EPIDEMIOLOGY

Higher depression risks in medium- than in high-density urban form across Denmark

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Urban areas are associated with higher depression risks than rural areas. However, less is known about how different types of urban environments relate to depression risk. Here, we use satellite imagery and machine learning to quantify three-dimensional (3D) urban form (i.e., building density and height) over time. Combining satellite-derived urban form data and individual-level residential addresses, health, and socioeconomic registers, we conduct a case-control study (n = 75,650 cases and 756,500 controls) to examine the association between 3D urban form and depression in the Danish population. We find that living in dense inner-city areas did not carry the highest depression risks. Rather, after adjusting for socioeconomic factors, the highest risk was among sprawling suburbs, and the lowest was among multistory buildings with open space in the vicinity. The finding suggests that spatial land-use planning should prioritize securing access to open space in densely built areas to mitigate depression risks.

INTRODUCTION

Between 2020 and 2050, the world's urban population is estimated to grow from 56 to 68%, adding approximately 2.5 billion additional people to those living in urban areas (*1*). One of the most notable concerns of urbanization is mental health and well-being, as urban living is considered to be an environmental risk factor for declining mental health (*2*, *3*). Factors such as crowding, intense pace, and the overstimulation of urban life contribute to higher social stress sensitivity (*4*), elevated distress (*5*), and mental fatigue (*6*). In addition, statistics across nine European countries and the United States show that depressive disorders are 39% more prevalent in urban than in rural areas (*7*). Compared to people born in rural areas, those born in urban areas have a 27% higher risk of developing depressive disorders (*8*).

As urban populations are projected to grow, how can urban planners limit the risk of depression for future cities? Recent studies have focused on how the size and density of cities are associated with depression. For example, a study across the United States revealed lower rates of depression in cities with larger population sizes, explained by denser socioeconomic networks in such cities (*9*). Other studies of the populations in Nordic countries, however, uncovered higher rates of depression-related hospitalization in densely populated neighborhoods (*10*) and higher rates among people born in the capital compared to those born in sparsely populated regions (*8*). Thus far, the relationships between population density, city size, and depression risk are still under debate, indicating that population density itself is not sufficient to explain variability in depression risk.

Many important aspects of urban space can hardly be captured along a one-dimensional (1D) spectrum. 3D urban form—varying combinations of building heights and the fraction of built-up area compared to open space (hereafter referred to as building density)—exists in different arrangements that can lead to the same population density but contribute differently to mental health risks. For example, high-rise buildings in a high-density arrangement can reduce sun exposure and increase local temperature, which are environmental pathways for increased risks of depressive symptoms (*11*–*14*). Conversely, higher buildings or denser urban form may benefit mental health through an increased population and opportunities for social interaction (*9*). Social interactions create a sense of community, reciprocity, and trustworthiness (collectively known as social capital), which are factors positively related to mental well-being (*5*, *9*, *15*, *16*) and protective against depression (*17*). On the other hand, low-density areas often have more space for nature and water bodies (*18*). Exposure to these areas can mitigate depression by providing open space for social interaction (*19*–*21*), absence of air pollution and noise (*22*), and psychological restoration (*23*). This complex and, at times, conflicting evidence suggests that 3D urban form can affect depression risk above what is reflected in an urban-rural dichotomy or a population density measurement. However, with previous studies focusing mainly on an urban-rural dichotomy or population density, there remains a lack of large-scale studies of depressive disorder risks that focus on 3D urban form.

Major obstacles for large-scale observational studies are the dependence on expensive survey data and census data lacking individual-level information (*24*, *25*). Numerous challenges must be addressed in estimating the relationship between 3D urban form

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and depression, including (i) identifying a large population with presence in diverse urban form that reflects the population of interest, (ii) quantifying urban form over time to estimate exposure in a time-sensitive manner while considering changes in cities' physical structure and population residential mobility, (iii) accurately assigning cohort members' exposure to urban form at a fine spatial scale (i.e., around residential location) rather than using aggregated estimates at an administrative level, (iv) collecting detailed information on important confounding factors that may distort the observed relationship between urban form and depression, and (v) combining the information above in a case-control framework for statistical inference with observational data.

Here, we leverage freely available satellite imagery and machine learning that we previously developed (*26*) to yield high-resolution data on building height and density across Denmark from 1987 to 2018. Then, we combine the urban form information with a national population-representative cohort, including individual-level data (addresses, depression diagnosis information, and socioeconomic variables) from the Danish Civil Registration System (*27*), allowing high-resolution characterization of longitudinal urban form exposure for millions of residents at the individual scale. Using a case-control approach, we assess how individuals' accumulated urban form exposure is associated with depressive disorders. Associations for building density and height are examined separately (basic model), together (mutually adjusted model), and together while controlling for socioeconomic risk factors (fully adjusted model). Our analyses address three questions: (i) What is the association between 3D urban form exposure and depression risks? (ii) Do these associations persist after controlling for known risk factors, such as socioeconomic factors? and (iii) What are the geographical patterns of 3D urban form's contribution to depression risks?

RESULTS

Changing urban form and urban form exposure

Using Landsat time-series satellite images and convolutional neural networks, we characterized building density (low, medium, and high) and building height (dichotomous, low rise below 10 m, and high rise) at 30-m resolution (see illustration in Fig. 1). We present cities' physical appearances in terms of density and height across Denmark in 2017 in Fig. 2. Large areas of high-density high-rise neighborhoods were located in the city centers. Another common 3D urban form was medium-density low-rise, which was often single-family housing areas. In rural areas, low-density low-rise was the most common form. Yet, density and height did not always covary. For example, we found high-density low-rise areas in or close to industrial and retail parks at the city outskirts. We also found the low-density high-rise form in recently developed areas with multistory apartments along urban canals and harbors.

In terms of change of urban form over time, built-up areas in Denmark increased from 4723 to 7369 km^2 (~55%) between 1987 and 2017 (Fig. 3). The largest increases were of low-density urban form (~1850 km^2), followed by medium-density (~680 km^2). Regarding height, low-rise areas increased ~2500 km^2 more than high-rise areas (~75 km^2). However, the population increase disproportionately occurred in high-rise areas, from only 13% of the population living in these areas in 1987 to 23% in 2017 (Fig. 3). In other words, while sprawling development left a bigger imprint on the physical landscape, the urban form exposure of individuals changed toward higher-density and high-rise forms.

Associations between urban form and depression

Between 1990 and 2018, 75,650 individuals above age 25 and born in Denmark after 1955 were diagnosed with depressive disorders in psychiatric inpatient facilities, outpatient visits to psychiatric departments, or emergency care, with quality addresses in Denmark. As we matched 10 controls for each case, our analyzed sample consisted of 75,650 cases with 756,500 matched controls without a depression diagnosis before the case's diagnosis date. Full descriptive characteristics of cases and controls are shown in Table 1. Cases were more likely to have foreign parents, parental history of depressive disorders, lower education, lower income, and to be unemployed and single compared to controls ($P < 0.05$) (Table 1).

The relative risks of depressive disorder varied by building density. Among the three levels of density, the strongest correlate of depressive disorder was medium density (i.e., 15 to 30% of built-up area compared to open space), with a 27% [95% confidence interval (CI): 24 to 31%] increased relative risk compared to low-density urban form in the basic model. This association was observed for both accumulated exposure (Table 2) and one-time exposure between 0 and 5 years before the index date (table S1), with a higher risk at the index date (29%, 95% CI: 26 to 32%) compared to 5 years before (19%, 95% CI: 16 to 23%). Urban form associations may be confounded by socioeconomic factors, but we observed that medium-density urban form was robustly associated with depressive disorders in the fully adjusted model (adjusting for individual socioeconomic status), with a 24% (95% CI: 20 to 28%) higher risk than low-density urban form (Table 2). Further adjustment of neighborhood socioeconomic status did not reduce the risk of medium-density urban form (28%, 95% CI: 24 to 33%) (table S4). The risk of high-density urban form was 10% (95% CI: 0 to 21%) higher than low density but significantly lower than medium density ($P < 0.05$).

Building height displayed a weaker association with depressive disorder risk than building density. In the basic model, we found risks to be 8% (95% CI: 5 to 10%) higher in high-rise than in low-rise areas (Table 2). However, the risk associated with high-rise buildings decreased when adjusting for building density, leading to a 7% (95% CI: 0 to 12%) lower risk than low-rise areas. When individual or neighborhood socioeconomic factors were included, high-rise areas did not carry significantly different risks for depression than low-rise areas (Table 2 and table S4). We found similar results when estimating the risks based on 3D urban form exposure within 250 and 1000 m of the residence (tables S2 and S3). Further adjustment for urbanicity had only a minor influence on the risk estimates (table S4).

We visualized the risks contributed by 3D urban form independently of socioeconomic factors based on the relative risk of the fully adjusted model and identified a geographical pattern in which higher values spread along the suburbs of cities and towns but not the city centers (Fig. 2). Lower values appear around rural areas and low-density high-rise areas, which often face water or green space in Danish cities.

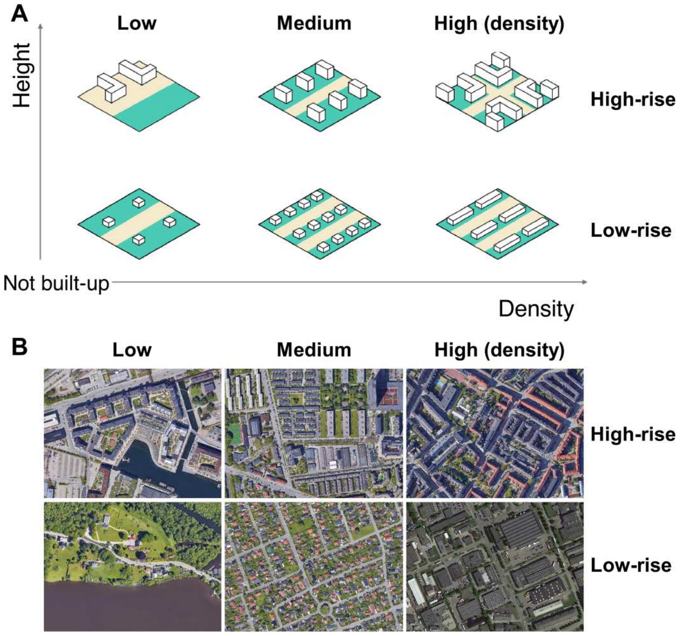

Fig. 1. 3D urban form. (**A**) Schematic illustration of the classification. (**B**) Empirical examples of the same classification from the Danish landscape.

DISCUSSION

The associations between urban form and depression risk uncovered here challenge the idea of a monotonic relationship between urbanicity and depression that has been a prevailing assumption in the literature (*7*), as higher building density and height are not consistently associated with higher risks of depression. Instead, medium-density neighborhoods are associated with higher risks than either higher or lower densities independently of socioeconomic factors. Furthermore, residents in multistory buildings carry greater risks than those in low-rise buildings in the basic model, but the association disappears when building density and height are both included in the model. This indicates that the risk of high-rise areas could be confounded by building density if 3D urban form is not properly accounted for. High-rise, low-density areas had a lower risk level compared to other high-rise areas, implying that the presence of open space is a key protective factor being missed in analyses of mental health in relation to building height. In Denmark, open space is mostly composed of green space (85%) and water bodies (9%) (table S5). We speculate that the relatively low risk observed in high-rise and low-density areas might be because they create indoor sun exposure and are often situated at the border between areas providing dynamic socioeconomic interaction (*9*) and green space and water bodies enabling psychological restoration (*28*). Such neighborhood-level environmental diversity has been found to promote subjective well-being (*29*), which regulates vulnerability to depression (*30*). Geographical patterns of urban form's contributions to depression risk show that, after adjusting for socioeconomic factors, the highest risk was among residents of sprawling suburbs. In contrast, the lowest risk was among those in rural areas and inner-city areas facing open space. Our results suggest that urban spatial planning has the potential to improve public mental health. Specifically, spatial land-use

Table 1. Descriptive characteristics of cases and matched controls. Covariates were measured at baseline, i.e., 5 years before the index date. IQR, interquartile range.

Variables	Cases (*n* = 75,650)	Controls (*n* = 756,500)
Age, median (IQR)	32 (26–40)	32 (26–40)
Gender, no. (%)		
Female	45,137 (59.67)	451,370 (59.67)
Male	30,513 (40.33)	305,130 (40.33)
Calendar year, no. (%)		
1985–1995	9,390 (12.41)	93,900 (12.41)
1996–2005	33,183 (43.86)	331,830 (43.86)
2006–2013	33,077 (43.72)	330,770 (43.72)
Parental country of origin, no. (%)		
Both born in Denmark	68,514 (90.57)	694,897 (91.86)
One parent born in Denmark	6,220 (8.22)	53,082 (7.02)
No parent born in Denmark	889 (1.18)	8,216 (1.09)
Unknown	27 (0.04)	305 (0.04)
Parental history of depressive disorders, no. (%)		
No	66,572 (88.00)	701,788 (92.77)
Yes	7,139 (9.44)	39,384 (5.21)
Unknown	1,939 (2.56)	15,328 (2.03)
Highest educational level, no. (%)		
Primary school	29,791 (39.38)	200,358 (26.48)
High school/vocational training	32,735 (43.27)	375,832 (49.68)
Higher education	12,195 (16.12)	175,167 (23.15)
Unknown	929 (1.23)	5,143 (0.68)
Employment status, no. (%)		
Employed, top level	4,259 (5.63)	78,678 (10.40)
Employed, medium level	9,508 (12.57)	133,964 (17.71)
Employed, basic level	41,801 (55.26)	440,783 (58.27)
Unemployed	13,568 (17.94)	64,371 (8.51)
Retired	6,487 (8.58)	38,507 (5.09)
Unknown	27 (0.04)	197 (0.03)
Income quintiles, no. (%)		
Lowest quintile	21,811 (28.83)	165,116 (21.83)
Second quintile	20,677 (27.33)	172,883 (22.85)
Third quintile	14,188 (18.75)	149,130 (19.71)
Fourth quintile	10,962 (14.49)	139,581 (18.45)
Highest quintile	8,012 (10.59)	129,790 (17.16)
Marital status, no. (%)		
Married couple	24,288 (32.11)	309,113 (40.86)
Cohabiting couple	18,329 (24.23)	195,442 (25.84)
Single	32,717 (43.25)	248,746 (32.88)
Unknown	316 (0.42)	3,199 (0.42)

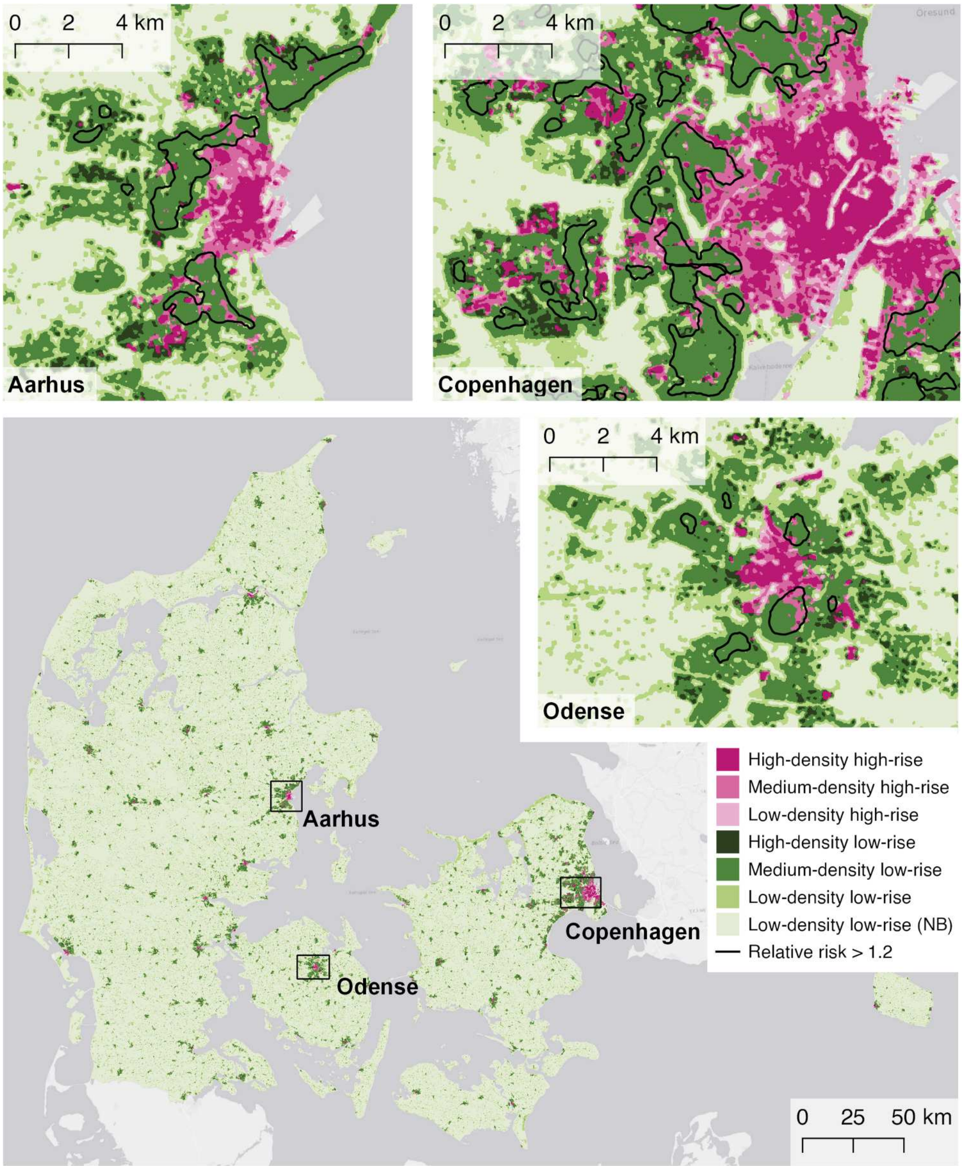

Fig. 2. Geographical distribution of building density, building height, and relative risks > 1.2 in 2017. Inset maps are the larger cities Aarhus, Odense, and Copenhagen. Low-density low-rise areas include both built-up areas and non–built-up areas (denoted as NB). In the multivariate analysis, solid lines represent areas where the urban form's contribution to the relative risk for depression was higher than 1.2. Relative risks were predicted by the full adjustments in Table 2 and Eq. 8 (i.e., adjusting for age, gender, calendar year, the other urban form measure, parental country of origin, parental history of depressive disorders, marital status, and socioeconomic variables), assuming that all these adjusted parameters held fixed. Thus, the figure does not reflect the relative risks attributed to demographic and socioeconomic variables such as age, income, education, and employment, which have geographic variations (www.ncrr.au.dk/data_zones).

planning should strive to secure access to open space in already dense multistory neighborhoods.

The research gap elaborating the associations between urban form and mental health is pressing as the global urban population rises. We consider large-scale assessments of mental health essential for urban planners and sustainability scientists to validate urban design effects. This study advances our understanding of how 3D urban form relates to depression in three main ways. First, we propose an innovative satellite image analysis combined with individual-level register data to quantify 3D urban form exposure. 3D urban form decomposes the built environment into two components, as opposed to a singular measure such as population density. This is important, as low-density high-rise and high-density low-rise areas may have similar population densities but differing contributions to a wide variety of sustainability goals. Recent climate research has shown that multistory buildings interspersed with large green spaces better mitigate extreme temperatures than very dense low-rise areas with little spacing in-between (*13*). This design also reduces transportation-related carbon emissions compared to sprawling urban form (i.e., sparsely spaced low-rise buildings) (*31*). Our results suggest additional benefits of this design in terms of mental health improvements.

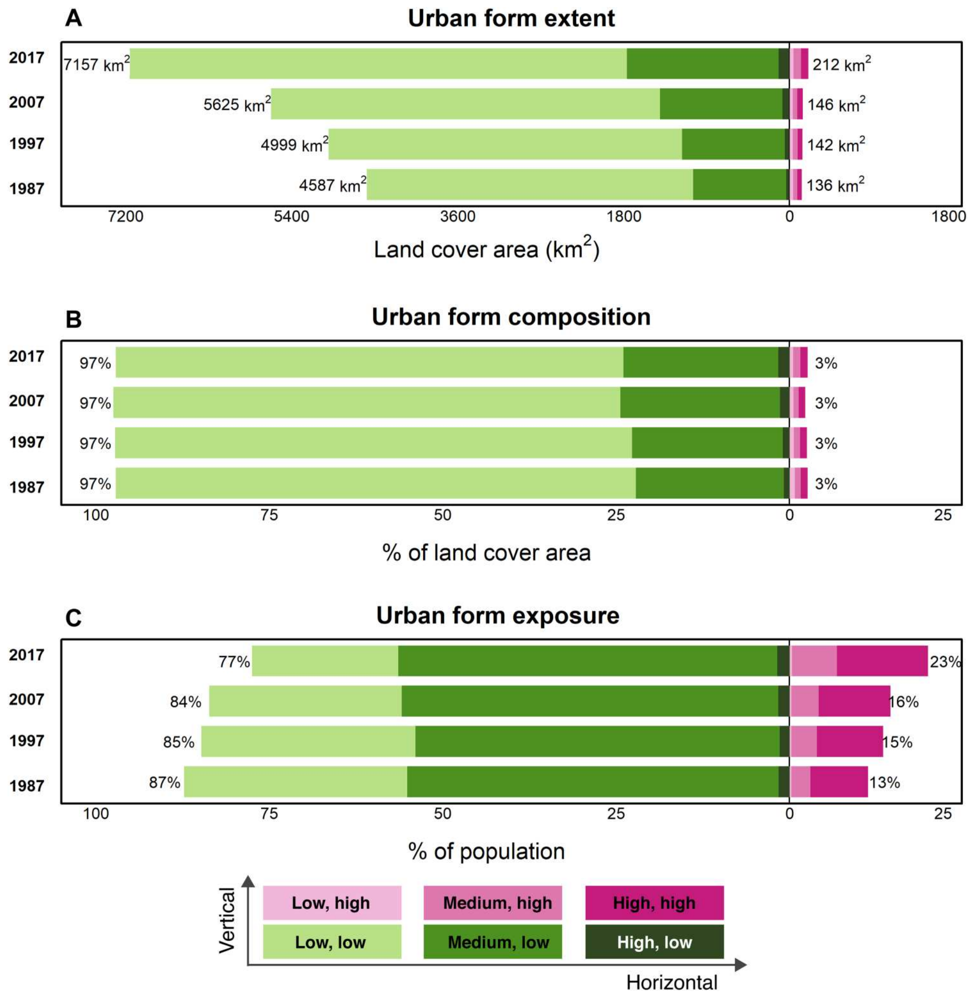

Fig. 3. Temporal change in the low-rise (left) and high-rise (right) urban forms of 1987, 1997, 2007, and 2017. (**A**) Urban form extent (km^2). (**B**) Urban form composition measured as the proportion in the total built-up area. (**C**) Urban form exposure measured as the proportion of the population inhabiting in such urban form.

Second, the time-matched case-control design overcomes one of the largest validity threats to test whether environmental factors of depression are robust to socioeconomic and other individual-level factors. A review revealed that only 20 and 40% of prior studies have included income and education measures, respectively, as a control for these potential confounders (*7*). Here, we found that even after adjusting for known risk factors (parental history of mental disease, age, gender, income, employment status, and education), associations between exposure to medium- and high-density environments and depression remain. However, our findings also show that the association between high-density urban form and depression is confounded by these factors. The relative risk of high-density urban form before adjusting for known risk factors is 19 percentage points higher than after adjusting. Another confounding issue is that urban form is associated with housing prices. Downtown areas with access to urban services, green space, canals, or shorelines are usually more expensive (*32*). At the same time, the association between poverty and mental health problems is well-established in psychiatric epidemiology (*33*). Urban revitalization might result in the gentrification of upgraded neighborhoods (*34*), which can lead to compounding risk factors when low-income groups are forced out and into urban form with a higher risk for developing depression. Thus, decision-makers and public officials should also bring environmental justice issues and public mental health to the table when designing regional plans and housing projects.

Last but not least, the results were specifically enabled by the use of artificial intelligence and satellite images combined with residential movement records that together allowed the estimation of high-resolution dynamic 3D urban form and individual-level exposure. While satellite imagery on its own shows that cities in Denmark sprawled over time, the coupling of datasets reveals an increasing population exposed to high-density and high-rise urban areas (Fig. 3). Our study thus demonstrates the utility of the coupled remote sensing and register-based approach to understand how urban planning may improve mental health.

Limitations and future directions

As far as we are aware, this is the first nationwide follow-up study that reveals the associations between 3D urban form and depression. Nevertheless, this study is not without limitations. First, our study design meant that we could only establish an association between 3D urban form and depression, rather than a causal

Table 2. Relative risk, estimated as incidence rate ratios, and 95% CIs for depressive disorders according to urban form/building density 500 m around the residential location. The cases and controls columns present the mean and SD of each urban form variable, which refer to the proportion of the given urban form within 500 m around the residential address. Bold typeface refers to significant risks compared to the reference. IRR, incidence rate ratio.

	Descriptive characteristics		Model results		
	Cases	Controls	Basic*	Mutually adjusted†	Fully adjusted‡
Accumulated exposure during the 5 years before index date	**Mean (SD)**	**Mean (SD)**	**IRR (95% CI)**	**IRR (95% CI)**	**IRR (95% CI)**
Building density, proportion					
Low (less than 15% built-up area)	0.47 (0.30)	0.49 (0.31)	1.00 (ref)	1.00 (ref)	1.00 (ref)
Medium (15 to 30%)	0.40 (0.25)	0.38 (0.26)	**1.27 (1.24–1.31)**	**1.28 (1.24–1.32)**	**1.24 (1.20–1.28)**
High (30% or above)	0.13 (0.22)	0.12 (0.22)	**1.18 (1.14–1.22)**	**1.29 (1.17–1.42)**	1.10 (1.00–1.21)
Building height, proportion					
Low (less than 10 m)	0.81 (0.31)	0.82 (0.31)	1.00 (ref)	1.00 (ref)	1.00 (ref)
High (10 m and above)	0.19 (0.31)	0.18 (0.31)	**1.08 (1.05–1.10)**	0.93 (0.88–1.00)	0.98 (0.92–1.05)

*Adjusted for age, gender, and calendar year. †Adjusted for age, gender, calendar year, and the "other" urban form measure. ‡Adjusted for age, gender, calendar year, the other urban form measure, parental country of origin, parental history of depressive disorders, marital status, and socioeconomic status (educational level, employment status, and income).

relationship. We were unable to adjust for genetic liability beyond the family history of mental illness. The associations we found might include potential reverse causality [e.g., if people suffering from undiagnosed depressive disorders chose to move and live in some types of urban form and then got diagnosed later on (*35*)]. Second, this study is limited in its generalizability. From a global perspective, our Danish study population has relatively high-income and low-income inequality. Denmark is a welfare state with universal health care, and therefore, mental health diagnosis and treatment are widely accessible to the public (*36*). Urban form in Denmark, as in other Northwestern European countries, is largely regulated by urban planning laws, making very tall buildings rare, whereas greater urban form diversity is found in other countries. It is possible that known social and environmental risk factors for depression related to very tall buildings and extremely dense environments, such as lighting conditions (*11*) and temperature (*13*), are not able to be tested in Danish cities. However, our satellite image analysis (see https://github.com/karenthchen/Association-between-three-dimensional-urban-form-and-depression) can be repeated globally and applied to country-specific contexts. Future studies based on long-term records of disease severity and recovery combined with historic urban form data could provide an opportunity to deepen our understanding of how 3D urban form affects mental health.

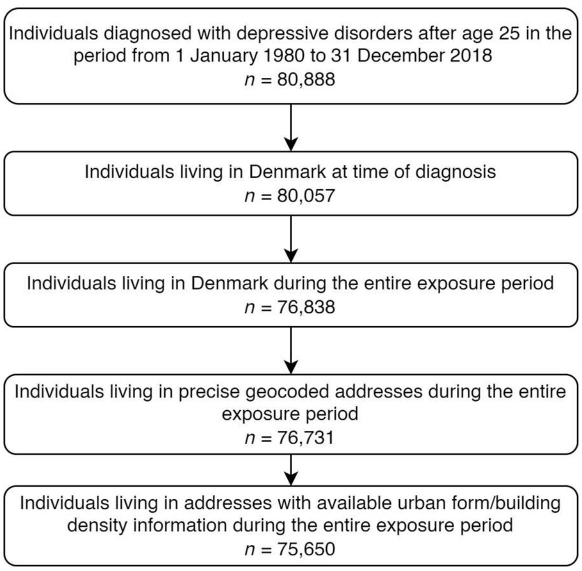

Fig. 4. Case inclusion process for depressive disorders. Case inclusion criteria include age, birthday, accurate location within Denmark, and complete exposure information.

MATERIALS AND METHODS

Study population

Individuals in Denmark are given a unique personal identification number at birth or immigration and registered in the Danish Civil Registration System (*27*). The registries include current and all past residential addresses and sociodemographic information for each individual and allow for linkage across different health registers. Our study cohort consists of all individuals born in Denmark between 1955 and 1993. By using the Danish Psychiatric Central Research Register (*37*), we identified all incident contacts (n = 80,888, including inpatient, outpatient, and emergency visits) with a depressive disorder (ICD-8: 296.09, 296.29, 298.09, 300.49; ICD-10: F32-33) between 1 January 1990 and 31 December 2018 for all individuals above age 25. We excluded individuals who had foreign addresses, imprecise geocoded addresses, or incomplete urban form information during the exposure period, leading to 75,650 cases in our analysis (Fig. 4). There are no private psychiatric inpatient facilities in Denmark, and the treatment of mental illness is covered by the national health care system and freely accessible to the public.

For each case, we randomly selected 10 controls from the study cohort using risk-set sampling, i.e., the control had to be alive and living in Denmark and not diagnosed with depression at the time the corresponding case was diagnosed (index date), leading to 75,650 cases with 756,500 matched controls. We selected controls by matching on the case's date of birth and gender. Given the matching on the date of birth, the approach adjusts the effect of age and calendar time (such as societal mental health awareness being higher in 2017 than in the 1990s).

Ethical review

The study was approved by the Danish Data Protection Agency, and data access was agreed by Statistics Denmark and the Danish Health Data Authority. Approval by the Ethics Committee and written informed consent from cohort members were not required in register-based studies according to the Danish Act on Processing of Personal Data, part 10 (www.retsinformation.dk/eli/lta/2020/1338). All unique personal identification numbers have been replaced by a scrambled unique identifier before the researchers' data access.

Quantification of urban form

For our environmental exposure variables, we used a classification of building height and density to represent 3D urban form types derived from our previous study (*26*). We did not include land use, population density, or green space in our models, as these partially interact with urban form, and we were interested in the direct association between urban form and mental health. We used the 30 m–by–30 m cells defined by Landsat imagery across Denmark and classified them based on a 150 m–by–150 m block around each cell. For the horizontal dimension, we trained a model to classify building density into three levels: low (below 15% of built-up area compared to open space), medium (15 to 30%), and high (30% and above). For the vertical dimension, we trained a model to classify the mean building height of the block into low-rise areas (below 10 m) and high-rise areas (10 m and above). See Fig. 1 for an illustration of these urban form types. We chose these definitions based on an urban form classification scheme for Denmark (*26*). The scheme uses the cuts of height and building density from local climate zones (*38*) with building density modification based on the Danish context (i.e., medium density was selected on the basis of Danish neighborhood samples with single-family housing).

We used a segmentation-based convolutional neural network to classify urban form based on Landsat satellite images (*26*). This combination has the dual upsides of being cost-efficient compared to manual mapping at large scales and being well suited for tasks requiring observation over time, such as changing urban form. Although the 30-m spatial resolution is not high, we chose Landsat imagery because it enables a long historical time frame (i.e., 1984–present) to analyze urban form, which other higher-resolution satellite platforms initiated recently cannot offer. Through Google Earth Engine, we accessed satellite images for Denmark from Landsat 5, Landsat 7, and Landsat 8 to cover the years 1987–2017. We used level 2 tier 1 products and applied the quality band to remove cloud and cloud shadow pixels, and scan line corrector–off gaps from Landsat 7. For each year, we gathered all available images from 1 May to 31 August using a 3-year window (±1 year) and chose the median of each band. This resulted in 100% coverage of quality pixels across the entire study area and period.

We produced training labels using a building height and boundary dataset generated from nationwide airborne LiDAR surveys for 2014, which was the most precise national-wide data for height (*23*). We trained two DeepLab models, which were based on a convolutional neural network using multiscale spatial pooling, for detecting building height and density, respectively (*26*, *39*). The models were able to use the training data for 2014 to predict urban form at other time points, as long as the satellite imagery was available. We used the trained models to classify annual building density and height for 1987–2017. We applied a Savitzky-Golay filter to the classification results to remove abnormal observations across the time series. Once the relationship between satellite images and urban form is established by the model, it can predict urban form at other times and places within reasonably similar contexts. The dataset was validated with reference data from LiDAR surveys and high-resolution aerial photos for 1995, 2006, and 2014, showing overall accuracies of 89 to 92% [detailed in (*26*)]. The validation years were chosen on the basis of data availability. This approach allows us to monitor urban expansion and regeneration processes across Denmark from 1987 to 2017 with a 1-year interval.

Urban form exposure

We used all individuals' current and past residential addresses obtained through the Danish Civil Registration System to calculate time-series exposure. We defined urban form exposure at 0, 1, 2, 3, 4, and 5 years before the index date. Thus, we considered only individuals who lived in Denmark during the 5 years before the index date. We estimated the exposure based on the residential address and calculated it as the proportion of each type of urban form within 500 m around the residential address, with a range of 0 to 100% for each urban form fraction. For example, an individual may be surrounded by 60% high-rise and 40% low-rise urban form within the 500-m vicinity. We performed sensitivity analysis by narrowing and widening the exposure zone (i.e., 250 and 1000 m). We used building height and density as separate variables rather than a classification based on their combination because some combinations were rare (e.g., "low-density high-rise" areas).

Individual-level covariates

We collected information about individual-level socioeconomic, demographic, and urbanicity variables from the registries at Statistics Denmark. We defined parental country of origin (none, one, or two parents born in Denmark), parental history of depressive disorders, marital status (single, cohabiting, and married), educational level (primary school, high school/vocational training, and higher education), employment status (employed, top level; employed, medium level; employed, basic level; unemployed; and retired), and income (age-, gender-, and calendar year–specific quintiles on the basis of the entire Danish population). We defined urbanicity in five categories: capital, suburb of the capital, other municipalities having more than 100,000 inhabitants, between 10,000 and 100,000 inhabitants, and less than 10,000 inhabitants. The urbanicity is linked to individuals based on their residential addresses. These covariates were based on the status 5 years before the index date. Besides individual socioeconomic status, we also collected neighborhood socioeconomic status (proportion of individuals with basic education, not employed, and low income). The neighborhood geographic unit is defined by Danish data zones, with a mean of 2820 residents per neighborhood (*40*).

Statistical analysis

We used conditional logistic regression to estimate odds ratios with 95% CIs with each case-control pair forming a separate stratum. Owing to the time-matching within each stratum, this method provides estimates of the corresponding incidence rate ratio, a measure of relative risk in epidemiology (*41*). We included the proportion of urban form around the residential place as a continuous variable (range: 0 to 100%), assuming a linear exposure-response association, with the reference being completely surrounded by a low-density and/or low-rise environment. All estimates were by design adjusted for age, gender, and calendar time. We started with either height or density in the model (basic model; Eqs. 1 and 2). Furthermore, we included both urban form measures in the model (mutually adjusted model; Eq. 3) and, lastly, added the parental country of origin, parental history of depressive disorders, marital status, and the socioeconomic variables (educational level, employment status, and income) in the fully adjusted model (Eq. 4). For each model, we regressed on accumulated exposure and 1-year exposure during the 5 years before the index date, respectively. We present the results based on accumulated exposure in the main text and the results of 1-year exposure in table S1. Results from sensitivity analysis narrowing and widening the exposure zone (i.e., 250 and 1000 m) are shown in tables S2 and S3. We also tested whether adjusting for urbanicity would change the associations between urban form and depression (supplementary model; Eq. 5). Last, we adjusted for neighborhood socioeconomic status to test whether the association between urban form and depression was independent of the neighborhood socioeconomic context (supplementary model; Eq. 6).

From the coefficients of conditional logistic regression, incidence rate ratios can be expressed by Eq. 7. Together, the relative risk contributed by urban form with the full adjustments, assuming that all the adjusted parameters held fixed in Eq. 4 can be represented as Eq. 8, which we used to illustrate the geographical pattern of relative risks shown in Fig. 2

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{11}\text{mediumdensity}_{ij} + \beta_{12}\text{highdensity}_{ij} \tag{1}$$

where $P(y_{ij} = 1)$ is the probability of developing a depressive disorder for individual i within the jth case-control matched set, β_{0j} denotes the contribution to the logit of all terms constant within the jth case-control matched set. The proportion of low density is a reference variable

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{2}\text{highrise}_{ij} \tag{2}$$

where the proportion of low rise is a reference variable.

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{11}\text{mediumdensity}_{ij} + \beta_{12}\text{highdensity}_{ij} + \beta_{2}\text{highrise}_{ij} \tag{3}$$

where the proportions of low-density and low-rise are reference variables for building density and height, respectively.

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{11}\text{mediumdensity}_{ij} + \beta_{12}\text{highdensity}_{ij} + \beta_{2}\text{highrise}_{ij} + \beta_{3}\text{parentalcountry}_{ij} + \beta_{4}\text{parentalhistory}_{ij} + \beta_{5}\text{maritalstatus}_{ij} + \beta_{6}\text{education}_{ij} + \beta_{7}\text{employment}_{ij} + \beta_{8}\text{income}_{ij} \tag{4}$$

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{11}\text{mediumdensity}_{ij} + \beta_{12}\text{highdensity}_{ij} + \beta_{2}\text{highrise}_{ij} + \beta_{3}\text{parentalcountry}_{ij} + \beta_{4}\text{parentalhistory}_{ij} + \beta_{5}\text{maritalstatus}_{ij} + \beta_{6}\text{education}_{ij} + \beta_{7}\text{employment}_{ij} + \beta_{8}\text{income}_{ij} + \beta_{9}\text{urbanicity}_{ij} \tag{5}$$

$$\text{logit}\{P(y_{ij}=1)\} = \beta_{0j} + \beta_{11}\text{mediumdensity}_{ij} + \beta_{12}\text{highdensity}_{ij} + \beta_{2}\text{highrise}_{ij} + \beta_{3}\text{parentalcountry}_{ij} + \beta_{4}\text{parentalhistory}_{ij} + \beta_{5}\text{maritalstatus}_{ij} + \beta_{6}\text{education}_{ij} + \beta_{7}\text{employment}_{ij} + \beta_{8}\text{income}_{ij} + \beta_{9}\text{NBH}-\text{education}_{ij} + \beta_{10}\text{NBH}-\text{unemployment}_{ij} + \beta_{11}\text{NBH}-\text{lowincome}_{ij} \tag{6}$$

$$\text{IRR}_k = \exp(\beta_k \times 100\%) \tag{7}$$

where IRR_k denotes the incidence rate ratio of being completely surrounded by urban form k compared to being completely surrounded by the reference urban form (i.e., low rise or low density), and β_k represents any of the urban form coefficients from Eqs. 1 to 6.

$$\text{IRR}_a = \exp(\beta_{11}\text{mediumdensity}_a + \beta_{12}\text{highdensity}_a + \beta_{2}\text{highrise}_a) \tag{8}$$

where IRR_a denotes the contribution of urban form to the relative risk of a given individual address a, and β_{11}, β_{12}, and β_2 are coefficients from the fully adjusted model (Eq. 4).

Supplementary Materials

This PDF file includes:

Tables S1 to S5

REFERENCES AND NOTES

1. United Nations, *World Urbanization Prospects 2018* (United Nations Department for Economic and Social Affiars, 2018).
2. D. Blazer, L. K. George, R. Landerman, M. Pennybacker, M. L. Melville, M. Woodbury, K. G. Manton, K. Jordan, B. Locke, Psychiatric disorders: A rural/urban comparison. *Arch. Gen. Psychiatry* **42**, 651–656 (1985).
3. D. Lecic-Tosevski, Is urban living good for mental health? *Curr. Opin. Psychiatry* **32**, 204–209 (2019).
4. F. Lederbogen, P. Kirsch, L. Haddad, F. Streit, H. Tost, P. Schuch, S. Wüst, J. C. Pruessner, M. Rietschel, M. Deuschle, City living and urban upbringing affect neural social stress processing in humans. *Nature* **474**, 498–501 (2011).
5. G. W. Evans, The built environment and mental health. *J. Urban Health* **80**, 536–555 (2003).
6. M. G. Berman, J. Jonides, S. Kaplan, The cognitive benefits of interacting with nature. *Psychol. Sci.* **19**, 1207–1212 (2008).
7. J. Peen, R. A. Schoevers, A. T. Beekman, J. Dekker, The current status of urban-rural differences in psychiatric disorders. *Acta Psychiatr. Scand.* **121**, 84–93 (2010).
8. E. Vassos, E. Agerbo, O. Mors, C. B. Pedersen, Urban–rural differences in incidence rates of psychiatric disorders in Denmark. *Br. J. Psychiatry* **208**, 435–440 (2016).
9. A. J. Stier, K. E. Schertz, N. W. Rim, C. Cardenas-Iniguez, B. B. Lahey, L. M. Bettencourt, M. G. Berman, Evidence and theory for lower rates of depression in larger US urban areas. *Proc Natl. Acad. Sci. U.S.A.* **118**, e2022472118 (2021).
10. K. Sundquist, G. Frank, J. Sundquist, Urbanisation and incidence of psychosis and depression: Follow-up study of 4.4 million women and men in Sweden. *Br. J. Psychiatry* **184**, 293–298 (2004).

11. X. Bonnefoy, Inadequate housing and health: An overview. *Int. J. Environ. Pollut.* **30**, 411–429 (2007).
12. A. Hansen, P. Bi, M. Nitschke, P. Ryan, D. Pisaniello, G. Tucker, The effect of heat waves on mental health in a temperate Australian city. *Environ. Health Persp.* **116**, 1369–1375 (2008).
13. Y. Li, S. Schubert, J. P. Kropp, D. Rybski, On the influence of density and morphology on the Urban Heat Island intensity. *Nat. Commun.* **11**, 2647 (2020).
14. B. Chun, J.-M. Guldmann, Spatial statistical analysis and simulation of the urban heat island in high-density central cities. *Lands. Urban Plan.* **125**, 76–88 (2014).
15. P. Barros, L. N. Fat, L. M. Garcia, A. D. Slovic, N. Thomopoulos, T. H. de Sá, P. Morais, J. S. Mindell, Social consequences and mental health outcomes of living in high-rise residential buildings and the influence of planning, urban design and architectural decisions: A systematic review. *Cities* **93**, 263–272 (2019).
16. E. Jung, J. Lee, K. Kim, The relationship between pedestrian environments and sense of community in apartment complexes in Seoul, Korea. *J Asian Archit Build Eng* **14**, 411–418 (2015).
17. E. Pérez, C. Braën, G. Boyer, G. Mercille, É. Rehany, V. Deslauriers, A. Bilodeau, L. Potvin, Neighbourhood community life and health: A systematic review of reviews. *Health Place* **61**, 102238 (2020).
18. R. G. Davies, O. Barbosa, R. A. Fuller, J. Tratalos, N. Burke, D. Lewis, P. H. Warren, K. J. Gaston, City-wide relationships between green spaces, urban land use and topography. *Urban Ecosyst.* **11**, 269–287 (2008).
19. N. Ujang, M. Kozlowski, S. Maulan, Linking place attachment and social interaction: Towards meaningful public places. *J. Place Manag. Dev.* **11**, 115–129 (2018).
20. Y. Zhang, G. Chen, Y. He, X. Jiang, C. Xue, Social Interaction in Public Spaces and Well-Being among Elderly Women: Towards Age-Friendly Urban Environments. *Int. J. Environ. Res. Public Health* **19**, 746 (2022).
21. W. Zhang, G. Lawson, Meeting and greeting: Activities in public outdoor spaces outside high-density urban residential communities. *Urban Des. Int.* **14**, 207–214 (2009).
22. M. Gascon, G. Sánchez-Benavides, P. Dadvand, D. Martínez, N. Gramunt, X. Gotsens, M. Cirach, C. Vert, J. L. Molinuevo, M. Crous-Bou, Long-term exposure to residential green and blue spaces and anxiety and depression in adults: A cross-sectional study. *Environ. Res.* **162**, 231–239 (2018).
23. I. Bray, R. Reece, D. Sinnett, F. Martin, R. Hayward, Exploring the role of exposure to green and blue spaces in preventing anxiety and depression among young people aged 14–24 years living in urban settings: A systematic review and conceptual framework. *Environ. Res.* **214**, 114081 (2022).
24. A. Curry, C. Latkin, M. Davey-Rothwell, Pathways to depression: The impact of neighborhood violent crime on inner-city residents in Baltimore, Maryland, USA. *Soc. Sci. Med.* **67**, 23–30 (2008).
25. G. Melis, E. Gelormino, G. Marra, E. Ferracin, G. Costa, The effects of the urban built environment on mental health: A cohort study in a large northern Italian city. *Int. J. Environ. Res. Public Health* **12**, 14898–14915 (2015).
26. T.-H. K. Chen, C. Qiu, M. Schmitt, X. X. Zhu, C. E. Sabel, A. V. Prishchepov, Mapping horizontal and vertical urban densification in Denmark with Landsat time-series from 1985 to 2018: A semantic segmentation solution. *Remote Sens. Environ.* **251**, 112096 (2020).
27. C. B. Pedersen, The Danish civil registration system. *Scand. J. Public Health* **39**, 22–25 (2011).
28. I. Markevych, J. Schoierer, T. Hartig, A. Chudnovsky, P. Hystad, A. M. Dzhambov, S. De Vries, M. Triguero-Mas, M. Brauer, M. J. Nieuwenhuijsen, Exploring pathways linking greenspace to health: Theoretical and methodological guidance. *Environ. Res.* **158**, 301–317 (2017).
29. K. Samuelsson, J. Colding, S. Barthel, Urban resilience at eye level: Spatial analysis of empirically defined experiential landscapes. *Landsc. Urban Plan.* **187**, 70–80 (2019).
30. R. A. Burns, K. J. Anstey, T. D. Windsor, Subjective well-being mediates the effects of resilience and mastery on depression and anxiety in a large community sample of young and middle-aged adults. *Aust. N. Z. J. Psychiatry* **45**, 240–248 (2011).
31. Y. Makido, S. Dhakal, Y. Yamagata, Relationship between urban form and CO2 emissions: Evidence from fifty Japanese cities. *Urban Clim.* **2**, 55–67 (2012).
32. W. Alonso, *A theory of the urban land market*. (Bobbs-Merrill Company, College Division, 1960).
33. D. Belle, Poverty and women's mental health. *Am. Psychol.* **45**, 385–389 (1990).
34. H. G. Larsen, A. L. Hansen, Gentrification—Gentle or traumatic? Urban renewal policies and socioeconomic transformations in Copenhagen. *Urban Stud.* **45**, 2429–2448 (2008).
35. C. B. Pedersen, Persons with schizophrenia migrate towards urban areas due to the development of their disorder or its prodromata. *Schizophr. Res.* **168**, 204–208 (2015).
36. K. Engemann, C. B. Pedersen, L. Arge, C. Tsirogiannis, P. B. Mortensen, J.-C. Svenning, Residential green space in childhood is associated with lower risk of psychiatric disorders from adolescence into adulthood. *Proc. Natl. Acad. Sci. U.S.A.* **116**, 5188–5193 (2019).
37. O. Mors, G. P. Perto, P. B. Mortensen, The Danish psychiatric central research register. *Scand. J. Public Health* **39**, 54–57 (2011).
38. I. D. Stewart, T. R. Oke, Local climate zones for urban temperature studies. *Am. Meteorol. Soc.* **93**, 1879–1900 (2012).
39. L.-C. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. L. Yuille, Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. *IEEE Trans. Pattern Anal. Mach. Intell.* **40**, 834–848 (2017).
40. C. B. Pedersen, S. Antonsen, A. Timmermann, M. G. Pedersen, L. Ejlskov, H. T. Horsdal, E. Agerbo, R. T. Webb, O. Raaschou-Nielsen, T. Sigsgaard, Urban-rural differences in schizophrenia risk: Multilevel survival analyses of individual-and neighborhood-level indicators, urbanicity and population density in a Danish National Cohort Study. *Schizophr. Bull. Open* **3**, sgab056 (2022).
41. D. Clayton, M. Hills, *Statistical Models in Epidemiology* (OUP Oxford, 2013).

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