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Chemical Contaminant Exposure among Pregnant Women: Socio-Ecological Characteristics and the Role of Migration Status

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Table of Contents

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~ À toute !

LIST OF ACRONYMS

ANSES	Agence nationale de sécurité sanitaire de l'alimentation, de l'environnement et du travail (French Agency for Food, Environmental and Occupational Health & Safety)
BFR	Brominated Flame Retardants
BMI	Body Mass Index
DAG	Directed Acyclic Graph
ELFE	Étude Longitudinale Française depuis l'Enfance (French Longitudinal Study of Childhood)
FFQ	Food Frequency Questionnaire
INSEE	Institut National de la Statistique et des Études Économiques (National Institute of Statistics and Economic Studies, France)
IQR	Interquartile Range
MeHg	Methylmercury
MICE	Multivariate Imputation by Chained Equations
PAH	Polycyclic Aromatic Hydrocarbons
PCB	Polychlorinated Biphenyls
PFAS	Per- and Polyfluoroalkyl Substances
PNNS	Programme National Nutrition Santé
SEC	Socio-Ecological Characteristics
SNMU	Sparse Non-negative Matrix Under-approximation
TDS	Total Diet Study
VIF	Variance Inflation Factor
TE-F-PAH	Dominated by metals and furans
PCB-BFR-Aso-MeHg	Includes brominated flame retardants (BFRs), polycyclic aromatic hydrocarbons (PAHs), and PCB 28
Pest-1	Primarily composed of pesticide residues
Pest-2	A distinct group of PAHs
Pest-3	A mixture of mycotoxins and pesticides
PFAA-Ge-Li	Encompasses perfluoroalkyl substances (PFAS), dioxins, and furans
Mixt3	Includes PFOA, metals, and bisphenol A (BPA)
Mixt4	Comprised of mycotoxins and acrylamide

ABSTRACT ENGLISH

Title: Chemical Contaminant Exposure among Pregnant Women: Socio-Ecological Characteristics and the Role of Migration Status

Background: Prenatal exposure to chemical contaminants is a public health concern, particularly for vulnerable populations such as pregnant women and immigrants. Social, behavioral, and environmental factors contribute to disparities in exposure patterns.

Methods: Data from the French ELFE birth cohort (n = 12,201) were used to assess exposure to 210 contaminants through diet during pregnancy. Exposure data were summarized into eight latent chemical mixture exposures using Sparse Non-negative Matrix Under-approximation (SNMU). A hierarchical regression framework was used to examine the socioecological characteristics (e.g., migration status, education, income, smoking) related to the exposure to chemical mixtures.

Results: Migration status, income, and smoking were associated with variation in chemical mixture exposures. Immigrant women had higher scores for PCB-BFR-MeHg, Pest-3, and Mixt-4. Smoking was positively associated with TE-F-PAH; higher income was negatively associated with TE-F-PAH and positively with PCB-BFR-MeHg. In stratified models by migration status, education and income were associated with higher exposures among descendants of immigrants, while BMI and smoking were associated with higher exposures among non-immigrants. Among immigrants, only unemployment was consistently associated with exposure.

Conclusion: Heterogeneous chemical mixture exposures during pregnancy were associated with indicators of social position and health behaviors. Applying a socioecological framework in combination with mixture modeling may help clarify how multilevel social factors shape environmental exposure patterns and support the development of targeted public health strategies.

Keywords: chemical mixtures, pregnancy, migration, social determinants, exposure disparities, SNMU

ABSTRACT FRENCH

Titre: Exposition aux contaminants chimiques chez les femmes enceintes : caractéristiques socio-écologiques et rôle du statut migratoire

Contexte: L'exposition prénatale aux contaminants chimiques représente un enjeu de santé publique, en particulier pour les populations vulnérables telles que les femmes enceintes et les immigrées. Des facteurs sociaux, comportementaux et environnementaux contribuent aux disparités dans les profils d'exposition.

Méthodes: Les données de la cohorte de naissance française ELFE (n = 12,201) ont été utilisées pour estimer l'exposition par voie alimentaire à 210 contaminants pendant la grossesse. Ces données ont été résumées en huit mélanges chimiques à l'aide de la méthode SNMU (Sparse Non-negative Matrix Under-approximation). Un modèle socioécologique a été utilisé pour examiner les associations entre les facteurs socio-écologiques (par exemple, statut migratoire, niveau d'éducation, revenu, tabagisme) et l'exposition aux mélanges.

Résultats : Le statut migratoire, le revenu et le tabagisme étaient associés aux expositions aux mélanges chimiques. Les femmes immigrantes présentaient des scores plus élevés pour les mélanges PCB-BFR-MeHg, Pest-3 et Mixt-4. Le tabagisme était positivement associé aux scores TE-F-HAP ; un revenu plus élevé était associé négativement à TE-F-HAP et positivement à PCB-BFR-MeHg. Dans les modèles stratifiés selon le statut migratoire, l'éducation et le revenu étaient associés à des expositions plus élevées chez les descendantes d'immigrés, tandis que l'IMC et le tabagisme l'étaient chez les non-immigrantes. Chez les immigrantes, seul le chômage était systématiquement associé à l'exposition.

Conclusion: Des expositions chimiques hétérogènes pendant la grossesse étaient associées à des indicateurs de position sociale et de comportements liés à la santé. L'application d'un modèle socioécologique en combinaison avec la modélisation de mélanges pourrait aider à clarifier comment les facteurs sociaux influencent les schémas et à soutenir le développement de stratégies de santé publique ciblées.

Mots-clés: mélanges chimiques, grossesse, migration, déterminants sociaux, disparités d'exposition, SNMU

INTRODUCTION

Chemical Exposure and Public Health Implications

Food is a major source of chemical exposure and presents a persistent concern for public health. According to the European Food Safety Authority (1), dietary contaminants include natural toxins (e.g., mycotoxins), environmental pollutants (e.g., PFAS, pesticides), and processing by-products (e.g., acrylamide, PAHs). These substances are associated with various adverse health outcomes and may disproportionately affect vulnerable populations, including pregnant women and immigrants (2). Understanding how these exposures are socially patterned is critical for addressing environmental health disparities.

Pregnant Women as a Vulnerable Population

Pregnancy is a physiologically dynamic period during which women may be more susceptible to chemical exposures. Hormonal fluctuations, increased blood volume, and higher nutritional demands can alter detoxification pathways and immune responses, potentially amplifying toxic effects (3). In France, pregnant women are commonly exposed to a wide range of dietary contaminants, including persistent organic pollutants and trace elements (4). These exposures have been linked to elevated oxidative stress, endocrine disruption, and complications such as gestational diabetes (5,6). Because prenatal exposure can affect both maternal and fetal health, identifying population-level characteristics is an essential public health priority.

Migration and Disparities in Chemical Exposure

Among these characteristics, migration status plays a central role in shaping exposure risk. Europe remains the world's leading destination for international migrants, and in 2025, France hosted approximately 7.5 million immigrants, 11.2% of the national population (7). Research consistently shows that environmental exposure patterns differ between immigrant and non-immigrant populations, often reflecting disparities in socioeconomic conditions, housing, occupation, and behavioral factors. For example, pregnant women of Latin American-origin in urban areas are often more exposed to air pollutants like nitrogen dioxide (NO_2), a disparity attributed to residential segregation and systemic inequities (8). In Canada, Canadian-born women tend to have higher concentrations of persistent pollutants including PCBs and organochlorine pesticides (9). Conversely, in the U.S., immigrant pregnant women have been found to carry lower PFAS burdens than their U.S.-born counterparts (10).

Dietary Patterns and Chemical Exposure in Immigrant Women

Diet is one of the most important behavioral pathways through which social position and migration status influence chemical exposure. In France, where immigrant women represent a significant share of the population (11) dietary patterns vary by migration history. Recent immigrants often report diets of higher nutritional quality, with lower consumption of ultra-processed foods during pregnancy (12). However, as acculturation progresses, these dietary advantages tend to diminish, and exposure risk may increase. For example, women who spent their entire lives in the U.S. had 38% higher urinary BPA concentrations than those born abroad, underscoring how acculturative dietary changes may elevate chemical exposure (13).

Yet diet is only part of the picture; broader socioeconomic and environmental conditions, such as employment, housing, and stress, also shape exposure risk and tend to vary systematically with migration status (14).

Research Gaps

Despite growing recognition that environmental exposures are structured by social characteristics, relatively little research has examined how these dynamics unfold across diverse immigrant populations. Most studies focus on single pollutants or isolated socioeconomic variables, without capturing the combined influence of structural, economic, and behavioral factors. Moreover, few analyses assess whether the relationship between these characteristics and exposure differ by migration status (9,14). To address this gap, the present study explores how a broad range of socio-ecological factors including migration status, education, income, employment, smoking, and BMI relate to dietary chemical mixture exposures during pregnancy. Using nationally representative data from the ELFE birth cohort (15), we also examine whether these associations vary across migration groups.

Objectives

Primary Objective: To examine how distal, intermediate and proximal socioecological characteristics are associated with chemical mixture exposure in pregnant women.

Secondary Objective: To assess how migration status moderates the associations between socioecological characteristics and chemical mixture exposures.

Hypotheses

Primary Hypothesis: Socioecological characteristics are associated with chemical mixture exposures among pregnant women: Distal factors: Migration status and education level. Intermediate factors: Household income and maternal employment status. Proximal factors: Tobacco use and BMI.

This socioecological framework is based on the Dahlgren and Whitehead socioecological model (16) and the model developed by Victora (17) which conceptualizes health characteristics as layered and interacting. Previous studies have linked these individual (e.g., tobacco use, BMI) and contextual (e.g., household income, migration status) characteristics to variations in exposure to metals, persistent organic pollutants, and endocrine-disrupting chemicals (6,9,14).

Secondary Hypothesis: Migration status and education are conceptualized as distal structural characteristics that may influence more intermediate factors such as employment status and household income, which in turn shape proximal behavioral characteristics such as tobacco use and BMI. We hypothesize that migration status moderates the associations between these socioecological factors and chemical contaminant exposure, such that the relationships between socioeconomic status (SES) or behavioral characteristics and exposure may differ across migration subgroups (12).

METHODS

Study Population

The ELFE study (French Longitudinal Study of Childhood) is a national, multidisciplinary birth cohort initiated in 2011, which includes 18,329 children born in a random sample of 349 maternity hospitals across metropolitan France (15). The study aimed to collect comprehensive socio-demographic data, including information from mothers gathered during a telephone interview at two months postpartum and from the maternity unit at the time of delivery. Recruitment occurred on 25 selected days across four waves, ensuring representation of each season and addressing potential seasonal confounding (15).

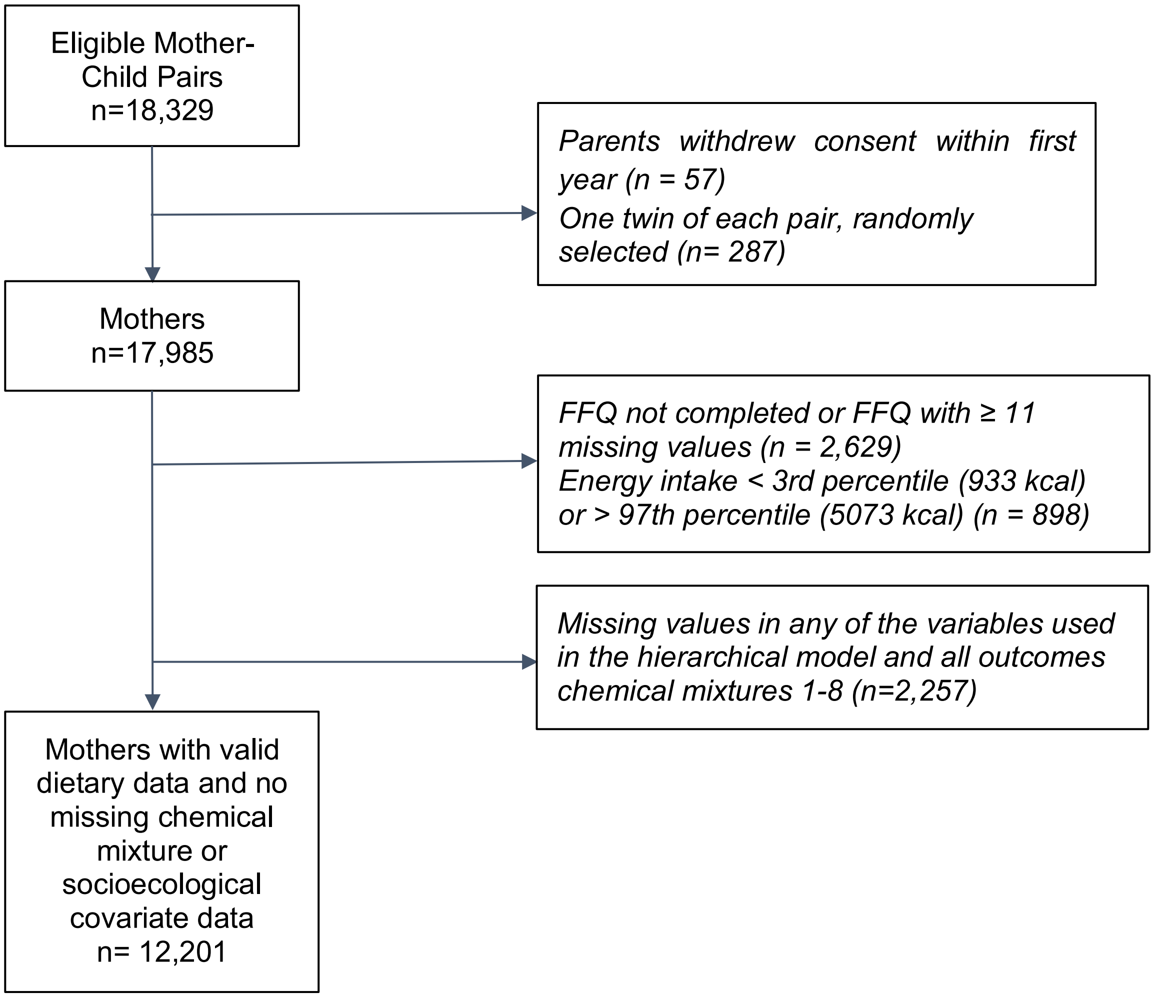
Ethical Considerations

All participants in the ELFE study provided written informed consent prior to inclusion. Consent forms were made available in multiple languages including French, Arabic, Turkish, and English to ensure accessibility. Fathers were also informed of the study and signed consent forms when present or were notified of their right to object to participation. The ELFE study received ethical approval from the Comité Consultatif sur le Traitement des Informations pour la Recherche en Santé, the Commission Nationale Informatique et Libertés (CNIL), and the Conseil National de l'Information Statistique. These approvals ensured compliance with French data protection laws and ethical standards for research involving human participants (15).

Sample Selection

From the initial ELFE cohort of 18,329 children, we excluded those whose parents withdrew consent during the first year (n = 57) and one randomly selected twin from each twin pair (n = 287), resulting in 17,985 mothers. Mothers with incomplete Food Frequency Questionnaires (FFQs) (n = 2,629) or implausible energy intakes, defined as below the 3rd percentile (< 933 kcal/day) or above the 97th percentile (> 5,073 kcal/day) (n = 898), were also excluded. Additionally, mothers with missing data on any covariates or on the eight derived chemical mixture were excluded (n = 2,257). The final analytic sample included 12,201 mothers based on complete case data (Figure 1).

Figure 1. Flowchart of sample selection.

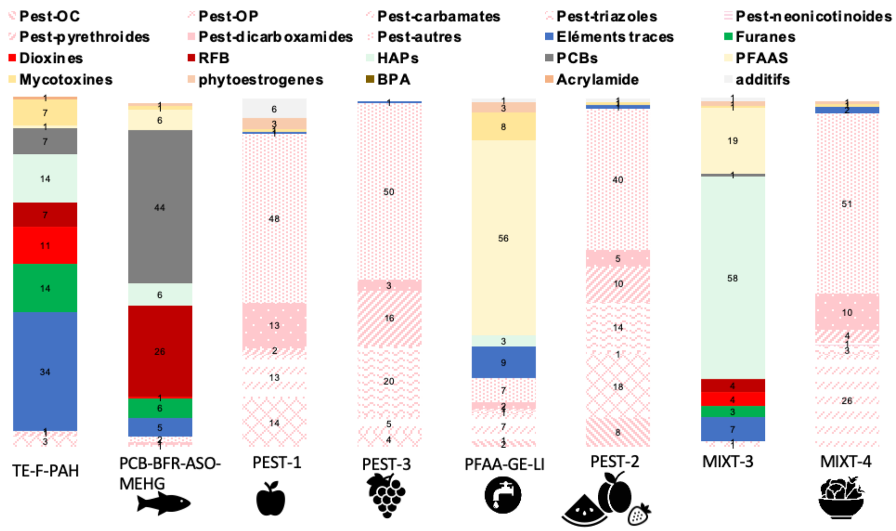


Outcomes

Exposure to 210 foodborne chemical contaminants was estimated by combining individual-level dietary intake data from the ELFE Food Frequency Questionnaire (FFQ) with contamination data from the first French Total Diet Study (EAT1) conducted by ANSES (4). The FFQ, administered during pregnancy, covered 115 food items and collected information on consumption frequency and portion size over the previous 3 months. These data were used to calculate the average daily intake of each food item. Contaminant concentrations were derived from EAT1, which analyzed 338 composite food items representative of the French diet. Foods were collected, prepared, and analyzed as consumed, providing realistic contamination estimates. The study covered a wide range of substances, including trace elements, persistent organic pollutants, and mycotoxins, using harmonized laboratory protocols. Exposure scores were computed as the product of average daily intake (g/day) and contaminant concentration (μg/g) per food item (4).

To address correlations among exposures, Sparse Non-Negative Matrix Under-Approximation (SNMU) was applied to the full set of 210 dietary chemicals. SNMU is a dimensionality reduction technique that groups co-occurring chemicals into interpretable mixture profiles, allowing for some overlap in chemical composition. This approach better reflects real-life co-exposure scenarios than single-compound analyses (4). Based on this approach, eight chemical mixtures (Figure 2) were identified and functioned as the outcome variables in this study. Each mixture score was treated as a continuous variable (18).

Figure 2. Composition of NMU chemical mixture scores from prenatal dietary exposure (18).



We analyzed NMU-defined chemical mixture groups based on co-occurrence patterns across multiple substance classes. To interpret the potential relevance of these mixtures for pregnancy, we summarized their composition and typical exposure sources (Table 1), drawing on prior literature on chemical occurrence in food, air, and consumer products (1,4,19).

Table 1. Composition and exposure context of NMU-defined chemical mixture groups (1,4,19).

Mixture Group	Main Components	Common Sources
TE-F-PAH	Trace elements (e.g., Cr VI, Pb, Co, V), furans, PAHs	Air pollution, food, water
PCB-BFR-Aso-MeHg	PCBs, PBDEs, PBBs, organic As, MeHg	Contaminated fish, dust, diet
Pest-1	Carbamates, organophosphates, fungicides	Food residues, agriculture
Pest-2	Pyrethroids, organophosphates, triazoles, additives	Household products, food
Pest-3	Pyrethroids, triazoles, carbamates, PAHs	Food, storage treatments
PFAA-Ge-Li	PFAAs, Li, Ge, mycotoxins, phytoestrogens	Water, packaging, diet
Mixt-3	Long-chain PFAAs, PAHs, Cd, Ag, HBCD, OCDD	Dust, food preparation, emissions
Mixt-4	Pesticides, Sn, Li, phytoestrogens	Diet, agriculture

Socio-Ecological Characteristics

Sociodemographic, socioeconomic, and behavioral variables were selected based on their theoretical relevance to dietary exposure and their availability in the ELFE cohort. All models were adjusted for maternal age (continuous) and parity (primiparous vs. multiparous).

Migration status was defined as non-immigrant, descendant of immigrants (born in France to at least one immigrant parent), or immigrant (born outside France). Maternal education was categorized into three levels: primary, secondary (middle or high school), and higher education.

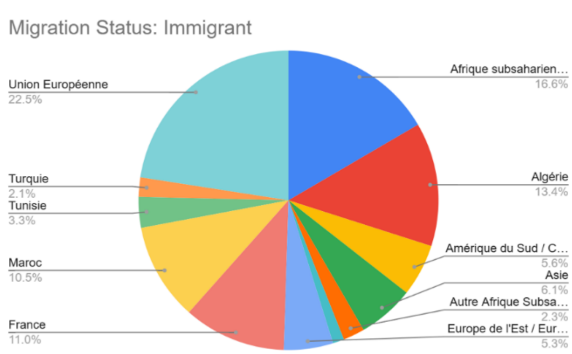
Socioeconomic conditions during pregnancy were assessed using standardized ELFE questionnaires administered during pregnancy and postnatally. Household income per consumption unit (over a two-month period, adjusted for household size) was categorized into low (< €1,064.58), intermediate (€1,064.58–€2,752.08), and high (> €2,752.08) levels based on national thresholds from INSEE's 2011 classification (7). Maternal employment status during pregnancy was categorized as employed or unemployed.

Behavioral and biological characteristics included smoking history and pre-pregnancy BMI. Smoking was classified as never smoked vs. ever smoked (before or during pregnancy), based on self-report. Pre-pregnancy BMI was calculated from self-reported height and weight and categorized according to WHO guidelines (20): underweight (<18.5 kg/m²), normal weight (18.5–24.9 kg/m²), overweight (25–29.9 kg/m²), and obese (≥30 kg/m²).

Geographic origins of mothers by migration status

Figure 4 shows the distribution of maternal geographic origins among immigrant mothers in the ELFE cohort. This group displayed substantial geographic diversity: 22.5% were born in the European Union, 16.6% in Sub-Saharan Africa, 13.4% in Algeria, 10.5% in Morocco, 6.5% in South and Central America, and 4.8% in Asia. Smaller proportions originated from Tunisia, Turkey, and Eastern Europe. These results highlight the heterogeneity of geographic origins within the immigrant population.

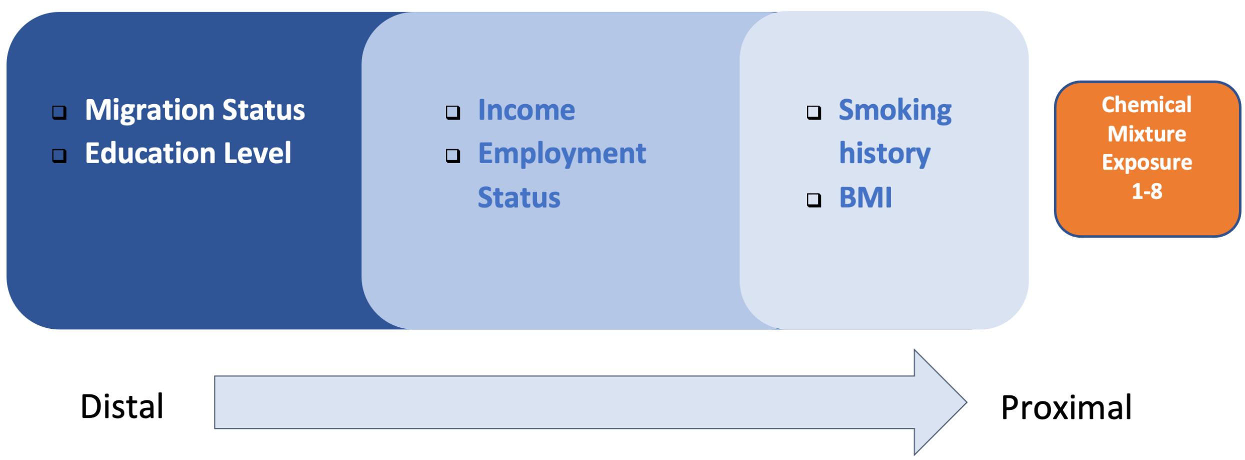
Figure 3. Geographic Origins of Mothers in the ELFE cohort with Immigrant as Migration Status



Hierarchical Approach

Regression models were limited to complete cases in this analysis; future work will incorporate strategies to address missing data like Multiple Imputation by Chained Equation (MICE). A socio-ecological modeling strategy was implemented, entering covariates in conceptually ordered blocks. This hierarchical approach (Figure 4), based on the framework proposed by Victora (17), is principally to avoid overadjustment for intermediate (i.e., mediating) variables. By respecting the assumed order of influence between variables, this approach allows for the estimation of total effects of distal characteristics, such as migration status or education, before adjusting for more intermediate variables like income or employment, and finally for proximal behavioral factors such as tobacco use and BMI. This strategy helps avoid merging total and direct effects and prevents masking the influence of structural characteristics. Potential interactions were tested using ANOVA to assess effect modification, and significant interactions (e.g., between migration status and maternal education) were retained for stratified modeling. Normality of continuous variables was evaluated using visual (e.g., histograms, QQ plots) and statistical tests (Shapiro-Wilk) to confirm model assumptions. We addressed categorical variables by combining or reclassifying categories to improve model stability. These steps were implemented in code to reduce error, bias, and model issues during the analysis.

Figure 4 Socio-Ecological Model 3.



Statistical Analyses

Handling of Missing Data

A complete-case analysis was conducted, whereby participants missing any variable used in the models were excluded (Figure 2). This approach ensured model consistency but resulted in the exclusion of participants with incomplete baseline data. Since most variables were collected at inclusion or within the first two months, the main limitation is not selection bias due to loss to follow-up, but rather missing data for participants who were still active in the cohort. Future analyses will implement (MICE) to handle this missing data and reduce loss of information more appropriately.

Descriptive Analyses

Differences between included and excluded samples (see Table 2 in the Results section) were assessed using Pearson's chi-squared test for categorical variables and the Wilcoxon rank sum test for continuous variables. Continuous variables were summarized as means (SD) or medians (IQR), depending on distribution. Categorical variables were reported as counts and percentages. Distributions were assessed visually using histograms with normal curves and statistically using the Shapiro–Wilk test.

Exploratory Correlation Analysis

A heatmap was constructed to describe preliminary associations between socio-ecological characteristics and chemical mixtures as seen in Appendix A. Depending on variable type, Pearson correlation, Spearman correlation, or eta-squared values were computed. These unadjusted associations were visualized according to significance levels to explore broad patterns and inform subsequent regression modeling.

Regression Analysis

Linear regression models were used to assess associations between sociodemographic variables and chemical mixtures: TE-F-PAH, PCB-BFR-ASO-MEHG, PEST-3, PEST-2 and MIXT4. These mixtures, previously derived using SNMU, were treated as continuous outcome variables.

Global Significance Testing

For categorical predictors with more than two levels (e.g., BMI, education), Type III ANOVA was used to evaluate overall significance using the *car::Anova()* function. This allowed for a global test of the variable's effect on the outcome, regardless of the significance of individual contrasts.

Interaction and Stratified Analyses

To assess potential effect modification within the socioecological framework, interaction terms between migration status and maternal education were tested for each chemical mixture, based on prior literature suggesting joint influences on exposure patterns (12). These terms were added to Block 1 models, and interaction significance was evaluated using likelihood ratio tests comparing nested linear models. Significant interactions were identified for Mixtures Pest-1, PFAA-Ge-Li, and Mixt3 for which stratified analyses were conducted. The present results focus on mixtures: TE-F-PAH, PCB-BFR-ASO-MEHG, PEST-3, PEST-2 and MIXT4, where there was no significant interaction.

Model Diagnostics

Model assumptions were evaluated for all regression models. Normality of residuals was tested using the Shapiro-Wilk test. To assess homogeneity of variance, Levene's Test was used to evaluate whether residuals had equal variance across categorical predictor groups (e.g., BMI, income terciles). Multicollinearity was assessed using Generalized Variance Inflation Factors (GVIF). These diagnostics were used to ensure valid inference from regression models.

Sensitivity Analyses

Sensitivity analyses have not yet been conducted. However, multiple imputation will be implemented to address missing data as part of the next phase of the analysis, planned for completion by the end of the internship.

Software

All analyses were performed using RStudio version 4.2.1. A significance level of $p < 0.05$ was used for all statistical tests. Key R packages included: ***dplyr, gtsummary, ggplot2, car, broom, sandwich, lmtest, officer, flextable, haven, labelled, effectsize.***

RESULTS

Descriptive

Participants included in the analysis (N = 12,201) differed from those excluded (N = 6,128) across several characteristics (Table 2). Included women were more likely to be non-immigrants (83% vs. 69%) and to hold higher education degrees (40% vs. 34%). They were also more frequently employed during pregnancy (76% vs. 58%) and more likely to fall within the medium income bracket (74% vs. 55%). A greater proportion had a normal BMI (65% vs. 60%) and were slightly older on average (31 vs. 30 years). No significant differences were observed for parity.

Table 2. Comparison of Included and Excluded Participants on Key Socio-Ecological Characteristics (ELFE Cohort)

Characteristic	**Excluded** N = 6,128[1]	**Included** N = 12,201[1]	**p-value**[2]
Migration Status			<0.001
Non-Immigrant	2,917 (69%)	10,089 (83%)	
Descendant of Immigrant	515 (12%)	1,207 (9.9%)	
Immigrant	775 (18%)	905 (7.4%)	
Education Level			<0.001
Primary Education	23 (0.7%)	19 (0.2%)	
Secondary Education - Middle School	212 (6.0%)	368 (3.0%)	
Secondary Education - High School	2,100 (59%)	6,986 (57%)	
Higher Education	1,196 (34%)	4,828 (40%)	
Tobacco History			0.011
History of Smoking	2,395 (41%)	5,305 (43%)	
Never Smoked	3,380 (59%)	6,896 (57%)	
Employment Status			<0.001
Unemployed	1,766 (42%)	2,924 (24%)	
Employed	2,437 (58%)	9,277 (76%)	
Parity			0.14
Primipara	1,955 (33%)	4,150 (34%)	
Multipara	3,986 (67%)	8,051 (66%)	
BMI			<0.001
Underweight (<18.5 kg/m²)	517 (9.1%)	890 (7.3%)	
Normal weight (18.5-24.9 kg/m²)	3,438 (60%)	7,982 (65%)	
Overweight (25-29.9 kg/m²)	1,094 (19%)	2,175 (18%)	
Obesity (≥30 kg/m²)	652 (11%)	1,154 (9.5%)	
Income Brackets by Household Consumption Unit (€/month)			<0.001
Low	1,237 (37%)	2,215 (18%)	

Characteristic	Excluded N = 6,128[1]	Included N = 12,201[1]	p-value[2]
Medium	1,841 (55%)	8,993 (74%)	
High	260 (7.8%)	993 (8.1%)	
Age	30 (5.59)	31 (4.76)	<0.001

[1]n (%); Mean (SD)
[2]Pearson's Chi-squared test; Wilcoxon rank sum test

Regression Results for Socio-Ecological Characteristics

We examined associations between estimated dietary chemical mixture exposures and maternal socio-ecological factors, organized using a socio-ecological framework. Using this framework, we observed that dietary chemical mixture exposures during pregnancy varied by structural, socioeconomic, and individual-level maternal characteristics. As no interaction with migration status was highlighted for 5 of the 8 mixtures TE-F-PAH, PCB-BFR-ASO-MEHG, PEST-3, PEST-2 and MIXT4, the socio-ecological regression models were conducted on the whole sample (Table 3).

Block 1 distal: (migration status and education level)—particularly migration status—were consistently linked to the different chemical mixtures, with higher exposures observed among immigrant women for three mixtures (PCB-BFR-ASo-MeHg, Pest-3, and Mixt-4), whereas maternal education was associated with only one mixture (Mixt-4). All models were adjusted for maternal age and parity.

Block 2 intermediate: (income and employment status) were differentially associated with chemical mixtures. Unemployment was positively associated with TE-F-PAH and Mixt-4 chemical mixtures. For income, associations varied in direction and magnitude across mixtures. Specifically, high income was positively associated with PCB-BFR-ASO-MEHG exposure, while associations for other mixtures were weaker and less consistent.

In Block 3 proximal: (tobacco use and BMI) ever smoking was associated with higher TE-F-PAH scores but lower scores for the PEST-3 and PEST-2 mixtures, and women considered overweight had lower Mixt-4 scores.

Table 3. Socio-ecological variables related to chemical mixture exposure in the whole population (n=12,201).

Block	Socio-Ecological Characteristic	TE-F-PAH	PCB-BFR-ASO-MEHG	PEST-3	PEST-2	MIXT4
Block 1: Distal	*Education Level*					
	Higher	-0.00889 [–0.332, 0.314]	+0.067 [–0.39, 0.25]	-0.190 [–0.79, 0.41]	-0.540 [–1.34, 0.26]	**+0.415 [0.219, 0.610]**
	Secondary (HS)	+0.015 [–0.310, 0.338]	0.13 [–0.45, 0.19]	+0.130 [–0.45, 0.19]	-0.180 [–0.78, 0.42]	**+0.329 [0.134, 0.523]**
	Secondary (MS)	+0.063 [–0.27, 0.39]	+0.159 [–0.48, 0.16]	-0.170 [–0.77, 0.44]	-0.540 [–1.35, 0.26]	**+0.237 [0.028, 0.446]**
	Primary	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]
	Migration Status					
	Non-immigrant	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]
	Descendant of immigrants	+0.003 [–0.04, 0.03]	**+0.053 [0.009, 0.097]**	**+0.150 [0.090, 0.208]**	+0.010 [–0.04, 0.06]	+0.040 [–0.02, 0.09]
	Immigrant	+0.006 [–0.03, 0.06]	**+0.110 [0.047, 0.166]**	**+0.294 [0.214, 0.375]**	+0.037 [–0.03, 0.10]	**+0.080 [0.006, 0.154]**
Block 2: Intermediate	*Income*					
	Income: Low (< €1,064.58)	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]
	Income: Intermediate (€1,064.58–€2,752.08),	-0.010 [–0.04, 0.02]	**+0.036 [0.01, 0.07]**	+0.020 [–0.07, 0.02]	+0.020 [–0.03, 0.06]	**+0.060 [0.01, 0.11]**
	Income: High (> €2,752.08)—	-0.050 [–0.09, 0.008]	**+0.110 [0.06, 0.16]**	+0.030 [–0.10, 0.04]	+0.070 [–0.01, 0.15]	+0.040 [–0.04, 0.11]
	Employment					
	Unemployed	**+0.050 [0.021, 0.073]**	+0.020 [–0.01, 0.04]	+0.020 [–0.03, 0.06]	+0.002 [–0.04, 0.04]	**+0.100 [0.03, 0.12]**
	Employed	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]
Block 3: Proximal	*BMI*					
	Underweight (18.5–24.9)	+0.013 [–0.02, 0.05]	+0.001 [–0.04, 0.04]	+0.010 [–0.05, 0.06]	+0.020 [–0.04, 0.08]	-0.020 [–0.08, 0.04]
	Overweight (25–29.9)	-0.005 [–0.03, 0.02]	-0.020 [–0.04, 0.01]	-0.014 [–0.05, 0.03]	+0.010 [–0.05, 0.03]	**-0.073 [–0.12, –0.03]**

	Obese (≥30)	-0.012 [–0.05, 0.02]	+0.020 [–0.03, 0.06]	+0.013 [–0.04, 0.07]	+0.020 [–0.03, 0.07]	-0.010 [–0.07, 0.05]
	Tobacco Use					
	Ever Smoker	**+0.053 [0.033, 0.072]**	-0.013 [–0.03, 0.01]	**-0.036 [–0.068, –0.005]**	**-0.032 [–0.062, –0.002]**	+0.030 [–0.002, 0.07]
	Never Smoker	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]	0 [Ref]

Note: Variables within each block were entered simultaneously. Block 2 models were adjusted for all covariates in Block 1, and Block 3 models were adjusted for covariates in both Blocks 1 and 2. ***Bolded*** *coefficients indicate 95% confidence intervals that do not include zero.*

Stratified Regression Results by Migration Status

Interaction Analysis: Interaction terms between migration status and maternal education were tested for each chemical mixture. Significant interactions were found for Pest-1 ($p = 0.0009$), PFAA-Ge-Li ($p = 0.0032$), and Mixt3 ($p = 0.0098$). For these mixtures, stratified analyses by migration status are presented in Tables 4-6, respectively. For the remaining mixtures (TE-F-PAH, PCB-BFR-Aso-MeHg, Pest-2, Pest-3, and Mixt4), no statistically significant interaction was observed ($p > 0.05$). In these cases, migration status was included as a Block 1 covariate without stratification.

Stratified models for Pest-1

Among non-immigrants, tobacco use, overweight, and obesity were negatively associated with the exposure. Among descendants of immigrants, education (at both the high school and higher education levels) was positively associated with the exposure and ever smoker was negatively associated with the exposure. Among immigrants, unemployment was positively associated with the exposure.

Table 4. Stratified Results by Migration Status: Pest-1 Mixture

Block	Socio-Ecological Characteristic	Non-Immigrant	Descendant of Immigrant	Immigrant
Block 1	*Education Level*			
	Primary	0 [Ref]	0 [Ref]	0 [Ref]
	Secondary: Middle School	+0.0989 [–0.3178, 0.5157]	+0.3553 [–0.0538, +0.7644]	+0.2104 [–0.5251, +0.9458]
	Secondary: High School	+0.1591 [–0.2461, 0.5643]	**+0.3329 [+0.1629, +0.5029]**	–0.1758 [–0.8061, +0.4546]
	Higher Education	+0.2785 [–0.1270, +0.6840]	**+0.2432 [+0.0367, +0.4496]**	+0.0884 [–0.5430, +0.7198]
Block 2	*Income*			
	Low (< €1,064.58)	0 [Ref]	0 [Ref]	0 [Ref]
	Intermediate (€1,064.58–€2,752.08),	–0.0204 [–0.0736, +0.0329]	+0.0092 [–0.1630, +0.1813]	–0.0255 [–0.2120, +0.1610]
	High (> €2,752.08)—	–0.0721 [–0.1560, +0.0118]	–0.1295 [–0.3934, +0.1344]	–0.1984 [–0.4920, +0.0952]
	Employment			
	Employed	0 [Ref]	0 [Ref]	0 [Ref]

	Unemployed	–0.0043 [–0.0515, +0.0429]	–0.0182 [–0.1662, +0.1298]	**+0.3198 [+0.1514, +0.4882]**
Block 3	*Tobacco Use*			
	Ever Smoker	**–0.0517 [–0.0881, –0.0152]**	**–0.1655 [–0.2847, –0.0462]**	–0.0814 [–0.2697, +0.1069]
	Never Smoker	0 [Ref]	0 [Ref]	0 [Ref]
	BMI			
	Normal weight (18.5–24.9 kg/m²)	0 [Ref]	0 [Ref]	0 [Ref]
	Underweight (<18.5 kg/m²)	+0.0287 [–0.0432, +0.1005]	+0.0407 [–0.1849, +0.2663]	–0.0400 [–0.3589, +0.2789]
	Overweight (25–29.9 kg/m²)	**–0.0700 [–0.1173, –0.0226]**	+0.0076 [–0.1526, +0.1678]	–0.0443 [–0.2295, +0.1410]
	Obese (≥30 kg/m²)	**–0.1627 [–0.2174, –0.1080]**	–0.0828 [–0.2840, +0.1184]	–0.0050 [–0.3044, +0.2944]

Note: Variables within each block were entered simultaneously. Block 2 models were adjusted for all covariates in Block 1, and Block 3 models were adjusted for covariates in both Blocks 1 and 2. ***Bolded*** *coefficients indicate 95% confidence intervals that do not include zero.*

Stratified models for PFAA-Ge-Li

Among non-immigrants, ever smoker and high BMI (overweight and obesity) were positively associated with exposure. Among descendants of immigrants, education at all levels (middle school, high school, and higher education) was negatively associated with exposure. Concerning descendants of immigrants, obesity was positively associated with exposure. Among immigrants, no statistically significant associations were found for any socio-ecological variable.

Table 5. Stratified Results by Migration Status: PFAA-Ge-Li

Block	Socio-Ecological Characteristic	Non-Immigrant	Descendant of Immigrant	Immigrant
Block 1	*Education Level*			
	Primary	0 [Ref]	0 [Ref]	0 [Ref]
	Secondary: Middle School	+0.0639 [–0.9081, 1.0358]	**–3.9206 [–4.2871, –3.5540]**	+0.2005 [–0.5305, 0.9316]
	Secondary: High School	+0.0980 [–0.8646, 1.0606]	**–3.7695 [–3.9497, –3.5894]**	–0.0762 [–0.7024, 0.5500]
	Higher Education	+0.2089 [–0.7529, 1.1708]	**–3.7278 [–3.9544, –3.5011]**	–0.0077 [–0.6345, 0.6191]
Block 2	*Income*			
	Low (< €1,064.58)	0 [Ref]	0 [Ref]	0 [Ref]
	Intermediate (€1,064.58–€2,752.08),	–0.0033 [–0.0647, 0.0582]	+0.0688 [–0.0888, 0.2263]	+0.0996 [–0.0531, 0.2522]
	High (> €2,752.08)	–0.0533 [–0.1430, 0.0365]	+0.1088 [–0.1577, 0.3754]	+0.2411 [–0.0254, 0.5075]
	Employment			
	Employed	0 [Ref]	0 [Ref]	0 [Ref]

	Unemployed	–0.0026 [–0.0566, 0.0515]	–0.0167 [–0.1618, 0.1284]	+0.0310 [–0.1139, 0.1759]
Block 3	*Tobacco Use*			
	Ever Smoker	**+0.0517 [+0.0113, +0.0920]**	+0.0772 [–0.0457, 0.2000]	+0.1136 [–0.0521, 0.2794]
	Never Smoker	0 [Ref]	0 [Ref]	0 [Ref]
	BMI			
	Normal weight (18.5–24.9 kg/m²)	0 [Ref]	0 [Ref]	0 [Ref]
	Underweight (<18.5 kg/m²)	–0.0315 [–0.1032, 0.0401]	+0.0228 [–0.2082, 0.2538]	+0.2275 [–0.0804, 0.5354]
	Overweight (25–29.9 kg/m²)	**+0.1059 [+0.0512, +0.1606]**	+0.0992 [–0.0599, 0.2583]	–0.0719 [–0.2365, 0.0926]
	Obese (≥30 kg/m²)	**+0.1031 [+0.0273, +0.1788]**	**+0.2936 [+0.0769, +0.5104]**	+0.1738 [–0.1073, 0.4550]

*Note**:** Variables within each block were entered simultaneously. Block 2 models were adjusted for all covariates in Block 1, and Block 3 models were adjusted for covariates in both Blocks 1 and 2.* ***Bolded*** *coefficients indicate 95% confidence intervals that do not include zero.*

Stratified models for Mixt3

Among non-immigrants, higher income (medium and high) was negatively associated with the exposure, while unemployment was positively associated with exposure. Ever smoker, as well as underweight, overweight, and obesity, were positively associated with exposure. Among descendants of immigrants, education at the secondary level (middle and high school) and ever smoker was positively associated with exposure. Among immigrants, no statistically significant associations were observed for any variable.

Table 6. Stratified Results by Migration Status: Mixt-3

	Socio-Ecological Characteristic	Non-Immigrant	Descendant of Immigrant	Immigrant
Block 1	*Education Level*			
	Primary	0 [Ref]	0 [Ref]	0 [Ref]
	Secondary: Middle School	+0.1002 [–0.0313, 0.2316]	+0.2613 [+0.0607, +0.4618]	+0.0416 [–0.1051, 0.1884]
	Secondary: High School	**+0.0262 [–0.0961, 0.1485]**	**+0.1174 [+0.0690, +0.1657]**	+0.0216 [–0.1116, 0.1548]
	Higher Education	–0.0496 [–0.1717, 0.0725]	+0.0525 [–0.0039, 0.1088]	+0.0235 [–0.1160, 0.1630]
Block 2	*Income*			
	Low (< €1,064.58)	0 [Ref]	0 [Ref]	0 [Ref]
	Intermediate (€1,064.58–€2,752.08),	**–0.0728 [–0.0954, –0.0501]**	–0.0068 [–0.0535, 0.0398]	+0.0312 [–0.0287, 0.0912]
	High (> €2,752.08)	**–0.0886 [–0.1177, –0.0594]**	–0.0117 [–0.0820, 0.0585]	+0.0446 [–0.0628, 0.1519]
	Employment			
	Employed	0 [Ref]	0 [Ref]	0 [Ref]
	Unemployed	**+0.0207 [+0.0041, +0.0373]**	–0.0174 [–0.0616, 0.0269]	–0.0243 [–0.0831, 0.0345]

Block 3	*Tobacco Use*			
	Ever Smoker	**+0.0577 [+0.0443, +0.0710]**	**+0.0523 [+0.0151, +0.0894]**	–0.0143 [–0.0728, 0.0441]
	Never Smoker	0 [Ref]	0 [Ref]	0 [Ref]
	BMI			
	Normal weight (18.5–24.9 kg/m²)	0 [Ref]	0 [Ref]	0 [Ref]
	Underweight (<18.5 kg/m²)	**+0.0227 [+0.0010, +0.0445]**	–0.0100 [–0.0830, 0.0629]	+0.0916 [–0.0547, 0.2380]
	Overweight (25–29.9 kg/m²)	**+0.0176 [+0.0011, +0.0341]**	–0.0030 [–0.0488, 0.0427]	+0.0366 [–0.0483, 0.1215]
	Obese (≥30 kg/m²)	**+0.0253 [0.0000, +0.0506]**	+0.0143 [–0.0451, 0.0737]	–0.0495 [–0.1075, 0.0085]

Note: Variables within each block were entered simultaneously. Block 2 models were adjusted for all covariates in Block 1, and Block 3 models were adjusted for covariates in both Blocks 1 and 2. ***Bolded*** *coefficients indicate 95% confidence intervals that do not include zero.*

Summary of Multicollinearity Diagnostics (VIF)

All GVIF-adjusted values (GVIF^(1/(2*Df))) were below 2, suggesting no evidence of problematic multicollinearity across models.

DISCUSSION

Key Findings

Across regression models, maternal socioecological characteristics were associated with variation in dietary chemical mixture exposures. Migration status emerged as key predictor, with higher exposures observed among immigrant women for several mixtures. Notably, exposures to persistent and pesticide-related mixtures such as PCB-BFR-ASO-MeHg and PEST-3 were higher among descendants of immigrants and particularly strong among immigrant women. These results are consistent with existing literature suggesting that immigrant populations may experience greater environmental exposures due to factors including dietary preferences, product use, housing conditions, and systemic inequities in environmental health risk (12,21,22).

Income and employment status also appeared to influence exposure profiles. For instance, unemployment was positively associated with Mixt-4 while higher income was inversely associated with TE-F-PAH scores but positively associated with PCB-BFR-ASO-MeHg exposure. These diverging associations underscore the complexity of how structural resources relate to dietary exposure, depending on contaminant type. At the behavioral level, ever smoker was associated with increased TE-F-PAH scores, while in BMI, overweight was linked to lower Mixt-4 exposure, whereas no consistent pattern was observed for any other mixtures.

Moderating Effect of Migration Status

Stratified analyses revealed that associations between socio-ecological factors and dietary chemical mixture exposures varied by migration status. The most consistent associations were observed among non-immigrants and descendants of immigrants, while relatively few significant characteristics emerged among immigrants. This pattern suggests that migration status may modify both the social distribution of exposure and the relevance of specific risk factors.

Non-Immigrant

Among non-immigrant women, several socio-ecological characteristics were associated with variation in exposure across all three mixtures. Lower income was associated with higher Mixt-3 exposure, and unemployment was associated with higher PEST-1 exposure. Ever smoking was positively associated with Mixt-3 and PFAA-Ge-Li exposures, while overweight and obesity were associated with higher exposures to Mixt-3 and PFAA-Ge-Li, but lower exposure to PEST-1. These findings align with previous evidence that lower income and unemployment are associated with higher exposure to mixtures like TE-F-PAH and Mixt-4 (12,21).

Descendants of Immigrants

Among descendants of immigrants, education and age appeared most relevant. Education was positively associated with exposure to Mixt-3, Mixt-4, and PEST-1, but negatively associated with PFAA-Ge-Li, suggesting mixture-specific patterns. Ever smoking was negatively associated with PEST-1 but positively associated with Mixt-3. Obesity was associated with higher PFAA-Ge-Li exposure. These associations may reflect differences in acculturation, socioeconomic position, and behavioral patterns, consistent with previous findings (9,23). Notably, the associations between education and both increased (Mixt-4) and decreased (PFAA-Ge-Li) exposure highlight the complex role of social position in shaping diet-related risk.

Immigrants

Among immigrant women, few associations were statistically significant. The primary exception was a positive association between unemployment and PEST-1 exposure. No consistent patterns were observed for education, income, tobacco use, or BMI. This may reflect more stable or traditional dietary behaviors, lower variability in lifestyle factors, or misalignment between modeled exposures and actual intake sources in this group. It may also indicate that structural and behavioral influences on exposure are less differentiated at earlier stages of acculturation.

Taken together, these results suggest that migration status may not only modify dietary chemical mixture exposures, but also condition the relevance of socio-ecological characteristics across groups. The stronger and more complex associations observed among non-immigrants and descendants of immigrants may reflect the influence of acculturation and integration on diet and lifestyle, potentially altering exposure pathways. In contrast, the limited variation in associations among immigrants underscores the importance of considering generational status in environmental exposure research.

Comparison to Existing Literature

These findings reinforce the idea that dietary chemical exposures during pregnancy are socially patterned and mediated by both structural and behavioral pathways. Higher education and income were associated with increased exposure to mixtures such as PCB-BFR-MeHg and Mixt-4, likely reflecting dietary choices involving fish, vegetables, or imported foods (18,24). Conversely, unemployment and smoking were associated with to higher scores for TE-F-PAH. Smoking was associated with pesticide mixtures Pest-2 and Pest-3 (25). These findings are consistent with environmental inequality literature (26). The inverse relationship between overweight status and Mixt-4, observed in non-immigrants, deviates from prior evidence associating higher adiposity with greater chemical burden (4), and may reflect specific food choices or limitations of BMI as an indicator of vulnerability. Stratified models clearly show that pooling all participants may obscure key subgroup differences, reinforcing the value of migration-stratified analysis in understanding the social patterning of environmental exposure.

Strengths and Limitations

This study has several limitations. Most notably, chemical exposures were estimated from dietary intake rather than measured using biomarkers, meaning they reflect potential external exposure rather than internal dose (27,28). They also do not account for individual variation in absorption, metabolism, or excretion. Additionally, because contamination data was derived from the French Total Diet Study (EAT), contaminant concentrations were fixed across participants. As a result, variability in exposure arises solely from differences in reported food consumption, not from individual variability in contaminant levels across food items. Nevertheless, dietary modeling offers a scalable way to estimate exposures to a broad range of dietary contaminants, including those for which validated biomarkers are lacking (4,18). Key covariates such as smoking and BMI were self-reported, which could introduce misclassification. The complete-case design may have biased the results toward more socioeconomically advantaged participants, as excluded individuals were more likely to be younger, non-immigrants, have higher pre-pregnancy BMI, and be less likely to be employed.

In addition, while the SNMU mixture patterns are data-driven and reflect real-world co-exposures, they rely on modeling choices and lack mechanistic interpretation. Finally, the exploratory nature of the analysis and the number of predictors tested increase the risk of false-positive findings.

These considerations underscore the limitations of modeled exposure data and raise questions about how best to capture complex, real-world exposures. Biomarker-based exposure assessment is often considered the gold standard because it captures internal dose and accounts for individual toxicokinetic variatio, but it also has important drawbacks. Biospecimen collection can be invasive, expensive, and impractical in large studies. For many non-persistent chemicals, biomarkers reflect only recent exposures unless repeat samples are collected (27,28). In contrast, the SNMU-derived chemical mixture scores used in this study provide a broad estimate of dietary exposure to a wide range of contaminants and can be applied at scale. This approach is especially valuable for identifying mixture profiles and socially patterned exposures in large populations, even for chemicals without validated biomarkers (4,18).

However, these scores should be interpreted as proxies for external exposure. Future work should combine modeled and biomarker data to improve exposure classification and enhance understanding of mixture-health relationships (29,30).

Despite these limitations, the study draws on several key strengths. Most notably, it benefits from the ELFE cohort's national coverage, large sample size, and prospective design. Exposure assessment was based on validated dietary intake tools, and the application of SNMU enabled the identification of co-exposure profiles that reflect realistic, population-level patterns of dietary contamination (27,28). While these profiles lack biological specificity, they offer a valuable lens to examine the distribution of exposure across social groups. The use of a socioecological framework provided a conceptual advantage by organizing characteristics across structural (distal), socioeconomic (intermediate), and behavioral/biological (proximal) levels. This approach allowed us to identify not only which factors are associated with exposure, but also how different layers of social context interact to shape chemical exposure risk. By accounting for multiple levels of influence, from migration status and education to income, employment, and individual behaviors such as smoking and diet, the framework supports a more integrated understanding of exposure disparities during pregnancy.

In summary, this study adds to growing evidence that chemical exposures through diet during pregnancy may be socially patterned. Migration status and income were among the most consistent predictors of dietary mixture scores, reinforcing the importance of equity-focused approaches in environmental health research. These findings highlight how structural, behavioral, and environmental factors intersect to shape exposure risk, supporting the continued development of scalable, integrated tools for exposure surveillance in diverse populations.

CONCLUSION

This exploratory study suggests that maternal sociodemographic and behavioral characteristics including migration status, income level, and smoking history, are associated with variation in prenatal chemical co-exposure profiles. These findings underscore the relevance of social patterning in dietary exposure and highlight migration status and socioeconomic disadvantage as important factors in identifying populations for targeted public health interventions to reduce exposure to specific chemical mixtures.

Given the consistent associations observed with migration status, future studies examining associations between chemical exposures and maternal or child health should account for migration as a key stratification variable. While the SNMU-based models offer valuable insight into real-world co-exposures, their limited specificity means findings should be interpreted with caution. Further work combining biomarker data with dietary modeling and exploring the mediating role of social position over time, will be critical for advancing both research and policy in environmental health equity.

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APPENDIX A

Variable	TE-F-PAH	PCB-BFR-Aso-MeHg	Pest-1	Pest-3	PFAA-Ge-Li	Pest-2	Mixt3	Mixt4
Migration Status	0.001	0.006	0.015	0.012	0.002	0.001	0.001	0.001
Mother Education	0.000	0.135	0.140	0.039	0.068	0.056	-0.188	0.116
Father Education	-0.011	0.128	0.112	0.021	0.049	0.060	-0.173	0.095
Income (terciles)	-0.018	0.117	0.104	0.015	0.033	0.062	-0.193	0.078
Mother Employment Status	0.001	0.001	0.000	0.000	0.000	0.000	0.004	0.000
Tobacco History	0.001	0.002	0.005	0.002	0.001	0.001	0.007	0.000
Passive Tobacco Exposure	0.000	0.004	0.004	0.000	0.000	0.001	0.007	0.001
Previous Pregnancies	0.008	0.003	0.000	0.001	0.000	0.001	0.004	0.001
PANDiet Score	0.374	0.299	0.260	0.178	0.052	0.166	0.024	0.220
Plant Diet Index (PDI)	0.108	-0.066	0.196	0.130	0.047	0.109	0.015	0.146
PNNS Adherence	0.230	0.341	0.274	0.121	0.052	0.141	-0.048	0.216
Mother BMI	0.009	-0.006	-0.041	0.009	0.035	-0.005	0.036	-0.026
Mother Age	0.064	0.130	0.134	0.069	-0.016	0.071	-0.029	0.102

Blue = negative association
Red = positive association.
Color intensity shows effect size magnitude.
Tests used:
Pearson correlation (continuous variables),
Spearman correlation (ordinal variables)
Eta² from ANOVA (categorical variables).