

Supplementary material

Details of hierarchical Bayesian RLM used for real data example

Let X_{ti} denote the exposure measurement of i^{th} ($i = 1, 2, \dots, N$) participant at t^{th} ($t = 1, 2, \dots, T$) time point. Also, j ($j = 1, 2, \dots, J$) denotes the participant's age group. In addition, y_{ij} denotes the oral cancer status of the participant and lx_{ij} denotes relevant life course exposure.

Likelihood:

$$lx_{ij} = \sum_{t=1}^T w_{tj} * x_{ti}$$

$$\text{logit}(p_{ij}) = \beta_0 + \delta_j * lx_{ij} + \lambda * C_i$$

$$y_{ij} \sim \text{Bernoulli}(p_{ij})$$

$$\delta_j \sim \text{Normal}(\delta, \sigma)$$

$$w_{t,j} \sim \text{Dirichlet}(\alpha)$$

$$\alpha = \phi * \kappa$$

Priors:

$$\phi \sim \text{Dirichlet}(1,1,1)$$

$$\kappa \sim \text{Poisson}(10)T(6,)$$

$$\delta \sim \text{Cauchy}(0,2.5)$$

$$\sigma \sim \text{Normal}(0,1)$$

$$\beta_0 \sim \text{Cauchy}(0,10)$$

$$\lambda \sim \text{Cauchy}(0,2.5)$$

Parameterizing the Dirichlet distribution as expected value (ϕ) and strength of prior evidence (κ) allow us to easily state prior on the average weight function. Since there is no prior study in the field on betel quid chewing, we give the weak prior ($\text{poisson}(10), \text{Dirichlet}(1,1,1)$) for these hyperparameters. The codes for the above model in JAGS is available upon request from the corresponding author.

Stan code for Bayesian Relevant life course exposure model (RStan 2.14)

```
data{
  int<lower=0> N;          #Number of observations
  int<lower=0> T;          #Time points/ life periods of measurement
  int n_cons;             #Number of co-variates

  matrix[N,T] expMat;     #Matrix of exposure measures
  matrix[N,n_cons] conMat; #Matrix of co-variates

  int<lower=0, upper=1> y[N]; #Binary outcome variable
  vector[T] Dalp;         #The parameters for dirichlet prior

  #Expected weights for critical period hypothesis
  vector[T] STC[T];

  #Reference vector of weights for accumulation period hypothesis
  vector[T] STA;
}
parameters{
  real alpha;             #Intercept
  real delta;             #Life-Time effect parameter
  vector[n_cons] lambda; #Parameters for co-variates
  simplex[T] W;          #Weights
}
transformed parameters{
  vector[N] xb;
  #Linear combination
  xb = alpha + delta*(expMat*W) + (conMat*lambda);
}
model{
  alpha ~ cauchy(0,5);    #Prior for Intercept
  delta ~ cauchy(0,2.5); #Prior for life-time effect

  for(i in 1:n_cons){
    lambda[i] ~ cauchy(0,2.5); #Priors for co-variates
  }
  W ~ dirichlet(Dalp);   #Prior for weights

  y ~ bernoulli_logit(xb); #Logistic likelihood
}
generated quantities{
  vector[T+1] EucDist;    #Euclidean Distances
  real exp_delta;        #Odds ratio of lifetime effect

  for(i in 1:T){
    EucDist[i] = distance(W, STC[i]);
  }

  EucDist[T+1] = distance(W,STA);

  exp_delta = exp(delta);
}
```

R code for simulation

R version 3.3.2

```
#Loading libraries
  library(MASS)
  library(boot)

  library(rstan)
  rstan_options(auto_write = TRUE)
  options(mc.cores = parallel::detectCores())

#Setting seed for random number generator
  set.seed(28278)

#Sample sizes
  N1 <- 700
  N2 <- 1500
  N3 <- 3000

#Mean & SD of variables
  mu <- c(0,0,0)
  sd <- c(1,1,1)
  sd2 <- sd %**% t(sd)

#Correlation Matrix
  rho <- 0.7
  corMat <- cbind(c(1,rho,rho^2),c(rho,1,rho),c(rho^2,rho,1))
  corMat

#Covariance Matrix
  Sigma <- sd2*corMat

#Simulating three correlated exposure variables
  X1 <- mvrnorm(N1, mu=mu, Sigma = Sigma, empirical=TRUE)
  X2 <- mvrnorm(N2, mu=mu, Sigma = Sigma, empirical=TRUE)
  X3 <- mvrnorm(N3, mu=mu, Sigma = Sigma, empirical=TRUE)

#True Parameter values
#Overall effect
  beta <- 2

#Critical Period model = 3
  WC3 <- c(0,0,1)

#Pure Accumulation model
  WA <- c(1/3,1/3,1/3)

#Sensitive period model 1st period >2nd peiod >3rd period
  WSe <- c(0.75,0.20,0.05)
```

```
#Simulating Outcomes
#Critical period outcome
y1C3 <- rbinom(N1, size=1, prob= inv.logit(beta*((X1 %**% WC3)[,1])))
y2C3 <- rbinom(N2, size=1, prob= inv.logit(beta*((X2 %**% WC3)[,1])))
y3C3 <- rbinom(N3, size=1, prob= inv.logit(beta*((X3 %**% WC3)[,1])))

#Accumulation outcome
y1A <- rbinom(N1, size=1, prob= inv.logit(beta*((X1 %**% WA)[,1])))
y2A <- rbinom(N2, size=1, prob= inv.logit(beta*((X2 %**% WA)[,1])))
y3A <- rbinom(N3, size=1, prob= inv.logit(beta*((X3 %**% WA)[,1])))

#Sensitive period outcome
y1Se <- rbinom(N1, size=1, prob= inv.logit(beta*((X1 %**% WSe)[,1])))
y2Se <- rbinom(N2, size=1, prob= inv.logit(beta*((X2 %**% WSe)[,1])))
y3Se <- rbinom(N3, size=1, prob= inv.logit(beta*((X3 %**% WSe)[,1])))

#Expected weight vectors
StC <- cbind(c(1,0,0),c(0,1,0),c(0,0,1))
StA <- WA
```

Supplementary Table 1. Posterior median of Euclidean distance from estimated weights to reference vectors of life course models

Sample size	True Life course Scenario	Reference vectors for standard life course scenarios*				
		C1	C2	C3	A	S
700	C3	1.29	1.30	0.15	0.67	1.09
	A	0.84	0.85	0.77	0.10	0.56
	S	0.31	1.13	1.22	0.53	0.09
1500	C3	1.38	1.38	0.05	0.77	1.18
	A	0.85	0.77	0.84	0.07	0.54
	S	0.30	1.12	1.24	0.54	0.06
3000	C3	1.36	1.36	0.07	0.75	1.16
	A	0.85	0.78	0.82	0.06	0.55
	S	0.34	1.08	1.23	0.52	0.05

*C1 = Critical period 1 ($w_1=1, w_2=0, w_3=0$); C2 = Critical period 2 ($w_1=0, w_2=1, w_3=0$); C3 = Critical period 3 ($w_1=0, w_2=0, w_3=1$); A = Accumulation ($w_1=w_2=w_3=0.333$), S = Sensitive period ($w_1=0.75, w_2=0.20, w_3=0.05$). The lowest Euclidean distances are in bold.

Supplementary Table 2. Posterior mean and 95% credible intervals for absolute bias of parameter estimates under different life course scenarios and sample sizes

Parameters	Sample Sizes	Life course scenario (parameter values)		
		Critical period	Accumulation	Sensitive period
W1	700	0.065 (0.004 – 0.154)	-0.017 (-0.134 – 0.099)	0.012 (-0.111 – 0.135)
	1500	0.021 (0.001 – 0.065)	-0.021 (-0.105 – 0.062)	0.017 (-0.068 – 0.104)
	3000	0.030 (0.002 – 0.075)	-0.024 (-0.084 – 0.036)	-0.007 (-0.065 – 0.053)
W2	700	0.054 (0.002 – 0.153)	-0.024 (-0.174 – 0.129)	-0.032 (-0.167 – 0.105)
	1500	0.019 (0.001 – 0.063)	0.036 (-0.073 – 0.146)	-0.019 (-0.118 – 0.076)
	3000	0.025 (0.020 – 0.072)	0.029 (-0.20 – 0.109)	0.012 (-0.060 – 0.080)
W3	700	-0.119 (-0.220 – -0.032)	0.041 (-0.077 – 0.157)	0.019 (-0.046 – 0.123)
	1500	-0.41 (-0.094 – -0.006)	-0.014 (-0.100 – 0.040)	0.002 (-0.047 – 0.076)
	3000	-0.055 (-0.106 – -0.013)	-0.005 (-0.066 – 0.055)	-0.005 (-0.047 – 0.050)
Lifetime effect	700	0.145 (-0.169 – 0.479)	0.086 (-0.228 – 0.417)	0.001 (-0.298 – 0.319)
	1500	0.052 (-0.158 – 0.270)	0.086 (-0.228 – 0.417)	0.061 (-0.151 – 0.280)
	3000	0.046 (-0.104 – 0.202)	-0.087 (-0.230 – 0.060)	0.066 (-0.087 – 0.223)

Supplementary Table 3. Comparing Bayesian RLM with the Structured approach using WAIC*

Approach	Model fit	Life course scenario		
		Critical period	WAIC (SE) Accumulation	Sensitive period
Structured approach	C1	888.39 (17.6)	783.39 (23.7)	679.72 (27.8)
	C2	818.98 (21.4)	736.73 (26.2)	789.28 (23.3)
	C3	642.02 (28.4)	769.93 (25.1)	879.25 (18.0)
	A	737.03 (24.9)	678.84 (28.2)	726.23 (26.4)
	S	643.80 (28.6)	682.22 (28.5)	672.64 (28.5)
Bayesian Relevant exposure model		642.15 (28.3)	682.19 (28.1)	671.51 (28.2)

*C1 = Critical period 1; C2 = Critical period 2; C3 = Critical period 3; A = Accumulation, S = Sensitive period. The lowest WAIC values are in bold.

Supplementary Table 4. Mean and Standard deviation of chew-years of betel quid chewing at three life periods (<20 years, 21-40 years, >40 years) by age group and case-control status

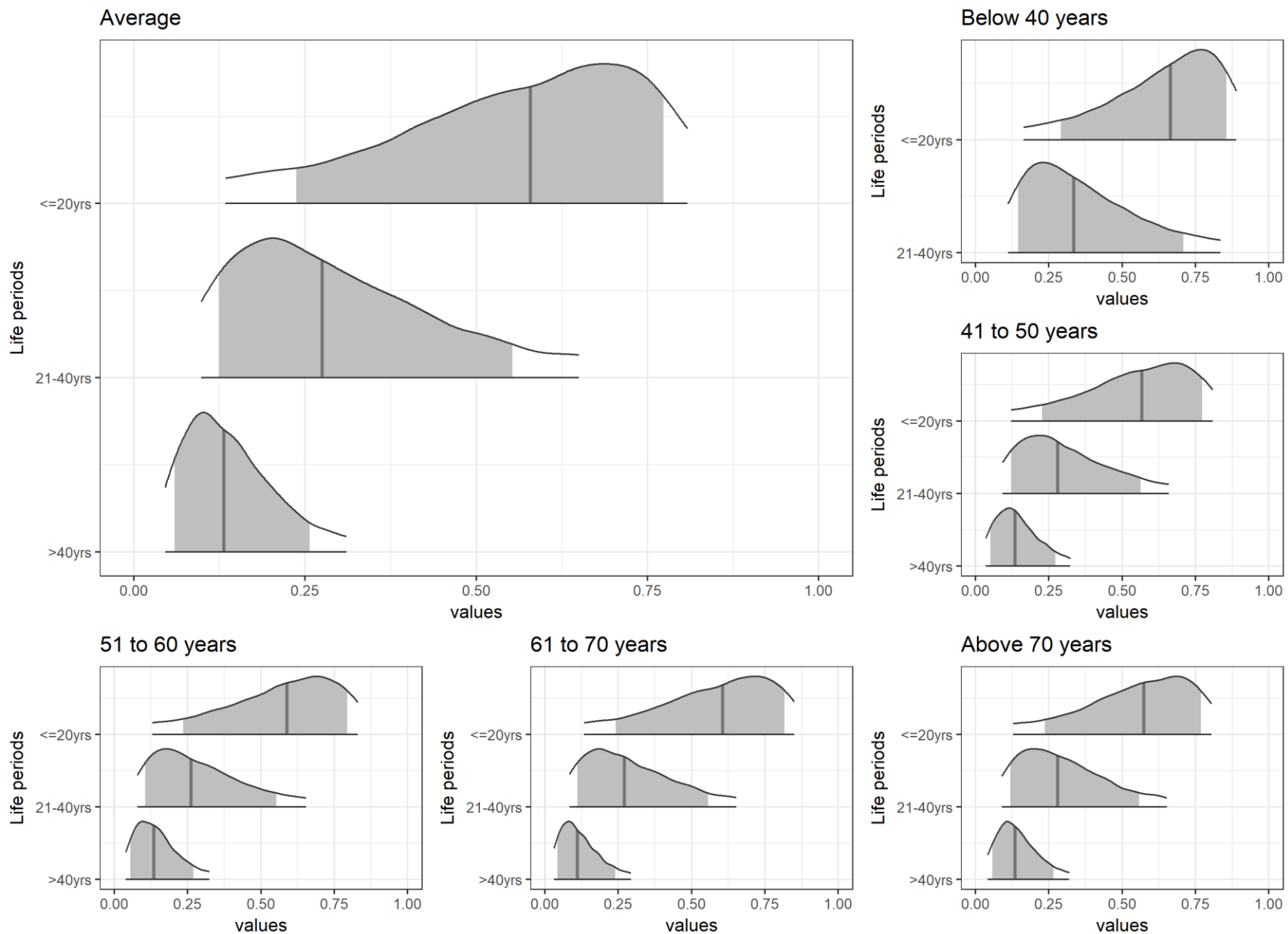
Life periods	Age groups									
	Below 40 years		41 to 50 years		51 to 60 years		61 to 70 years		Above 70 years	
	Control	Case	Control	Case	Control	Case	Control	Case	Control	Case
< 20 years of age	7.5 (10.6)	12.08 (16.8)	0.50 (0.1)	10.44 (16.3)	1.29 (2.6)	10.81 (17.0)	1.10 (3.3)	10.37 (17.7)	10.19 (20.0)	13.32 (18.3)
21 to 40 years of age	11.50 (4.9)	126.27 (97.8)	24.65 (29.3)	119.35 (103.1)	51.43 (60.8)	90.31 (69.4)	66.14 (65.7)	93.88 (79.0)	71.82 (77.6)	121.45 (117.1)
> 40 years of age	NA	NA	12.45 (2.7)	48.93 (48.6)	74.97 (52.5)	99.80 (66.8)	169.34 (161.3)	175.58 (117.1)	169.77 (176.8)	283.65 (160.4)

Supplementary Table 5. Mean and 95% credible interval for life period specific weights for chew-years of Betel quid chewing for different age-groups

Life periods	Age groups				
	Below 40 years	41 to 50 years	51 to 60 years	61 to 70 years	Above 70 years
< 20 years of age	61.7 (7.3 – 90.9)	53.4 (5.7 – 83.7)	55.1 (5.8 – 85.6)	56.5 (6.0 – 87.8)	53.8 (5.9 – 82.9)
21 to 40 years of age	38.3 (9.1 – 92.7)	31.5 (6.9 – 72.8)	29.8 (5.9 – 72.4)	30.5 (6.7 – 72.4)	31.1 (6.8 – 73.2)
> 40 years of age	NA	15.1 (2.2 – 37.5)	15.1 (2.6 – 37.7)	12.9 (2.2 – 34.7)	15.2 (2.8 – 37.5)

Supplementary Table 6. Distribution of selected characteristics of HeNCe Life Study - India

	Control (n=350)		Case (n=371)	
	n (%)	Mean ± SD	n (%)	Mean ± SD
Age		60 ± 11		60 ± 11
Sex				
Female	167 (0.45)		154 (0.44)	
Male	204 (0.55)		196 (0.56)	
Education				
Low	182 (0.49)		267 (0.76)	
High	189 (0.51)		83 (0.24)	
Material deprivation index		20.44 ± 7.1		13.80 ± 6.4
Pack-years of tobacco smoking		12.18 ± 26.3		16.05 ± 28.2
Liter of ethanol consumed		0.18 ± 1.1		0.76 ± 3.0
Betel quid				
Never	306 (0.82)		97 (0.28)	
Ever	65 (0.18)		253 (0.72)	



Supplementary Figure 1. Posterior densities of life period specific weights for chew-years of betel quid chewing for different age groups and average over groups

Supplementary Table 7. Life time effect of betel quid chewing on risk of development of head and neck cancer among ever users

	OR (95% Credible intervals)
Average	1.04 (1.00 – 1.15)
Age-group specific	
Below 40 years	1.04 (0.99 – 1.16)
41 to 50 years	1.07 (1.01 – 1.26)
51 to 60 years	1.05 (1.01 – 1.14)
61 to 70 years	1.04 (1.01 – 1.14)
Above 70 years	1.02 (1.00 – 1.04)

SAS code for Bayesian RLM

```
/*Bayesian Relevant Life Course Exposure model*/
/*Three life periods example*/
/*Binary outcome with logistic likelihood and no confounders*/

/*Using Marginal priors on weights*/

proc mcmc data=Data nbi=50000 nmc=100000 outpost=OutData
          init = random monitor=(lw1 lw2 lw3 beta0 delta w);

  parms lw1 lw2 lw3 ;
  array w[3];
  w[1] = exp(lw1)/(exp(lw1)+ exp(lw2)+ exp(lw3));
  w[2] = exp(lw2)/(exp(lw1)+ exp(lw2)+ exp(lw3));
  w[3] = exp(lw3)/(exp(lw1)+ exp(lw2)+ exp(lw3));

  parms beta0 delta ;
  prior beta0 ~ cauchy(0,2.5);
  prior delta ~ cauchy(0,2.5);

  prior lw1 ~ beta(1,1);
  prior lw2 ~ beta(1,1);
  prior lw3 ~ beta(1,1);

  p = logistic(beta0+ delta*(w[1]*x1+w[2]*x2+w[3]*x3));
  model y ~ binomial(1,p);
run;

/*Using Joint multivariate prior on weights*/

proc mcmc data=Data nbi=50000 nmc=100000 outpost=DataOut
          init=random diag=(mcse ess) propcov=quanew;

  array dal[3];
  begincnst;
    do i =1 to 3;
      dal[i] = 1;
    end;
  endcnst;

  array w[3];
  parms w;
  parms beta0 delta;

  prior beta0 ~ cauchy(0,2.5);
  prior delta ~ cauchy(0,2.5);
  prior w~dirichlet(alpha=dal);

  p = logistic(beta0+ delta*(w1*x1+w2*x2+w3*x3));
  model y ~ binomial(1,p);
run;
```