**Regression trees analysis of the Canadian Longitudinal Study on Aging (CLSA)  
to identify potential indicators (and intersections between sex and social factors) of receiving formal and informal home care**

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**Abstract**

OBJECTIVES*:*

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

**Introduction:**

1. *Issue:*

As populations age and baby boomers entering older age, the increase in the prevalence of chronic diseases and functional limitations and subsequently the need for care increases ("World Population Ageing 2020 Highlights: Living arrangements of older persons ", 2020). Care needs can be defined based on restriction in ADL/IADL and presence of chronic diseases as reported in one Canadian study using CLSA data (Zhang & Sun, 2020). Patterns of receiving of care, particularly home care seem to be more a function of complex interplay between individual characteristics, social network, and contextual/policy level factors. Theoretical models are frequently referred to in the literature describing patterns of care needs but usually fail to identify factors that predict such needs. No such research exists in Canada despite availability of rich databases such as CLSA.

1. *Factors that define (predict) receiving and giving care:*

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

The ‘needs’ factors represent the most immediate reason for seeking care, and arise from functional, physical and cognitive health problems (Bassetti & Rebba, 2015; Paraponaris et al., 2012; Penkunas et al., 2017; Van Houtven & Norton, 2004). The predisposing factors are risks existing before the onset of the impairment that created the need for care, such as age, sex, and health behaviours. The enabling factors are structural and contextual characteristics related to care availability, such as income (Bertogg & Strauss, 2020; Rodríguez, 2013; Van Houtven & Norton, 2004), health insurance, local policies (Blomberg et al., 2012; Suanet et al., 2012), and a social support network (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 sometime overlap. For example, sex can be both. Women, in general, have a more established social network that can be called upon, if needed, for informal care. On the other hand, female sex is a recognized risk factor for a variety of chronic diseases that precipitate a in need of care. Within families care usually is provided disproportionally across sex groups. ~~by males and females.~~ In traditional relationships women tend to be expected to be caregivers more than is so for men (Henz, 2009). This gendered role when mixed with spousal care can be described as ‘care by default’ delivered to men by women and arising from lifelong co-habitation and a close emotional bond (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 is gendered as well (Schmidt, 2017). Women are more likely to give up paid work to become family caregivers. Cultural norms also add complexity to care behaviour. In some cultures informal care is an expected substitute for formal care (Bolin et al., 2008)

Although predicted needs for informal and formal care are assumed to be similar, different care behaviours may be influenced differentially by enabling and predisposing factors. For example, persons with higher socio-economic status (i.e., with higher income/home-owners) are more likely than those of lower socioeconomic status to share or outsource care-giving with a formal service provider while persons from low SES are more likely to be recipients of informal care (Bertogg & Strauss, 2020). Current theoretical models (Andersen & Newman, 2005; Messeri et al., 1993) can identify factors that define *needs* for care as well as those factors that *predispose* individuals to be in need. Additionally, these models are able to describe what factors *enable* individual to access better care. Although these models are suitable to describe determinants of health care utilization properly, they are deficient in explaining the interplay between these care indicators.

1. *Intersectionality approach*

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

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 methods separate samples into homogenous subcategories grouping individuals by distinct social locations. This provides direct quantitative information on intersectionality (Bauer & Scheim, 2019; Cairney et al., 2014). These methods are a special category within more general machine learning techniques (Bi et al., 2019) and provide easy to understand graphical depiction (in the form of a recursive 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 among those with no limitation in daily activities precipitate a need to receive care.

*Rationale for our study:* \*\*need to explicitly state our aim

Few have considered intersections between ADL, SRH, and social factors. In other words, between real physical needs, perception of need and SES. We wished to do this as well as differentiate between receiving formal and informal care. Whether formal and informal care are related or are distinct provisions is debated (Lyons & Zarit, 1999). A classic model, the substitution model suggests an inverse relationship between formal and informal (Greene, 1983), whereas according to the complementarity model (Chappell & Blandford, 1991), formal and informal care have different structural characteristics. In this exploratory analysis we analyzed formal and informal care in separate models to identify specific predictor of formal and informal care use(?).

**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 were sampled from those residing 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 on a First Nations reserve or in an institution, 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 uses for the Comprehensive Cohort of the. Recruitment from provincial health registries (14% of the sample) follows random sampling of chosen eligible persons. 86% of the sample were recruited through random digit dialing by selection of a random sample of landline telephone numbers for a given geographic area. After establishing the eligibility in answered calls, consent was obtained. To ensure representativeness, the CLSA sample was stratified within provinces according to age group, sex, and distance from the data collection site, to ensure adequate representation of various demographic groups.

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

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

Participants were asked to response directly to whether they received formal home care services and/or informal home care services.

**2.4. Assessment of potential predictors**

2.4.1 Sociodemographic factors:

Information on sex, highest educational attainment (less than secondary school, secondary school graduation, some post-secondary, post-secondary graduation) and household income 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 area place of residence was classified into ‘urban core’, ‘other urban’, and ‘rural’, a standard n proxy measure for place of residence in Canada as per precedents (Pong et al., 2009). Additional *socio-demographic characteristics* included age in years, country of birth, and time since immigration (in years).

*2.4.2 Family related variables:*

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

*2.4.3 Physical and mental health factors:*

To measure function of participants we used a composite variable 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 created by CLSA modified the original measure modules of the OARS Multidimensional Assessment Questionnaire (Fillenbaum, 2013), excluding questions regarding meal preparation ability. Evaluation of perception of health was 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 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 deprivation Material and Social Derivation Indices (MSDI) for all Canadian census dissemination areas (DA) were downloaded July 21, 2017 by CANUE from the ‘*Institut national de santé publique du Québec’* (INSPQ) website and linked to participants' postal codes. This is a well-validated approach in Canada (REF).

**2.5. Statistical analysis**

Descriptive analyses were performed to estimate the distributions of all covariates in the whole 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 receiving informal care and receiving formal care.

To identify combinations of significant variables that predict receiving care 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 3 decades ago (Kass, 1980) mostly for data mining purposes and have been used in health research with increasing frequently (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 ordered to allow more predictors in the model we set the tree depth limitation to five (instead of three levels which is the default for CHAID) and selected flexible stopping criteria for splitting: 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 to the formal care models from 41 to 35 and for 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 v.27.

**Results**:

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

The main conclusion from the two regression trees was that except function as measured by ADL/IADL that was the most important predictors, other predictors varied considerably across formal and informal care. Therefore we report the detailed results separately for formal and informal care outcomes.

*Formal care receiving 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%) of those who received. with overall risk of misclassification of 4.5%. The risk remained almost the same (4.6%) after 10 folds cross-validation.

The primary predictor of receiving formal care was limitations in ADL and IADL. Among those with moderate to severe functional limitations 57% received formal care. The proportion of receiving formal care dropped to 22.4% for those with mild limitation. When need was quantified further, having a partner best predicted receipt of formal care for those with any ADL limitations, from mild to 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., after partner status) identified the following as predictors for formal care: SRH (for moderate/severe + partner: 32.2% in good SRH receiving care versus 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%). Within the younger than 75 years group, SRH and family-related variables such as partner status and living arrangement were important predictors, whereas in the older than 75 group self-report of depression also played a role. Sex, that is, being a man or a woman, was not a branch point for formal care.

*Informal care receiving,*

The regression tree generated by the CHAID algorithm for informal care showed 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 care. Overall risk of misclassification, therefore, was calculated to 10.6%. The risk increased slightly to 10.8% after 10 folds 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, and country of birth was predictive for those with no depression symptoms. Canadian born participants were slightly more likely to receive informal care than were foreign born individuals (28% vs 22%).

Patterns of receiving informal care was more complex among those (7.3%) with no ADL limitations showing intersections between sex, immigration status and health factors. Country of birth was a predictor of receiving informal care among 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).

**Discussion:***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 . More importantly, we found when the level of ADL changes, predictors of receiving care also change.

*1.1. Different predictors for formal vs informal*: sex, country of birth and years since immigration were only predictors of informal care. Reason: healthcare system in Canada covers formal care (family factor still important in those with no ADL limitations) but informal is also a function of cultural background. They are different ‘care’ behavious (Lyons & Zarit, 1999).

*1.2. Stable tree models*: formal care 4.5% risk of misclassification the same (approximately) after 10-fold cross-validation. Informal care 4.5% risk of misclassification the same (approximately) after 10-fold cross-validation

*1.3. Why receiving care while no ADL limitation:*

In this group 562 people (2.4%) received formal care and 2183 individuals (8.1%) received informal care. ADL limitation is only one reason for care receiving. The tree shows other predictors (such as age, SRH) but the work is exploratory and should confirmed with etiological analysis.

*2. Advantages of a regression tree approach*

Identification of risk factors in low-risk populations (for example age in the good ADL for informal care). Quantification of intersectionality by recursive and step-wise subgroupings, combinations of these subgroups can be interpreted as social locations (Bauer & Scheim, 2019).

*3. Specific strength of this study*

Most studies with a similar research question used different versions of regression analysis (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 on poor health (such as bad ADL) as the sole indicator of needs for care. Withing group heterogeneity usually is overlooked in epidemiological studies with traditional analytic approach. Regression tree is an alternative approach to address this concern.

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

Identification of subgroups that received care more frequently means they are vulnerable. Might need more direct clinical attention or public health interventions. Those groups that receive care but have no ADL limitation may need specific attention, since usual approaches don’t consider then as vulnerable. Examples????

Table 1: Descriptive results by types of home care received\_CLSA\_CARE

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Variable | Description | Total | Formal  Only | Informal  Only | Mixed Care | No care | Pvlaue |
| Sex | Female  Male | 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 | 45-54  55-64  65-74  75+ | 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 | Single  With partner  Divorced/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 graduation  Some post-secondary  Post-secondary degree/diploma  Missing | 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 more  Missing/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 | Canada  Other | 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 | ≤10  11-20  >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 | Rural  Urban 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 Problems  Mild problems  Moderate/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 | No  Yes  Missing | 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 | None  At least one  Missing | 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 | Good  Poor  Missing | 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 | Good  Poor  Missing | 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 |
| Cognition |  |  |  |  |  |  |  |
| Material Factor Score Quintile within Province | 1 (lowest)  2  3  4  5 (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)  2  3  4  5 (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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