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Multiple maternal occupational exposures during pregnancy and intrauterine growth: analysis of the French Longitudinal Study of Children - ELFE cohort, using data-driven approaches

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ABSTRACT

Objective: To use data-driven approaches to investigate maternal multi-occupational exposures during pregnancy and their effects on intrauterine growth.

Methods: Maternal occupational exposure to 47 factors during pregnancy was evaluated with job-exposure matrices in the French ELFE cohort. The outcomes of interest were birthweight (BW), small for gestational age (SGA) and head circumference (HC). Occupational exposures associated with these outcomes were identified by EWAS, LASSO, and random forest. The five exposures with the strongest effects selected with these approaches were included in a final multivariate model with significant interactions.

Results: We included 12,851 women. The most important occupational factors predictive of SGA were endocrine disruptors, high strain, kneeling/squatting, job demands, physical effort. No significant associations were detected when these variables were combined in a final model. For BW, the most important variables were leaning forward/sideways, using a computer screen, ultrafine particles, physical effort, airborne germs, repetitive actions. The use of a computer screen significantly decreased BW and, for women not exposed to airborne germs,

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leaning forward/sideways significantly increased BW. For HC, repetitive actions, oxygenated solvents, kneeling/squatting, airborne germs, working outdoors were the most important predictive factors. Repetitive actions and working outdoors significantly decreased HC. HC also decreased in women exposed to both airborne germs, and oxygenated solvents. Similar results were found for women who worked during the third trimester.

Conclusion: Our findings highlight potential roles of chemical, biological and postural factors and their interactions in determining intrauterine growth. These results highlight the importance of considering multiple exposures in occupational health studies.

1. Introduction

A study of 13 European birth cohorts showed that 80.2 % of women work during pregnancy (Casas et al., 2015). A large proportion of these women may be exposed to various occupational factors of a chemical, physical, biological, strenuous, organizational or psychosocial nature. Simultaneous exposure to multiple factors may also be frequent. For example, the results of the French national occupational health survey conducted in 2014 indicated that over 40 % of pregnant mothers were exposed to at least three potential occupational risk factors during pregnancy, and about 30 % were exposed to at least five risk factors (Henrotin et al., 2018). Moreover, a previous study showed that women were exposed to a median of 6 occupational factors during pregnancy (Tartaglia et al., 2024). Occupational exposure to certain factors during pregnancy has been associated with intrauterine growth retardation and, in particular, with infants being born small for gestational age (SGA) (Cai et al., 2020; Croteau, 2020; Rekha et al., 2023; Ulin et al., 2024), with a low birthweight (BW) (Cai et al., 2020; Croteau, 2020; Rekha et al., 2023; Ulin et al., 2024; Bonzini et al., 2007; Palmer et al., 2013) or small head circumference (HC) (Cai et al., 2020; Croteau, 2020; Rekha et al., 2023; Ulin et al., 2024).

Most studies of the relationship between occupational exposures and intrauterine growth to date have focused on only one or a small number of occupational exposures (Cai et al., 2020; Croteau, 2020; Rekha et al., 2023; Ulin et al., 2024; Bonzini et al., 2007; Palmer et al., 2013), analyzed by linear and logistic regression techniques. However, such models are subject to limitations in handling multiple and correlated exposures, which may yield unstable parameter estimates with large standard errors (Stafoggia et al., 2017). Furthermore, it is not possible to consider confounding and interactive effects involving multiple exposures in single-exposure studies. More advanced statistical methods are, therefore, required for studies of the complex associations between multiple exposures and intrauterine growth.

Different methods were identified, according to the research question (Joubert et al., 2022), which can be to estimate the overall effect of the mixture, to identify exposures associated with the outcome, to identify most important exposures associated with the outcome, to determine specific exposure patterns, to study the association between an outcome and a priori defined groups of exposure. Data-driven approaches based on machine learning can address some of these issues, and in particular that of identification of most important exposures associated with the outcome. Several studies have compared the performance of different machine-learning models for the identification of associations between the exposome and health (Agier et al., 2016; Barrera-Gómez et al., 2017; Lenters et al., 2018; Sun et al., 2013). These studies have failed to identify any single model as universally better. Various methods can be used to address different questions. They can be classified into three groups, as shown by Staffogia et al.: (1) dimension reduction, (2) variable selection, and (3) clustering (Stafoggia et al., 2017). It is possible to combine different methods to increase the likelihood of capturing different aspects of the relationships between occupational exposure and intrauterine growth, including interactions between factors, facilitating a pluralist approach to data interpretation (Stafoggia et al., 2017). We used two variable selection approaches (Exposome-wide association study – EWAS, and least absolute shrinkage and selection operator – LASSO) and one clustering approach (random forest) to take advantage of the strengths of these different methods and compensate for their limitations. Variable selection is an alternative to dimension reduction that can decrease complexity and the risk of redundancy. EWAS can identify analytically important exposure-outcome pairs across all measured exposures (Chung et al., 2024). LASSO is a penalized regression technique particularly useful for high-dimensional data with many potential predictors (Tibshirani, 1996). The random forest approach is non-parametric and can be used to capture complex interactions and patterns within the data (Stafoggia et al., 2017; 4).

The objective of this study was to explore multiple maternal occupational exposures during pregnancy and their relationship to intrauterine growth, through a combination of these three data-driven approaches.

2. Methods

2.1. Population study

The French Longitudinal Study of Children (ELFE) cohort is the first French national study dedicated to monitoring participants from birth to adulthood. The methodology of the ELFE cohort has been described in detail elsewhere (Charles et al., 2020). Briefly, maternity hospitals were selected based on a two-stage stratified random sampling plan. First, maternity wards located in metropolitan France were randomly selected at the national level from a sampling base stratified by the institution's status (private/public) and according to the number of births per year and region. Recruitment took place within 320 French maternity departments in 2011. Single or multiple live births at $\geq$ 33 weeks of gestation (premature babies >33 weeks of gestation are included in the study), for which the mothers were $\geq$18 years old, did not plan to leave France within three years and had signed an informed consent form, were included in the ELFE cohort. Overall, 18,270 children were followed up in this cohort.

For this study, we excluded multiples pregnancies (n = 574), pregnancies resulting in neonates with major congenital malformation (n = 377) as defined by the European surveillance system for congenital abnormalities ("European Platform for Rare Disease Registration"), and mothers who did not work during their pregnancies (n = 4137) (Appendix C).

The ELFE study was approved by the Consultative Committee for the Treatment of Information in Health Research (CCTIRS), the National Commission for Data Protection and Liberties (CNIL), and the competent ethics committee (CPP - Committee for the Protection of Persons). The study was also approved by the National Council for Statistical Information (CNIS).

2.2. Data collection

Sociodemographic data were collected by face-to-face interviews at the maternity unit and medical data were collected from medical records. Information about the occupations of the women during pregnancy, including job title, was collected during the face-to-face interviews, which took place during the women's stay in the maternity unit after the delivery, and through an additional questionnaire completed two months after the delivery. Additional details can be obtained from: https://www.elfe-france.fr/en.

2.3. Assessment of occupational exposure

The occupational exposures investigated here were characterized with job-exposure matrices (JEMs) linked to the jobs of the mothers based on a common job coding system. All mothers included in this study held only one job during their pregnancy. Participant-reported jobs were coded by one expert, according to the International Standard Classification of Occupations (ISCO-1968) and the French classification of professions and socioprofessional categories (PCS-2003). Industry activities were coded according to the International Standard Industrial Classification of All Economic Activities (ISIC-1975) and the French nomenclature of activities (NAF-2003). We used 12 JEMs and one database to evaluate the occupational exposures of the pregnant women (Table 1). We selected general population JEMs, preferably from the French (or European or North American) population, and characterizing the exposure close to 2011. JEM selected to be applied in our population study included at least one type of occupational exposure that has been suspected to have a potential effect on reproduction (fertility issues, malformations, intrauterine growth) (Teysseire et al., 2019; Certenais et al., 2019). If an occupational exposure was present in multiple JEMs, we prioritized the one developed using the French population. The description of JEMs applied to the Elfe cohort is described in Appendix A. The occupational exposures evaluated are listed in Table 1. We studied 17 chemical, 8 physical, 4 biological, 12 strenuous, 3 organizational and 3 psychosocial factors. For each type of exposure, we built a dichotomous (exposed, not exposed) categorical exposure variable based primarily on probability (0–50 %, ≥50 %) or, if the probability was unknown, intensity of exposure. The unexposed group was chosen as the reference group, for each occupational exposure of interest, that allow to be specific to the exposure of interest. Only 29 of the 47 occupational exposures characterized were included in the final analysis, because each of the other exposures concerned fewer than ten women (chlorinated and petroleum solvents, arsenic, cadmium, chromium, iron, lead, nickel, welding fumes, polycyclic aromatic hydrocarbons, benzo-a-pyrene, carbon monoxide, non-thermal intermediate frequency, radiofrequency, thermal intermediate frequency, ultraviolet).

2.4. Outcomes

BW is the weight of the newborn at birth, expressed in grams. SGA was defined as a BW under the 10th percentile for gestational age and sex according to WHO curves (de Onis et al., 2007; Verspyck et al., 2022). HC is the fronto-occipital circumference measured at birth, in centimeters.

2.5. Statistical analysis

We performed a two-step analysis.

We first ranked exposures, selecting the most important occupational exposures with three different data-driven approaches: EWAS, LASSO and random forest. A short summary of the methods used is provided below and the tuning parameters for each method are presented in appendix B.

EWAS identifies analytically important exposure-outcome pairs across all measured exposures (Chung et al., 2024). It corresponds to multiple single-exposure approaches based on logistic (for SGA) and linear (for BW and HC) regressions, depending on the outcome. The *p*-values were corrected for multiple testing with a threshold for the effective number of tests (Li et al., 2012). This method is adapted from Bonferroni correction, with an estimation of the number of truly independent tests based on the correlation structure of the exposure variables. We then divided the nominal significance by the effective number of tests calculated. The variable importance score was based on the *p*-values obtained. The occupational exposures with the lowest *p*-values were considered to be the most important, and had a lower score.

LASSO, a penalized regression technique particularly useful for high-dimensional data with many potential predictors, selects the most important variables within a group of highly correlated variables (Stafoggia et al., 2017) by shrinking all coefficients toward zero. As LASSO is sensitive to a tuning parameter (lambda), the final set of variables of importance was chosen by the stability selection procedure (Hofner and Hothorn, 2021). The variable importance score was calculated according to the selection probabilities. Exposures with the highest selection probabilities were considered to be the most important and had lower scores.

The random forest approach is a non-parametric approach to classification and regression based on the aggregation of a decision tree, facilitating the capture of complex interactions and patterns within the data (Stafoggia et al., 2017; Breiman, 2001). The variable importance score was calculated from the difference between the out-of-bag (OOB) error on the perturbed OOB samples, and the initial OOB error. The most important exposures had a lower score.

For each approach, all exposures were ranked according to the importance of their contribution to the prediction of the outcome, with lower values corresponding to the most important variables. An overall ranking was then calculated, based on the median of the three ranks for a given factor (Ohanyan et al., 2022).

The final model for each outcome was constructed by including the top five occupational exposures identified for each health outcome in the exposure ranking step. We explored all potential second-term interactions between each of the selected variables, by logistic (for SGA) and linear (for BW and HC) regressions including interaction terms. The final logistic (for SGA) or linear (for BW and HC) models, thus, contained the five most important occupational exposures and potentially important interaction terms (cutoff: $p < 0.15$).

Missing data on occupational exposures were imputed by a method based on chain equations with the mice package in R software to generate five tables, by five iterations. The imputation model contains all the occupational exposure variables, and all covariates.

We used a DAG (Appendix C) to adjust all models described above for educational level (low, high-school, university), pre-pregnancy BMI (<18.5 kg/m^2, 18.5–24.9 kg/m^2, 25.0–29.9[kg/m^2, ≥30 kg/m^2), tobacco use (yes, no) and alcohol consumption (continuous, number of glasses per day) during pregnancy for the SGA analysis. For the BW and HC analyses, we also adjusted for gestational age (continuous) and the sex of the infant (female, male), strong determinants of intrauterine growth. These variables were not included for SGA analysis since these factors are already considered in the construction of this outcome variable.

Effect estimates are presented as odds ratios (OR) for logistic regressions and beta (β) for linear regressions.

We performed a sensitivity analysis on mothers who continued working until the third trimester of pregnancy, excluding those who stopped working earlier, as this period appears to carry the highest risk for fetal growth, particularly for weight gain (Lepercq and Boileau, 2005). In humans, intrauterine fetal growth is quite slow until the 23rd week of gestation, and then accelerates before peaking around the 34th week (Lepercq and Boileau, 2005).

The analyses were performed with R Core Team (2023) software, using the packages mice (Buuren et al., 2023) for multiple imputation, rexposome (rexposome project n) for EWAS, stabs (Hofner and Hothorn, 2021) for LASSO, and VSURF (Genuer et al., 2022) for random forest.

3. Results

3.1. Population

Our study population consisted of 12,851 women (Appendix D). Comparisons between included and excluded participants are presented

Table 1
Assessment of maternal occupational exposures in the French National ELFE cohort.

Factors	Job exposure matrix or database	Construction	Occupation nomenclatures	Industry activities nomenclatures	Metrics	Temporal axis/Gender-specific	Exposure parameter used in analyses
1) Chemical factors							
Chlorinated solvents [a,e]	Matgéné – chlorinated solvents France (Dananché and Févotte, 2009)	Experts	ISCO-1968 PCS-1994	NAF-1993	Probability Frequency Intensity	Yes 1950–2007/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Oxygenated solvents [b]	Matgéné – oxygenated solvents France (Dananché et al., 2015)	Experts	ISCO-1968 PCS-1994	NAF-1993	Probability Frequency Intensity	Yes 1950–2012/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Petroleum solvents [c,e]	Matgéné – petroleum solvents France (Pilorget et al., 2007)	Experts	ISCO-1968 PCS-1994	NAF-1993	Probability Frequency Intensity	Yes 1947–2005/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Detergents	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Pesticides	Pestipop France (Carles et al., 2018)	Experts Questionnaires	PCS-2003	NAF-2003	Probability Frequency	No/No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Heavy metals Arsenic [e] Cadmium [e] Chromium [e] Iron [e] Lead [e] Nickel [e]	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Ultrafine particles	MatPUF France (Audignon-Durand et al., 2021)	Experts	ISCO-1968	NAF-1993	Probability Frequency	Yes 1950–2014/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Welding fumes [e]	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Polycyclic aromatic hydrocarbon[e] Benzo-a-pyrene [e]	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Gas Carbon monoxide [e]	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Endocrine disruptor [d]	EDC United Kingdom (Brouwers et al., 2009)	Experts	ISCO-1988	–	Probability	No/No	Not exposed: probability between 0 and 10 % Exposed: probability >10 %
2) Physical factors							
Ionizing radiation	CANJEM Canada (Sauvé et al., 2018)	Experts	ISCO-1968 CCDO-1971 NOC-2011 SOC-2010	–	Probability Intensity Frequency	Yes 1920–2005/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Low-frequency magnetic fields	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %

(continued on next page)

Table 1 (*continued*)

Factors	Job exposure matrix or database	Construction	Occupation nomenclatures	Industry activities nomenclatures	Metrics	Temporal axis/Gender-specific	Exposure parameter used in analyses
Non-thermal intermediate frequency (IFELF) [e] Radiofrequency (RF) [e] Thermal intermediate frequency (IFRF) [e]	RF-JEM France, UK, New Zealand, Germany, Israel, USA and Canada (Migault et al., 2019)	Literature-based measurement data and study participant questionnaire information	ISCO-1988	–	Probability Intensity	Yes 1974–2013/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
Ultraviolet [e]	FinJEM Finland (Kauppinen et al., 2014)	Experts	ISCO-1988	–	Probability Intensity	Yes 1995–2009/ No	Not exposed: probability between 0 and 50 % Exposed: probability >50 %
3) Biological factors							
Airborne germs	Mat O Covid France (Descatha et al., 2021)	Experts	PCS-2003 ISCO-2008	–	Probability	No/No	Not exposed: probability between 5 and 50 % Exposed: probability >50 %
Cytomegalovirus, parvovirus B19 Hepatitis A, E Hepatitis B, C, HIV	Eficatt[f] France (Base de données EFICATT)	Experts	ISCO-1968	–	Exposed/ Not exposed	No/No	Not exposed Exposed
4) Physically strenuous factors							
Strength Intensity of physical effort Carrying loads 10–25 kg Handling of loads >4 kg	JEM Constances France (Evanoff et al., 2019)	Questionnaires	PCS-2003	–	Bias-corrected mean	No/No	<u>For intensity of physical efforts</u>: Not exposed: no physical effort, extremely light, very light, light Exposed: slightly difficult, challenging, very difficult, extremely difficult, exhausting <u>For others factors:</u> Not exposed: almost never, rarely Exposed: often, almost always
Work posture Arms held up above the shoulders Standing Kneeling or squatting Leaning forward or sideways Repetitive actions	JEM Constances France (Evanoff et al., 2019)	Questionnaires	PCS-2003	–	Bias-corrected mean	No/No	<u>For intensity of physical efforts</u>: Not exposed: no physical effort, extremely light, very light, light Exposed: slightly difficult, challenging, very difficult, extremely difficult, exhausting <u>For others factors:</u> Not exposed: almost never, rarely Exposed: often, almost always
Vibrations Using vibrating tools Driving construction machinery Driving a vehicle Using a computer screen or control panel	JEM Constances France (Evanoff et al., 2019)	Questionnaires	PCS-2003	–	Bias-corrected mean	No/No	<u>For intensity of physical efforts</u>: Not exposed: no physical effort, extremely light, very light, light Exposed: slightly difficult, challenging, very difficult, extremely difficult, exhausting <u>For others factors:</u> Not exposed: almost never, rarely

(*continued on next page*)

Table 1 (*continued*)

Factors	Job exposure matrix or database	Construction	Occupation nomenclatures	Industry activities nomenclatures	Metrics	Temporal axis/Gender-specific	Exposure parameter used in analyses
							Exposed: often, almost always
5) Organizational factors							
Night work	Matgéné – night work France (Houot et al., 2022)	Questionnaires	PCS-1982 PCS-2003	NAF-1993 NAF-2003 NAF-2008	Probability	Yes 1993–2017/ Yes	Not exposed: no or 0 % Exposed: yes (ELFE data[g]) or >50 % (JEM data when missing data)
Interruption of tasks Working outdoors	JEM Constances France (Evanoff et al., 2019)	Questionnaires	PCS-2003	–	Bias-corrected mean	No/No	For intensity of physical efforts: Not exposed: no physical effort, extremely light, very light, light Exposed: slightly difficult, challenging, very difficult, extremely difficult, exhausting For others factors: Not exposed: almost never, rarely Exposed: often, almost always
6) Psychosocial factors							
Low decision authority High job demands High strain	Swedish psychosocial JEM Sweden (Almroth et al., 2021; Solovieva et al., 2022)	Questionnaires	SSYK-1996	–	Intensity	No/Yes	For decision, demands: Not exposed: low, medium, medium low Exposed: high, medium high For job strain: Not exposed: low, passive Exposed: high, active

[a] Chlorinated solvents: at least one of the following: trichloroethylene, tetrachloroethylene, dichloromethane, tetrachloromethane, trichloromethane.
[b] Oxygenated solvents: at least one of the following: alcohols, ethylene glycol, ketones/esters, diethyl ether, tetrahydrofuran.
[c] Fuels and petroleum-based solvents: at least one of the following: benzene, special petroleum products and other aliphatic petroleum-based solvents, gasoline, white spirit and aliphatic petroleum-based solvents, kerosene/fuel oils/diesel).
[d] Endocrine disrupters: at least one of the following: polycyclic aromatic hydrocarbons, polychlorinated organic compounds, pesticides, phthalates, organic solvents, bisphenol A, alkylphenolic compounds, brominated flame retardants, metals (arsenic, cadmium, copper, lead, and mercury), other molecules (benzophenones, parabens, and siloxanes).
[e] These occupational exposures were not studied because fewer than five women were exposed.
[f] Some biological factors were evaluated with database.
[g] For night work, exposure data were collected from ELFE questionnaires. Missing data (n = 3194) were replaced with data from the JEM.

in Appendix E: the included mothers mostly had a university level of education (69.2 % vs xxx% for non-included), less tobacco consumption (17.9 % vs 25.5 %), less frequently hospitalized (14.6 % vs 21.1 %) and with less cases of SGA (8.6 % vs 16.7 % for non-included). Others characteristics were similar among groups. The mean age of these women at inclusion was 31.1 years (SD = 4.7 years). More than two thirds had a university degree (n = 8863; 69.2 %). Before pregnancy, most of the women had a normal BMI (n = 8604; 67.9 %). During pregnancy, just under 20 % of mothers smoked (n = 2279; 17.9 %) or consumed alcohol (n = 2077; 18.7 %). The mean duration of work during pregnancy was 27 weeks (SD = 7.9 weeks), with only 10.2 % (n = 1283) of mothers stopping work in the first trimester, 32.5 % (n = 4074) stopping work in the second trimester and 57.3 % (n = 7179) in the third trimester. Mean gestational age at delivery was 39.3 weeks (SD = 1.4 weeks). The mean BW of the neonates was 3338.8 g (SD = 471.3 g), and 8.6 % of the neonates were SGA. The mean HC of the neonates was 34.4 cm (SD = 1.4 cm) (Table 2).

3.2. *Occupational characteristics during pregnancy*

During pregnancy, the majority of mothers worked in professional and technical (41.2 %), followed by clerical (23.9 %), service (16.6 %), sales (11.1 %), managerial (3.6 %), production (3.1 %), and agricultural (0.8 %) jobs (Appendix F).

During pregnancy, the most common chemical exposures among mothers were oxygenated solvents (20.3 %) and detergents (17.7 %). Regarding physical factors, 10 % of women were exposed to low-frequency magnetic fields. Among biological factors, airborne microbes affected one-third of the population (33.3 %), while exposure to cytomegalovirus/parvovirus B19 (17.3 %) and hepatitis B/C (15.4 %) was also noted. The most prevalent strength-related factor was the intensity of physical efforts (47.5 %). Postural factors included frequent use of a computer screen or control panel (66.6 %) and prolonged standing (58.8 %). In terms of organizational factors, 57.8 % of mother's experienced task interruptions at work, while fewer than 10 % were exposed to night shifts. Finally, among psychosocial factors, 51.8 % of women faced high strain, 40 % had highly demanding jobs, and 40.1 % had limited decision-making authority at work (Table 3). The

Table 2
Characteristics of the population. ELFE study, France, $n = 12{,}851$.

	All $N = 12{,}851$		SGA $N = 1084$		Not SGA $N = 11{,}480$	
	n (%)	Mean (SD[a])	*n* (%)	Mean (SD[a])	*n* (%)	Mean (SD[a])
Socioeconomic data						
Maternal age (years)		31.1 (4.7)		31.0 (4.9)		31.1 (4.7)
Unknown	52		5		26	
Mother's nationality						
French	12,161 (95.5)		1025 (95.4)		10,897 (95.5)	
Other nationality	571 (4.5)		48 (4.5)		505 (4.4)	
Stateless	4 (0.0)		1 (0.1)		3 (0.0)	
Unknown	115		10		75	
Maternal education level[b]						
Low	249 (1.9)		38 (3.5)		210 (1.8)	
High-school	3692 (28.8)		368 (34.1)		3237 (28.2)	
University	8863 (69.2)		673 (62.4)		8012 (69.9)	
Unknown	47		5		21	
In a relationship	12,287 (96.5)		1011 (94.0)		11,028 (96.7)	
Unknown	120		9		81	
Marital status						
Single	4474 (35.6)		456 (43.1)		3931 (34.9)	
Cohabiting	2221 (17.7)		170 (16.1)		2015 (17.9)	
Married	5733 (45.7)		420 (39.7)		5186 (46.1)	
Divorced	116 (0.9)		12 (1.1)		104 (0.9)	
Widow	13 (0.1)		0 (0.0)		12 (0.1)	
Unknown	294		26		232	
Monthly household income (Euros)						
<2500	2289 (18.9)		241 (23.5)		1990 (18.4)	
2500–4000	6713 (55.5)		568 (55.4)		6013 (55.7)	
>4000	3095 (25.6)		217 (21.2)		2792 (25.9)	
Unknown	754		58		685	
Before pregnancy						
Body mass index (kg/m^2)						
<18.5	932 (7.4)		130 (12.1)		778 (6.9)	
18.5–24.9	8573 (67.6)		723 (67.4)		7685 (67.7)	
25.0–29.9	2116 (16.7)		148 (13.8)		1934 (17.0)	
≥30	1052 (8.3)		71 (6.6)		955 (8.4)	
Unknown	178		12		128	
Diabetes (type 1 or 2)	115 (0.9)		14 (1.3)		100 (0.9)	
Unknown	371		24		237	
Chronic high blood pressure	284 (2.3)		35 (3.3)		243 (2.1)	
Unknown	268		18		142	
During pregnancy						
Parity						
Primiparous	6153 (48.3)		631 (58.9)		5393 (47.3)	
Multiparous	6587 (51.7)		440 (41.1)		6016 (52.7)	
Unknown	111		13		71	
Number of deliveries		1.4 (0.7)		1.4 (0.8)		1.4 (0.7)
Unknown	6857		674		5975	
Hypertensive disorders	405 (3.2)		91 (8.6)		310 (2.8)	
Unknown	360		22		212	
Preeclampsia	149 (1.2)		51 (4.8)		96 (0.9)	
Unknown	360		22		212	
Smoking	2279 (17.9)		302 (28.1)		1936 (17.0)	
Unknown	136		10		97	
Alcohol consumption						
No	9024 (81.3)		753 (81.6)		8104 (81.4)	
<1 glass per month	1637 (14.7)		131 (14.2)		1464 (14.7)	
≥1 glass per month	440 (4.0)		39 (4.2)		390 (3.9)	
Unknown	1750		161		1522	
Time at which stopped work						
1st trimester	1283 (10.2)		151 (14.1)		1116 (9.9)	
2nd trimester	4074 (32.5)		397 (37.2)		3627 (32.1)	
3rd trimester	7179 (57.3)		520 (48.7)		6565 (58.1)	
Unknown	315		16		172	
Duration of work during pregnancy (weeks)		27.4 (7.9)		25.9 (8.5)		27.5 (7.8)
Unknown	376		23		238	
Hospitalization	1857 (14.6)		304 (28.4)		1507 (13.2)	
Unknown	130		12		86	
Workplace adjustment[d]	1663 (15.1)		141 (15.3)		1489 (15.1)	
Unknown	1828		160		1624	
Childbirth						

(*continued on next page*)

Table 2 (*continued*)

	All $N = 12{,}851$		SGA $N = 1084$		Not SGA $N = 11{,}480$	
	n (%)	Mean (SD[a])	n (%)	Mean (SD[a])	n (%)	Mean (SD[a])
Gestational age (weeks of gestation)		39.3 (1.4)		37.5 (2.0)		39.5 (1.2)
Unknown	200		10		81	
Mode of delivery						
Cesarean	2141 (17.1)		279 (26.2)		1835 (16.3)	
Vaginal delivery	10,376 (82.9)		784 (73.8)		9449 (83.7)	
Unknown	334		21		196	
Infant's sex						
Female	6283 (49.3)		584 (54.0)		5573 (48.6)	
Male	6458 (50.7)		497 (46.0)		5901 (51.4)	
Unknown	110		3		6	
Birthweight (in grams)		3338.8 (471.3)		2531.8 (356.1)		3415.2 (402.0)
Unknown	272		4		20	
Small for gestational age [c]	1084 (8.6)		–		–	
Severely small for gestational age [c]	407 (3.2)		–		–	
Unknown	287		–		–	
Head circumference (in centimeters)		34.4 (1.4)		32.6 (1.2)		34.6 (1.3)
Unknown	1439		171		985	

[a] SD: standard deviation.
[b] Low = never attended school, or attended only primary and middle school; High = educated to level certificate of vocational aptitude, professional qualifications, high-school diploma; University = attended a higher education establishment.
[c] SGA defined as a BW below the 10th percentile for gestational age and sex according to WHO curves. Severely SGA = BW below the 3rd percentile for gestational age and sex.
[d] Workplace adjustment, carried out by the occupational physician, refers to modifications or accommodations made to a job, work environment, or way of working to support an employee's health, safety, or productivity — particularly in cases of disability, illness, or specific needs.

correlations between these occupational exposures are detailed in Appendix G.

3.3. *Multiple occupational exposures during pregnancy and their effects on intrauterine growth*

The exposure ranking step, in the EWAS (Appendix H1), LASSO (Appendix H2) and random forest (Appendix H3) approaches, identified exposure to endocrine disrupters, high strain, kneeling or squatting, a highly demanding job and the intensity of physical effort as the most important occupational exposures for SGA (Table 4, Appendix H4). The final model, including these five variables and an interaction between endocrine disrupter and high strain, job demands and intensity of physical effort (Appendix H5), revealed no significant associations (Fig. 1A). However, there was a non-significant increase in the risk of the infant being SGA associated with occupational exposure to high strain (OR = 1.15, 95 % CI = 0.94 to 1.40) (Fig. 1A). The results of analyses considering only the top five most important exposures selected by EWAS, LASSO or random forest separately are presented in Appendix H6.

The exposure ranking step, in the EWAS (Appendix I1), LASSO (Appendix I2) and random forest (Appendix I3) approaches revealed that leaning forward or sideways, using a computer screen or control panel, ultrafine particles, the intensity of physical effort, airborne germs and repetitive actions were the most important occupational exposures related to BW (Table 5, Appendix I4). The final model, including these variables and interactions between leaning forward or sideways and airborne germs, ultrafine particles and intensity of physical effort (Appendix I5), indicated that leaning forward or sideways during work was positively associated with BW (β = 38, 95 % CI = 4.6 to 71), and using a computer screen or control panel was negatively associated with BW (β = −22, 95 %CI = −44 to −0.57). A significant interaction between leaning forward or sideways and exposure to airborne germs was also detected ($p = 0.03$) (Fig. 1B). Among women not exposed to airborne germs, leaning forward or sideways increased BW significantly, by 38 g (95 % CI = 4.6 to 71). By contrast, no such association was detected in women exposed to airborne germs (Fig. 1D). We found that 36.1 % of the women in occupations involving leaning forward or sideways without exposure to airborne microbes were cleaners and helpers, 10 % were teachers and 9.5 % were social workers. Women whose jobs involved both leaning forward or sideways and exposure to airborne germs were healthcare professionals in 45.5 % of cases (27.3 % were nurses, midwives, medical or radiology technicians and 18.2 % were nursing assistants) and preschool and primary school teachers in 22.9 % of cases. The results of the analyses considering only the results of the EWAS, LASSO or random forest approaches are presented separately in Appendix I6.

The exposure ranking step, in the EWAS (Appendix J1), LASSO (Appendix J2) and random forest (Appendix J3) analyses for HC revealed that repetitive actions, oxygenated solvents, kneeling or squatting, airborne germs, and working outdoors were the most important occupational exposures related to this outcome (Table 6, Appendix J4). The final model included these five variables and interactions between oxygenated solvents and repetitive actions, oxygenated solvents and kneeling, and between oxygenated solvents and airborne germs (Appendix J5). In this final model, repetitive actions (β = −0.09, 95 % CI = −0.16 to −0.03), exposure to oxygenated solvents (β = −0.28, 95 % CI = −0.42 to −0.14) and working outdoors (β = −0.13, 95 % CI = −0.22 to −0.03) were significantly associated with HC and there was a significant interaction between exposures to oxygenated solvents and airborne germs ($p = 0.04$) (Fig. 1C). Exposure to oxygenated solvents was associated with a decrease of 0.13 (95 % CI = −0.26 to 0.00) cm and 0.28 (95 % CI = −0.42 to −0.14) cm in the HC of neonates born to women exposed and unexposed, respectively, to airborne germs (Fig. 1E). The women exposed to oxygenated solvents but not to airborne germs were employed as cleaners (26.9 %), laboratory technicians (10.6 %) and nurses (10.2 %). In terms of industrial activity codes, 10.8 % worked as medical auxiliaries and 10.1 % were involved in cleaning activities. The women exposed to both oxygenated solvents and airborne microbes included 27.5 % nurses and 25.1 % nursing assistants. Most of the women (53.5 %) worked in hospitals according to the industrial activities' nomenclature. The results of the separate analyses of exposures selected by EWAS, LASSO or random forest are presented in Appendix J6.

3.4. *Sensitivity analyses*

Sensitivity analyses on women who continued work until the third trimester of pregnancy are presented in Appendix H7 for SGA, Appendix I7 for BW, and Appendix J7 for HC. The results for SGA and HC were

Table 3
Description of the occupational exposure of women during pregnancy. ELFE study, France, $n = 12{,}851$.

	Not exposed n (%)	Exposed n (%)	Missing
Chemical factors			
Solvents			
Chlorinated	12,453 (99.9)	10 (0.1)[a]	388
Oxygenated	9881 (79.7)	2520 (20.3)	450
Petroleum	12,351 (99.7)	37 (0.3)[b]	463
Detergents	10,226 (82.3)	2193 (17.7)	432
Pesticides	10,310 (99.2)	80 (0.8)	2461
Heavy metals			
Arsenic	12,640 (100.0)	0[a]	211
Cadmium	12,620 (100.0)	0[a]	231
Chromium	12,637 (100.0)	0[a]	214
Iron	12,636 (100.0)	2 (0.0)[a]	213
Lead	12,606 (100.0)	0[a]	245
Nickel	12,636 (100.0)	0[a]	215
Nanoparticles			
Ultrafine particles	11,137 (94.2)	689 (5.8)	1025
Welding fumes	12,636 (100.0)	2 (0.0)[a]	213
Polycyclic aromatic hydrocarbons	12,637 (100.0)	0[a]	214
Benzo(a)pyrene	12,644 (100.0)	0[a]	214
Carbon monoxide	12,270 (100.0)	0[a]	578
Endocrine disruptors and other chemicals	11,966 (95.6)	549 (4.4)	336
Physical factors			
Ionizing radiation	10,059 (82.8)	2083 (17.2)	709
Low-frequency magnetic fields	10,658 (89.3)	1277 (10.7)	916
Non-thermal intermediate frequency		0[a]	1368
Radiofrequency (E field)		23 (0.2)[b]	1368
Radiofrequency (H field)		8 (0.1)[a]	1368
Thermal intermediate frequency (E field)		0[a]	1368
Thermal intermediate frequency (H field)		0[a]	1368
Ultraviolet		89 (0.7)[b]	664
Biological factors			
Airborne germs	8062 (66.7)	4019 (33.3)	770
Cytomegalovirus, parvovirus B19	10,280 (82.7)	2145 (17.3)	426
Hepatitis A, E	11,512 (92.6)	919 (7.4)	420
Hepatitis B, C, human immunodeficiency virus	10,517 (84.6)	1914 (15.4)	420
Strenuous factors			
Strength			
Intensity of physical effort	6316 (52.5)	5716 (47.5)	819
Carrying loads of 10–25 kg	11,204 (92.6)	897 (7.4)	750
Handling loads >4 kg	9827 (81.6)	2222 (18.4)	802
Posture			
Arms raised above the shoulders	10,624 (86.7)	1631 (13.3)	596
Standing	4996 (41.5)	7037 (58.5)	818
Kneeling or squatting	9098 (74.9)	3054 (25.1)	699
Leaning forward or sideways	8420 (68.7)	3834 (31.3)	597
Repetitive actions	7832 (64.2)	4375 (35.8)	644
Vibration			
Using vibrating tools	12,372 (99.2)	105 (0.8)	374
Driving construction machinery	12,462 (98.8)	150 (1.2)	239
Driving a vehicle	11,388 (93.2)	828 (6.8)	635
Using a computer screen or control panel	4049 (33.4)	8073 (66.6)	729
Organizational factors			
Night work	10,803 (92.5)	876 (7.5)	1172
Interruption of tasks	5088 (42.2)	6979 (57.8)	784
Working outdoors	11,195 (92.4)	923 (7.6)	733
Psychosocial factors			
Low level of decision-making authority	6951 (59.9)	4651 (40.1)	1249
Highly demanding job	6962 (60.0)	4642 (40.0)	1247
High strain	5596 (48.2)	6008 (51.8)	1247

[a] These variables have been deleted from the final model (n exposed <10).
[b] These variables have been also deleted from the final model (n exposed for SGA <10).

Table 4
Ranking of occupational exposures for SGA across different approaches (EWAS, LASSO, random forest), with the median rank for each occupational exposure. ELFE study, France, $n = 12{,}851$.

	EWAS	LASSO	Random forest	Median[a]
Endocrine disrupter	1	2	24	2
High strain	3	14	2	3
Kneeling or squatting	4	9	4	4
Highly demanding job	1	18	5	5
Intensity of physical effort	9	6	6	6
Handling of loads >4 kg	7	16	7	7
Working outdoors	6	8	21	8
Hepatitis B, C, HIV	4	23	9	9
Repetitive actions	12	5	10	10
Standing	19	10	8	10
Interruption of tasks	11	4	15	11
Ionizing radiation	7	26	12	12
Cytomegalovirus, parvovirus B19	12	27	11	12
Airborne germs	28	7	13	13
Oxygenated solvents	14	1	14	14
Using a computer screen or control panel	16	22	3	16
Hepatitis A, E	9	24	16	16
Leaning forward or sideways	17	17	1	17
Carrying loads of 10–25 kg	22	15	18	18
Driving a vehicle	18	11	22	18
Raising arms above the shoulders	26	12	19	19
Detergents	19	28	20	20
Night work	15	21	23	21
Low decision authority	21	25	17	21
Driving construction machinery	22	13	28	22
Pesticides	24	19	27	24
Ultrafine particles	25	3	26	25
Low-frequency magnetic fields	27	29	25	27
Using vibrating tools	29	20	29	29

[a] The rankings are sorted by median overall rank across approaches.

similar. For BW, using a computer screen or control panel was going in the same direction, but this result was not significant; and leaning forward or sideways was going in the opposite direction.

4. Discussion

We used data-driven approaches based on three independent statistical methods to identify the most important occupational exposures for the outcomes considered. In the resulting final regression models incorporating the top five exposures and relevant interaction terms, we identified several significant associations between occupational exposures and birth outcomes. For BW, leaning forward or sideways and using a computer screen or a control panel were identified as relevant exposures and there was a significant interaction between leaning forward or sideways and exposure to airborne germs. Repetitive actions, exposure to oxygenated solvents and working outdoors were associated with HC, and there was an interaction between oxygenated solvents and exposure to airborne germs. No significant associations with SGA were identified. These findings were confirmed for women who continued to work into the third trimester of pregnancy. To the best of our

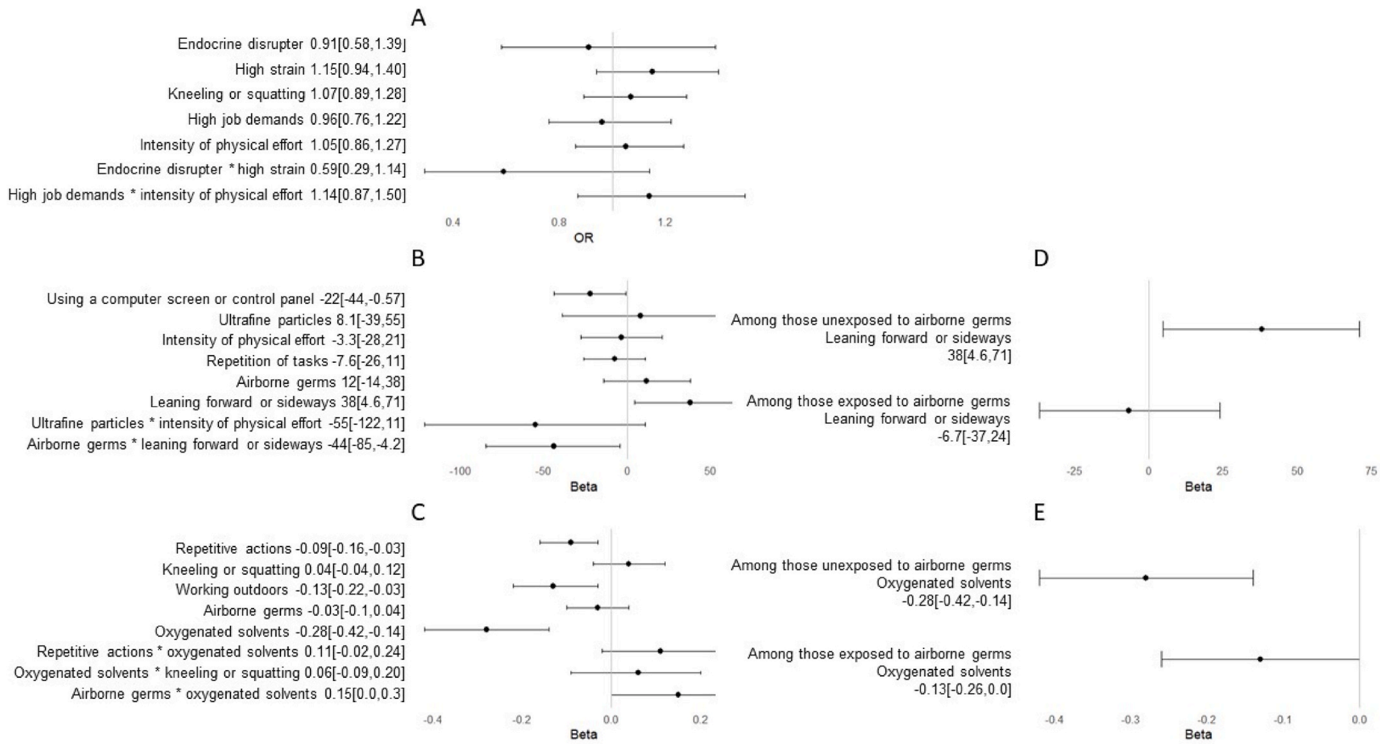

Fig. 1. Relationship between the five most important occupational exposure variables and SGA (A), BW (B), and HC (C), with significant interactions shown. Stratification for exposure to airborne microbes for BW (D) and HC (E). For SGA, analyses were adjusted for educational level, BMI, tobacco consumption, and alcohol consumption,; For BW and HC, analyses were adjusted for educational level, BMI, tobacco consumption, alcohol consumption, gestational age, and the sex of the infant. ELFE study, France.

Table 5
Ranking of occupational exposures for BW across different approaches (EWAS, LASSO, random forest), with the median rank for each occupational exposure. ELFE study, France, $n = 12{,}851$.

	EWAS	LASSO	Random forest	Median[a]
Leaning forward or sideways	1	2	3	2
Using a computer screen or control panel	1	11	2	2
Ultrafine particles	3	3	26	3
Intensity of physical effort	4	9	1	4
Airborne germs	6	6	9	6
Repetitive actions	28	4	6	6
Standing	7	14	5	7
Working outdoors	4	8	21	8
Oxygenated solvents	18	1	10	10
Kneeling or squatting	10	17	4	10
Interruption of tasks	24	7	11	11
Cytomegalovirus, parvovirus B19	12	27	12	12
Endocrine disruptors	13	5	22	13
Driving a vehicle	8	13	24	13
Handling of loads >4 kg	8	15	14	14
High strain	16	16	7	16
Driving construction machinery	17	10	28	17
Hepatitis B, C, HIV	15	28	17	17
Carrying loads 10–25 kg	21	12	19	19
Raising arms above the shoulders	20	19	15	19
Detergents	23	20	13	20
Hepatitis A, E	10	24	20	20
Pesticides	19	21	27	21
Low decision authority	22	23	18	22
Low-frequency magnetic fields	14	22	23	22
Using vibrating tools	24	18	29	24
High job demands	27	25	8	25
Night work	26	26	25	26
Ionizing radiation	29	29	16	29

[a] The rankings are sorted by the median overall rank across approaches.

Table 6
Ranking of occupational exposures for HC across different approaches (EWAS, LASSO, random forest), with the median rank for each occupational exposure. ELFE study, France, $n = 12{,}851$.

	EWAS	LASSO	Random forest	Median[a]
Repetitive actions	2	2	12	2
Oxygenated solvents	4	1	8	4
Kneeling or squatting	12	6	4	6
Airborne germs	12	5	6	6
Working outdoors	1	7	22	7
Standing	11	9	2	9
High strain	5	21	9	9
Intensity of physical effort	19	10	3	10
Endocrine disruptors	10	4	21	10
Leaning forward or sideways	28	11	1	11
Handling loads >4 kg	22	12	10	12
Hepatitis B, C, HIV	6	26	13	13
Raising arms above the shoulders	7	23	14	14
Ultrafine particles	14	3	26	14
Low decision authority	8	28	16	16
Pesticides	15	16	28	16
Using a computer screen or control panel	21	17	7	17
High job demands	17	22	11	17
Interruption of tasks	26	8	17	17
Driving a vehicle	18	14	24	18
Carrying loads 10–25 kg	20	15	19	19
Low-frequency magnetic fields	16	19	23	19
Hepatitis A, E	9	27	20	20
Night work	3	20	25	20
Using vibrating tools	22	18	27	22
Cytomegalovirus, parvovirus B19	24	25	5	24
Ionizing radiation	28	24	18	24
Detergents	25	29	15	25
Driving construction machinery	27	13	29	27

[a] The rankings are sorted by the median overall rank across approaches.

knowledge, this is the first study to assess the contributions to intrauterine growth, using data driven approaches, of a large set of occupational exposures during pregnancy. These results are consistent with those of a previous analysis of the same ELFE cohort, which used a clustering approach to identify four distinct maternal occupational exposome profiles (Tartaglia et al., 2024). One profile, characterized by "postural constraints and psychosocial factors" was found to be associated with a higher risk of SGA and HC, among women who continued to work into the third trimester of pregnancy. These findings reinforce the role of postural and psychosocial constraints on intrauterine growth outcomes.

In the exposure ranking step, the ranks assigned to each type of occupational exposure differed between the three methods used. However, in most cases, the final top five occupational exposures based in the median were ranked within the top five for at least two of the three methods (EWAS, LASSO, random forest). Combining several different methods increases the likelihood of capturing the most important occupational exposures and their relationships to intrauterine growth. However, the results of the analyses of final models based on the results of a single method (EWAS, LASSO or RF) differed from those of the final model based on the median score (combining EWAS, LASSO and random forest results). This can be explained by the fact that EWAS likely focuses on univariate associations and may highlight exposures with strong marginal effects, LASSO performs variable selection with penalization, favoring factors with more consistent effects when accounting for others, and random forest, being a tree-based ensemble method, can minimize variables that are less important in complex, nonlinear interactions. The combination of different methods may have increased clarity and performance and improved the visualization of the results, while reducing the risks associated with high dimensionality (Ohanyan et al., 2022). We used two of the three methods recommended by Staffogia et al. (Stafoggia et al., 2017) — variable selection (EWAS, LASSO) and clustering (random forest) — but not the third (dimension reduction). Variable selection is an alternative to dimension reduction and is sufficient to reduce complexity and to decrease the risk of redundancy. The data-driven approach used here allowed an exploratory analysis of a complex dataset of occupational exposures. For the final model, we selected a cut-off of five variables to include, based on consensus among five co-authors (MT, CG, AP, RG, FD). While this threshold provided a manageable number of exposures for interpretation, a different cut-off could have been chosen, which might have led to slightly different results. Finally, single-exposure approaches often identify a larger proportion to significant associations and underestimate effects (Stafoggia et al., 2017).

In our final model, using a computer screen or control panel was associated with a significant decrease in BW. To the best of our knowledge, no previous epidemiological study on this type of occupational exposure has ever before reported an association with BW. Screen work may serve as a proxy for working in a seated position. The postural constraints associated with working in this position during pregnancy may explain the decrease in BW or simply because it is associated with a lower exposure to an important other factor, such as found in musculoskeletal disorders (Mediouni et al., 2015). We also observed a significant interaction between leaning forward or sideways and exposure to airborne germs, resulting in a significant increase in BW by 38 g (95 % CI = 4.6 to 71) exclusively in women who were not exposed to airborne germs but whose occupations involved leaning forward or sideways. Leaning forward or sideways was investigated in one previous study (Bonzini et al., 2009), but no association was found with SGA, BW, or HC, and there are no biological/pathophysiological hypotheses to account for a possible effect of this factor. Most of the women in this category were cleaners and helpers (36.1 %), teachers (10.0 %), and social workers (9.5 %), and many stopped working during the second trimester (46.4 %). By contrast, the women exposed to both leaning and airborne germs (most of whom were healthcare professionals (45.5 %) and preschool and primary school teachers (22.9 %)) most frequently stopped working during the third trimester (45.1 %). Stopping work earlier or the absence of exposure to airborne germs at work may decrease the cumulative impact of exposures and promote optimal conditions for intrauterine growth.

Several significant associations were observed in our final model for HC. We found that repetitive actions, working outdoors and exposure to oxygenated solvents were all significantly associated with a smaller HC. The effect of repetitive actions may be explained by limiting changes in posture, potentially decreasing venous return and causing muscle tension, particularly in the back, shoulders, and wrists. For women working in awkward postures or exposure to vibrations, concerns have been raised about a potential increase in the risk of intrauterine growth retardation (Interventions recommandées par l). In their 2023 review, Rekha et al. found that working outdoors increased the risk of heat-related diseases, with the increase in body temperature of the mother potentially affecting the unborn child (Rekha et al., 2023). In addition, women who work outdoors are more likely to perform physical work, with multiple constraints, such as exposure to high and low temperatures, outdoor air pollution, or pesticides. We also found that occupational exposure to oxygenated solvents was associated with a significantly smaller HC. Animal studies have shown that some solvents can cross the placental barrier (Donald et al., 1991; Elkin et al., 2020; Loch-Caruso et al., 2019) and that several of these solvent may be neurotoxic. In humans, several studies have highlighted the potential impact of these occupational exposures on neurodevelopment, but very few have investigated their impact on HC. Enderle et al. (2023) reported a significant decrease in HC related to these exposures based on the same population study. Interestingly, our study confirmed this result through a data-driven approach with adjustment for the most important other occupational exposures. It also showed that this effect was greater (but in the same direction) in women unexposed to airborne germs. Similarly, in a cluster analysis study, the profile "postural and strength constraints, chemical and biological factors" they identified showed high exposure to oxygenated solvents and airborne germs (Tartaglia et al., 2024). Although not significantly associated with HC in that analysis, this exposure pattern supports our finding that the combination of these factors may play a role in fetal growth. The women exposed to oxygenated solvents but not to airborne germs were cleaners (26.9 %), laboratory technicians (10.6 %), and nurses working as medical auxiliaries (10.2 %). The women exposed to both oxygenated solvents and airborne germs included 27.5 % nurses, and 25.1 % nursing assistants. Medical professionals may be exposed to airborne germs through regular contact with patients. They also use oxygenated solvents, such as certain alcohols used for disinfection.

Finally, no significant association was found with SGA, contrary to published reports of an association between some occupational exposures, such as solvents (Enderle et al., 2023; Ahmed and Jaakkola, 2007), pesticides (Shirangi et al., 2020), ultrafine particles (Manangama et al., 2019, 2020), physical effort (Vrijkotte et al., 2009; Arafa et al., 2007; Hanke and Hausman, 2000), standing (Croteau et al., 2006; Fortier et al., 1995; Cerón-Mireles et al., 1996; Lj et al., 1990), using vibrating tools (Skröder et al., 2021), low level of decision-making authority (Sejbaek et al., 2018), high strain (Vrijkotte et al., 2009; Arafa et al., 2007; Larsen et al., 2013) and SGA. Furthermore, in 2018, Sejbaek et al. reported a multiplicative interaction between lifting and stress, significantly increasing the risk of the neonate being SGA (Sejbaek et al., 2018). These differences may be explained by differences in the characterization of occupational exposures (measurement, questionnaire or JEM), and/or the thresholds used to define exposure. For our analysis, we decided, a priori, to define exposure with a 50 % threshold to increase specificity. However, this increase in specificity is achieved at the cost of a decrease in sensitivity, which may explain, at least partly, why some of the relationships between occupational exposures and intrauterine growth reported in previous studies did not emerge in this analysis.

Our assessment of 47 types of occupational exposure during pregnancy was based on JEMs or database. However, other factors, such as occupational exposure to noise (Ulin et al., 2024) or heat (Rekha et al., 2023), potentially associated with adverse pregnancy outcomes might also have been of relevance. Internationally recognized JEMs ensure standardized evaluations, despite their limitation of classifying all workers doing the same job in an identical manner (Ge et al., 2018). JEMs based on international data obtained outside of France (endocrine disrupters, FinJEM, Swedish psychosocial JEM, RF-JEM, CANJEM) may had led to the misclassification of some of the exposures assessed, although this effect is probably minimal within high-income countries. Only two gender-specific JEMs (Matgéné night work and Swedish psychosocial JEM) were used. For biomechanical factors, JEM Constances have shown similar predictivity between gender and non-gender JEM (Wuytack et al., 2024). As most non-gender-specific JEMs are based on male populations, there may have been some misclassification of exposure, potentially causing a bias in exposure estimates. Temporal dimensions were included in some JEMs, to account for changes in work practices and regulations, especially for exposure to chemicals. For biological, strenuous, and psychosocial exposures, temporal stability was assumed. In the variability of JEM validity and the existence of fewer tools for psychosocial and strenuous exposures may also introduce non-differential measurement errors, with a potential impact on the results.

We excluded non-working pregnant women to limit the healthy worker effect, as they are generally in poorer health, at higher risk of adverse pregnancy outcomes, and predominantly exposed to poorly characterized non-occupational environments (Casas et al., 2015).

The strengths of this study include the large number of participants from the French Longitudinal Study of Children, the ELFE study, for whom detailed data are available concerning the occupation of women during pregnancy, including the duration of work during pregnancy, outcomes of interest and confounding factors. A second strength is the details of tasks making it possible for a single expert to code occupations according to international and national occupations (ISCO-1968 and PCS-1994) and industrial activities (CITI-1975 and NAF-2003) nomenclatures. This made it possible to use different JEMs to characterize and analyze a large number of occupational exposures ($n = 47$). A third strength was the combination of different statistical approaches, considering complex multiple exposures and interactions, to find the most consistent associations between exposure and intrauterine growth. This approach complements previous work using unsupervised clustering methods to explore patterns during pregnancy (Tartaglia et al., 2024). While our current analysis prioritized variable selection and interactions, the clustering method provides an alternative yet complementary perspective, emphasizing the real-life co-occurrence of exposures across multiple domains.

However, this study also had several limitations. The first of these limitations was the use of JEMs, as previously discussed. We cannot rule out the possibility that occupational exposures subject to smaller measurement errors may have been more likely to be selected. Moreover, several occupational exposures could not be studied in this study because of the small number of exposed women. Indeed, the cut-off of $n < 10$ was applied to ensure model stability in this data-driven framework. Some of these occupational exposures were found associated with fetal growth in epidemiological and/or experimental studies, which leads us to consider them in future studies with larger sample size to allow to properly analyze potential harmful exposure with low prevalence. Finally, the application of machine learning methods in the context of the occupational exposome has been limited to date, because most of the available data are qualitative. For example, other statistical methods such as Bayesian kernel machine regression, more appropriate in the mixture studies, can't be applied in this study because of the qualitative nature of exposures variables. The development of robust statistical approaches tailored to the unique characteristics of the occupational exposome, often involving complex and multivariate datasets, will be required to overcome this limitation. Simulated data would facilitate this process by providing a controlled environment in which to test and validate these methods. By creating realistic scenarios, simulated data enable researchers to identify potential biases, to assess the reliability of analytical tools, and to optimize methodologies before their application to real-world datasets.

5. Conclusion

This study highlights the potential effects of certain chemical, biological, and physically strenuous work factors on intrauterine growth, particularly for BW and HC, with significant interactions stressing the importance of considering multiple exposures in this domain of research. The data-driven approach we have used, without a priori hypothesis, for which it seems necessary to better understand the biological and pathophysiological mechanisms that may exist. Confirmation in additional studies is required, but such consolidated results on multiple exposures are important to adapt prevention strategies more effectively for pregnant women.

CRediT authorship contribution statement

Marie Tartaglia: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Calvin Ge:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Anjoeka Pronk:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Nathalie Costet:** Writing – review & editing, Methodology. **Sabyne Audignon-Durand:** Writing – review & editing, Resources. **Marie-Tülin Houot:** Writing – review & editing, Resources. **Katarina Kjellberg:** Writing – review & editing, Resources. **Maxime Turuban:** Writing – review & editing, Resources. **Nel Roeleveld:** Writing – review & editing, Resources. **Jack Siemiatycki:** Writing – review & editing, Resources. **Camille Carles:** Writing – review & editing, Resources. **Corinne Pilorget:** Writing – review & editing, Resources. **Daniel Falkstedt:** Writing – review & editing, Resources. **Sanni Uuksulainen:** Writing – review & editing, Resources. **Michelle C. Turner:** Writing – review & editing, Resources. **Alexis Descatha:** Writing – review & editing, Resources. **Marie Noëlle Dufourg:** Writing – review & editing, Resources. **Fleur Delva:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Ronan Garlantézec:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Contributors

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Competing interests

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Appendix A. Supplementary data

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References

Agier, L., Portengen, L., Chadeau-Hyam, M., Basagaña, X., Giorgis-Allemand, L., Siroux, V., et al., 2016. A systematic comparison of linear regression-based statistical methods to assess exposome-health associations. Environ. Health Perspect. 124, 1848–1856. https://doi.org/10.1289/EHP172.

Ahmed, P., Jaakkola, J.J.K., 2007. Exposure to organic solvents and adverse pregnancy outcomes. Hum. Reprod. 22, 2751–2757. https://doi.org/10.1093/humrep/dem200.

Almroth, M., Hemmingsson, T., Sörberg Wallin, A., Kjellberg, K., Burström, B., Falkstedt, D., 2021. Psychosocial working conditions and the risk of diagnosed depression: a Swedish register-based study. Psychol. Med. 52, 1–9. https://doi.org/10.1017/S003329172100060X.

Arafa, M.A., Amine, T., Abdel Fattah, M., 2007. Association of maternal work with adverse perinatal outcome. Can. J. Public Health 98, 217–221. https://doi.org/10.1007/BF03403716.

Audignon-Durand, S., Gramond, C., Ducamp, S., Manangama, G., Garrigou, A., Delva, F., et al., 2021. Development of a job-exposure matrix for ultrafine particle exposure: the MatPUF JEM. Ann. Work Expo. Health 65, 516–527. https://doi.org/10.1093/annweh/wxaa126.

Barrera-Gómez, J., Agier, L., Portengen, L., Chadeau-Hyam, M., Giorgis-Allemand, L., Siroux, V., et al., 2017. A systematic comparison of statistical methods to detect interactions in exposome-health associations. Environ. Health 16, 74. https://doi.org/10.1186/s12940-017-0277-6.

Base de données EFICATT - publications et outils - INRS n.d. https://www.inrs.fr/publications/bdd/eficatt.html (accessed May 26, 2023).

Bonzini, M., Coggon, D., Palmer, K.T., 2007. Risk of prematurity, low birthweight and pre-eclampsia in relation to working hours and physical activities: a systematic review. Occup. Environ. Med. 64, 228–243. https://doi.org/10.1136/oem.2006.026872.

Bonzini, M., Coggon, D., Godfrey, K., Inskip, H., Crozier, S., Palmer, K.T., 2009. Occupational physical activities, working hours and outcome of pregnancy: findings from the Southampton women's survey. Occup. Environ. Med. 66, 685–690. https://doi.org/10.1136/oem.2008.043935.

Breiman, L., 2001. Random forests. Mach. Learn. 45, 5–32. https://doi.org/10.1023/A:1010933404324.

Brouwers, M.M., van Tongeren, M., Hirst, A.A., Bretveld, R.W., Roeleveld, N., 2009. Occupational exposure to potential endocrine disruptors: further development of a job exposure matrix. Occup. Environ. Med. 66, 607–614. https://doi.org/10.1136/oem.2008.042184.

Buuren, S van, Groothuis-Oudshoorn, K., Vink, G., Schouten, R., Robitzsch, A., Rockenschaub, P., et al., 2023. Mice: Multivariate Imputation by Chained Equations.

Cai, C., Vandermeer, B., Khurana, R., Nerenberg, K., Featherstone, R., Sebastianski, M., et al., 2020. The impact of occupational activities during pregnancy on pregnancy outcomes: a systematic review and metaanalysis. Am. J. Obstet. Gynecol. 222, 224–238. https://doi.org/10.1016/j.ajog.2019.08.059.

Carles, C., Bouvier, G., Esquirol, Y., Pouchieu, C., Migault, L., Piel, C., et al., 2018. Occupational exposure to pesticides: development of a job-exposure matrix for use in population-based studies (PESTIPOP). J. Expo. Sci. Environ. Epidemiol. 28, 281–288. https://doi.org/10.1038/jes.2017.26.

Casas, M., Cordier, S., Martínez, D., Barros, H., Bonde, J.P., Burdorf, A., et al., 2015. Maternal occupation during pregnancy, birth weight, and length of gestation: combined analysis of 13 European birth cohorts. Scand. J. Work. Environ. Health 41, 384–396. https://doi.org/10.5271/sjweh.3500.

Cerón-Mireles, P., Harlow, S.D., Sánchez-Carrillo, C.I., 1996. The risk of prematurity and small-for-gestational-age birth in Mexico City: the effects of working conditions and antenatal leave. Am. J. Publ. Health 86, 825–831. https://doi.org/10.2105/ajph.86.6.825.

Certenais, T., Manangama, G., Coelho, J., Brochard, P., Sentilhes, L., Teysseire, R., et al., 2019. Expositions à des facteurs de risque sur la reproduction en milieu professionnel. Arch. Maladies Prof. Environnement 80, 489–502. https://doi.org/10.1016/j.admp.2019.09.004.

Charles, M.A., Thierry, X., Lanoe, J.-L., Bois, C., Dufourg, M.-N., Popa, R., et al., 2020. Cohort profile: the French national cohort of children (ELFE): birth to 5 years. Int. J. Epidemiol. 49, 368–369j. https://doi.org/10.1093/ije/dyz227.

Chung, M.K., House, J.S., Akhtari, F.S., Makris, K.C., Langston, M.A., Islam, K.T., et al., 2024. Decoding the exposome: data science methodologies and implications in exposome-wide association studies (ExWASs). Exposome 4, osae001. https://doi.org/10.1093/exposome/osae001.

Croteau, A., 2020. Occupational lifting and adverse pregnancy outcome: a systematic review and meta-analysis. Occup. Environ. Med. 77, 496–505. https://doi.org/10.1136/oemed-2019-106334.

Croteau, A., Marcoux, S., Brisson, C., 2006. Work activity in pregnancy, preventive measures, and the risk of delivering a small-for-gestational-age infant. Am. J. Publ. Health 96, 846–855. https://doi.org/10.2105/AJPH.2004.058552.

Dananché, B., Févotte, J., 2009. Eléments techniques sur l'exposition professionnelle à cinq solvants chlorés. Matrices emplois-expositions À Cinq Solvants Chlorés.

Dananché, B., Févotte, J., Pilorget, C., El Yamani, M., 2015. Eléments techniques sur l'exposition professionnelle à cinq solvants ou familles de solvants oxygénés aliphatiques. Présentation De Matrices emplois-expositions : Aux Alcools, Aux Cétones Et Esters, À L'Éthylène Glycol, Au Diéthyléther, Au Tétrahydrofurane, À Au Moins Un Des Cinq Solvants Ou Familles De Solvants.

de Onis, M., Onyango, A.W., Borghi, E., Siyam, A., Nishida, C., Siekmann, J., 2007. Development of a WHO growth reference for school-aged children and adolescents. Bull. World Health Organ. 85, 660–667. https://doi.org/10.2471/blt.07.043497.

Descatha, A., Fadel, M., Pitet, S., Verdun-Esquer, C., Esquirol, Y., Legeay, C., et al., 2021. Matrice emplois-exposition pour le SARS-CoV-2 (COVID-19) : création de « Mat-O-Covid », validité et perspectives. Arch. Maladies Prof. Environnement 82, 487–493. https://doi.org/10.1016/j.admp.2021.07.008.

Donald, J.M., Hooper, K., Hopenhayn-Rich, C., 1991. Reproductive and developmental toxicity of toluene: a review. Environ. Health Perspect. 94, 237–244. https://doi.org/10.1289/ehp.94-1567945.

Elkin, E.R., Harris, S.M., Su, A.L., Lash, L.H., Loch-Caruso, R., 2020. Placenta as a target of trichloroethylene toxicity. Environ. Sci. Process Impacts 22, 472–486. https://doi.org/10.1039/c9em00537d.

Enderle, I., De Lauzun, V., Metten, M.A., Monperrus, M., Delva, F., Blanc-Petitjean, P., et al., 2023. Maternal occupational exposure to organic solvents and intrauterine growth in the ELFE cohort. Environ. Res. 224, 115187. https://doi.org/10.1016/j.envres.2022.115187.

Evanoff, B.A., Yung, M., Buckner-Petty, S., Andersen, J.H., Roquelaure, Y., Descatha, A., et al., 2019. The CONSTANCES job exposure matrix based on self-reported exposure to physical risk factors: development and evaluation. Occup. Environ. Med. 76, 398–406. https://doi.org/10.1136/oemed-2018-105287.

Fortier, I., Marcoux, S., Brisson, J., 1995. Maternal work during pregnancy and the risks of delivering a small-for-gestational-age or preterm infant. Scand. J. Work. Environ. Health 21, 412–418. https://doi.org/10.5271/sjweh.56.

Ge, C.B., Friesen, M.C., Kromhout, H., Peters, S., Rothman, N., Lan, Q., et al., 2018. Use and reliability of exposure assessment methods in occupational case-control studies in the general population: past, present, and future. Ann. Work Expo. Health 62, 1047–1063. https://doi.org/10.1093/annweh/wxy080.

Genuer, R., Poggi, J.-M., Tuleau-Malot, C., 2022. VSURF: Variable Selection Using Random Forests.

Hanke, W., Hausman, K., 2000. [reproduction disorders in women occupationally exposed to pesticides]. Med. Pr. 51, 257–268.

Henrotin, J.-B., Vaissière, M., Etaix, M., Dziurla, M., Malard, S., Lafon, D., 2018. [Occupational risks during pregnancy: feedback from occupational medical services]. Gynecol. Obstet Fertil. Senol. 46, 20–27. https://doi.org/10.1016/j.gofs.2017.10.029.

Hofner, B., Hothorn, T., 2021. Stabs: Stability Selection with Error Control.

Houot, M.-T., Tvardik, N., Cordina-Duverger, E., Guénel, P., Pilorget, C., 2022. A 34-year overview of night work by occupation and industry in France based on census data and a sex-specific job-exposure matrix. BMC Public Health 22, 1441. https://doi.org/10.1186/s12889-022-13830-5.

Interventions recommandées par l'OMS pour améliorer la santé de la mère et du nouveau-né n.d. https://www.who.int/fr/publications/i/item/WHO_MPS_07.05. (Accessed 19 November 2024).

Joubert, B.R., Kioumourtzoglou, M.-A., Chamberlain, T., Chen, H.Y., Gennings, C., Turyk, M.E., et al., 2022. Powering research through innovative methods for mixtures in epidemiology (PRIME) program: novel and expanded statistical methods. Int. J. Environ. Res. Publ. Health 19, 1378. https://doi.org/10.3390/ijerph19031378.

Kauppinen, T., Uuksulainen, S., Saalo, A., Mäkinen, I., Pukkala, E., 2014. Use of the Finnish information system on occupational exposure (FINJEM) in epidemiologic, surveillance, and other applications. Ann. Occup. Hyg. 58, 380–396. https://doi.org/10.1093/annhyg/met074.

Larsen, A.D., Hannerz, H., Juhl, M., Obel, C., Thulstrup, A.M., Bonde, J.P., et al., 2013. Psychosocial job strain and risk of adverse birth outcomes: a study within the Danish national birth cohort. Occup. Environ. Med. 70, 845–851. https://doi.org/10.1136/oemed-2013-101453.

Lenters, V., Vermeulen, R., Portengen, L., 2018. Performance of variable selection methods for assessing the health effects of correlated exposures in case-control studies. Occup. Environ. Med. 75, 522–529. https://doi.org/10.1136/oemed-2016-104231.

Lepercq, J., Boileau, P., 2005. Physiologie de la croissance fœtale. EMC - Gynécol.-Obstétrique 2, 199–208. https://doi.org/10.1016/j.emcgo.2005.04.005.

Li, M.-X., Yeung, J.M.Y., Cherny, S.S., Sham, P.C., 2012. Evaluating the effective numbers of independent tests and significant p-value thresholds in commercial genotyping arrays and public imputation reference datasets. Hum. Genet. 131, 747–756. https://doi.org/10.1007/s00439-011-1118-2.

Lj, L., J, V., E, K., M, de O., 1990. The effect of maternal work on fetal growth and duration of pregnancy: a prospective study. Br. J. Obstet. Gynaecol. 97. https://doi.org/10.1111/j.1471-0528.1990.tb01718.x.

Loch-Caruso, R., Hassan, I., Harris, S.M., Kumar, A., Bjork, F., Lash, L.H., 2019. Trichloroethylene exposure in mid-pregnancy decreased fetal weight and increased placental markers of oxidative stress in rats. Reprod. Toxicol. 83, 38–45. https://doi.org/10.1016/j.reprotox.2018.11.002.

Manangama, G., Migault, L., Audignon-Durand, S., Gramond, C., Zaros, C., Bouvier, G., et al., 2019. Maternal occupational exposures to nanoscale particles and small for gestational age outcome in the French longitudinal study of children. Environ. Int. 122, 322–329. https://doi.org/10.1016/j.envint.2018.11.027.

Manangama, G., Audignon-Durand, S., Migault, L., Gramond, C., Zaros, C., Teysseire, R., et al., 2020. Maternal occupational exposure to carbonaceous nanoscale particles and small for gestational age and the evolution of head circumference in the French Longitudinal study of children - Elfe study. Environ. Res. 185, 109394. https://doi.org/10.1016/j.envres.2020.109394.

Mediouni, Z., Bodin, J., Dale, A.M., Herquelot, E., Carton, M., Leclerc, A., et al., 2015. Carpal tunnel syndrome and computer exposure at work in two large complementary cohorts. BMJ Open 5, e008156. https://doi.org/10.1136/bmjopen-2015-008156.

Migault, L., Bowman, J.D., Kromhout, H., Figuerola, J., Baldi, I., Bouvier, G., et al., 2019. Development of a job-exposure matrix for assessment of occupational exposure to high-frequency electromagnetic fields (3 kHz-300 GHz). Ann. Work Expo. Health 63, 1013–1028. https://doi.org/10.1093/annweh/wxz067.

Ohanyan, H., Portengen, L., Huss, A., Traini, E., Beulens, J.W.J., Hoek, G., et al., 2022. Machine learning approaches to characterize the obesogenic urban exposome. Environ. Int. 158, 107015. https://doi.org/10.1016/j.envint.2021.107015.

Palmer, K.T., Bonzini, M., Harris, E.C., Linaker, C., Bonde, J.P., 2013. Work activities and risk of prematurity, low birth weight and pre-eclampsia: an updated review with meta-analysis. Occup. Environ. Med. 70, 213–222. https://doi.org/10.1136/oemed-2012-101032.

Pilorget, C., Dananché, B., Luce, D., Févotte, J., 2007. Eléments techniques sur l'exposition professionnelle aux carburants et solvants pétroliers. Matrice emplois-expositions Aux Carburants Et Solvants Pétroliers.

Rekha, S., Nalini, S.J., Bhuvana, S., Kanmani, S., Vidhya, V., 2023. A comprehensive review on hot ambient temperature and its impacts on adverse pregnancy outcomes. J. Mother Child 27, 10–20. https://doi.org/10.34763/jmotherandchild.20232701.d-22-00051.

Rexposome project n.d. https://isglobal-brge.github.io/rexposome/(accessed June 3, 2024).

Sauvé, J.-F., Siemiatycki, J., Labrèche, F., Richardson, L., Pintos, J., Sylvestre, M.-P., et al., 2018. Development of and selected performance characteristics of CANJEM, a general population job-exposure matrix based on past expert assessments of exposure. Ann. Work Expo. Health 62, 783–795. https://doi.org/10.1093/annweh/wxy044.

Sejbaek, C.S., Bay, H., Larsen, A.D., Kristensen, P., Schlünssen, V., Andersen, A.-M.N., et al., 2018. Combined exposure to lifting and psychosocial strain at work and adverse pregnancy outcomes—A study in the Danish National Birth Cohort. PLoS One 13, e0201842. https://doi.org/10.1371/journal.pone.0201842.

Shirangi, A., Wright, J., Blair, E.M., McEachan, R.R., Nieuwenhuijsen, M.J., 2020. Occupational chemical exposures in pregnancy and fetal growth: evidence from the born in Bradford study. Scand. J. Work. Environ. Health 46, 417–428. https://doi.org/10.5271/sjweh.3878.

Skröder, H., Pettersson, H., Norlén, F., Gustavsson, P., Rylander, L., Albin, M., et al., 2021. Occupational exposure to whole body vibrations and birth outcomes - a nationwide cohort study of Swedish women. Sci. Total Environ. 751, 141476. https://doi.org/10.1016/j.scitotenv.2020.141476.

Solovieva, S., Undem, K., Falkstedt, D., Johansson, G., Kristensen, P., Pedersen, J., et al., 2022. Utilizing a nordic crosswalk for occupational coding in an analysis on occupation-specific prolonged sickness absence among 7 million employees in Denmark, Finland, Norway and Sweden. Int. J. Environ. Res. Publ. Health 19, 15674. https://doi.org/10.3390/ijerph192315674.

Stafoggia, M., Breitner, S., Hampel, R., Basagaña, X., 2017. Statistical approaches to address multi-pollutant mixtures and multiple exposures: the state of the science. Curr. Environ. Health Rep. 4, 481–490. https://doi.org/10.1007/s40572-017-0162-z.

Sun, Z., Tao, Y., Li, S., Ferguson, K.K., Meeker, J.D., Park, S.K., et al., 2013. Statistical strategies for constructing health risk models with multiple pollutants and their interactions: possible choices and comparisons. Environ. Health 12, 85. https://doi.org/10.1186/1476-069X-12-85.

Tartaglia, M., Costet, N., Audignon-Durand, S., Carles, C., Descatha, A., Falkstedt, D., et al., 2024. Profiles of the maternal occupational exposome during pregnancy and associations with intrauterine growth: analysis of the French Longitudinal study of children - ELFE study. Environ. Res. 267, 120669. https://doi.org/10.1016/j.envres.2024.120669.

Teysseire, R., Lecourt, M., Canet, J., Manangama, G., Sentilhes, L., Delva, F., 2019. Perception of environmental risks and behavioral changes during pregnancy: a cross-sectional study of French postpartum women. Int. J. Environ. Res. Publ. Health 16, E565. https://doi.org/10.3390/ijerph16040565.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. Roy. Stat. Soc. B 58, 267–288.

Ulin, M., Edokobi, N., Ganjineh, B., Magann, E.F., Whitham, M.D., 2024. The impact of environmental and occupational noise on maternal and perinatal pregnancy outcomes. Obstet. Gynecol. Surv. 79, 219–232. https://doi.org/10.1097/OGX.0000000000001262.

Verspyck, E., Gascoin, G., Senat, M.-V., Ego, A., Simon, L., Guellec, I., et al., 2022. Les courbes de croissance anté- et postnatales en France – recommandations pour la pratique clinique du Collège national des gynécologues et obstétriciens français (CNGOF) et de la Société française de néonatologie (SFN). Gynécologie Obstétrique Fertilité & Sénologie 50, 570–584. https://doi.org/10.1016/j.gofs.2022.06.008.

Vrijkotte, T.G.M., van der Wal, M.F., van Eijsden, M., Bonsel, G.J., 2009. First-trimester working conditions and birthweight: a prospective cohort study. Am. J. Publ. Health 99, 1409–1416. https://doi.org/10.2105/AJPH.2008.138412.

Wuytack, F., Evanoff, B.A., Dale, A.M., Gilbert, F., Fadel, M., Leclerc, A., et al., 2024. Comparison between musculoskeletal pain and gender-specific, non-gendered job-exposure matrix and self-reported exposures in CONSTANCES. J. Occup. Rehabil. 34, 594–605. https://doi.org/10.1007/s10926-023-10148-w.