

Associations between the fast-food environment and diabetes prevalence in the Netherlands: a cross-sectional study



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Summary

Background Diabetes is a major health concern and is influenced by lifestyle, which can be affected by the neighbourhood environment. Specifically, a fast-food environment can influence eating behaviours and thus diabetes prevalence. Therefore, our aim was to assess the relationship between fast-food environment and diabetes prevalence for urban and rural environments in the Netherlands, using multiple indicators and buffer sizes.

Methods In this cross-sectional study, data on a nationwide sample of adults older than 19 years in the Netherlands were taken from the 2012 Dutch national health survey (from Public Health Monitor), in which participants were surveyed on topics related to health and lifestyle behaviour. Fast-food outlet exposures were determined within street-network buffers of 100 m, 400 m, 1000 m, and 1500 m around residential addresses. For each of these buffers, three indicators were calculated: presence (yes or no) of fast-food outlets, fast-food outlet density, and ratio. Logistic regression analyses were carried out to assess associations of these indicators with diabetes, adjusting for potential confounders and stratifying into urban and rural areas.

Findings 387 195 adults were surveyed, 284 793 of whom were included in the study. 22 951 (8%) reported having diabetes. Fast-food outlet exposures were positively associated with diabetes prevalence. We did not observe large differences between urban and rural areas. The effect estimates were small for all indicators. For example, in the 400 m buffer in the urban environment, the odds ratio (OR) for having diabetes among people with a fast-food outlet present compared with those without, was 1.006 (95% CI 1.003–1.009) using the presence indicator. The presence indicator showed higher effect estimates and the most consistent results across buffer sizes (ranging from OR 1.005 [95% CI 1.000–1.010] with the 1000 m buffer to 1.016 [1.005–1.028] with the 1500 m buffer in urban areas and from 1.002 [0.998–1.005] with the 1500 m buffer to 1.009 [1.006–1.018] with the 100 m buffer in rural areas) compared with the density and ratio indicators.

Interpretation The results confirm the evidence that the fast-food outlet environment is a diabetes risk factor. All data included were at the individual level and the variability was ensured by the spatial distribution and number of participants. In this study, we only accounted for residential exposure because we were unable to account for exposure outside the residential environment. The findings of this study encourage local governments to consider the potential adverse effects of fast-food exposures and aim at minimising unhealthy food access.

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Introduction

Diabetes is one of the main global health threats in the 21st century.^{1–3} Globally, one in ten adults aged 20–79 years had diabetes in 2021.⁴ The prevalence of diabetes is estimated to increase even further, from 2.8% in 2000 to 4.4% in 2030.⁵ Also, in the Netherlands, the proportion of people prescribed diabetes medication increased from 3.8% in 2006 to 4.6% in 2012.⁶ There are two main types of diabetes that can affect the general population: type 1 diabetes and type 2 diabetes. Type 1 diabetes is almost exclusively determined by genetics and represents less than 10% of the total diabetes cases.⁷ By contrast, type 2 diabetes is highly determined by modifiable, mainly lifestyle-related factors, such as physical inactivity, poor diet, smoking, and alcohol consumption.^{1,3}

It is becoming accepted that the structure of the neighbourhood environment influences health behaviours.^{8,9} A fast-food environment usually promotes a ready-to-eat meal lifestyle due to convenience and a way to socialise.¹⁰ Access to fast-food also promotes impulsive eating¹⁰ and binge eating.¹¹ This is because fast-food makes eating easy and fast due to accessibility, availability, and affordability,¹² and reasoned forethought is usually replaced by dysfunctional impulsivity.^{13,14} In many countries,^{15,16} the number of fast-food outlets is increasing. In the Netherlands, the number of food outlets has increased by 8% from 2008 to 2012.¹⁷ Given that most fast-food is energy dense and nutrient poor, its consumption might cause an increased body-mass index and type 2 diabetes.^{18,19}

Some studies have reviewed the associations between fast-food exposures and diabetes.^{20,21} However, most of

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Research in context

Evidence before this study

We searched PubMed and Google Scholar with no date restrictions. The searched terms we used were: “fast food outlet”, “food exposures”, “food environment”, “unhealthy food environment” AND “diabetes”, “diabetes type 2”, “diabetes mellitus”. The search was limited to English language publications. From the literature search we found only four studies (two cross-sectional, one longitudinal, and one including both cross-sectional and longitudinal analyses) that have examined the association between the fast-food environment and diabetes at an individual level, although diabetes is a major global health threat. Furthermore, there is no consensus on the buffer size and the indicator used to assess fast-food environment exposure in the studies. None of the individual-level studies evaluated differences between urban and rural areas.

Added value of this study

This study relied on a large, general population and is, to our knowledge, the largest study to examine the associations between the fast-food environment and diabetes prevalence in the Netherlands. All data used were at an individual level. Moreover, we were able to adjust for potential confounders and risk factors, including socioeconomic and lifestyle factors and air pollution, to disentangle the actual effect of fast-food

exposures on diabetes. The fast-food exposure indicator and the buffer size are of key importance to be able to judge the evidence. Therefore, to measure the fast-food environment we used several buffer sizes and indicators because there is no standardised method to assess exposures. Fast-food exposures were objectively measured using four different sizes of street-network buffers around residential addresses and classified into urban and rural areas on the basis of the urbanisation level. We found associations between fast-food environment exposures and diabetes prevalence. The magnitude of the associations was more pronounced for the presence indicator, which it showed greater effect estimates than the other indicators.

Implications of all the available evidence

Our findings add to the evidence that the fast-food environment affects diabetes prevalence. The magnitude of the associations varied with selected buffer size and indicator. The findings should motivate further research in fast-food environment exposure assessment. Furthermore, the findings encourage local governments to consider the potential health-related adverse effects of fast-food exposures, given the increasing number of fast-food outlets, and the size of the populations exposed.

the studies are at an aggregated level, comparing area-level diabetes and area-level fast-food exposures.^{22–29} Of the four studies with analyses at the individual level (table 1),^{21,30–32} one does not represent general populations.³⁰ Furthermore, none of the individual-level studies evaluated differences between urban and rural areas, whereas studies that classified into urban and rural or metropolitan and non-metropolitan found important differences in associations between diabetes and food environment between these areas.^{33,34} There is no consensus on the buffer-size used in individual level studies. The most used buffer-size to measure the food environment was 1 km for the European studies,^{21,35} 1 mile (1.6 km) for the US studies.^{31,32} However, there is evidence that the fast-food environment within smaller buffers (400 m or 500 m) is also related to health outcomes such as cardiovascular disease, obesity,^{33,36} and diabetes.²² Finally, only one of the individual-level studies²¹ was done in Europe and at a national level, and is therefore most comparable with the current study. This European study reported small positive associations between fast-food outlet density and diabetes prevalence.²¹ For example, participants exposed to the highest density fast-food restaurant category (>10·70 units/km²) reported significantly higher odds of type 2 diabetes (odds ratio [OR] 1·112 [95% CI 1·02–1·21]) compared with participants with no exposure within a 1000 m buffer.²¹

Despite the increasing need to identify the relationship between the fast-food environment and diabetes, the scientific evidence is ambiguous as there is no standard

way for quantifying the fast-food environment. To address this challenge, we aimed to investigate the associations between fast-food environment exposures and diabetes prevalence by using various exposure indicators and buffer sizes, for rural and urban subpopulations separately.

We hypothesise that greater fast-food exposure will result in elevated diabetes prevalence. It is also hypothesised that for smaller buffers, the associations with diabetes will be stronger in urban areas than in rural areas. Finally, we expect that diabetes prevalence will vary among the fast-food exposure indicators used.

Methods

Study design and population

This is a cross-sectional study among a nationwide sample of adults in the Netherlands and aimed to examine the associations between exposures to the fast-food outlet environment and diabetes. To characterise exposure to the fast-food outlet environment we applied multiple buffer sizes and indicators. Furthermore, the analysis was stratified into urban and rural areas. The study population was derived from the Public Health Monitor (Gezondheidsmonitor) 2012, a national health survey for which the data were collected by Statistics Netherlands (Central Bureau Statistics of the Netherlands [CBS]), 28 Public Health Services, and the National Institute for Public Health and the Environment in the Netherlands (RIVM). The monitored population was uniformly distributed over major cities, towns, and rural

	Gebreab et al (2017) ³⁰	Christine et al (2015) ³¹	Auchincloss et al (2009) ³²	Sarkar et al (2018) ²¹
Country	USA	USA	USA	UK
City	Jackson, MS	Baltimore city and Baltimore County, MD; Forsyth County, NC; and New York City and Bronx, NY	Baltimore city and Baltimore County, MD; Forsyth County, NC; and New York City and Bronx, NY	National
Population	3670	5124	2285	347 551
Study design	Longitudinal and cross-sectional	Longitudinal	Longitudinal	Cross-sectional
Indicator	(1) density of favourable food store density; (2) density of unfavourable food store density	(1) GIS-based access to healthy food; (2) survey-based access to healthy food	Survey-based food environment	(1) Fast-food outlet density; (2) street distance
Buffer size	1 mile (1.6 km)	1 mile (1.6 km)	1.6 miles (2.5 km)	1 km
Urban vs rural	No	No	No	No
Confounder adjustment	Age, sex, socioeconomic status, family history of diabetes, smoking status, and alcohol consumption	Age, sex, race or ethnicity, educational level, family history of type 2 diabetes, and the presence of chronic stress, household income, alcohol consumption, smoking status, and neighborhood socioeconomic status	Age, sex, race or ethnicity, household income, household assets, educational level, cigarette smoking status, alcohol consumption, and family history of diabetes, physical activity, diet index, and body-mass index	Age, ethnicity, educational level, household income, employment status, smoking status, alcohol intake, body-mass index, vascular disease, dietary variables, activity-related variables
Result	Associations between food store density and diabetes incidence (HR 1.34 [95% CI 1.12–1.60]); no significant associations with diabetes prevalence	No association for the GIS-based measure; associations between the survey-based measure and diabetes (HR 0.88 [95% CI 0.79–0.98])	(HR 0.63 [95% CI 0.42–0.93])	(OR 1.045 [0.97–1.13])

GIS=geographical information system. HR=hazard ratio. OR=odds ratio.

Table 1: Summary of individual-level studies examining the associations between fast-food outlet exposures and diabetes

areas. Adults older than 19 years were surveyed³⁷ on topics related to health and lifestyle behaviour.

Differences between the included participants and the general Dutch population has previously been examined (for the same dataset).³⁸ The comparison showed that the data are skewed towards the older population by design, with nearly 38% being aged 65 years or older; whereas in the general Dutch population only 16% are aged 65 years or older. Furthermore, people of Dutch origin are over-represented in the Public Health Monitor (87% compared with 79% in the general Dutch population), whereas people in the lowest household income quintile are underrepresented (9% compared with 20% in the general Dutch population), probably due to differential response rates.³⁸ There is no ethics statement for this national study.

Outcome definition and potential confounders

The outcome for our analysis is diabetes prevalence, the measure of which we defined by combining the answers for the self-reported doctor-diagnosed diabetes question from the Public Health Monitor with the information on diabetes medication prescriptions. If any of the two were positive, then the combined measure was assigned yes; if both were negative, then the combined measure was assigned no. Using the combined measure increases the sensitivity of the outcome definition and limits the risk

of false negatives. Information about the type of diabetes (type 1 or type 2) was not available.³⁸

The confounders we used in our models were based on literature^{21,38,39} and included individual characteristics (age, sex, marital status, and country of origin [ie, where the participant or at least one of their parents was born if outside of the Netherlands; we classified Dutch origin as participants with both parents born in the Netherlands]), socioeconomic factors (highest achieved education level, household income, and neighbourhood socioeconomic status), individual lifestyle risk factors (smoking status and smoking intensity, alcohol consumption, and physical activity), and environmental exposures (air pollution).

Information for most confounders (education, paid occupation, marital status, smoking, alcohol consumption, and physical activity) was included in the Public Health Monitor. To derive data for additional potential confounders, the Public Health Monitor was enriched by CBS with information on country of origin and standardised household income at an individual level. Additionally, individual data on medication prescription for the same year was linked, using a database maintained by Health Care Netherlands (Zorginstituut Nederland, 2012). The database contains all medication that is paid by all insurance companies in the framework of the national obligatory basic health insurance for all

For more on **Netherlands population data** see <http://statline.cbs.nl>

For more on the **Zorginstituut Nederland database** see <https://www.zorginstituutnederland.nl/>

residents of the Netherlands. Furthermore, with data from the Dutch Institute for Social Research,⁴⁰ CBS and RIVM added the mean neighbourhood socioeconomic status of the four-digit postal code area a person lives in, representing educational, occupational, and economical status of a neighbourhood.⁴⁰ We categorised neighbourhood socioeconomic status into quintiles, where the first quintile represents the highest socioeconomic status. For physical activity, we included activities with moderate-intensity metabolic equivalent and higher (score >3). To assess long-term air pollution (NO₂) at the home addresses, we used European Study of Cohorts for Air Pollution Effects (ESCAPE maps, described elsewhere^{41,42}), which are land-use regression models. Home address concentrations of NO₂ were calculated by applying the land-use regression in PCRaster software using 5×5 m grids.⁴³ The association between air pollution and diabetes is probably due to systematic inflammation or oxidative stress induced by NO₂ or particulate matters, with following impact on metabolic pathways.³⁸ Health outcomes and individual data were obtained for 2012. The air pollution models were created in 2009.

Fast-food exposure indicators

To identify fast-food restaurants, we used a commercial database (Locatus, 2014), which maintains independently sourced retail information collected annually by on-site surveys. In this database, all food outlets are objectively registered under 32 food categories. As fast-food outlets, we included three food categories: fast-food outlets (Locatus code #59.210.171), delivery or take-away outlets (#59.210.180), and grillroom or kebab-outlets (#59.210.215).

In contrast to most previous studies which usually use 1 km buffers or larger, we included relatively small buffer sizes considering the small scale of Dutch cities and the mixed land use pattern that Dutch cities usually follow. The Dutch urban structure makes most services easily reachable on foot or by bike. As such, the 100 m buffer captures the immediate exposure, representing food outlets a person gets exposed to every time they leave or reach home. The 400 m buffer represents the functional neighbourhood that corresponds to 5-min walking or 2-min cycling at a moderate pace.⁴⁴ The 1000 m (10 min walking or 4 min cycling) and 1500 m (15 min walking or 5 min cycling) buffers are the most commonly used buffers in previous research.²¹ We geocoded all Dutch addresses and we applied street network buffers around them. To calculate the buffers, we used PCRaster Python⁴³ and Numpy.⁴⁵ Street network buffers represent realistic exposures, which were calculated as the walking distance along the road network with highways removed.

We used various indicators to represent fast-food exposure. The first indicator was the presence (yes or no) of fast-food outlets within certain street network buffer sizes (100 m, 400 m, 1000 m, and 1500 m). The second indicator was the fast-food outlet density indicator within

a 400 m, 1000 m, and 1500 m buffer. The density indicator was expressed as the total number of fast-food outlets within certain street-network buffers and was divided into quartiles. Finally, the third indicator was the fast-food outlet ratio, calculated by dividing the number of fast-food outlets by the total number of food outlets within 400 m, 1000 m, and 1500 m buffers, and was also divided into quartiles. We used ratio to represent a net-negative food environment. For example, if only fast-food outlets are present (eg, two) the ratio measure would be high (2/2=1) and therefore indicate an unhealthier environment compared with a case where different outlets were also available (eg, in addition to the two fast food outlets, one grocery store and one supermarket were available, resulting in a ratio of 2/4=0.5). To calculate the ratio, we excluded all participants living in buffers without any food retailers because it would not be possible to calculate those indicators of exposure. The 100 m buffer was not applied for the density and ratio indicators because it was impossible to compute quartiles for those indicators for the smallest buffer due to the large number of buffers containing no food outlets. By using three different indicators we aimed to identify whether the presence of fast-food outlets has a greater effect on diabetes prevalence than the net-negative (ratio) food environment. Furthermore, the presence of fast-food outlets and fast-food outlet density indicators are absolute indicators, whereas fast-food outlet ratio is a relative indicator.

The linkage between the fast-food dataset and the Public Health Monitor data was based on the participants' addresses. The linkage was done in a secured environment and after the linkage the addresses were removed and were substituted by codes to respect data privacy.

Statistical analysis

We built a priori six logistic regression models to obtain the OR and 95% CI of the associations between fast-food outlet exposure and presence of diabetes (yes or no). We adjusted for possible confounders incrementally starting from the completely unadjusted (crude) model (model 0). Model 1 was adjusted for sex and age. Model 2a added individual socioeconomic characteristics (highest achieved education level, household income, marital status, and country of origin) to model 1. Model 2b added lifestyle risk factors (smoking habits, alcohol consumption, and physical activity) to model 2a. Model 3a added neighbourhood socioeconomic status score to model 2b. Model 3b added air pollution to model 3a. We further checked the variance of inflation for the variables included in our models and verified that there was no issue of multicollinearity (variance of inflation <3). Additionally, we did a sensitivity analysis by adjusting for supermarkets and grocery stores, which can be considered to contribute to a beneficial food environment. We also tested for interactions between fast-food outlet density and individual income and education.

For more on the Locatus database see <https://locatus.com/>

We ran the models for all the indicators for both urban and rural areas. The distinction between urban and rural was based on the CBS categorisation.⁴⁶ CBS includes five categories to define rural areas (<1000 addresses within 1 km²) and the remaining three categories to define urban areas (1000–2500 addresses within 1 km²).

We entered all indicators of food exposures as categorical variables by defining their categories either

based on quartiles or by entering 1 and 0 for presence and absence of fast-food outlets. We used as base category the category with the lowest number for all buffers (100 m, 400 m, 1000 m, and 1500 m). All confounders were specified as categorical variables except the number of cigarettes smoked and alcohol consumption, which were entered as continuous variables. The statistical analyses were done in R version 3.2.2.

	Urban (n=159 315)		Rural (n=125 478)		p value* urban versus rural
	No diabetes	Diabetes	No diabetes	Diabetes	
Diabetes	145 429 (91.3%)	13 886 (8.7%)	116 413 (92.8%)	9 065 (7.2%)	<0.0001
Sex					
Female	78 137 (53.7%)	6 315 (45.5%)	61 118 (52.5%)	3 987 (44.0%)	<0.0001
Male	67 292 (56.3%)	7 571 (55.5%)	55 295 (57.5%)	5 078 (66.0%)	..
Age, years	<0.0001
19–40	35 747 (24.6%)	3 20 (2.3%)	23 140 (19.9%)	1 86 (2.1%)	..
41–64	58 574 (40.3%)	3 776 (27.2%)	53 586 (46.0%)	2 466 (27.2%)	..
65–74	33 210 (22.8%)	5 820 (41.9%)	27 162 (23.3%)	3 809 (42.0%)	..
≥75	17 898 (12.3%)	3 970 (28.6%)	12 525 (10.8%)	2 604 (28.7%)	..
Education level	0.53
Primary or less	10 773 (7.4%)	1 025 (7.4%)	8 570 (7.4%)	654 (7.2%)	..
Lower-secondary	48 021 (33.0%)	4 599 (33.1%)	38 225 (32.8%)	3 061 (33.8%)	..
Higher-secondary	43 053 (29.6%)	4 077 (29.4%)	34 776 (29.9%)	2 656 (29.3%)	..
University	43 582 (30.0%)	4 185 (30.1%)	34 842 (29.9%)	2 694 (29.7%)	..
Paid occupation	75 965 (52.2%)	2 658 (19.1%)	63 679 (54.7%)	1 896 (20.9%)	<0.0001
Household income, €	<0.0001
<15 200	14 779 (10.2%)	1 659 (11.9%)	8 386 (7.2%)	853 (9.4%)	..
15 200–19 400	23 080 (15.9%)	3 675 (26.5%)	17 645 (15.2%)	2 317 (25.6%)	..
19 401–24 200	30 112 (20.7%)	3 297 (23.7%)	24 596 (21.1%)	2 072 (22.9%)	..
24 201–31 000	36 412 (25.0%)	2 873 (20.7%)	30 464 (26.2%)	1 930 (21.3%)	..
>31 000	41 046 (28.2%)	2 382 (17.2%)	35 322 (30.3%)	1 893 (20.9%)	..
Marital status	<0.0001
Married or living together	101 504 (69.8%)	9 287 (66.9%)	91 462 (78.6%)	6 671 (73.6%)	..
Unmarried or never married	21 919 (15.1%)	857 (6.2%)	11 553 (9.9%)	410 (4.5%)	..
Divorced	10 691 (7.4%)	1 371 (9.9%)	5 279 (4.5%)	458 (5.1%)	..
Widowed	11 315 (7.8%)	2 371 (17.1%)	8 119 (7.0%)	1 526 (16.8%)	..
Country of origin	<0.0001
Morocco	1 226 (0.8%)	251 (1.8%)	95 (0.1%)	23 (0.3%)	..
Turkey	1 907 (1.3%)	240 (1.7%)	115 (0.1%)	10 (0.1%)	..
Surinam	1 962 (1.3%)	436 (3.1%)	178 (0.2%)	28 (0.3%)	..
Bonaire, Sint Eustatius, Saba, Curaçao, Aruba, Sint Maarten	837 (0.6%)	79 (0.6%)	127 (0.1%)	10 (0.1%)	..
Other non-high income	3 355 (2.3%)	303 (2.2%)	695 (0.6%)	41 (0.5%)	..
Other high income	13 878 (9.5%)	1 515 (10.9%)	7 751 (6.7%)	786 (8.7%)	..
Netherlands†	122 264 (84.1%)	11 062 (79.7%)	107 452 (92.3%)	8 167 (90.1%)	..
Neighbourhood socioeconomic status score	<0.0001
<30	35 292 (24.3%)	2 594 (18.7%)	22 303 (19.2%)	1 552 (17.1%)	..
30–34	23 655 (16.3%)	2 106 (15.2%)	34 017 (29.2%)	2 565 (28.3%)	..
34–38	19 876 (13.7%)	1 986 (14.3%)	34 185 (29.4%)	2 747 (30.3%)	..
38–43	26 165 (18.0%)	2 417 (17.4%)	19 670 (16.9%)	1 683 (18.6%)	..
>43	40 441 (27.8%)	4 783 (34.4%)	6 238 (5.4%)	518 (5.7%)	..

(Table 2 continues on next page)

	Urban (n=159 315)		Rural (n=125 478)		p value* urban versus rural
	No diabetes	Diabetes	No diabetes	Diabetes	
(Continued from previous page)					
Smoking habit	<0.0001
Current	29 850 (20.5%)	2360 (17.0%)	20 443 (17.6%)	1251 (13.8%)	..
Former	56 016 (38.5%)	7200 (51.9%)	47 235 (40.6%)	4945 (54.6%)	..
Never	59 563 (41.0%)	4326 (31.2%)	48 735 (41.9%)	2869 (31.6%)	..
Alcohol consumption	<0.0001
Current	121 588 (83.6%)	9244 (66.6%)	100 345 (86.2%)	6471 (71.4%)	..
Former	8142 (5.6%)	1818 (13.1%)	5839 (5.0%)	1108 (12.2%)	..
Never	15 699 (10.8%)	2824 (20.3%)	10 229 (8.8%)	1486 (16.4%)	..
Physical activity, >3 metabolic equivalent	<0.0001
<375 min/week	36 999 (25.4%)	5712 (41.1%)	24 880 (21.4%)	3310 (36.5%)	..
375–750 min/week	38 050 (26.2%)	3063 (22.1%)	28 446 (24.4%)	1949 (21.5%)	..
751–1440 min/week	36 547 (25.1%)	2888 (20.8%)	31 013 (26.6%)	2064 (22.8%)	..
>1440 min/week	33 833 (23.3%)	2223 (16.0%)	32 074 (27.6%)	1742 (19.2%)	..
Body-mass index	<0.0001
Underweight	2269 (1.6%)	64 (0.5%)	1300 (1.1%)	37 (0.4%)	..
Healthy range	72 498 (49.9%)	3239 (23.3%)	56 847 (48.8%)	2161 (23.8%)	..
Overweight	53 724 (36.9%)	5966 (43.0%)	45 200 (38.8%)	4040 (44.6%)	..
Obese	16 938 (11.6%)	4617 (33.2%)	13 066 (11.2%)	2827 (31.2%)	..
Glasses of alcohol per week	2.11 (5.63)	2.10 (6.13)	1.73 (5.02)	1.56 (5.19)	<0.0001
Cigarettes per week	7.17 (9.34)	5.56 (9.16)	7.32 (9.13)	5.86 (9.07)	<0.0001
NO ₂ , µg/m ³	26.98 (5.69)	27.29 (5.70)	19.87 (3.69)	20.13 (3.60)	<0.0001
Presence of fast-food outlets					
100 m	10 311 (7.1%)	1115 (8.0%)	3315 (2.8%)	342 (3.8%)	<0.0001
400 m	70 566 (48.5%)	7490 (53.9%)	31 104 (26.7%)	2915 (32.2%)	<0.0001
1000 m	134 471 (92.5%)	13 131 (94.6%)	79 095 (67.9%)	6646 (73.3%)	<0.0001
1500 m	143 302 (98.5%)	13 772 (99.2%)	90 319 (77.6%)	7313 (80.7%)	<0.0001
Fast-food outlet density					
400 m	1.42 (2.55)	1.54 (2.53)	0.42 (0.85)	0.52 (0.93)	<0.0001
1000 m	7.64 (10.33)	7.93 (10.08)	1.65 (1.80)	1.88 (1.87)	<0.0001
1500 m	15.15 (19.50)	15.60 (19.18)	2.46 (2.48)	2.67 (2.46)	<0.0001
Fast-food outlet ratio					
400 m	0.24 (0.25)	0.25 (0.25)	0.17 (0.25)	0.18 (0.24)	<0.0001
1000 m	0.21 (0.13)	0.21 (0.12)	0.15 (0.25)	0.16 (0.14)	<0.0001
1500 m	0.20 (0.08)	0.20 (0.08)	0.14 (0.11)	0.15 (0.11)	<0.0001

Data are n (%) or mean (SD). *p value derived from t test (for continuous variables) and χ^2 test (for categorical variables) to test if the urban and rural samples follow similar distributions †Both parents born in the Netherlands.

Table 2: Public Health Monitor participants' characteristics and fast-food exposures stratified by diabetes prevalence for participants in urban and rural areas

Role of the funding source

The funder of the study had no role in study design, data collection, data analysis, data interpretation, or the writing of the report.

Results

387 195 adults were surveyed. Due to missing values on potential confounders, 284 793 individuals were included in the study, of whom 22 951 (8%) reported having diabetes (table 2). Most participants lived in urban areas (159 315 [55.9%]) and were of Dutch origin

(248 945 [87.3%]). Fast-food outlets were more likely to be in urban areas than in rural areas (table 2). For all fast-food outlet indicators, people with diabetes had greater fast-food outlet exposures than people without diabetes.

For the urban areas, the presence and mean density of fast-food outlets were greater for the larger buffers (tables 3, 4). Notably, for the 1500 m buffer, the fast-food outlet presence was high for all participants, making it difficult to evaluate associations with diabetes for this buffer using the presence indicator. Although presence and density were greater for the larger buffers, the mean

ratio was smaller for the 1500 m buffer than the 1000 m buffer.

The results of the fully adjusted logistic regression models used to examine the association between the fast-food outlet environment and diabetes prevalence in urban areas are shown in tables 3 and 4. The effect of adjustment for covariates is shown in the appendix (pp 2–3, 5). Overall, for all the fast-food environment indicators and the buffer sizes used in the analyses, the associations were positive with small effect estimates.

The participants who were exposed to fast-food outlets (≥ 1 outlet within the buffer) had significantly greater odds of having diabetes for all buffers in the fully adjusted models (table 3). The smaller the buffer-size applied, the greater the resulting effect estimate; however, the effect estimates were small. The greater effect estimates for the 1500 m buffer (compared with the smaller buffer) did not follow this trend, but care should be taken with interpreting these results because of the low proportion of participants with no exposure.

In urban areas, fast-food outlet density within 400 m was significantly associated with diabetes prevalence (table 4). ORs were small, with no increasing trend from first to third quartiles. For the models adjusted for supermarkets and grocery stores, the effect estimates were smaller than for the unadjusted model, but they remained significant (appendix p 8). Effect estimates were inconsistent and non-significant for the 1000 m and 1500 m buffer (table 4). We further found no evidence of systematic differences in associations of fast-food outlet density and diabetes prevalence by individual income or education (all p values for interactions >0.05 ; appendix pp 9–10). The effect estimates for the confounders included in the full model are shown in the appendix (p 7).

Fast-food outlet ratio was positively associated with diabetes prevalence for all buffers in urban areas (table 4). The associations were significant for some of the quartile categories for the 1000 m and 1500 m buffer (table 4). Specifically, the association between fast-food outlet ratio and diabetes prevalence was only significant for the second highest quartile for the 1000 m buffer. For the 1500 m buffer, the fast-food outlet ratio was significantly associated with diabetes prevalence for the two highest quartiles. For the 1000 m and 1500 m buffers, the ORs increased from the first to the third quartiles. Similar to the other two indicators, the effect estimates were greater in models with less adjustment for possible confounders. In the first models, the effect estimates were greater and significant for all the quartile categories up to the model adjusted for neighbourhood socioeconomic status (appendix p 5).

Similar to the urban areas, for all fast-food outlet indicators in the rural areas people with greater exposures are more likely to have diabetes (table 2). Within larger buffers, the proportion of participants with a fast-food outlet present and the mean density indicators had higher values. However, for the ratio indicator, the mean

	Participants	OR (95% CI)
100 m buffer		
No fast-food outlets	148 163 (93%)	1 (ref)
Fast-food outlets present	11 152 (7%)	1.008 (1.002–1.013)
400 m buffer		
No fast-food outlets	81 251 (51%)	1 (ref)
Fast-food outlets present	78 064 (49%)	1.006 (1.003–1.009)
1000 m buffer		
No fast-food outlets	11 152 (7%)	1 (ref)
Fast-food outlets present	148 163 (93%)	1.005 (1.000–1.010)
1500 m buffer		
No fast-food outlets	1593 (1%)	1 (ref)
Fast-food outlets present	157 722 (99%)	1.016 (1.005–1.028)
The complete model is adjusted for age, sex, marital status, origin, highest achieved education level, household income, neighbourhood socioeconomic status, smoking habits, alcohol consumption, physical activity, and air pollution. The participants column shows the number and proportion of participants in each category. OR=odds ratio.		
Table 3: Associations of fast-food outlet presence with diabetes prevalence in the fully adjusted model in urban areas		

See Online for appendix

fast-food outlet ratio was not greater in the 1500 m buffer than the 1000 m buffer.

The results of the fully adjusted logistic regression models used to examine the associations between fast-food outlet indicators and diabetes prevalence in the rural areas are shown in tables 5 and 6. The effect of adjustment for covariates is shown in the appendix (pp 2, 4, 6). As in urban areas, the associations were positive, with small effect estimates for most of the models.

The participants who were exposed to fast-food outlets (≥ 1 outlets within the buffer) had significantly greater odds of diabetes for the 100 m, 400 m, and 1000 m buffers compared with those who were not exposed to fast-food outlets (table 5). For the largest buffer (1500 m), we did not observe significantly greater odds of having diabetes among those exposed to fast-food outlets compared with those not exposed (table 5).

For the fast-food density indicator, we observed positive associations between fast-food outlet density and diabetes prevalence in rural areas (table 6). The associations were significant for some of the quartile categories of all the buffers. Specifically, within a 400 m buffer, participants with two fast-food outlets had significantly greater odds of having diabetes than those with no fast-food outlets. For the 1000 m buffer, participants exposed to two or more than three fast-food outlets showed significantly greater odds of having diabetes than those exposed to no or just one fast-food outlet. Finally, for the largest buffer (1500 m) the association was significant only for those with 3–4 units per buffer for the fully adjusted model. The effect sizes were attenuated by adjusting for potential confounders (appendix p 4). Furthermore, we found no evidence of systematic differences in associations between fast-food outlet density and diabetes by individual

	Fast-food outlet density			Fast-food outlet ratio		
	Density range, number of fast-food outlets per buffer	Participants	OR (95% CI)	Ratio range, ratio of number of fast-food outlets to all available food outlets	Participants	OR (95% CI)
400 m buffer						
Quartile 0	0-0	81 251 (51%)	1 (ref)	0-00-0-00	39 829 (25%)	1 (ref)
Quartile 1	1-1	31 863 (20%)	1-007 (1-003-1-010)	0-01-0-20	47 795 (30%)	1-003 (0-998-1-007)
Quartile 2	2-3	27 084 (17%)	1-006 (1-002-1-010)	0-21-0-40	43 015 (27%)	1-003 (0-998-1-008)
Quartile 3	4-60	19 118 (12%)	1-006 (1-001-1-011)	0-41-1-00	28 677 (18%)	1-003 (0-998-1-008)
1000 m buffer						
Quartile 0	0-0	49 388 (31%)	1 (ref)	0-00-0-14	39 829 (25%)	1 (ref)
Quartile 1	1-3	32 236 (20%)	1-001 (0-997-1-005)	0-15-0-19	39 829 (25%)	1-000 (0-996-1-005)
Quartile 2	4-8	41 422 (26%)	1-002 (0-998-1-006)	0-20-0-26	41 422 (26%)	1-005 (1-001-1-010)
Quartile 3	9-153	36 642 (23%)	1-000 (0-996-1-004)	0-27-1-00	38 236 (24%)	1-004 (0-999-1-008)
1500 m buffer						
Quartile 0	0-5	47 795 (30%)	1 (ref)	0-00-0-15	39 829 (25%)	1 (ref)
Quartile 1	6-9	38 236 (24%)	0-997 (0-993-1-000)	0-16-0-19	39 829 (25%)	1-003 (0-999-1-007)
Quartile 2	10-17	35 049 (22%)	1-001 (0-998-1-005)	0-20-0-25	39 829 (25%)	1-005 (1-001-1-009)
Quartile 3	18-245	38 236 (24%)	0-998 (0-994-1-002)	0-26-1-00	39 829 (25%)	1-006 (1-002-1-010)

The complete model is adjusted for age, sex, marital status, origin, highest achieved education level, household income, neighbourhood socioeconomic status, smoking habits, alcohol consumption, physical activity, and air pollution. The participants column shows the number and proportion of participants in each category. OR=odds ratio.

Table 4: Associations of fast-food outlet density and ratio with diabetes prevalence in the fully adjusted model in urban areas

	Participants	OR (95% CI)
100 m buffer		
No fast-food outlets	121 714 (97%)	1 (ref)
Fast-food outlets present	3764 (3%)	1-009 (1-006-1-018)*
400 m buffer		
No fast-food outlets	91 599 (73%)	1 (ref)
Fast-food outlets present	33 879 (27%)	1-003 (1-000-1-006)*
1000 m buffer		
No fast-food outlets	40 153 (32%)	1 (ref)
Fast-food outlets present	85 325 (68%)	1-004 (1-001-1-007)
1500 m buffer		
No fast-food outlets	27 605 (22%)	1 (ref)
Fast-food outlets present	97 873 (78%)	1-002 (0-998-1-005)

The complete model is adjusted for age, sex, marital status, origin, highest achieved education level, household income, neighbourhood socioeconomic status, smoking habits, alcohol consumption, physical activity, and air pollution. The participants column shows the number and proportion of participants in each category. OR=odds ratio.

Table 5: Associations of fast-food outlet presence with diabetes prevalence in the fully adjusted model in rural areas

middle quartiles (quartile 1 and quartile 2) of fast-food outlets within a 1000 m buffer, reported significantly greater odds of having diabetes. For the 400 m and 1500 m buffers, the associations were not significant in the fully adjusted model.

Discussion

The results of this study showed that in a large, adult population living in the Netherlands, fast-food outlet exposure was associated with greater odds of having diabetes in both urban and rural areas, compared with no fast-food outlet exposure. For all tested indicators and buffer sizes, we observed small effect estimates. The magnitude of the ORs varied with selected buffer size and indicator. We observed the strongest association between diabetes prevalence and the presence indicator. The effect of buffer size on the ORs differed with the indicator. Overall, the positive effect estimates were small, as in previous studies.^{21,30,32,47}

For the fast-food outlet presence and density indicators, we showed larger effect estimates for the smaller buffers than the larger buffers. This finding is in agreement with a previous study²¹ that showed a protective effect with increased street distance to the nearest fast-food outlet. However, it should be noted that compared with the other estimates, we showed a very large effect estimate for the 1500 m buffer for the fast-food outlet presence indicator in urban areas, which is hard to interpret due to the small number of participants with no exposure (2127 [1.5%] of the population without diabetes and

income or education (all p values for interactions >0.05; appendix pp 9–10).

Similar to the density, the fast-food ratio indicator showed significant associations for some of the exposure categories in rural areas (table 6). Participants in the

	Fast-food outlet density			Fast-food outlet ratio		
	Density range, number of fast-food outlets per buffer	Participants	OR (95% CI)	Ratio range, ratio of number of fast-food outlets to all available food outlets	Participants	OR (95% CI)
400 m buffer						
Quartile 0	0-0	91 599 (73%)	1 (ref)	0.00-0.00	60 229 (48%)	1 (ref)
Quartile 1	1-1	22 586 (18%)	1.002 (0.999-1.006)	0.01-0.19	22 586 (18%)	1.001 (0.995-1.007)
Quartile 2	2-2	7 529 (6%)	1.007 (1.001-1.013)	0.20-0.40	26 350 (21%)	1.001 (0.996-1.006)
Quartile 3	3-16	5 019 (4%)	1.002 (0.994-1.009)	0.41-1.00	16 312 (13%)	1.002 (0.996-1.009)
1000 m buffer						
Quartile 0	0-0	40 153 (32%)	1 (ref)	0.00-0.00	22 586 (18%)	1 (ref)
Quartile 1	1-1	32 624 (26%)	1.001 (0.998-1.005)	0.01-0.13	36 389 (29%)	1.005 (1.000-1.009)
Quartile 2	2-2	21 331 (17%)	1.004 (1.000-1.009)	0.14-0.20	40 153 (32%)	1.004 (1.000-1.009)
Quartile 3	3-44	31 370 (25%)	1.006 (1.003-1.010)	0.21-1.00	26 350 (21%)	1.003 (0.998-1.007)
1500 m buffer						
Quartile 0	0-1	53 956 (43%)	1 (ref)	0.00-0.00	22 586 (18%)	1 (ref)
Quartile 1	2-2	21 331 (17%)	0.999 (0.995-1.003)	(0.01-0.13)	36 389 (29%)	1.002 (0.998-1.007)
Quartile 2	3-4	26 350 (21%)	1.004 (1.000-1.008)	(0.14-0.20)	40 153 (32%)	1.003 (0.998-1.007)
Quartile 3	5-69	22 586 (18%)	1.003 (0.999-1.007)	(0.21-1.00)	26 350 (21%)	1.003 (0.998-1.008)

The complete model is adjusted for age, sex, marital status, origin, highest achieved education level, household income, neighbourhood socioeconomic status, smoking habits, alcohol consumption, physical activity, and air pollution. The participants column shows the number and proportion of participants in each category. OR=odds ratio.

Table 6: Associations of fast-food outlet density and ratio with diabetes prevalence in the fully adjusted model in rural areas

114 [0.8%] of the population with diabetes). In contrast with the presence and density indicators, we found greater effect estimates for the larger buffer sizes (1000 m and 1500 m) for the fast-food outlet ratio.

Explaining the different effects of buffer sizes on the indicators, it can be conceived that fast-food outlets in the immediate environment can trigger an unhealthy eating behaviour because they will attract the attention of residents by visual exposure,⁴⁸ regardless of whether healthier options are available. We further hypothesise that fast-food outlets that require travelling (10–15 min on foot or 4–5 min by bike) do not trigger impulsive eating as much as those that do not require travelling, which might explain the weaker associations found for the larger buffers. However, when there are no alternative food options within the broader environment, the fast-food exposure in the larger buffers seems to be more important than within the smaller buffers. Therefore, the gravity model (the closer the outlet is, the more appealing it gets⁴⁹) might be more relevant when applying absolute indicators such as fast-food presence and density, and not when applying relative indicators (eg, ratio).⁵⁰

Regarding the urban–rural distinction, we did not find large differences in effects. However, for the density and ratio indicators, we found slightly smaller effect estimates in rural areas than in urban areas, especially for the 400 m and 1000 m buffers. The smaller effects in rural compared with urban areas can be explained by the different structure of the rural areas: rural areas are sparsely populated and the distances to fast-food outlets are greater.

Although the overall findings suggest a possible link between fast-food outlet exposures and diabetes prevalence, the clinical relevance is questionable due to the small effect estimates.

One of the strengths of this study was that it relied on a large, general population for which fast-food exposures were objectively measured. All data were at an individual level, while the variability is ensured by the spatial distribution and the number of the participants. Moreover, we adjusted for potential confounders, including socioeconomic and lifestyle factors and air pollution, to disentangle the actual effect of fast-food exposures on diabetes prevalence. Furthermore, we used four different sizes of street-network buffers around residential addresses. We were also able to classify urban and rural areas based on the urbanisation level. Finally, we used several food exposure indicators because there is no standardised methodology for food exposure indicators.

Some limitations should also be addressed. First, there is a 2-year temporal mismatch between the datasets, with the exposure dataset being the most recent (2014). Second, we have not accounted for neighbourhood self-selection. Another limitation is that we accounted for only residential exposure because we were unable to account for exposure outside the residential environment (eg, the work environment, during commuting, and availability via fast-food delivery services). This limitation will lead to underestimation of the exposures and might explain the small effects found in this study. Another limitation is that for a chronic condition, such as diabetes, it would be informative to have the fast-food environment exposures

for previous addresses for the participants who have relocated. We additionally did not have information about parental diabetes. Furthermore, little is known about the relationship between presence of fast-food outlets and actual food consumption, but the relationship is likely to be weak. Clearly, food consumption is the relevant risk factor for disease. We argue that even in the absence of data on the relationship between environmental fast-food presence and individual consumption, it is of interest for public policies to understand possible links between the food environment and health. Furthermore, we were unable to distinguish between type 1 and type 2 diabetes. However, it is more likely we have included more people with type 2 diabetes because this type is notably more prevalent.⁷ The small proportion of people younger than 40 years with diabetes within our population is an indication that most of the cases in our cohort are of type 2 diabetes. Finally, comparing the results of the current study with others is difficult because studies of this kind either follow a different design or are carried out in the USA, which has a different urban morphology to the Netherlands. The difficulty in comparing the findings between studies is also due to the use of different indicators and buffer sizes.

Therefore, future studies should explore the relation between fast-food exposure and diabetes by additionally accounting for fast-food exposures in the working environment and during commuting to get the complete individual exposure. Furthermore, longitudinal data would help to investigate diabetes incidence. Finally, based on our findings, buffers smaller than 1 km are also meaningful for studies of this kind and should be used in future research.

Our findings add to the evidence that the fast-food environment is associated with diabetes. The magnitude of the associations varied with selected buffer size and indicator. We observed the strongest association for the fast-food presence indicator. We did not observe clear differences in effect estimates between urban and rural areas. The findings encourage local governments to consider the potential health-related adverse effects of fast-food exposures, given the increasing number of fast-food outlets, and the size of the population exposed.

Contributors

A-MN conceived the manuscript. A-MN, OS, ML prepared, accessed, and verified the environmental data. A-MN and MS prepared, accessed, and verified the health data. A-MN, MS, OS, and ML had full access to the initial datasets. The dataset linkage was done in a Central Bureau Statistics of the Netherlands secured environment with access granted to a limited number of people due to the inclusion of sensitive personal data: A-MN and IV had full access to the final dataset and DK could observe the data without entering the secured environment himself. A-MN wrote the initial draft. MP, DK, IV, GH, NJ, and DEG did a critical revision of the manuscript. A-MN did the initial analyses. MP, DK, IV, and GH provided important feedback on how the study can be improved. All authors read and approved the final manuscript and had final responsibility for the decision to submit for publication.

Declaration of interests

We declare no competing interests.

Data sharing

The datasets generated or analysed during the current study are not publicly available due to the sensitive nature of the raw data, but the calculated exposures are available from the corresponding author on reasonable request.

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