are documented family-related predictors of receiving formal and informal care at home (Kjær & Siren, 2020) and in the community (Rodríguez, 2013; Solé-Auró & Crimmins, 2014).

*2.4.3 Physical and mental health factors:*

To measure functional status we used a composite variable from within the CLSA that calculates the total number of times the respondent indicated needing help with an activity or being completely unable to do an activity in the Activities of Daily Living (ADL) and Instrumental Activities of Daily Living (IADL). This derived variable is a modification of the original measure modules of the Duke Older Americans Resources and Services ( OARS) Multidimensional Assessment Questionnaire (Fillenbaum, 2013) that excludes questions regarding meal preparation ability. Perception of health was evaluated via two direct questions: “Would you say your health is excellent, very good, good, fair, poor?” and “Would you say your mental health is excellent, very good, good, fair, poor?” For analysis, we collapsed the first three categories into ‘good’ and the last two into ‘poor’ Self-Rated Health (SRH) and Self-Rated Mental Health (SRMH) categories. The 10-item version of the Centre for Epidemiologic Studies Depression (CESD) scale was used to measure depression (Andresen et al., 1994), and number of chronic conditions was entered into the analysis as a dichotomous variable (‘no self-report of chronic condition’ vs ‘at least one’).

*2.4.4 Contextual factors*

To measure contextual indicators of deprivation, Material and Social Derivation Indices (MSDI) for all Canadian census dissemination areas (DA) were downloaded from the ‘*Institut national de santé publique du Québec’* (INSPQ) website and linked to participants' postal codes (Gamache et al., 2019).

**2.5. Statistical analysis**

Descriptive analyses were performed to estimate the distributions of all covariates for the overall sample and across the four care groups: 1) receiving formal care only, 2) receiving informal care only, 3) receiving a mix of formal and informal care, 4) receiving no care. Differences in distributions were compared statistically by Chi-square test for contingency tables.

Separate models were generated for informal care and formal care use.

To identify combinations of significant variables that predict care use we performed recursive partitioning regression tree analysis using Chi-Squared Automatic Interaction Detection (CHAID) analysis (Ma, 2018) as the growing method. Tree-Structured modeling techniques were developed more than three decades ago (Kass, 1980) mostly for data mining purposes and have been used in health research with increasing frequency (Igarashi et al., 2014; Su et al., 2011). CHAID is a classification method that examines the relative importance of each of the predictors in explaining the occurrence of the preceding outcome level. It chooses the optimal partition based on χ2 calculated statistical significance adjusted using the Bonferroni correction. In order to allow more predictors in the models we set the tree depth limitation to five (instead of three levels which is the default for CHAID) and relaxed stopping criteria for splitting to a maximum size of 50 for parent nodes and of 20 for child nodes. This approach resulted in large trees with some nodes sized as small as 3. To generate more interpretable trees and meaningful nodes we then modified these criteria. In the final trees no parent node smaller than 100 was allowed to split and the minimum size for end nodes was set to 40. Applying this restriction decreased the final number of nodes of the formal care model from 41 to 35 and of informal care model from 38 to 36. To test trees’ stability and confirm the validity of the prediction accuracy (i.e., the correct classifications) of the models we ran a 10-fold cross-validation. This standard method of validation divides the sample randomly into 10 mutually exclusive subgroups, then each of the 10% folds serves once as a test sample while the rest of the sample (90%) is used to validate findings. The cross-validation risk, which is the proportion of cases incorrectly classified after adjustment for prior probabilities and misclassification, is the average of risk estimated across the 10 test samples. CHAID algorithm only prints the full-sample classification table.

We conducted analyses separately for formal and informal care. All analyses were performed using SAS version 9.4 (SAS Institute, Cary, NC, USA) and SPSS version 27.

**3. Results**:

**3.1 Overview**

Slightly more than half of participants (50.9%) were female, 67% of the population lived with a partner and more than 77% had postsecondary education. The overall sample had high function: almost 90% reported no ADL or IADL limitation or perceived their health as good (table 1). Women received both formal and informal home care more frequently (2.7% vs 1.9% in men for formal care and 10.1% vs 7.0% for informal care).

The main conclusion from the two regression trees was that while function as measured by ADL/IADL was the most important predictor in both models, other predictors varied considerably across formal and informal care use groups. This is also consistent with theoretical conceptualizations that consider formal and informal care use as different entities (Chappell & Blandford, 1991; Lyons & Zarit, 1999). We, therefore, report the detailed results separately for formal and informal care outcomes.

**3.2 Formal care use regression tree**

By generating a total of 35 nodes and 19 terminal nodes CHAID correctly classified 28,870 (99.9%) as not receiving formal care and 133 (9.1%) as receiving care, with an overall risk of misclassification of 4.5%. The risk remained almost the same (4.6%) after 10 fold cross-validation.

 The primary predictor of receiving formal care was limitation in ADL and IADL. Among those with moderate to severe functional limitations 57% received formal care. The proportion receiving formal care dropped to 22.4% among those with mild limitation. When need was quantified further, not having a partner best predicted receipt of formal care for those with ADL limitations, whether these were mild, moderate, or severe. Among the moderate to severely limited group, 39.5% of those with a partner received formal care compared with 76.4% of those with no partner. Comparable proportions for the mild limitation group were 15.5% and 29.9%, respectively. Further dissecting each of the categories thus far (i.e. beyond partner status) identified the following as predictors for formal care: SRH (for moderate/severe ADL limitation+ partner: 32.2% in good SRH received care vs 50.0% in the poor SRH group), living arrangement + SRH for the mild limitation with no partner group, and SRH + age for mild limitation with partner group.

Among those with no functional limitations (89.9%), only 2.4% received formal care. This allocation of formal care was predicted best by age (45-64 Y– 1.6%, 65-74 Y– 2.6%, 75+ Y– 5.5%). Among those less than age 75 years, SRH and family-related variables such as partner status and living arrangement were important predictors, whereas in the older than 75 group, self-reported depression also played a role. Sex, that is, being a man or a woman, was not a branch point for formal care.

**3.3 Informal care use regression tree**

The regression tree generated by the CHAID algorithm for informal care use had almost twice the risk of misclassification. The final tree that included a total of 36 nodes and 19 terminal nodes correctly classified 26,470 (99.1%) of those who did not receive informal care and 427 (12.7%) of those who received this level of care. Overall risk of misclassification, therefore, was calculated at10.6%. The risk increased slightly to 10.8% after 10 fold cross-validation.

As with formal care, the main predictors of informal care, were ADL, SRH, partner status and depression, however, unlike formal care CHAID identified sex, and immigration status as additional predictors. With moderate to severe ADL limitations partner status remained an important predictor but only among women. In this group almost 86% of women with a partner received informal care compared with only 60% of women with no partner. Age was a predictor of receiving informal care regardless of SRH status in those with mild functional limitations. Country of birth was predictive for those with no depression symptoms. Canadian-born participants were somewhat more likely to receive informal care than were foreign-born individuals (28% vs 22%).

Patterns of receiving informal care were more complex among those (7.3%) with no ADL limitations, showing intersections among sex, immigration status and health factors. Country of birth was a predictor of receiving informal care for men (child nodes of node 12) with poor SRH but not for women. In those with good SRH and no chronic condition, years of immigration predicted informal care receiving only for women (child nodes of node 21).

**4.Discussion:
4.1. What we found**

In this exploratory analysis we found different predictors for formal vs informal care receiving among adults living in the community (those residing in a care facility were not included in the CLSA). More importantly, we found when the level of ADL changes, predictors of care use also change.

* + 1. *Different predictors for formal vs informal*

The main predictors for both types of care were ADL/IADL followed by marital status, SRH, age, number of chronic conditions, and depression. SES measured either at the individual level by income and education or at a contextual level by deprivation indices and residence location were not significant predictors of care use. These are potential sources of inequalities but apparently in Canada's egalitarian healthcare system they do not produce marginalization in terms of care. Sex, country of birth, and years since immigration were only predictors of informal care use. One possible explanation for the absence of such socio-demographic predictors for formal care is that such care is often provided by the state at no added cost to the individual. Family factors were, however, important in providing different aspects of care to those with no ADL limitations and informal care use was also a function of individual cultural background. These findings are consistent with existing precedents that consider informal and formal care receiving as different ‘care’ behaviours (Lyons & Zarit, 1999). Sex was not a factor for formal care use, but given that most men are likely to be married (while women live alone) do we want to/can say something more about this in the conclusions from a gender perspective? It seems to confirm the idea that married men tend to receive fewer services (than married women) which on the other hand could reinforce burden on their female carers.

* + 1. *Unmet needs*

Our regression tree models hinted at potential unmet needs. For example, 43% of individuals with moderate to severe ADL limitations did not receive formal home care. However, this might be explained by marital status as those with partners are less likely to received formal care (40% vs 76% in those with no partner). The spouse may be filling the formal care gap by providing informal care.

*4.1.3. Care use while no ADL limitation*

In the group of participants with no ADL limitations 562 people (2.4%) received formal care and 2183 individuals (8.1%) received informal care. ADL limitation, although a very important predictor of care use, is only one reason for seeking care. We identified other predictors such as living arrangement, age, and SRH in participants with no ADL limitation, however, results of recursive partitioning remain exploratory and should be confirmed via future etiological analyses.

**4.2. Advantages of a recursive partitioning approach**

Ordinary regression models are focused on the estimation of the risk in high-risk groups. Identification of risk factors in lower-risk populations (for example in those with no ADL limitations) is an advantage of recursive partitioning models.By recursive and stepwise subgroupings, combinations of these subgroups can be interpreted as social locations and hence provide a *quantification* of intersectionality (Bauer & Scheim, 2019). Furthermore, within-group heterogeneity usually is overlooked in epidemiological studies that use traditional analytic approaches while regression trees reveal the sources of this heterogeneity.

**4.3. Specific strengths of this study**

Most existing studies with similar research questions analysed data via regression analyses (Bauer & Scheim, 2019; Floridi et al., 2021). The few that used regression trees (Igarashi et al., 2014; Nakabe et al., 2019; Penkunas et al., 2017) did not conceptualize determinants of receiving care based on intersectional theories. We have demonstrated the shortcomings of relying exclusively on diminished function (such as looking only those with ADL limitations) as the sole indicator of needs for care, by identifying factors (for example age and living arrangement in those with no ADL limitations) that predict care use in higher functioning individuals. Both models, constructed following the CHAID algorithm, produced stable trees after 10-fold cross-validation with4.6% risk of misclassification for formal care use and 10.7% risk of misclassification for informal car use.

**4.4. Limitations**

CLSA follows a very robust sampling strategy and is representative of middle-aged and older Canadians living in the community. Not including those in institutions is not a problem in this study because our aim was identification of home care predictors, however, some excluded groups such as those living in First Nations communities, or those unable to speak French or English, may represent different care use behaviours that were not captured in this analysis.

* 1. **Clinical, social and public health policy implications**

Identification of subgroups that received home care more frequently means they are vulnerable and perhaps need more direct clinical attention or public health interventions. Those groups that receive home care but have no ADL limitation may need specific attention, since usual healthcare approaches focused on physical health needs don’t consider them as vulnerable. As the population ages, a deeper understanding of care use patterns will be essential for designing care systems which ensure access to high-quality care for all those who need it.

Table 1: Descriptive results by types of home care use

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Description  | Total  | FormalOnly | InformalOnly | Mixed Care | No care | Pvlaue |
| Sex  | FemaleMale | 15308 (50.9)14762 (49.1) | 409 (2.7)282 (1.9) | 1551 (10.1)1033 (7.0) | 491 (3.2)277 (1.9) | 12857 (83.9)13170 (89.1) | <0.0001 |
| Age  | 45-5455-6465-7475+ | 7592 (25.3)9847 (32.8)7356 (24.5)5275 (17.5) | 76 (1.0)127 (1.3)176 (2.4)312 (5.9) | 636 (8.4)844 (8.6)602 (8.2)502 (9.5) | 109 (1.4)193 (2.0)179 (2.4)287 (5.4) | 6771 (89.2)8683 (88.1)6399 (89.9)4174 (79.0) | <0.0001 |
| Marital status | SingleWith partnerDivorced/widowed/Separated | 2650 (8.8)20638 (68.6)6774 (22.5) | 93 (3.5)309 (1.5)289 (4.3) | 220 (8.3)1712 (8.3)652 (9.6) | 92 (3.5)365 (1.8)311 (4.6) | 2245 (84.6)18252 (88.4)5522 (81.4) | <0.0001 |
| Education | Less than secondary secondary graduationSome post-secondaryPost-secondary degree/diplomaMissing  | 1640 (5.5)2833 (9.4)2238 (7.4)23309 (77.5)50 (0.2) | 70 (4.3)74 (2.6)67 (3.0)477 (2.1)3 (6.0) | 167 (10.2)224 (7.9)234 (10.5)1956 (8.4)3 (6.0) | 75 (4.6)83 (2.9)87 (3.9)521 (2.2)2 (4.0) | 1328 (81.0)2452 (86.6)1850 (82.7)20355 (87.3)42 (84.0) | <0.0001 |
| Income  | Less than $20,000$20,000-$50,000$50,000-$100,000$100,000-$150,000$150,000 or moreMissing/refused | 4368 (14.5)10529 35.0)9689 (32.2)2517 (8.4)1465 (4.9)1502 (5.0) | 162 (3.7)276 (2.6)156 (1.6)37 (1.5)16 (1.1)44 (2.9) | 534 (12.2)945 (9.0)709 (7.3)163 (6.5)91 (6.2)142 (9.4) | 190 (4.4)309 (2.9)161 (1.7)36 (1.4)19 (1.3)53 (3.5) | 3482 (79.7)8999 (85.5)8663 (89.4)2281 (90.6)1339 (91.4)1263 (84.1) | <0.0001 |
| Country of born | CanadaOther  | 24620 (81.9)5447 (18.1) | 582 (2.4)108 (2.0) | 2184 (8.9)400 (7.3) | 650 (2.6)118 (2.2) | 21204 (86.1)4821 (88.5) | <0.0103 |
| Time since immigration | ≤1011-20>20 Not-immigrant  | 254 (1.0)432 (2.0)4761 (15.8)24620 (81.2) | 3 (1.2)4 (1.0)102 (2.1)582 (2.4) | 9 (3.5)38 (8.8)353 (7.4)2184 (8.9) | 0 (0)3 (1.0)115 (2.4)650 (2.6) | 242 (95.3)387 (89.6)4191 (88.0)21204 (86.1) | <0.0001 |
| Living arrangement  | Single generational Two generational 3 & more generational Missing  | 20969 (69.7)8526 (28.3)508 (1.8)67 (0.2) | 599 (2.9)76 (1.0)11 (2.2) 5 (7.5) | 1834 (8.8)693 (8.1)49 (9.7)8 (11.9) | 609 (2.9)139 (1.6)17 (3.4)3 (4.5) | 17927 (85.5)7618 (89.4)431 (84.8)51 (76.12) | <0.0001 |
| Residence  | RuralUrban core Other urban Missing  | 2422 (8.1)26059 (86.7)1211 (4.0)378 (1.3) | 36 (1.5)611 (2.3)29 (2.4)15 (4.0) | 207 (8.5)2240 (8.6)94 (7.8)43 (11.4) | 55 (2.3)678 (2.6)23 (1.9)12 (3.2) | 2124 (87.7)22530 (86.5)1065 (87.9)308 (81.5) | =0.038 |
| Physical limitation (ADL & IADL) | No ProblemsMild problemsModerate/severe Missing | 27037 (89.9)2558 (8.5)369 (1.2)106 (0.4) | 368 (1.4)261 (10.2)57 (15.4)5 (4.7) | 1899 (7.0)552 (21.6)105 (28.3)28 (26.4) | 284 (1.1)319 (12.5)153 (41.5)12 (11.3) | 24486 (90.6)1426 (55.8)54 (14.6)61 (57.6) | <0.0001 |
| Depression  | NoYesMissing  | 25182 (83.7)4763 (15.8)125 (0.4) | 486 (1.9)194 (4.1)11 (8.8) | 1953 (7.8)613 (12.9)18 (14.4) | 491 (2.0)269 (5.7)8 (6.4) | 22252 (88.4)3687 (77.4)88 (70.4) | <0.0001 |
| Chronic condition  | NoneAt least oneMissing | 2253 (7.5)27606 (91.8)211 (0.7) | 5 (0.2)679 (2.5)7 (3.3) | 77 (3.4)2498 (9.1)9 (4.3) | 9 (0.4)754 (2.7)5 (2.4) | 2162 (96.0)23675 (85.8)190 (90.1) | <0.0001 |
| SRH | GoodPoorMissing | 27272 (90.7)2776 (9.2)22 (0.1) | 526 (1.9)164 (5.9)1 (4.6) | 2037 (7.5)543 (19.6)4 (18.2) | 495 (1.8)272 (9.8)1 (4.6) | 24214 (88.8)1797 (64.7)16 (72.7) | <0.0001 |
| SRMH | GoodPoorMissing | 28395 (943.4)1650 (5.5)25 (0.1) | 621 (2.2)68 (4.1)2 (8.0) | 2301 (8.1)282 (17.1) 1 (4.0) | 653 (2.3)114 (6.9)1 (4.0) | 24820 (87.4)1186 (71.9)21 (84.0) | <0.0001 |
| Material Factor Score Quintile within Province | 1 (lowest)2345 (Highest) Missing  | 10842 (36.1)7479 (24.9)4915 (16.4)3447 (11.5)2236 (7.4)1151 (3.8) | 235 (2.2)157 (2.1)111 (2.3)81 (2.4)71 (3.2)36 (3.1) | 891 (8.2)648 (8.7)451 (9.2)297 (8.6)196 (8.8)101 (8.8) | 251 (2.3)185 (2.5)126 (2.6)102 (3.0)67 (3.0)37 (3.2) | 9465 (87.3)6489 (86.8)4227 (86.0)2967 (86.1)1902 (85.1)977 (84.9) | =0.0253 |
| Social Factor Score Quintile within Province | 1 (lowest)2345 (Highest) Missing | 5279 (17.6)5512 (18.3)5187 (17.3)6028 (20.1)6918 (23.0)1151 (3.8) | 79 (1.5)103 (1.9)112 (2.2)144 (2.4)217 (3.1)36 (3.1) | 363 (6.9)440 (8.0)434 (8.4)575 (9.5)671 (9.7)101 (8.8) | 93 (1.8)97 (1.8)114 (2.2)179 (3.0)248 (3.6)37 (3.2) | 4744 (89.9)4872 (88.4)4527 (87.3)5130 (85.1)5777 (83.6)977 (84.9) | <0.0001 |

Values inside parentheses are row percent

Pvalues are from Chi-square tests

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