The interaction between individual, social and environmental factors and their influence on dietary intake among adults in Toronto

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Abstract

Health outcomes related to vegetable and fruit consumption are widely recognized in the literature. This study investigates how dietary intake is influenced by individual, social, and environmental factors in the Toronto Census Metropolitan Area. The analysis and findings are based on data from the Canadian Community Health Survey which provides self-reported vegetable and fruit intake from 6,513 adults in 2009-2010. Food environment measures were constructed from commercial databases using kernel density estimates and network drive times. Spatial and multivariable techniques were used to determine the associations between diet, the food environment, and other health and socioeconomic factors. Particular emphasis was given to understanding the interaction between the food environment and socioeconomic position. Unexpectedly, supermarket density was found to have an inverse association with vegetable and fruit intake. Interaction terms for individuals with low income and reduced mobility produced different responses in men and women, confirming that the influence of the food environment is not uniform for all subgroups.

KEYWORDS

Food environment, Geographic Information Systems, socioeconomic position, vegetable and fruit intake

1 | INTRODUCTION

Diet has long been linked to a number of chronic disease outcomes and it continues to be investigated as a risk factor to human health (WHO & FAO, 2003). In Canada, poor diet accounts for the greatest disease burden, above tobacco use and high body mass index (Institute for Health Metrics & Evaluation, 2013). Despite increasing consumer awareness and ever expanding food choices, the prevalence of diet-related conditions points to a shortcoming of the conventional food system. In urban settings, much attention has focused on whether the modern food environment adequately and equitably supports the nutritional needs of the population. In recent years, there have been numerous attempts to parameterize these environments and measure the accessibility and availability of healthy food...
(Shearer et al., 2015; Crawford, Jilcott Pitts, McGuirt, Keyserling, & Ammerman, 2014; Bader, Purciel, Yousefzadeh, & Neckerman, 2010). Similarly, there have been many efforts to measure dietary behaviours and correlated health outcomes using a variety of health and diet recall surveys (Fung et al., 2009; Dansinger, Gleason, Griffith, Selker, & Schaefer, 2005; Hu, van Dam, & Liu, 2001). Yet, few studies explore the connections between these two modes of inquiry.

Previous approaches to nutrition research assumed that individuals act independently of their environment or socioeconomic background (Nestle et al., 1998). More recently, researchers have embraced ecological frameworks which recognize that a number of contexts and environmental factors influence behavior and that these interactions can take place along different dimensions (e.g. physical, sociocultural, or economic) and at different scales (e.g. individual, organizational, or regional; Tremblay & Richard, 2014; Richard, Gauvin, & Raine, 2011). Moreover, the interaction between dimensions and/or scales may matter more than any one factor by itself (Sallis, Owen, & Fisher, 2008). For example, the presence alone of stores selling fruit and vegetables does not guarantee increased vegetable and fruit intake. One of the most commonly cited conceptual frameworks for modeling eating patterns, proposed by Glanz, Sallis, Saelens, and Frank (2005), considers the influences of social, environmental, and policy variables on individual behaviors. The model further deconstructs the food environment into four subtypes: the community nutrition environment, organizational nutrition environment, consumer nutrition environment, and information environment (Glanz et al., 2005).

To date, most food environment research has focused on the community nutrition environment which is characterized by the location, type, and accessibility of food outlets. These characteristics can be measured by examining the geographic distribution of outlets and their attributes or by recording consumer perceptions of those outlets (Health Canada, 2013). Typically, Geographic Information Systems (GIS) are used to derive objective measures for the accessibility and availability of food by calculating the proximity, density, and diversity of food outlets (Black, Moon, & Baird, 2014). These measures have formed the basis for food desert investigations which traditionally focus on identifying neighborhoods where poor geographical access to food outlets coincides with high levels of poverty (Cummins & Macintyre, 2002). While food deserts are thought to be prevalent in the United States, evidence of this phenomenon elsewhere is inconclusive (Beaulac, Kristjansson, & Cummins, 2009). In Canada, investigations in Montreal and Edmonton found limited evidence of food deserts, even when smaller independent supermarkets and fruit and vegetable stores were excluded from analysis (Apparicio, Cloutier, & Shearmur, 2007; Smoyer-Tomic, 2006). Similarly, the most deprived neighborhoods in Toronto have been found to contain twice the expected number of healthy food retailers (Polsky, Moineddin, Glazier, Dunn, & Booth, 2014).

A notable limitation to the food desert literature is that findings are rarely connected to dietary or health outcomes (Cummins, 2007). Where studies have made this link, vegetable and fruit intake has commonly been used as an outcome measure (Casi, Sorensen, Subramanian, & Kawachi, 2012). Recent research has produced mixed evidence that there is a measurable relationship between food environments and vegetable and fruit intake. Of 42 research papers reviewed by Black, Moon, and Baird (2014), only a quarter of them show that there is an association between the density of healthy food stores and improved dietary outcomes and a fifth of the studies show an association between proximity to healthy food stores and vegetable and fruit intake. These results are likely due, in part, to a lack of standardized measures and methodologies which make comparison between studies challenging (Larson & Story, 2009; Charreire et al., 2010). Some researchers have begun to advocate for better calibrated GIS techniques to measure food availability and accessibility, such as kernel density estimates and network drive times instead of buffered densities and Euclidean distances, respectively (Casi et al., 2012; Charreire et al., 2010). In Canada, the relationship between the community nutrition environment and dietary outcomes has received less attention and with mixed results. An extensive study in Waterloo, Ontario found significant relationships between objective food environment measures and body mass index (BMI), but the relationships between these measures and diet quality were not significant (Minaker et al., 2013). By comparison, a study using a national retailer database found a relationship between the percentage of healthy food outlets and vegetable and fruit intake, but only among men in major urban areas (Clary, Ramos, Shareck, & Kestens, 2015). However, it is not unusual for secondary source databases to be representative of fewer than 80% of retailers in an area (Clary & Kestens, 2013). Indeed, both proprietary and government-sourced databases have been shown to be prone to inconsistent classifications, geospatial inaccuracies, and a bias towards undercounting food outlets (Fleischhacker, Evenson, Sharkey, Pitts, & Rodriguez, 2013; Forsyth, Lytle, & Riper, 2010; Liese et al., 2010).
In addition, the influence of the food environment on dietary outcomes is thought to be mediated by a number of other influences. For instance, neighborhood-level socioeconomic status has been implicated in dietary outcomes (Ball, Crawford, & Mishra, 2006; Winkler, Turrell, & Patterson, 2006) and Macintyre’s (2007) deprivation amplification hypothesis proposes that disadvantaged neighbourhoods produce poorer quality environments which, in turn, embellish individual disadvantages. While it is not explicit in the model proposed by Glanz et al. (2005), Lytle (2009) suggests that the food environment interacts with individual and social factors such that a restricted food environment (i.e. lacking in food availability or accessibility) may limit the expression of individual and social influences on diet (Figure 1). A corollary to this model is that individuals who are more socioeconomically constrained may be more susceptible to the influence of the food environment on their diet (Health Canada, 2013). For example, individuals with lower income or reduced mobility may be more reliant on their local food environment than those who have additional time and resources to travel further to do their shopping. It follows that constrained groups may show a greater range in diet quality across food environments. This hypothesis, along with the other conceptual models reviewed here, remain largely untested in the literature.

The purpose of this study is to characterize the relationship between the food environment and dietary behavior in a Canadian context. Using the Toronto Census Metropolitan Area (CMA) as the study area, this research considers the influence of individual, social, and environmental factors on vegetable and fruit intake using self-reported data from the Canadian Community Health Survey (Statistics Canada, 2011). Furthermore, this study seeks to test the corollary of Lytle’s (2009) conceptual model that the influence of the food environment on vegetable and fruit intake is more pronounced among individuals who are socioeconomically constrained.

2 METHODS

2.1 Study area

The Toronto CMA, with just over 6 million people and spanning 5,905 km², anchors a broader and fast growing urbanized area (called the Greater Golden Horseshoe) approaching nine million people (Statistics Canada, 2015a, b). As with...
many large metropolitan areas, the Toronto CMA is ethnically and culturally diverse with visible minorities representing 47% of the population (Statistics Canada, 2013).

2.2 | Canadian community health survey

Vegetable and fruit intake along with other health-related and sociodemographic data were obtained from the 2009-2010 Canadian Community Health Survey (CCHS) Share File, a cross-sectional survey administered by Statistics Canada (2011). Conducted over a two-year cycle, the CCHS collects population-level information on health determinants, health status, and health system utilization from 130,000 respondents across Canada. The survey has a multistage stratified design and sampling is balanced over the duration of the year to account for seasonal variation. DMTI’s Spatial CanMap Postal Code Suite (DMTI, 2011) was used to link postal codes (similar to US ZIP codes, but at a much finer resolution, these are typically assigned to a single block face between intersections or a single apartment building) with geographic precision for 6,513 respondents in the Toronto CMA. Respondents who were under the age of 20 were excluded from this study because their dietary habits were more likely to be determined by the household maintainer. Similarly, respondents with missing records on fruit and vegetable consumption, who were pregnant, or who lived outside of an urban area were also excluded. In addition, to account for possible edge effects in the spatial analysis, a 5 km inner buffer from the Toronto CMA boundary (excluding Lake Ontario) was created and respondents living within this buffer were excluded from the analysis. Survey weights provided by Statistics Canada to produce estimates for the entire population were normalized by dividing the weight for each respondent included in the study by the average weight of the sample size. These weights were used throughout the analysis.

Since 2001, the CCHS has used survey questions from the Centers for Disease Control’s Behavioral Risk Factor Surveillance System to determine vegetable and fruit intake (BRFSS; Pérez, 2002). The BRFSS fruit and vegetable module provides a derived variable for total daily frequency of consumption; but since it does not take quantity into account, estimates cannot be compared to the recommendations in the Canada Food Guide (Pérez, 2002). However, while the BRFSS fruit and vegetable module tends to underreport vegetable and fruit consumption, it has been validated against other vegetable and fruit intake assessment methods (Smith-Warner, Elmer, Fosdick, Tharp, & Randall, 1997) and in a Canadian context using similar, but slightly different questions (Traynor, Holowaty, Reid, & Gray-Donald, 2006).

Based on standards followed in the literature, a set of individual-level health, demographic, socioeconomic, and lifestyle covariates were selected from the CCHS that have been shown to be potential determinants of vegetable and fruit consumption. These included: age; marital status; mental health (measured as sense of belonging to a local community); incidence of chronic diseases (diabetes, cardiovascular disease, high blood pressure, and cancer); presence of a disability that requires assistance preparing meals or shopping for groceries; daily energy expenditure on physical activity; body mass index; smoking habits; immigration status; adjusted household income (adjusted by household size and grouped by decile); and driving habits in the last 12 months (Azagba & Sharaf, 2011; Dubowitz et al., 2008; Pérez, 2002).

2.5 | Spatial analysis

Since spatial data can display positive spatial autocorrelation which can bias ordinary least squares regression (OLS) models (Anselin, 2001), the global Moran’s I statistic was used to test whether vegetable and fruit consumption was more similar among neighboring respondents than would be expected under a spatially random distribution. Moran’s I tends towards 0 when there is no spatial autocorrelation and takes positive values of less than 1 when there is clustering. The Getis-Ord Gi* statistic was then used to detect local hot spots and cold spots across the study area and the spatial patterns were visually inspected to assist with identifying explanatory variables.

As an outcome of the spatial autocorrelation analysis, additional ethnocultural variables were included as covariates. These variables were derived by grouping responses to mother language and ethnicity questions with consideration for regional similarities in diet. Respondents whose mother language was Italian, Greek, or Portuguese were
grouped to create a Mediterranean variable (other Mediterranean countries of origin are not reported in the CCHS). Similarly, respondents who identified as Chinese, Korean, Japanese, Southeast Asian, or Filipino were grouped to create an East and Southeast Asian variable. South Asian, Black, and Latin American ethnicities were each included as separate variables.

2.6 | Food retailer databases

Food retailer locations were obtained from two proprietary commercial databases: the Centre for the Study of Commercial Activity’s retail store database and DMTI’s Enhanced Points of Interest database, both of Canadian retailers (CSCA, 2010; DMTI, 2010). Both databases are compiled annually and include a list of business names, addresses, geographic coordinates, and standard industry classification (SIC) codes. Food stores, full-service department stores, and warehouse food retailers that were located in the Toronto CMA in 2010 were extracted using SIC codes. The inclusion of stores within the 5 km inner buffer and exclusion of respondents in this area ensured that all stores within 5 km of each respondent were included in the analysis, minimizing possible edge effects. The databases were joined to improve data completeness and duplicate data were removed. Because combining databases increases the risk of overcounting (due to errors and closed outlets; Liese et al., 2010), a combination of local knowledge, business name internet searches, and searches through Google Street View’s historical imagery were used to validate retail locations, help determine whether they were operating in 2010, and identify whether they sold vegetables and fruit. Stores that were estimated to be over 5,000 ft² were classified as supermarkets in this study. This cut-off was selected as a way to include small- to medium-sized urban-format supermarkets, such as Sobey’s Express and Urban Fresh stores, which are prevalent in Toronto’s densely populated neighborhoods.

To model the food environment, kernel density estimates were created using store locations from the merged retailer databases. Similar to the methodology employed by Thornton, Pearce, Macdonald, Lamb, and Ellaway (2012), a cell size of 100 m and kernel sizes of 0.5, 1, 2.5, and 5 km were used to produce kernel density estimate surfaces for all stores selling vegetables and fruit and for supermarkets alone. For each of the eight kernel density estimate surfaces produced, the value at each CCHS respondent’s location was recorded. In addition, an accessibility measure was calculated using the ArcGIS Business Analyst extension (Esri, 2014) to find the network drive time for each respondent to the nearest store selling vegetables and fruit and to the nearest supermarket.

2.7 | Statistical analysis

Descriptive and multivariable analyses were conducted to assess the association between vegetable and fruit consumption and individual, social, and environmental factors. Because the magnitude of the effect on diet of some covariates differed between men and women, data and analyses were stratified by gender. The mean difference in vegetable and fruit consumption was compared using t-tests or ANOVA for each of the independent variables. To reduce the influence of any skewed distribution on the mean, vegetable and fruit intake was truncated for men and women at three multiples of the standard deviation.

Multiple linear regression using OLS estimators was used to model the relationship between vegetable and fruit intake against the independent variables. The dependent variable (untruncated) was transformed using the natural log to normalize the distribution which was highly skewed to the right. The model was then run with each of the eight kernel density estimates and the network drive time variables to determine which representation of the food environment contributed the most explanatory power to the model. Diagnostics were run on the final model in GeoDa (Anselin, 2015), a spatial data analysis software package, to test for spatial dependence between the error terms (spatial error) or between the dependent variable observations (spatial lag). The regression was run again using the model specified by the spatial diagnostic tests to improve its fit. Finally, to test Lytle’s conceptual model that there is an interaction between socioeconomic position and the food environment, two
dummy variables were created from CCHS survey questions to represent a low-income group (respondents in the bottom three deciles of adjusted household income) and a reduced mobility group (respondents who had not driven a vehicle in the last 12 months). Interaction terms for each of these groups were created by taking the product of the dummy variable and the food environment variable.

3 | RESULTS

Males respondents (n = 3,199) consumed 4.6 (SD = 2.3) vegetables and fruit per day on average and had a mean age of 45.1 years (not shown). Female respondents (n = 3,314) consumed 5.2 (SD = 2.5) vegetables and fruit per day on average and had a mean age of 46.1 years (not shown). The mean value of vegetable and fruit consumption for each independent variable is given in Table 1.

| TABLE 1 | Descriptive statistics and mean daily vegetables and fruit consumption for each independent variable, stratified by sex |
| Independent variable | Male (n=3,199) | Female (n=3,314) |
| | % | Mean (SD) | % | Mean (SD) |
| Age group | | | | |
| 20-24 | 10.8 | 4.5 (2.3)   | 9.4 | 5.0 (2.6)   |
| 25-34 | 19.7 | 4.4 (2.4)   | 18.5 | 5.0 (2.3)   |
| 35-44 | 21.1 | 4.5 (2.2)   | 21.8 | 5.1 (2.3)   |
| 45-54 | 19.6 | 4.4 (2.3)   | 20.9 | 5.2 (2.5)   |
| 55-64 | 16.0 | 4.6 (2.3)   | 14.8 | 5.4 (2.7)   |
| 65+ | 12.8 | 5.1 (2.3)   | 14.7 | 5.2 (2.3)   |
| Marital status | | | | |
| Married/Common-law | 65.6 | 4.7 (2.3) | 59.5 | 5.4 (2.4) |
| Divorced/Separated/Widowed | 8.2 | 4.1 (2.4) | 16.6 | 5.0 (2.6) |
| Single | 26.0 | 4.5 (2.4) | 23.7 | 4.8 (2.5) |
| Children present in household | | | | |
| Yes | 31.6 | 4.5 (2.3) | 34.8 | 5.1 (2.4) |
| No | 68.4 | 4.6 (2.3) | 65.2 | 5.2 (2.5) |
| Sense of belonging | | | | |
| Very strong | 16.1 | 4.9 (2.4) | 15.3 | 5.8 (2.5) |
| Somewhat strong | 44.8 | 4.9 (2.4) | 49.9 | 5.3 (2.4) |
| Somewhat weak | 28.6 | 4.1 (2.1) | 22.5 | 4.8 (2.3) |
| Very weak | 10.0 | 4.1 (2.2) | 11.6 | 4.5 (2.7) |
| Has chronic health condition | | | | |
| Yes | 23.4 | 4.6 (2.3) | 23.2 | 5.0 (2.5) |
| No | 76.6 | 4.6 (2.3) | 76.8 | 5.2 (2.4) |
| Needs help preparing meals or shopping | | | | |
| Yes | 4.3 | 5.1 (2.8) | 8.4 | 4.8 (2.5) |
| No | 95.7 | 4.6 (2.3) | 91.6 | 5.2 (2.4) |
| BMI | | | | |
| Underweight | 1.5 | 3.2 (2.1) | 4.7 | 5.2 (2.6) |
| Normal weight | 43.3 | 4.5 (2.2) | 54.7 | 5.3 (2.4) |
| Overweight | 38.5 | 4.7 (2.3) | 24.4 | 5.2 (2.5) |
| Obese | 15.9 | 4.6 (2.5) | 13.2 | 4.7 (2.4) |

(Continues)
In total, 1,011 retail locations that sold fruit and vegetables were identified between the CSCA (2010) and DMTI (2010) datasets. Forty-nine percent were classified as supermarkets (Figure 2) and, of these, 82% were operated by major chains (Table 2). The distribution of Toronto’s retail food stores by size and brand affiliation can be found in TABLE 1 (Continued)

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Male (n=3,199)</th>
<th>Female (n=3,314)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Physical activity</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Active</td>
<td>25.5</td>
<td>16.4</td>
</tr>
<tr>
<td>Moderately active</td>
<td>23.0</td>
<td>22.7</td>
</tr>
<tr>
<td>Inactive</td>
<td>50.6</td>
<td>60.5</td>
</tr>
<tr>
<td><strong>Type of smoker</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>15.9</td>
<td>9.4</td>
</tr>
<tr>
<td>Occasional</td>
<td>6.5</td>
<td>3.4</td>
</tr>
<tr>
<td>Non-smoker</td>
<td>76.5</td>
<td>86.6</td>
</tr>
<tr>
<td><strong>Highest Education Achieved</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-secondary</td>
<td>66.2</td>
<td>62.0</td>
</tr>
<tr>
<td>Other post-secondary</td>
<td>9.0</td>
<td>10.4</td>
</tr>
<tr>
<td>High school</td>
<td>15.4</td>
<td>17.0</td>
</tr>
<tr>
<td>Some high school</td>
<td>6.1</td>
<td>7.8</td>
</tr>
<tr>
<td><strong>Income</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Higher (8-10 deciles)</td>
<td>25.0</td>
<td>16.9</td>
</tr>
<tr>
<td>Middle (4-7 deciles)</td>
<td>31.6</td>
<td>31.2</td>
</tr>
<tr>
<td>Lower (1-3 decile)</td>
<td>25.3</td>
<td>30.1</td>
</tr>
<tr>
<td><strong>Immigrant</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>52.2</td>
<td>56.0</td>
</tr>
<tr>
<td>No</td>
<td>44.6</td>
<td>41.1</td>
</tr>
<tr>
<td><strong>East and Southeast Asian</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>28.6</td>
<td>28.2</td>
</tr>
<tr>
<td>No</td>
<td>71.4</td>
<td>71.8</td>
</tr>
<tr>
<td><strong>Black</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>6.1</td>
<td>8.0</td>
</tr>
<tr>
<td>No</td>
<td>90.4</td>
<td>88.8</td>
</tr>
<tr>
<td><strong>Latin American</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>2.3</td>
<td>3.4</td>
</tr>
<tr>
<td>No</td>
<td>94.2</td>
<td>93.4</td>
</tr>
<tr>
<td><strong>Mediterranean</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>10.2</td>
<td>11.5</td>
</tr>
<tr>
<td>No</td>
<td>89.8</td>
<td>88.5</td>
</tr>
<tr>
<td><strong>South Asian</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>13.4</td>
<td>13.1</td>
</tr>
<tr>
<td>No</td>
<td>83.1</td>
<td>83.7</td>
</tr>
<tr>
<td><strong>Drove vehicle in last 12 months</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td>84.2</td>
<td>66.2</td>
</tr>
<tr>
<td>No</td>
<td>13.8</td>
<td>32.3</td>
</tr>
</tbody>
</table>

Based on daily vegetable and fruit intake with outliers reassigned to three times the standard deviation.

a,b,c Values with unlike superscript letters denote significant differences between group means ($p < 0.05$).

For ANOVA, Tukey’s HSD post hoc test was run for groups where assumptions of homogeneity of variance were met.

When assumptions of homogeneity of variance were violated, the Brown-Forsythe test was used and the Games-Howell post hoc test was run to determine significance between groups.
Table 2. The average kernel density estimates for each respondent are given in Table 3 and the kernel density surfaces are shown in Figure 3. Because most small stores were within close proximity to a supermarket, the coverage of the kernel density surfaces for all stores and supermarkets were nearly identical (Table 3). At a kernel bandwidth of 5 km, 99.7% of respondents had a kernel density estimate greater than zero (Table 3). Kernel density estimates were also correlated with population density ($r = 0.259$ to $0.583$, $p < 0.001$ from the smallest to largest bandwidths; Statistics

**FIGURE 2** Locations of stores selling fruit and vegetables

Table 2. Summary of food retailers by store size and brand affiliation

<table>
<thead>
<tr>
<th>Store size in m² (ft²)</th>
<th>Independent</th>
<th>Major Chain</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Other stores selling fruit and vegetables, under 465 (5,000)</td>
<td>499</td>
<td>7</td>
<td>506</td>
</tr>
<tr>
<td>0 to 464 (0 to 4,999)</td>
<td>290</td>
<td>3</td>
<td>293</td>
</tr>
<tr>
<td>Not provided (estimated)*</td>
<td>209</td>
<td>4</td>
<td>213</td>
</tr>
<tr>
<td>Supermarkets, 465 (5,000) and over</td>
<td>92</td>
<td>413</td>
<td>505</td>
</tr>
<tr>
<td>465 to 1,393 (5,000 to 14,999)</td>
<td>40</td>
<td>32</td>
<td>72</td>
</tr>
<tr>
<td>1,394 to 2,322 (15,000 to 24,999)</td>
<td>31</td>
<td>62</td>
<td>93</td>
</tr>
<tr>
<td>2,323 to 4,645 (25,000 to 49,999)</td>
<td>15</td>
<td>158</td>
<td>173</td>
</tr>
<tr>
<td>4,645 to 9,290 (50,000 to 99,999)</td>
<td>2</td>
<td>76</td>
<td>78</td>
</tr>
<tr>
<td>9,290 (100,000) and over</td>
<td>0</td>
<td>48</td>
<td>48</td>
</tr>
<tr>
<td>Not provided (estimated)*</td>
<td>4</td>
<td>37</td>
<td>41</td>
</tr>
</tbody>
</table>

Total | 591 | 420 | 1,011 |

*When a store size was not provided in the retailer database, the store was estimated to be less than 465 m² or greater than 465 m² using Google Street View.
Respondents were located an average of 659 meters from the nearest store selling fruit and vegetables (including supermarkets) and 817 m from the nearest supermarket.

Vegetable and fruit consumption for male and female respondents was positively, spatially autocorrelated across the study area (men: $I = 0.0108$, $p < 0.002$; women: $I = 0.0079$, $p < 0.001$; not shown). A 5 km distance threshold had the greatest statistical power. Due to provisions set by Statistics Canada to limit the risk of re-identifying CCHS respondents, results from the hot spot analysis for each gender cannot be presented; however, a combined hot spot map aggregated to hexagonal cells (cell sizes smaller than five have been suppressed) is shown in Figure 4 for illustrative purposes. Local $G_i^*$ clusters of hot spots and cold spots were similar for both men and women. Hot spots can be seen in Oakville, the east side of Brampton, Woodbridge, and southern Scarborough (Figure 4). A central cold spot extends from the downtown core up to mid-town, from the northern part of Scarborough into Markham, and smaller cold spots can be found in the west end of Brampton, Ajax, and Keswick (Figure 4). These local areas of spatial autocorrelation show similarities to the distribution of ethnocultural communities in the Toronto CMA (Figure 5).

In the multiple linear regression model, the kernel density estimate for supermarkets with a bandwidth of 5 km had the most explanatory power over the other kernel density surfaces. The two proximity variables (network drive time to all stores selling fruit and vegetables and network drive time to supermarkets) did not make a significant contribution to the model and were excluded from analysis.

Table 4 shows the initial OLS model, spatial regression results, and models with interaction terms for income, mobility, and income and mobility combined for men and women. Since the dependent variable has been log transformed, the estimated coefficient represents the percentage change in vegetable and fruit consumption with each unit increase of that independent variable. For both genders, there was an inverse relationship between supermarket density and fruit and vegetable consumption (Table 4). There were also gender-specific differences with respect to variables that explain fruit and vegetable consumption. For example, highest education attainment and immigrant status were significant for men, but for women the presence of children in the household, chronic health conditions, and body mass index were significant (Table 4).

Of the ethnocultural variables analyzed, East and Southeast Asian and South Asian backgrounds were significant for men, while Mediterranean backgrounds were significant for women (Table 4).

Spatial diagnostics on the OLS regression models for men and women indicated non-stationarity in the coefficients (Breusch-Pagan test, $p < 0.05$; not shown). For men, the residuals were not spatially autocorrelated and for women there was spatial error dependence (Lagrange Multiplier test, $p < 0.05$; not shown). Using a spatial error regression model for the latter improved model fit (not shown), but did not entirely remove spatial dependence (maximum likelihood estimation < 0.05). The spatial error regression models also produced notable shifts in the coefficient values compared to the OLS model suggesting model specification issues (not shown).
FIGURE 3  Kernel density estimate surfaces for all stores selling fruit and vegetables and supermarkets at 0.5, 2.5, and 5 km bandwidths. Red hues indicate the maximum density estimate, therefore the color scale is different for each cell. The 5 km bandwidth kernel density estimate for supermarkets (framed in black) was selected for analysis.
For men, both the interaction terms for the low-income group (Table 4, Model 2) and reduced mobility group (Table 4, Model 3) produced a more negative slope and a more positive intercept (Figure 6). These results suggest that men in socioeconomically constrained groups are likely to consume more vegetables and fruit than unconstrained individuals in food environments with fewer supermarkets; but the steeper slope suggests that the influence of the food environment on vegetable and fruit intake is stronger for the constrained group. Therefore, as supermarket density increases, men in the constrained group are likely to consume similar or fewer vegetables and fruit than men in the unconstrained group. For women, the near opposite was observed: the slope for the constrained group became slightly positive and the intercept decreased (Figure 6). This suggests that women in socioeconomically constrained groups are likely to consume fewer vegetables and fruit than unconstrained individuals in food environments with fewer supermarkets; however, as supermarket density increases, the fruit and vegetable intake of women in the constrained group did not change considerably. Therefore, it is apparent from the shallower slope that women in the constrained group are not as strongly influenced by the food environment as women in the unconstrained group. Combining the two interaction terms did not lead to significant results for men or women (not shown).

4 | DISCUSSION

This study investigated individual, social, and environmental factors that explain vegetable and fruit consumption among respondents to the 2009-2010 CCHS in Toronto, Canada (Statistics Canada, 2011). It was found that supermarket density had an inverse relationship with vegetable and fruit consumption, that proximity to food retailers did not explain dietary intake, and that a variety of socioeconomic variables, including ethnocultural factors, mediated
these relationships. An interaction between socioeconomic position and the food environment was observed, although to opposite effect in men compared to women.

This first finding is unexpected as other studies have largely uncovered either no relationship or a positive relationship between supermarket density and vegetable and fruit intake (Black et al., 2014). Two exceptions, Powell et al. (2009) and Zenk et al. (2009), found an inverse relationship between smaller grocery stores and vegetable and fruit intake; however, this distinction is difficult to disambiguate in the Toronto CMA where there is a crowded continuum of food stores from small, urban-format chain stores to larger superstores. In the present study, supermarket density was strongly correlated with population density, so it follows that the density of other food retailers, such as convenience stores, restaurants, and fast food outlets, also increase with population density. The availability of other food choices could be confounding expected results, especially since prepared and convenience foods may be more attractive than fruit and vegetables for some consumers; therefore, in future studies a relative measure that expresses vegetable and fruit retailers as a ratio to stores that sell less healthy foodstuffs might provide clearer insight. Recent findings from Clary et al. (2015) also came to this conclusion using CCHS data in a national-scale study. Furthermore, in-store food environments (as characterized by the relative cost and shelf space of vegetables and fruit) may need to be considered as many retailers can be a source of both healthy and unhealthy food products. For example, a study in North Carolina found that women who lived near superstores tended to weigh more than those who did not (Gustafson et al., 2011).

The second finding that proximity measures do not explain vegetable and fruit intake is consistent with some literature (Williams, Ball, & Crawford, 2010; Pearce, Hiscock, Blakely, & Witten, 2008; Pearson, Russell, Campbell, & Barker, 2005) and not surprising in Toronto’s retail environment where consumers have a lot of choice and the average distance to the

FIGURE 5  Census tracts with top decile concentrations of East and Southeast Asian, Mediterranean, and South Asian ethnocultural groups
**Table 4** Summary of multiple linear regression results describing relationship between log-transformed daily vegetable and fruit consumption and independent variables stratified by sex

<table>
<thead>
<tr>
<th>Variable</th>
<th>Men</th>
<th>Women</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1 (Initial model)</td>
<td>Model 2 (Low income interaction)</td>
</tr>
<tr>
<td>Intercept</td>
<td>1.26 (0.11)**</td>
<td>1.12 (0.11)**</td>
</tr>
<tr>
<td>Age</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Marital Status</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Married/Common-Law</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Divorced/Separated/Wid.</td>
<td>−0.14 (0.05)**</td>
<td>−0.15 (0.05)**</td>
</tr>
<tr>
<td>Single†</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Children present in household</td>
<td>−0.02 (0.03)</td>
<td>−0.04 (0.03)</td>
</tr>
<tr>
<td>Sense of Belonging</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Very strong</td>
<td>0.23 (0.05)**</td>
<td>0.23 (0.05)**</td>
</tr>
<tr>
<td>Somewhat strong</td>
<td>0.22 (0.04)**</td>
<td>0.22 (0.04)**</td>
</tr>
<tr>
<td>Somewhat weak</td>
<td>0.10 (0.04)*</td>
<td>0.10 (0.04)*</td>
</tr>
<tr>
<td>Very weak†</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Has chronic health condition</td>
<td>−0.05 (0.03)</td>
<td>−0.06 (0.03)</td>
</tr>
<tr>
<td>Needs help with shopping</td>
<td>0.14 (0.06)*</td>
<td>0.13 (0.06)*</td>
</tr>
<tr>
<td>Body mass index</td>
<td>0.00 (0.00)</td>
<td>0.00 (0.00)</td>
</tr>
<tr>
<td>Physical activity</td>
<td>0.04 (0.01)**</td>
<td>0.04 (0.01)**</td>
</tr>
<tr>
<td>Type of Smoker</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily</td>
<td>−0.11 (0.03)**</td>
<td>−0.11 (0.03)**</td>
</tr>
<tr>
<td>Occasional</td>
<td>−0.01 (0.05)</td>
<td>−0.01 (0.05)</td>
</tr>
<tr>
<td>Non-smoker†</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Highest Education Achieved</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-secondary</td>
<td>−0.05 (0.04)</td>
<td>−0.04 (0.04)</td>
</tr>
<tr>
<td>Other post-secondary</td>
<td>−0.14 (0.06)*</td>
<td>−0.13 (0.06)*</td>
</tr>
<tr>
<td>High school</td>
<td>−0.13 (0.05)*</td>
<td>−0.11 (0.05)*</td>
</tr>
<tr>
<td>Some high school†</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Variable</td>
<td>Men Model 1 (Initial model)</td>
<td>Men Model 2 (Low income interaction)</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------</td>
<td>--------------------------------------</td>
</tr>
<tr>
<td>Adjusted household income</td>
<td>0.01 (0.01)</td>
<td>0.02 (0.01)**</td>
</tr>
<tr>
<td>Immigrant</td>
<td>0.08 (0.03)**</td>
<td>0.08 (0.03)**</td>
</tr>
<tr>
<td>Ethnocultural group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>East and Southeast Asian</td>
<td>−0.16 (0.04)**</td>
<td>−0.15 (0.04)**</td>
</tr>
<tr>
<td>Black</td>
<td>−0.20 (0.05)</td>
<td>−0.09 (0.05)</td>
</tr>
<tr>
<td>Latin American</td>
<td>−0.14 (0.08)</td>
<td>−0.15 (0.08)</td>
</tr>
<tr>
<td>Mediterranean</td>
<td>0.01 (0.04)</td>
<td>0.02 (0.04)</td>
</tr>
<tr>
<td>South Asian</td>
<td>0.20 (0.04)**</td>
<td>0.08 (0.04)</td>
</tr>
<tr>
<td>Food Environment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Supermarket density</td>
<td>−0.29 (0.05)**</td>
<td>−0.20 (0.06)**</td>
</tr>
<tr>
<td>Socioeconomic restriction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low income group</td>
<td>−</td>
<td>0.24 (0.06)**</td>
</tr>
<tr>
<td>Non-driver group</td>
<td>−</td>
<td>−</td>
</tr>
<tr>
<td>Interaction terms</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low income × supermarket density</td>
<td>−</td>
<td>−0.38 (0.12)**</td>
</tr>
<tr>
<td>Non-driver × supermarket density</td>
<td>−</td>
<td>−</td>
</tr>
</tbody>
</table>

* *p < 0.05, ** *p < 0.01, *** *p < 0.001.
† Reference category.
All models use standardized survey weights.
nearest store is relatively small. Furthermore, it is reasonable to expect that the principal commercial establishment that one shops for groceries is not necessarily the closest (Drewnowski, Aggarwal, Hurvitz, Monsivais, & Moudon, 2012). To address this, researchers have been turning to approaches that incorporate analysis of GPS-tracked activities or travel survey data, recognizing that most human activity is not restricted to predetermined geographies (Marquez & Guo, 2001; Sherman, Spencer, Preisser, Gesler, & Arcury, 2005; Vallée, Cadot, Roustit, Parizot, & Chauvin, 2011; Sadler & Gilliland, 2015). In a food environment context, these “activity spaces” have been found to be not only larger than residential neighborhoods, but weakly associated with them, suggesting that food environment exposure from daily travel patterns may be more important than residential exposure (Zenk et al., 2011; Gustafson, Christian, Lewis, Moore, & Jilcott, 2013). However, while one’s residential food environment may not resemble one’s activity space food environment, Kestens et al. (2012) showed that individual-level and residential area characteristics are nevertheless good predictors of food environment exposure and Zenk et al. (2011) have noted the difficulty of disambiguating a selection bias among individuals who seek out specific food environments from those who are influenced by the environmental features in their “regular” activity spaces.

Though the relationship between ethnicity and vegetable and fruit consumption has previously been observed in Canada (Quadir & Akhtar-Danesh, 2010), the results from the stratified analysis in this study suggest a possible interaction between gender and ethnicity. From a public health perspective, it is important to understand how diet relates to cultural norms and, with respect to gender, if there are within-culture differences. It is also not known if ethnocultural diets are mediated by the presence of ethnic markets or culturally-specific in-store products. In multicultural cities like Toronto, further investigation along these lines could provide insight into the relationship between the food environment and the healthy immigrant effect, a phenomenon that describes the decline in the health of immigrants following their arrival (Beiser, 2005; Newbold, 2006).

This study also found that vegetable and fruit intake remained practically unchanged among socioeconomically constrained women across food environments. Since this restriction did not produce a response in both genders, this study lends support to Lytle’s conceptual model for men, but not women. Because much of the food environment
literature does not stratify by gender, it is difficult to make comparisons with other studies; nevertheless, these results suggest that gender-specific explanatory factors merit further study. Clary et al. (2015) made a similar observation, noting that the effects of the food environment on diet are not universal for all population sub-groups. In this study, the diagnostics for the OLS regression for women suggested model misspecification, possibly due to the omission of a critical variable. Perceptual and attitudinal differences between men and women towards diet may offer an explanation. For instance, Emanuel, McCully, Gallagher, and Updegraff (2012) found that women reported greater perceived behavioral control than men with respect to fruit and vegetable intake; for example, in the presence of junk food, women are more confident that they can eat healthfully. In addition, women are shown to score higher than men on an eating-related, self-determination index (SDI) and that eating-related SDI is significantly associated with dietary intake (Leblanc, Bégin, Corneau, Dodin, & Lemieux, 2015). While these studies do not directly relate eating behaviors to the food environment, they identify gender-specific differences that suggest women are more likely to be influenced by individual factors and that their diets are not as strongly influenced by their surroundings.

For policy makers, Lytle’s (2009) model can also provide a framework for understanding the potential outcomes of public health interventions targeted at individual, social, or environmental factors. Perhaps as a consequence of the rise of food environment research, interventions that seek to enhance the food environment (or make it less restrictive) have been increasingly proposed by public health advocates. For example, nine out of 10 strategies put forward by the Centers for Disease Control and Prevention (2011) to encourage vegetable and fruit consumption focus on improving access and availability. Similarly, Toronto’s public health unit has initiated a number of projects that attempt to increase the availability of vegetables and fruit in public spaces (City of Toronto, n.d.). However, this study finds that there is an inverse association between the availability of vegetables and fruit and their consumption. This does not suggest that a new farmers’ market or healthy corner store will precipitate a decrease in vegetable and fruit intake; but, it is clear that these types of interventions do not directly address these findings, particularly if exposure to unhealthy food products is an underlying factor. Furthermore, given that this study found that women with reduced mobility tended to consume fewer vegetables and fruit in neighborhoods with low supermarket density, a social intervention such as increasing access to transportation in these neighborhoods may be a more effective measure, especially since this could yield additional benefits to wellbeing, the economy, and the environment.

A number of limitations in this study should be recognized. Given the cross-sectional nature, causal relationships could not be investigated. Therefore, the influence of consumers on the food environment or the food environment on migration (i.e. market forces) cannot be discounted. Given the voluntary nature of the CCHS, the survey is not representative of all sub-population groups, as evidenced by response rates for married and common-law couples and individuals with post-secondary education that exceeded Toronto CMA population averages. In addition, the self-reported nature of the study is susceptible to inflation or underestimation, especially for height and weight which are used to calculate BMI (Akhtar-Danesh, Dehghan, Merchant, & Rainey, 2008). Similarly, the BRFSS food frequency questions are subject to reporting error and tend to produce lower estimates of vegetable and fruit intake than more extensive dietary assessments (Smith-Warner, et al., 1997). It is also possible that the small differences between the geocoded postal code and respondent address could influence results, especially for respondents in less dense, suburban areas which tend to have longer block faces. As already mentioned, the study makes assumptions that most shopping activity takes place within the retail food environment immediately around the home; similarly, the study does not consider other effect modifiers of exposure such as modes of transportation. While the food environment measures take into account geographical availability and accessibility, other factors such as quality, price, and the amount of shelf space devoted to fruit and vegetables have not been investigated. Finally, by limiting the analysis to the individual record level, the study avoids some issues encountered due to aggregation bias and the Modifiable Areal Unit Problem, but it does not take into consideration potential multilevel effects.

5 | CONCLUSIONS

This study identifies individual, social, and environmental factors that explain fruit and vegetable consumption in the Toronto CMA. While the availability of food as measured by supermarket density was shown to influence dietary
behaviors in men and women, this association was found to be inverse and unexpected. This study also lends support to other findings that advocate for parameterizing the food environment using relative measures of healthy to unhealthy food outlets over absolute measures. In addition, the presence of gender-specific model differences suggests that interaction effects require further attention in the food environment literature. Finally, while we acknowledge that continued methodological testing is needed to refine and standardize the tools and measures used in food environment research, this study makes an attempt to introduce hypothesis testing using Lytle’s (2009) conceptual model as a starting point. The mixed results between men and women suggest further investigation of Lytle’s model is warranted.

NOTE
1 Urban status is determined in the 2009-2010 CCHS using Statistics Canada’s classification which defines urban areas as having a population greater than 1,000 and a population density of 400 or more people per square kilometre (Statistics Canada, 2013).

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