

## **1. Age**

Participants were asked to indicate their sex by selecting one of three options: female, male, or prefer not to answer. Age categories were divided into nine groups: under 60 years, early 60s (60-64 years), late 60s (65-69 years), early 70s (70-74 years), late 70s (75-79 years), early 80s (80-84 years), late 80s (85-89 years), early 90s (90-94 years), and late 90s (95-99 years). The median values were calculated as the midpoint of each age range. Due to only 1.25% being 85 years or older, we narrowed down the age range

## **2. Sports and Exercise experience**

Sports and exercise participation patterns were assessed through past and present engagement. The questionnaire evaluated five distinct categories of participation: individual sports, team sports, contact sports (such as basketball and soccer involving physical contact with opponents), exercise/sports participation with friends, and solitary exercise/sports activities. For each category, participants were asked to indicate their involvement using a three-point response scale ('yes,' 'no,' or 'unsure'). For analytical purposes, responses were dichotomized: 'yes' was coded as 1, while both 'no' and 'unsure' responses were coded as 0, creating binary variables for each category of sports participation.

The age of initiation for participants' current sports and exercise activities was assessed using a single question: 'At what approximate age did you begin your current sports/exercise activities?' Responses were categorized into 14 age groups: teens, twenties, thirties, early forties (40-44 years), late forties (45-49 years), early fifties (50-54 years), late fifties (55-59 years), early sixties (60-64 years), late sixties (65-69 years), early seventies (70-74 years), late seventies (75-79 years), early eighties (80-84 years). For statistical analyses, each age category was converted to its median value. Responses indicating 'no participation in sports/exercise' were coded as 0.

To assess the duration of current sports and exercise participation, participants were asked: 'How long have you been engaging in your current sports/exercise activities?' Response options were categorized into seven intervals: no participation in sports/exercise, less than 1 year, 1 to less than 3 years, 3 to less than 5 years, 5 to less than 10 years, 10 to less than 20 years, and 20 years or more. For statistical analyses, duration categories were converted to midpoint values. No participation in sports/exercise was coded as 0 years.

### 3. Bayesian sparse regression model

We employed a Bayesian sparse regression model with horseshoe priors for variable selection. This approach was chosen because the Horseshoe Bayesian Quantile Regression provides superior performance in sparse settings through its global-local shrinkage prior, demonstrating lower coefficient bias and better forecast accuracy compared to alternative Bayesian methods, particularly in high-dimensional datasets with few significant predictors [1,2]. Given our large sample size ( $n > 5,000$ ), we chose to focus on probability distributions through Bayesian approach rather than traditional p-value-based significance testing, as the latter can lead to potentially misleading statistical significance in large samples even when effect sizes are negligible. This Bayesian approach thus enables us to better quantify uncertainty and assess the practical significance of relationships in our data. The model included a global shrinkage parameter ( $\tau$ ) following a half-Cauchy distribution and local shrinkage parameters ( $\lambda$ ) for each predictor variable. The regression coefficients ( $\beta$ ) were modeled with normal distributions, with variances determined by both global and local shrinkage parameters. Shrinkage coefficients ( $\kappa$ ) were calculated as  $1/(1 + \lambda^2)$ , representing the probability of variable inclusion. Numeric predictor variables were standardized using `StandardScaler()` from `scikit-learn` library (version 1.4.0), while categorical variables (0 and 1) were included in the model without scaling. The response variable was standardized to have a mean of zero and a standard deviation of one. The model was fitted using the No-U-Turn Sampler (NUTS) with 4 chains, 15,000 warmup iterations, and 30,000 posterior samples per chain. Variables with inclusion probabilities ( $1 - \kappa$ ) greater than 0.5 were considered relevant predictors.

The model can be formally expressed as:

Prior Distributions:

$$\begin{aligned}\beta_0 &\sim N(0, 5^2) \\ \tau &\sim \text{Half-Cauchy}(1) \\ \lambda_j &\sim \text{Half-Cauchy}(1), \text{ for } j = 1, \dots, P \\ \beta_j &\sim N(0, (\tau\lambda_j)^2), \text{ for } j = 1, \dots, P \\ \sigma^2 &\sim \text{InverseGamma}(3, 2)\end{aligned}$$

Shrinkage Coefficients:

$$\kappa_j = 1/(1 + \lambda_j^2)$$

Likelihood:

$$\begin{aligned}y_i &\sim N(\mu_i, \sigma^2) \\ \mu_i &= \beta_0 + \sum_j (x_{ij}\beta_j)\end{aligned}$$

where  $P$  is the number of predictors,  $x_{ij}$  represents the  $j$ -th predictor for the  $i$ -th observation,

and  $y_i$  is the response variable.

#### **4. convergence diagnostics**

##### **4.1. Humour style**

For affiliative humour, R-hat values exceeded the recommended threshold for eight variables (Age: 1.39, Start\_age: 1.20, Sport\_years: 1.31, work\_moderate\_MET: 1.23, work\_METs: 1.11, transportation\_METs: 1.16, Past\_ex\_friends: 1.31, Present\_ex\_friends: 1.14). For self-enhancing humour, R-hat values exceeded the recommended threshold for four variables (leisure\_high\_MET: 1.29, sedenraty: 1.25, sex: 1.27, Past\_ex\_alone: 1.37).

##### **4.2. Humour coping style**

For self-enhancing humour coping, R-hat values exceeded the recommended threshold for eight variables (Start\_age: 1.16, Sport\_years: 1.21, work\_moderate\_MET: 1.20, transportation\_METs: 1.20, leisure\_high\_MET: 1.17, sedentary: 1.17, Past\_ex\_alone: 1.18, Present\_ex\_friends: 1.13). Cooperative humour coping showed convergence issues for three variable (work\_moderate\_MET: 1.15, sex: 1.12, Present\_ex\_friends: 1.11), Aggressive humour coping demonstrated high R-hat values for eight variables (work\_high\_MET: 1.10, sex: 1.11, past\_ex\_friends: 1.12), and self-mocking humour coping demonstrated high R-hat values for four variables (Age: 1.10).

##### **4.3. Loneliness**

For loneliness, R-hat values exceeded the recommended threshold for three variables (Age: 1.18, affiliative humour: 1.39, Present\_ex\_friends: 1.12).

#### **References**

- 1 Kohns D, Szendrei T. Horseshoe prior Bayesian quantile regression. *J R Stat Soc Ser C Appl Stat.* 2023;73:193–220. doi: 10.1093/jrssc/qlad091
- 2 Potjagailo G, Kohns D. Flexible Bayesian MIDAS: Time-variation, group-shrinkage and sparsity. *SSRN Electron J.* Published Online First: 2023. doi: 10.2139/ssrn.4488238