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Food, Built and Socio-Economic Environments and Maternal–Infant Outcomes: A Geospatial and Structural Equation Modelling of 163 000 Births

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Keywords: Australia | gestational diabetes mellitus | large-for-gestational age | Melbourne | overweight

ABSTRACT

Objectives: To examine the combined influence of food environment, built environment, socio-economic status and individual factors (maternal age, parity, smoking status and need for an interpreter) on maternal overweight, gestational diabetes mellitus (GDM) and large-for-gestational age (LGA) births in Australia.

Design: Retrospective cohort study.

Setting: Melbourne, Australia.

Population: 163 760 singleton pregnancies/births.

Main Outcomes Measures: Primary outcomes: maternal overweight, GDM and LGA births.

Methods: Structural equation modelling (SEM) assessed direct and indirect associations, with maternal overweight as a mediator. LCA was used to classify risk variation across socio-economic strata.

Results: Among 163 760 births, a higher density of unhealthy food outlets, lower liveability scores and greater socio-economic disadvantage were associated with maternal overweight. Maternal overweight strongly predicted GDM ($c = 0.118$, 95% CI: 0.113–0.124; $p < 0.001$) LGA births ($c = 0.058$, 95% CI: 0.053–0.059; $p < 0.001$), while higher liveability and walkability environments were protective against maternal overweight ($c = -0.011$, 95% CI: −0.019 to −0.002; $p < 0.05$). LCA identified a high-risk subgroup

(85.1% overweight, 34.4% GDM) concentrated in socio-economically disadvantaged areas with poor access to healthy food and more walkable neighbourhoods.
Conclusions: Environmental and socio-economic factors have significant independent influences on maternal overweight, GDM and LGA births. Addressing food access disparities, improving the walkability and liveability of residential areas and ensuring equitable healthcare infrastructure could reduce maternal health risks and promote better pregnancy outcomes.

1 | Background

The global prevalences of overweight and obesity among women of reproductive age have been increasing over the past decades, with 39% of the world's women now classified as overweight (body mass index (BMI) ≥ 25 kg/m^2) or 15% as obese (BMI ≥ 30 kg/m^2) [1]. Elevated maternal BMI has important implications for perinatal outcomes as it increases the risk of gestational diabetes mellitus (GDM) [2, 3], which in turn increases the likelihood of preeclampsia, caesarean delivery, and type 2 diabetes for both the mother and child. Elevated BMI is also associated with large-for-gestational age (LGA) babies, LGA defined as the 90th centile weight adjusted by gestational age and sex, which raises the risks of birth trauma, Caesarean birth and neonatal intensive care unit admission, as well as childhood metabolic disorders [2, 4–6].

Lower socio-economic status (SES) is associated with worse health outcomes, including maternal overweight or obesity [6, 7]. The effect of socio-economic disadvantage may be partially mediated through the physical environment, including the food retail environment [8] and other built environment indicators, such as liveability, social infrastructure access and walkability [9, 10].

Much of the existing data on the relationship between SES, environment and perinatal outcomes has major methodological limitations. Most studies examine single outcomes—such as GDM, maternal BMI or LGA infants—without addressing their interconnected nature. Furthermore, research often focuses on isolated factors, such as socio-economic status or food outlet density, without accounting for the combined effects of multiple neighbourhood environmental determinants. Individual-level factors, such as parity, smoking and maternal age, also play a significant role in shaping maternal outcomes. Furthermore, the COVID-19 pandemic has further complicated maternal health by disrupting healthcare services and limiting physical activity. However, reports on its effects on maternal weight remain mixed, with some studies reporting heightened metabolic risks and weight gain, [11] while others suggest a continuation of preexisting upward trends during the pandemic [12].

We aimed to examine the combined and individual effects of SES, the food environment, built environment, and individual-level factors on maternal overweight, GDM, and LGA births in Melbourne, Australia. We also analysed our dataset for population clusters with differing perinatal risk profiles based on co-occurring outcomes.

2 | Methods

2.1 | Design

We conducted a retrospective cohort study using individual-level maternal and newborn data from the Greater Melbourne area, Australia, spanning approximately 5600 km^2 and encompassing both the city and its suburbs [13]. Some indicators were derived at the postcode level [termed as POA (postal area) in Australia Bureau of Statistics], where postcodes, defined by Australia Post, represent small geographic areas with comprehensive data availability [13]. The median land area of Melbourne postcodes is approximately 9.5 km^2, and the median population is around 11 000 residents per postcode, based on 2021 ABS data [14].

Our study design followed the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) [15] guidelines and adhered to the Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReSt) statement to ensure methodological rigour and transparency (Tables S1 and S2) [16].

2.2 | Study Population and Outcomes

In Australia in 2023, 25% of pregnant women were classified as overweight (≥ 25 kg/m^2) and another 25% as obese (≥ 30 kg/m^2) [17] The prevalence of GDM and LGA is 18% [18] and 8%–15%, respectively.

We used a research dataset from the Collaborative Maternity and Newborn Dashboard (CoMaND) for the COVID-19 pandemic project, which collected maternal and newborn outcomes from all 12 public maternity services in Melbourne during the COVID-19 pandemic [19]. For this analysis, we only included singleton pregnancies born ≥ 20 weeks' gestation during the 4-year period from January 2020 to December 2023. We defined the lockdown-exposed cohort as births from January 2020 to December 2021, and the post-lockdown cohort as those from January 2022 to December 2023. Further methodological details are available elsewhere [19]. In this analysis, we focussed on three maternal and newborn outcomes:

a. Maternal overweight/obesity—A pre-pregnancy or early pregnancy BMI of ≥ 25.0 kg/m^2, encompassing both the overweight category (25.0–29.9 kg/m^2) and obesity (≥ 30.0 kg/m^2) [20].
b. GDM—Diabetes identified for the first time during pregnancy, as defined by the Australian Diabetes in

b. Pregnancy Society, with criteria including a fasting glucose level of ≥ 5.1 mmol/L or a 2-h glucose level of ≥ 8.5 mmol/L following a 75 g oral glucose tolerance test (OGTT)

c. LGA—Birthweight greater than or equal to 90th percentile for gestational age and sex (using a population-based sex-specific birthweight chart) [21, 22].

2.3 | Postcode Level Socio-Economic and Environmental Data Sources

The detailed methods of our data sources for postcode-level indicators are included in Supporting Information. In summary, we obtained the following:

- Socio-economic Indexes for Areas—Index of Relative Socio-economic Advantage and Disadvantage (SEIFA–IRSAD) scores sourced from the 2021 Australian Census [14]. The SEIFA–IRSAD is an ordinal measure initially scored from 1 to 10, with 10 representing the least disadvantaged areas and 1 indicating the most disadvantaged areas.
- Liveability Index: This index measures the quality of communities based on safety, social cohesion, environmental sustainability, affordable housing, and access to employment, education, services and public spaces through well-connected transport infrastructure (2021).
- Social Infrastructure Index (2021) reflects access to key community services and facilities.
- Distance to General Practitioner (GP) in metres (2021) sourced from the Australian Urban Observatory Databases [23].

We extracted 2019 and 2023 food environment data from OpenStreetMap (OSM, OpenStreetMap Foundation, Cambridge, UK) [24] using 'amenity' features to map food outlets across metropolitan Melbourne and regional Victoria. Outlets were classified following Needham et al. [25] into *Healthy* (supermarkets, butchers and greengrocers), *Less Healthy* (cafes, restaurants, bakeries and convenience stores), and *Unhealthy* (fast-food outlets, pubs, bars and biergartens). Data cleaning and processing were performed in R [26]. Food outlet counts were calculated within 500-m and 1500-m buffers from each postcode centroid. The 500-m buffer reflects a 5 to 10 min walk, capturing walkable access common in urban areas [27]. Larger buffers (1000 m and 1500 m) account for short drives typical in suburban and rural areas [28]. Food outlet density was calculated per 10 000 population for each postcode to standardise counts and account for population differences.

2.4 | Data Preprocessing

We used Multiple Imputation by Chained Equations (MICE) to handle missing data (Figure S2). This method creates multiple imputed datasets to account for the uncertainty caused by missing values, recovering statistical power and minimising the risk of bias. Variables included in the imputation model were COVID-19 lockdown exposure, individual-level covariates such as maternal age, parity, smoking status (yes or no), infant sex, need for interpreter and postcode-level environmental exposures (e.g., food environment indicators, IRSAD, walkability, liveability, social infrastructure index, average distance to the closest GP) and outcomes such as maternal overweight, GDM and LGA. After the imputation process, 20 imputed datasets were generated, and all subsequent analyses were pooled using Rubin's rules to account for the variability between imputations [29].

2.5 | Statistical Analysis

All analyses used R version 4.0.2 (R Foundation for Statistical Computing, Vienna, Austria) [26]. We generated the 4-year prevalence of maternal overweight, GDM and LGA for each postcode and visualised these prevalence rates using Tableau 2024.1 [30] and Mapbox [31].

We constructed a Directed Acyclic Graph (DAG) to visualise and assess the hypothesised causal relationships between food environment exposures, maternal overweight, GDM and LGA (Figure S1). Variable selections were guided by a priori subject matter expertises. Due to the high correlation of maternal country of birth with SEIFA–IRSAD and the need for an interpreter, as well as its concurrent limitation to reflect maternal nativity [32], we excluded the maternal country of birth from the models.

2.5.1 | Structural Equation Modelling—Examining the Combined Effects of External Environment and Individual-Level Factors

We used structural equation modelling (SEM) to evaluate the direct and indirect effects of food and built environment exposures on maternal overweight, GDM and LGA, with maternal overweight modelled as a mediator and GDM and LGA as outcomes. Individual-level covariates, including maternal age, smoking status and parity, were incorporated alongside environmental factors such as walkability and social infrastructure indices. The model accounted for clustering by postcode and reported standardised path coefficients with 95% confidence intervals.

Mediation analysis explored whether maternal overweight mediated the relationship between food environment exposures and GDM and LGA. A moderated mediation analysis further assessed whether the mediating effect of BMI varied by socio-economic status by including interaction terms between IRSAD and maternal overweight.

2.5.2 | Latent Class Analysis—Analysing Potential Population Subgroups With Differing Perinatal Risk Profiles

Latent class analysis (LCA) is an unsupervised learning technique that we used to explore differences in class membership across socio-economic strata. We stratified the LCA by IRSAD quintiles. The optimal number of latent classes was determined using Bayesian Information Criterion (BIC). Markov Chain

Monte Carlo simulations were conducted to assess the robustness of LCA results across IRSAD groups. Using posterior probabilities from the LCA, 1000 simulations were run to predict class membership for everyone, evaluating the stability of these memberships. The proportion of individuals assigned to each class was summarised for each simulation. Further details about LCA diagnostics were included in Table S4.

3 | Results

We included a total of 163 760 individuals across the 3-year study period; 84 955 (51.88%) from the COVID-19 lockdown period and 78 805 (48.12%) from the post-lockdown period (See Table S3 for summary statistics).

Figure 1 illustrates the spatial patterns of maternal health and socio-economic conditions across Greater Melbourne. Broadly, areas with higher IRSAD scores, particularly in the central and eastern districts of Melbourne, tended to have better maternal outcomes, while disadvantaged regions in the west and north experienced higher burdens of maternal overweight and GDM. These geographic trends are consistent with the findings of our previous study, which focused on area-level patterns of maternal health across Melbourne [33].

3.1 | Structural Equation Model

Table 1 presents the standardised structural coefficients (c) and 95% confidence intervals from the SEM.

Maternal overweight was positively associated with GDM (GDM; $c=0.118$, 95% CI: 0.113 to 0.124, $p<0.001$) and LGA infants (LGA; $c=0.058$, 95% CI: 0.055 to 0.062, $p<0.001$).

Exposure to the COVID-19 lockdown period was associated with a lower likelihood of maternal overweight ($c=-0.027$, 95% CI: -0.034 to -0.020, $p<0.001$). The density of unhealthy food outlets within 500 m was positively associated with maternal overweight

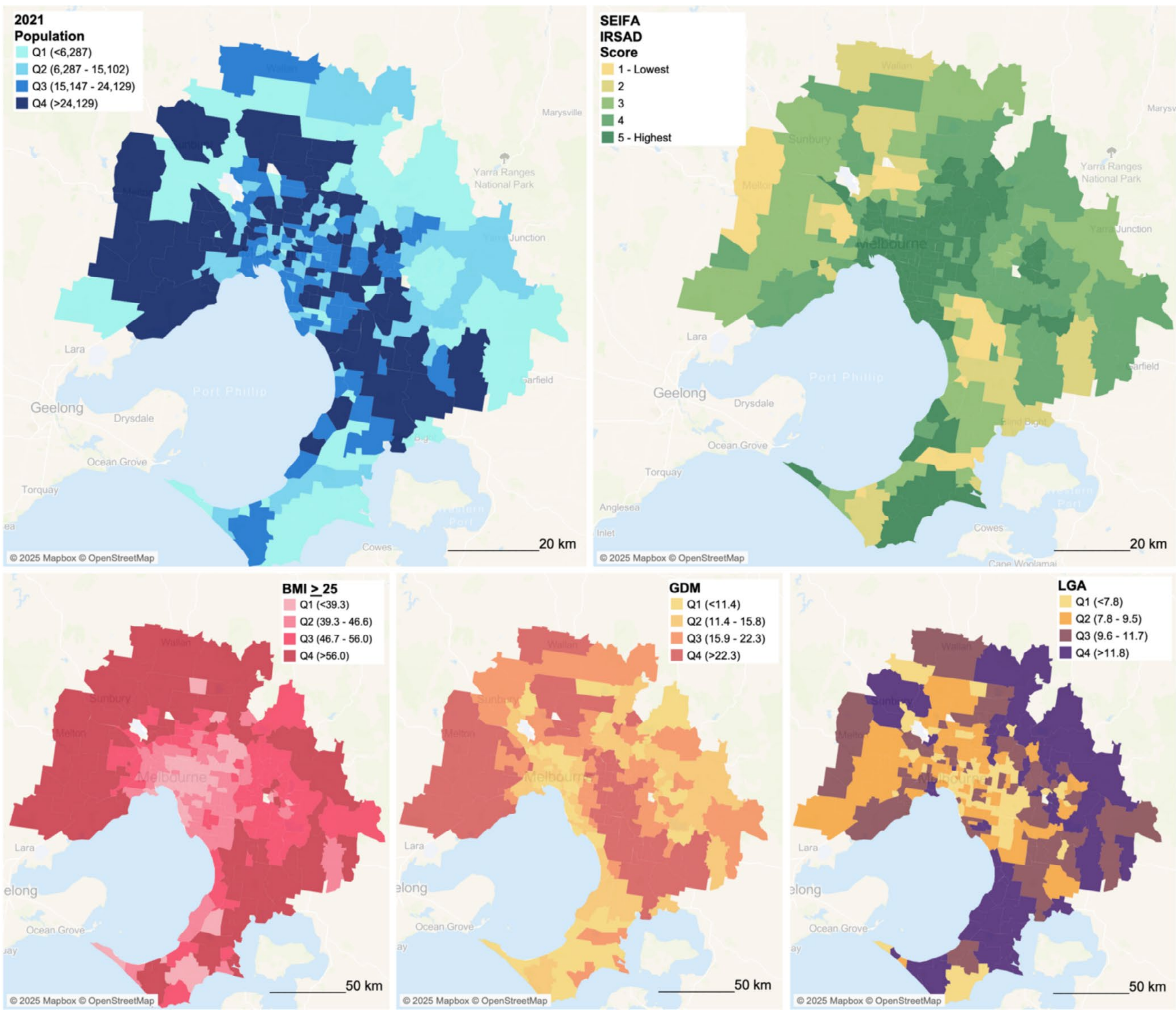

FIGURE 1 | Postcode-level population, IRSAD–quintile and quartile of prevalences of maternal overweight, GDM, and LGA in Metropolitan Melbourne, Australia. SEIFA IRSAD—Socio-Economic Indexes for Areas, Index of Relative Socio-economic Advantage and Disadvantage.

TABLE 1 | Structural Equation Modelling results and standardised coefficients of the association between exogenous/explanatory variables and maternal overweight, gestational diabetes, and LGA.

Exogenous (explanatory) variables	Endogenous (outcome) variables		
	Maternal overweight (c, 95% CI)	GDM (c, 95% CI)	LGA (c, 95% CI)
Maternal overweight	n/a	0.118 (0.113 to 0.124)***	0.058 (0.055 to 0.062)***
Gestational diabetes	n/a	n/a	−0.008 (−0.012 to −0.004)***
Postcode level factors			
COVID-19 lockdowns	−0.027 (−0.034 to −0.020)***	0.009 (0.004 to 0.015)***	0.003 (−0.001 to 0.007)
Healthy food outlet density 500 m	−0.007 (−0.063 to 0.049)	0.033 (−0.010 to 0.075)	−0.008 (−0.027 to 0.011)
Healthy food outlet density 1000 m	0.003 (−0.031 to 0.037)	−0.037 (−0.071 to −0.004)*	0.013 (−0.003 to 0.029)
Healthy food outlet density 1500 m	−0.050 (−0.071 to −0.029)***	0.024 (0.002 to 0.046)*	−0.007 (−0.017 to 0.003)
Unhealthy food outlet density 500 m	0.014 (0.004 to 0.023)**	−0.006 (−0.014 to 0.001)	−0.003 (−0.008 to 0.002)
Unhealthy food outlet density 1000 m	−0.005 (−0.024 to 0.013)	−0.012 (−0.030 to 0.007)	0.004 (−0.004 to 0.013)
Unhealthy food outlet density 1500 m	0.008 (−0.005 to 0.022)	−0.001 (−0.015 to 0.012)	0.003 (−0.004 to 0.010)
IRSAD	−0.014 (−0.019 to −0.009)***	−0.009 (−0.011 to −0.006)***	0.002 (0.001 to 0.003)**
Liveability	−0.011 (−0.019 to −0.002)*	−0.015 (−0.022 to −0.008)***	0.001 (−0.002 to 0.003)
Social infrastructure index	−0.005 (−0.014 to 0.003)	0.005 (−0.003 to 0.013)	−0.000 (−0.004 to 0.003)
Individual-level factors			
Parity	0.070 (0.062 to 0.079)***	0.000 (−0.005 to 0.006)	0.051 (0.047 to 0.055)***
Vaccinated with pertussis	−0.011 (−0.020 to −0.002)*	0.028 (0.021 to 0.035)***	−0.001 (−0.006 to 0.004)
Smoking status (Yes)	0.087 (0.074 to 0.101)***	−0.020 (−0.032 to −0.009)***	−0.026 (−0.034 to −0.018)***
Maternal age	0.011 (0.008 to 0.014)***	0.048 (0.043 to 0.053)***	−0.005 (−0.007 to −0.004)***
Gestation at first antenatal visit	0.002 (0.002 to 0.003)***	−0.002 (−0.002 to −0.001)***	−0.001 (−0.001 to −0.000)***
Need for interpreter	−0.102 (−0.127 to −0.077)***	0.089 (0.074 to 0.104)***	−0.018 (−0.027 to −0.009)***

Note: Density is per 10000 population.
Abbreviation: M, metres.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

(per 10-outlet increase: $c = 0.14$, 95% CI: 0.04 to 0.23, $p < 0.01$), while healthy food outlet density within 1500 m was inversely associated with maternal overweight (per 10-outlet increase: $c = -0.50$, 95% CI: −0.71 to −0.29, $p < 0.001$). Socio-economic advantage, measured by SEIFA–IRSAD, was inversely associated with maternal overweight ($c = -0.014$, 95% CI: −0.019 to −0.009, $p < 0.001$). Liveability scores were also inversely associated with maternal overweight ($c = -0.011$, 95% CI: −0.019 to −0.002, $p < 0.05$).

GDM was inversely associated with LGA infants ($c = -0.008$, 95% CI: −0.012 to −0.004, $p < 0.001$). Exposure to the COVID-19 lockdown period was associated with a slight increase in GDM ($c = 0.009$, 95% CI: 0.004 to 0.015, $p < 0.01$). Higher healthy food outlet density within 1000 m was associated with a reduced risk of GDM (per 10-outlet increase: $c = -0.37$, 95% CI: −0.71 to −0.004, $p < 0.05$). Socio-economic advantage was inversely associated with GDM ($c = -0.009$, 95% CI: −0.011 to −0.006, $p < 0.001$). Liveability scores were also inversely associated with GDM ($c = -0.015$, 95% CI: −0.022 to −0.008, $p < 0.001$). No significant associations were observed between lockdown and LGA. Socio-economic advantage was positively associated with LGA ($c = 0.002$, 95% CI: 0.001 to 0.003, $p < 0.01$).

At the individual level, parity was positively associated with maternal overweight ($c = 0.070$, 95% CI: 0.062 to 0.079, $p < 0.001$) and LGA ($c = 0.051$, 95% CI: 0.047 to 0.055, $p < 0.001$). Smoking during pregnancy was associated with higher maternal overweight ($c = 0.087$, 95% CI: 0.074 to 0.101, $p < 0.001$) and lower likelihoods of GDM ($c = -0.020$, 95% CI: −0.032 to −0.009, $p < 0.001$) and LGA ($c = -0.026$, 95% CI: −0.034 to −0.018, $p < 0.001$). Maternal age was positively associated with GDM ($c = 0.048$, 95% CI: 0.043 to 0.053, $p < 0.001$) and inversely associated with LGA ($c = -0.005$, 95% CI: −0.007 to −0.004, $p < 0.001$). A need for an interpreter was negatively associated with maternal overweight ($c = -0.102$, 95% CI: −0.127 to −0.077, $p < 0.001$) and positively associated with GDM ($c = 0.089$, 95% CI: 0.074 to 0.104, $p < 0.001$) but inversely associated with LGA ($c = -0.018$, 95% CI: −0.027 to −0.009, $p < 0.001$).

3.2 | Mediation and Moderation Analyses

In the mediation analysis (Table 2), the direct effect of maternal overweight on LGA was significant, with an estimate of 0.070 (95% CI: 0.064 to 0.076, $p < 0.001$). GDM had a small but significant negative direct effect on LGA (Estimate = −0.008, 95% CI: −0.012 to −0.004, $p < 0.001$). The indirect effect of maternal overweight on LGA through GDM was minimal (Estimate = −0.001, 95% CI: −0.001 to 0.000, $p < 0.001$). However, the total effect of maternal overweight on LGA (direct + indirect) remained strong (Estimate = 0.069, 95% CI: 0.063 to 0.075, $p < 0.001$). Taken together, these results suggest that the strong relationship between maternal overweight and LGA infants is not mediated through GDM.

We examined the interaction between maternal overweight and IRSAD using moderation analysis. The interaction term was not statistically significant for GDM, indicating no meaningful moderation effect, indicating that the relationship between maternal overweight and GDM did not vary meaningfully across levels of socio-economic status. However, a significant negative moderation effect was observed for LGA (Estimate = −0.002, 95% CI: −0.003 to −0.001, $p < 0.001$), suggesting that the association between maternal overweight and LGA was weaker in areas with higher socio-economic advantage.

3.3 | Latent Class Analysis

Table 3 presents the results of the LCA, summarising the probabilities of key outcomes (maternal overweight, GDM and LGA) across two latent classes, as well as the class proportions stratified by SEIFA quintiles. In Class 1, the probability of overweight is 85.1%, GDM is 34.4% and LGA is 15.1%, suggesting that individuals in this class are at higher risk for these adverse outcomes. In contrast, Class 2 shows lower probabilities for these outcomes, with 28.3% for maternal overweight, 11.3% for GDM

TABLE 2 | Mediation and moderation results.

Predictor	Outcome	Estimate	95% CI	*p*
Direct effects				
Maternal overweight (*c*)	Gestational diabetes	0.118	(0.113, 0.124)	< 0.001
IRSAD	Gestational diabetes	−0.009	(−0.011, −0.006)	< 0.001
Healthy Outlet density 1500 m	Gestational diabetes	0.024	(0.002, 0.046)	0.03
Healthy Outlet density 1000 m	Gestational diabetes	−0.037	(−0.071, −0.004)	0.029
Smoking during pregnancy	Gestational diabetes	−0.021	(−0.032, −0.009)	0.001
Maternal overweight (*b*)	LGA	0.058	(0.055, 0.062)	< 0.001
Gestational diabetes (*a*)	LGA	−0.008	(−0.012, −0.004)	< 0.001
Socio-economic position	LGA	0.003	(0.002, 0.004)	< 0.001
Indirect effects				
maternal overweight → GDM → LGA (a*c)	LGA	−0.001	(−0.001, 0.0001)	< 0.001
Total effects				
Maternal overweight (b + a*c)	LGA	0.057	(0.054, 0.061)	< 0.001
Moderation (interaction)				
Maternal overweight|Socio-economic position (SEIFA)	Gestational diabetes	−0.002	(−0.005, 0.000)	0.092
Maternal overweight|Socio-economic position (SEIFA)	LGA	−0.002	(−0.003, −0.001)	< 0.001

TABLE 3 | Latent class analysis results.

	Class 1 probability (%) (95% CI)	Class 2 probability (%) (95% CI)
Probability of outcome per risk group		
BMI ≥ 25 kg/m^2	85.1	28.3
GDM	34.4	11.3
LGA	15.1	5.8
Class proportion		
Overall	44.0 (43.8–44.3)	55.96 (55.8–56.2)
SEIFA		
Quintile 1—most disadvantaged	58.1 (57.4–58.7)	41.9 (41.3–42.5)
Quintile 2	60.2 (59.5–60.8)	39.9 (39.3–40.4)
Quintile 3	53.4 (52.9–53.9)	46.6 (46.1–47.1)
Quintile 4	37.7 (37.2–38.1)	62.3 (61.9–62.8)
Quintile 5—least advantaged	18.7 (18.3–19.1)	81.3 (80.9–81.7)

and 5.8% for LGA. The class proportions reveal that Class 1 accounts for 44.0% (95% CI: 43.8 to 44.3%) of the population, while Class 2 constitutes 56.0% (95% CI: 55.7% to 56.2%). Stratification by SEIFA quintiles highlights a socio-economic gradient. In Quintile 1 (most disadvantaged), 58.1% (95% CI: 57.4 to 58.7%) belong to Class 1, indicating a higher burden of adverse outcomes in more disadvantaged areas.

4 | Discussion

4.1 | Main Findings

We examined the independent associations of individual- and postcode-level factors on maternal overweight, GDM and LGA using a robust dataset and employing multiple analytical approaches. Our analysis confirms the known associations between maternal overweight and both GDM and LGA, and contributes novel data on the independent influence of the food, built environment and socio-economic disparities in the distribution of adverse perinatal health outcomes. Our unsupervised LCA analysis revealed two subgroups with distinct outcome profiles that were strongly associated with postcode-level socio-economic disadvantage.

The significant direct association of maternal overweight with both GDM and LGA is already well documented in the literature [34–36]. Interestingly, the mediation analysis revealed that while maternal overweight directly increases the risk of LGA, GDM plays a negligible role in mediating this relationship. This dispels previous assumptions that the effect of maternal weight on LGA is attributable to hyperglycaemia [34, 37]. The observed marginal effect of GDM on LGA in our population may reflect the effectiveness of Australia's universal screening and treatment programme for GDM [38]. Universal access to high-quality care including blood sugar control, foetal growth surveillance and timed birth may have attenuated the expected positive association between GDM and LGA. Alternatively, this finding may be influenced by unmeasured confounders, such as gestational weight gain, dietary interventions or differences in glycaemic severity, which were not captured in the present analysis.

The lower prevalence of maternal overweight during the lockdown period has several potential explanations. These findings may reflect statistical correction to the mean following a period of increasing maternal BMI demonstrated in our previous research [12]. Alternatively, it may reflect a change in the demographic profile of women giving birth during the economic turndown associated with the pandemic. A national study of birth trends in Australia reported a nationwide fertility increase in 2021, but Victoria (that state with the strictest pandemic restrictions) notably exhibited slower growth, especially in low-income or high-unemployment areas in Melbourne [39]. This may have resulted in proportionately more women of high SES giving birth during lockdown, thus affecting the prevalence of high maternal BMI.

4.2 | Interpretation

Maternal overweight was independently associated with the proximity of unhealthy food outlets, and negatively associated with higher densities of healthy food outlets. This supports the concept of the 'obesogenic environment', which posits that easy access to high-calorie, low-nutrient foods contributes to unhealthy weight gain [8]. Conversely, higher liveability scores, reflecting better infrastructure and access to recreational spaces, were associated with lower BMI independent of SES. While the effect sizes for food outlet densities and liveability were modest at the individual level, small effect sizes are expected in studies examining structural determinants of health, as these influences often operate indirectly through complex pathways involving mediators like access to resources, stressors and social norms [40]. These complex interactions dilute the direct impact on individuals but can still lead to substantial public health effects when scaled across populations, [41] particularly in communities with widespread exposure to unhealthy environments or limited access to health-promoting infrastructure.

Our study also demonstrates significant socio-economic disparities in maternal health outcomes in metropolitan Melbourne. Higher SES, as indicated by SEIFA–IRSAD scores, was inversely associated with maternal overweight and GDM, reinforcing existing literature that links lower SES with poorer health outcomes [7, 42]. This socio-patterned distribution of health risks contributes to cumulative disadvantage, where multiple risk factors coalesce to exacerbate health disparities [7, 42]. Addressing these socio-economic inequalities is important for improving maternal and neonatal health outcomes, necessitating comprehensive policies that enhance access to healthcare, nutritious food and supportive environments for disadvantaged populations [43, 44].

At the individual level, several factors were significantly associated with maternal health outcomes. Parity was positively associated with maternal overweight and LGA, corroborating previous research that links repeated pregnancies with increased weight gain and higher birth weights [45]. Additionally, women with higher parity tend to be older [45]. Smoking during pregnancy exhibited a paradoxical relationship; it was positively associated with elevated BMI but negatively associated with GDM and LGA. The inverse relationship of smoking with GDM may be attributable to nicotine's effects on appetite suppression and glucose metabolism [46, 47] or reflect unmeasured confounding or bias in the study, as illustrated elsewhere [48]. The negative association between smoking and LGA is expected given the adverse impact on placental function and foetal growth [49]. Older maternal age was positively associated with GDM and negatively associated with LGA. This is consistent with existing studies that identify advanced maternal age as a risk factor for GDM due to age-related declines in insulin sensitivity [50], while the negative association with LGA may reflect the association of maternal age with foetal growth restriction, the use of assisted reproductive technology, and other comorbidities such as preeclampsia that affect placental function.

4.3 | Strengths and Limitations

This study possesses several strengths that enhance the robustness and applicability of its findings. The large sample size of 163 760 individuals provides substantial statistical power and allows for a more precise estimation of associations across diverse population subgroups. The use of SEM offers a nuanced exploration of both direct and indirect relationships, while also identifying distinct risk profiles based on socio-economic and environmental factors. This dual-methodological approach provides a more comprehensive understanding of how individual, socio-economic and environmental factors influence maternal health outcomes, including maternal overweight, GDM and LGA. The inclusion of both individual-level and postcode-level variables ensures a holistic understanding of the multifaceted determinants influencing maternal and perinatal health outcomes.

Our study is limited by the use of observational data, which precludes the establishment of causal inferences, as unmeasured confounders may influence the observed associations. Variables such as dietary intake, physical activity levels and psychological stress were not available, potentially omitting important factors impacting our outcomes of interest. Additionally, we used SEM with linear assumptions; therefore, potentially missing any non-linear relationships. However, SEM remains a widely accepted method for analysing complex relationships between multiple variables as it can simultaneously estimate multiple pathways and account for measurement error, unlike traditional regression approaches. Another study's limitation is the inability to fully account for behavioural changes during the COVID-19 lockdown period, such as smoking in pregnancy, which may have influenced some of the observed associations.

The study's focus on the Melbourne region limits the generalisability of the findings to other settings with different socio-economic and environmental contexts. The use of postcode centroids to assign food environment exposures has the potential to introduce spatial misclassification. Individuals may reside several kilometres from the centroid, leading to systematic underestimation of food access in larger postcodes. Future research should aim to incorporate longitudinal data, explore non-linear modelling approaches and include additional variables to mitigate these limitations and further elucidate the pathways underlying maternal health disparities.

5 | Conclusion

Environmental factors, particularly the density of unhealthy food outlets, appear to be independently associated with increased maternal BMI, and as a result, more LGA infants. The identification of distinct high-risk groups among socio-economically disadvantaged populations signals the need for targeted public health interventions. To achieve meaningful population-level improvements, efforts must extend beyond individual behavioural change and address structural contributors to obesity, including the broader food environment.

Author Contributions

M.B.M.: conceptualisation, methodology, software, validation, data curation, formal analysis, visualisation, writing – original draft and funding acquisition; L.H.: conceptualisation, validation, data curation, visualisation, writing – review and editing, funding acquisition and supervision; D.L.R.: conceptualisation, validation, data curation, formal analysis, writing – review and editing, and funding acquisition; C.L.W.: validation, resources, and writing – review and editing; H.J.: conceptualisation, validation, formal analysis, and writing – review and editing, funding acquisition; P.M.S.: validation, resources, and writing – review and editing; J.M.S.: validation, resources, formal analysis, and writing – review and editing; J.F.: validation, resources, writing – review and editing; K.R.P.: validation, data curation, formal analysis, and writing – review and editing; B.W.M.: validation, resources, and writing – review and editing; S.P.: validation, writing – review and editing, and funding acquisition; S.P.W.: validation, writing – review and editing, and funding acquisition; N.P.: validation and writing – review and editing.

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Ethics Statement

Ethical approval for this study was granted by Mercy Health Human Research Ethics Committee (Ref. no 2023–044) issued on November 6, 2023. No waiver of individual consent was required for this study.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available upon reasonable request from researchers at approved research institutes, subject to approval from the HREC and data sharing agreements.

References

1. H. Das, J. Tiwari, S. Jena, and K. K. Sahu, "Maternal Health Situation in the Empowered Action Group States: How Far We Reached: A Comparative Analysis of National Family Health Survey-3 and 4," *International Journal of Community Medicine and Public Health* 8, no. 8 (2021): 3970.

2. M. A. Leddy, M. L. Power, and J. Schulkin, "The Impact of Maternal Obesity on Maternal and Fetal Health," *Reviews in Obstetrics and Gynecology* 1, no. 4 (2008): 170–178.

3. M. A. Salameh, O. Oniya, R. S. Chamseddine, and J. C. Konje, "Maternal Obesity, Gestational Diabetes, and Fetal Macrosomia: An Incidental or a Mechanistic Relationship?," *Maternal-Fetal Medicine* 5, no. 1 (2023): 27–30.

4. D. Mitanchez, C. Yzydorczyk, B. Siddeek, F. Boubred, M. Benahmed, and U. Simeoni, "The Offspring of the Diabetic Mother – Short- and Long-Term Implications," *Best Practice & Research. Clinical Obstetrics & Gynaecology* 29, no. 2 (2015): 256–269.

5. K. Kc, S. Shakya, and H. Zhang, "Gestational Diabetes Mellitus and Macrosomia: A Literature Review," *Annals of Nutrition and Metabolism* 66, no. Suppl. 2 (2015): 14–20.

6. M. K. Kahr, M. A. Suter, J. Ballas, et al., "Geospatial Analysis of Food Environment Demonstrates Associations With Gestational Diabetes," *American Journal of Obstetrics and Gynecology* 214, no. 1 (2016): 110.e1–110.e9.

7. M. Marmot, "Social Determinants of Health Inequalities," *Lancet* 365, no. 9464 (2005): 1099–1104.

8. E. Pineda, J. Stockton, S. Scholes, et al., "Food Environment and Obesity: A Systematic Review and Meta-Analysis," *BMJ Nutrition, Prevention & Health* 7 (2024): e000663.

9. C. Higgs, M. Lowe, P. Hooper, et al., "Policy Relevant Health Related Liveability Indicator Datasets for Addresses in Australia's 21 Largest Cities," *Scientific Data* 10, no. 1 (2023): 113.

10. M. Rao, S. Prasad, F. Adshead, and H. Tissera, "The Built Environment and Health," *Lancet* 370, no. 9593 (2007): 1111–1113.

11. L. Hui, M. Marzan, M.-A. Davey, et al., *COVID-19 Communique: A Report on Maternal and Newborn Outcomes During the COVID-19 Pandemic* (Safer Care Victoria, 2023).

12. A. J. Goldsack, M. B. Marzan, D. L. Rolnik, et al., "Trends in Maternal Body Mass Index, Macrosomia and Caesarean Section in First-Time Mothers During the Pandemic: A Multicentre Retrospective Cohort Study of 12 Melbourne Public Hospitals," *BMC Pregnancy and Childbirth* 24, no. 1 (2024): 706.

13. Australian Bureau of Statistics, "A. Australian Statistical Geography Standard (ASGS)," (2021), accessed June, 12, 2023, https://www.abs.gov.au/statistics/statistical-geography/australian-statistical-geography-standard-asgs.

14. Australian Bureau of Statistics, "Population: Census," (2021), Canberra, Australia.

15. A. Knottnerus and P. Tugwell, "STROBE—A Checklist to Strengthen the Reporting of Observational Studies in Epidemiology," *Journal of Clinical Epidemiology* 61, no. 4 (2008): 323.

16. P. Jia, C. Yu, J. V. Remais, et al., "Spatial Lifecourse Epidemiology Reporting Standards (ISLE-ReSt) Statement," *Health & Place* 61 (2020): 102243.

17. Australian Institute of Health Welfare, *Overweight and Obesity* (Australian Institute of Health Welfare, 2023).

18. Australian Institute of Health Welfare, *Australia's Mothers and Babies 2018: In Brief* (Australian Institute of Health and Welfare, 2020).

19. L. Hui, M. B. Marzan, S. Potenza, et al., "Collaborative Maternity and Newborn Dashboard (CoMaND) for the COVID-19 Pandemic: A Protocol for Timely, Adaptive Monitoring of Perinatal Outcomes in Melbourne, Australia," *BMJ Open* 11, no. 11 (2021): e055902.

20. Australia Institute of Health and Welfare, "Australia's Mothers and Babies," (2024), Australia Institute of Health and Welfare, AIHW: Canberra, Australia.

21. T. A. Dobbins, E. A. Sullivan, C. L. Roberts, and J. M. Simpson, "Australian National Birthweight Percentiles by Sex and Gestational Age, 1998–2007," *Medical Journal of Australia* 197, no. 5 (2012): 291–294.

22. Royal Australian and New Zealand College of Obstetricians and Gynecologists, "Diagnosis and Management of Suspected Fetal Macrosomia," (2021), Royal Australian and New Zealand College of Obstetricians and Gynecologists, RANZCOG.

23. Australian Urban Observatory, "Australian Urban Observatory, AUO, R.U. Centre for Urban Research, Editor," (2023).

24. M. Haklay and P. Weber, "Openstreetmap: User-Generated Street Maps," *IEEE Pervasive Computing* 7, no. 4 (2008): 12–18.

25. C. Needham, C. Strugnell, S. Allender, and L. Orellana, "Beyond Food Swamps and Food Deserts: Exploring Urban Australian Food Retail Environment Typologies," *Public Health Nutrition* 25, no. 5 (2022): 1140–1152.

26. R Core Team, *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical, in Computing, 2020).

27. L. E. Thornton, K. E. Lamb, and K. Ball, "Fast Food Restaurant Locations According to Socioeconomic Disadvantage, Urban–Regional Locality, and Schools Within Victoria, Australia," *SSM-Population Health* 2 (2016): 1–9.

28. C. E. Caspi, G. Sorensen, S. V. Subramanian, and I. Kawachi, "The Local Food Environment and Diet: A Systematic Review," *Health & Place* 18, no. 5 (2012): 1172–1187.

29. D. B. Rubin, "Inference and Missing Data," *Biometrika* 63, no. 3 (1976): 581–592.

30. Tableau Software, LLC, *Tableau Desktop* (Salesforce), (2024).

31. Mapbox, Inc., "Mapbox, Inc," Washington, DC, (2024).

32. Australia Institute of Health and Welfare, *Chronic Health Conditions Among Culturally and Linguistically Diverse Australians* (Australia Institute of Health and Welfare, 2021).

33. M. B. Marzan, D. L. Rolnik, J. Jiang, et al., "Geospatial Determinants of Maternal Overweight, Gestational Diabetes and Large for Gestational Age Birthweight in Melbourne During and After COVID-19 Lockdowns," *Australian and New Zealand Journal of Obstetrics and Gynaecology* (2025).

34. P. M. Catalano, "The Impact of Gestational Diabetes and Maternal Obesity on the Mother and Her Offspring," *Journal of Developmental Origins of Health and Disease* 1, no. 4 (2010): 208–215.

35. C. Monod, G. Kotzaeridi, T. Linder, et al., "Maternal Overweight and Obesity and Its Association With Metabolic Changes and Fetal Overgrowth in the Absence of Gestational Diabetes Mellitus: A Prospective Cohort Study," *Acta Obstetricia et Gynecologica Scandinavica* 103, no. 2 (2024): 257–265.

36. Z. Yang, H. Phung, L. Freebairn, R. Sexton, A. Raulli, and P. Kelly, "Contribution of Maternal Overweight and Obesity to the Occurrence of Adverse Pregnancy Outcomes," *Australian and New Zealand Journal of Obstetrics and Gynaecology* 59, no. 3 (2019): 367–374.

37. E. M. Aubry, S. Oelhafen, N. Fankhauser, L. Raio, and E. L. Cignacco, "Adverse Perinatal Outcomes for Obese Women Are Influenced by the Presence of Comorbid Diabetes and Hypertensive Disorders," *Scientific Reports* 9, no. 1 (2019): 9793.

38. D. A. Randall, J. M. Morris, P. Kelly, and S. J. Glastras, "Are Newly Introduced Criteria for the Diagnosis of Gestational Diabetes Mellitus Associated With Improved Pregnancy Outcomes and/or Increased Interventions in New South Wales, Australia? A Population-Based Data Linkage Study," *BMJ Open Diabetes Research & Care* 9, no. 1 (2021): e002277.

39. I. Mooi-Reci, M. Wooden, and F. Zilio, "Baby Bump or Baby Slump? COVID-19, Lockdowns, and Their Effects on Births in Australia," *Social Science & Medicine – Population Health* 25 (2024): 101604.

40. A. V. Diez Roux, "Conceptual Approaches to the Study of Health Disparities," *Annual Review of Public Health* 33 (2012): 41–58.

41. E. C. Matthay, E. Hagan, L. M. Gottlieb, et al., "Powering Population Health Research: Considerations for Plausible and Actionable Effect Sizes," *Social Science & Medicine – Population Health* 14 (2021): 100789.

42. K. F. Ferraro and J. A. Kelley-Moore, "Cumulative Disadvantage and Health: Long-Term Consequences of Obesity?," *American Sociological Review* 68, no. 5 (2003): 707–729.

43. K. Thomson, M. Moffat, O. Arisa, et al., "Socioeconomic Inequalities and Adverse Pregnancy Outcomes in the UK and Republic of Ireland: A Systematic Review and Meta-Analysis," *BMJ Open* 11, no. 3 (2021): e042753.

44. S. N. Zenk, L. L. Lachance, A. J. Schulz, G. Mentz, S. Kannan, and W. Ridella, "Neighborhood Retail Food Environment and Fruit and Vegetable Intake in a Multiethnic Urban Population," *American Journal of Health Promotion* 23, no. 4 (2009): 255–264.

45. J. Dai, Y. Shi, Y. Wu, et al., "The Interaction Between Age and Parity on Adverse Pregnancy and Neonatal Outcomes," *Frontiers in Medicine* 10 (2023): 1056064.

46. B. Tarasi, J. Cornuz, C. Clair, and D. Baud, "Cigarette Smoking During Pregnancy and Adverse Perinatal Outcomes: A Cross-Sectional Study Over 10 Years," *BMC Public Health* 22, no. 1 (2022): 2403.

47. S. Reeves and I. Bernstein, "Effects of Maternal Tobacco-Smoke Exposure on Fetal Growth and Neonatal Size," *Expert Review of Obstetrics & Gynecology* 3, no. 6 (2008): 719–730.

48. M. A. Luque-Fernandez, H. Zoega, U. Valdimarsdottir, and M. A. Williams, "Deconstructing the Smoking-Preeclampsia Paradox Through a Counterfactual Framework," *European Journal of Epidemiology* 31, no. 6 (2016): 613–623.

49. R. J. Selvaratnam, U. Sovio, E. Cook, F. Gaccioli, D. S. Charnock-Jones, and G. C. S. Smith, "Objective Measures of Smoking and Caffeine Intake and the Risk of Adverse Pregnancy Outcomes," *International Journal of Epidemiology* 52, no. 6 (2023): 1756–1765.

50. Y. Li, X. Ren, L. He, J. Li, S. Zhang, and W. Chen, "Maternal Age and the Risk of Gestational Diabetes Mellitus: A Systematic Review and Meta-Analysis of Over 120 Million Participants," *Diabetes Research and Clinical Practice* 162 (2020): 108044.

Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Appendix S1:** bjo18357-sup-0001-AppendixS1.docx.