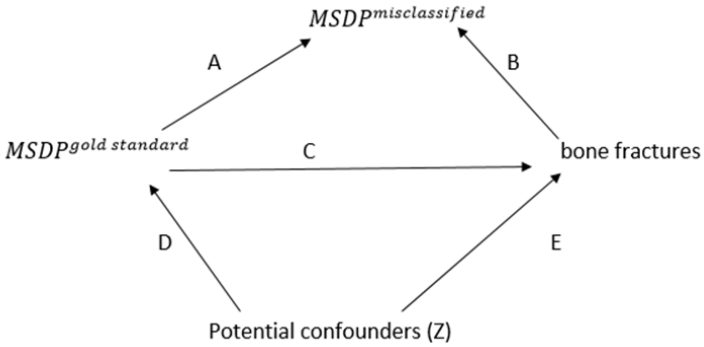
Supplementary material 2. Bayesian analysis

The relationship between MSDP and risk of bone fractures adjusted for potential confounders presented in below directed acyclic graph (DAG) as described by MacLehose et al.;[34]



According to the presented DAG, to estimate true effect of MSDP on the bone fractures, 3 regression models needs to be specified.

(a) Outcome model that specified the effect of MSDP measured via gold standard on the bone fractures (arrow C) adjusted for potential confounders (arrow E) e.g. in an ordinary logistic regression.

(b) Exposure model that specified the effect of potential confounders on the MSDP measured via gold standard (arrow D).

(c) Measurement model that specified the effect of both MSDP measured via gold standard (arrow A) and bone fractures (arrow B) on the MSDP measured via inaccurate method; as follow:

$\log(\text{odds for } MSDP^{misclassified}{}_i | MSDP^{gold\ standard}{}_i,\ bone\ fractures_i = \alpha_0 MSDP^{gold\ standard}{}_i(1-bone\ fractures_i) + \alpha_1(1-MSDP^{gold\ standard}{}_i)(1-bone\ fractures_i) + \alpha_2 MSDP^{gold\ standard}{}_i bone\ fractures_i + \alpha_3\ (1-MSDP^{gold\ standard}{}_i) bone\ fractures_i$

Here, we only adjust MSDP misclassification according to measurement model because original data from included studies were not available to perform 3 models simultaneously.

To conduct sensitivity analysis according to measurement model, crude data about MSDP (yes vs. no) and bone fracture (yes vs. no) were acquired from the included studies and they were extracted carefully into 2×2 tables. Then Bayesian analysis with incorporating prior information about the magnitude and direction of misclassification in MSDP was performed.

In the above measurement model, α_0 and α_1 are sensitivity and false-positive rate (FPR=1–specificity) reporting MSDP among mother who her/his child suffered from bone fractures, respectively. α_2 and α_3 are corresponding figures among mothers with normal children, respectively. The values of sensitivities and FPRs are equal to 1.00 when misclassification did not exist in the observed data. To specify values of measurement model parameters, we apply 2 approaches of deterministic and probabilistic sensitivity analyses. In the deterministic approach, sensitivities and FPRs are known but fixed. Hence, for doing this approach, the parameters were based on the study of Verkerk et al.[35] so that, gold standard was prospective self-reported smoking and parameters were $\alpha_0=0.91$, $\alpha_1=0.06$, $\alpha_2=0.94$, $\alpha_3=0.09$, respectively.

In probabilistic sensitivity analyses, sensitivities and FPRs are unknown and assumed to be distributed according to a continuous probability distribution. The parameters of sensitivities and FPRs falls between 0 and 1, so beta distribution with parameters b1 and b2 is a natural choice. For sensitivities, b1 is the number of mothers who reported MSDP truly, whereas b2 is the number of mothers who report not MSDP but are exposed truly. For FPRs, b1 the number of mother who report MSDP but not exposed truly and b2 is the number of mothers who report not MSDP and not exposed truly. We set the values of b1 and b2 from the study by Verkerk et al.[2]

Moreover, in the Bayesian model a non-informative prior was assumed for intercept term (N (0, 10^6); normal distribution with mean 0 and variance 10^6). A very weakly informative prior was considered for effect of MSDP on bone fractures (N (0, 3.54); normal distribution with mean 0 and variance 3.54) as, we are 95% certain the relative measure for effect of MSDP on bone fractures falls between 1/40 and 40.

Posterior estimates of effect of MSDP on the bone fractures (posterior median, 2.5th and 97.5th quantiles; 95% credible intervals) were obtained using Markov Chain Monte Carlo (MCMC) algorithm. We ran 20,000 MCMC iterations, with 5,000 discarded in burn-in-phase on 2 parallel chains. The Brooks-Gelman-Rubin (BGR) diagnostic, autocorrelation plot and Monte Carlo (MC) error were diagnostic criterion of model convergence. The Bayesian analysis was performed using OpenBUGS 3.2.3. Bayesian analysis codes is as follow;

Deterministic sensitivity analyses

```
model {
  # N observations
  for (i in 1:N) {
    out[i] ~ dbern(p[i])
```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```
    logit(p[i]) <- b0 + b1*exp[i]
ex[i]~ dbern(pm[i])
pm[i]<-a0*(exp[i])*(1-out[i])+a1*(1-exp[i])*(1-out[i])+a2*(out[i])*(exp[i])+
a3*(1-exp[i])*(out[i])

  }
# Priors
 b0   ~ dnorm(0.0,1.0E-6)
 b1  ~ dnorm(0.0,3.54)

a0 <-0.91
a1 <-0.06
a2 <- 0.94
a3 <- 0.09

  }
```

Probabilistic sensitivity analyses

```
model {
  # N observations
  for (i in 1:N) {
    out[i] ~ dbern(p[i])
    logit(p[i]) <- b0 + b1*exp[i]
ex[i]~ dbern(pm[i])
pm[i]<-a0*(exp[i])*(1-out[i])+a1*(1-exp[i])*(1-out[i])+a2*(out[i])*(exp[i])+
a3*(1-exp[i])*(out[i])
  }
# Priors
 b0   ~ dnorm(0.0,1.0E-6)
 b1  ~ dnorm(0.0,3.54)

a0 ~ dbeta(0.91, 0.09)
a1 ~ dbeta(0.06, 0.94)
a2 ~ dbeta(0.94, 0.06)
a3 ~ dbeta(0.09,0.91) }
```

References

1. MacLehose RF, Olshan AF, Herring AH, Honein MA, Shaw GM, Romitti PA. Bayesian methods for correcting misclassification: an example from birth defects epidemiology. Epidemiology 2009;20:27-35.
2. Verkerk PH, Buitendijk SE, Verloove-Vanhorick SP. Differential misclassification of alcohol and cigarette consumption by pregnancy outcome. Int J Epidemiol 1994;23:1218-25.