Quantifying Sex-differences in Anthropometry: a Bayesian approach

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I. INTRODUCTION

Injury and fatality risks in automotive crashes show varying degrees of differences between men and women [1-2]. These differences can be the result of factors intrinsic to the human body (such as differences in morphology or material properties) and of extrinsic factors, such as the design of vehicle environment (seat, restraint system). Anthropometry can have an influence on both of these factors. In this paper, we present an approach to evaluating sex-differences of anthropometric measures with the aim of using this information in the development of human surrogates for biomechanics.

By virtue of men being taller (and hence heavier) than women, anthropometric measures can be expected to have different distributions between the sexes within a population. To understand the influence of sex on anthropometric measures, we investigated the male-female differences for two scenarios relevant to current deliberations in road safety. First, a size-matched comparison was made where the man and the woman are of the same global anthropometric characteristics (for example, height and mass). Second, an average female is compared to an average male.

II. METHODS

Bayesian linear regression was used to model anthropometric measures from ANSUR II dataset [3]. As the goal of the analysis was to assess the plausible range of an anthropometric measure for a specific person (and at times an uncommon person when described by a specific stature, BMI, or sex), a model was required. Bayesian models are flexible but, more importantly, they can be used to generate posterior predictive draws, which can be treated as though the dataset is a large population sample, accounting for variation in anthropometry among people as well as model uncertainty. Two anthropometric measures — neck circumference and neck link (vertical distance between tragion and seventh cervical vertebra) — were considered for this preliminary study. Height, BMI and sex were selected as the predictors.

The likelihood and prior distribution of the models were defined as:

$$y = \mu + \varepsilon$$
$$\varepsilon \sim Normal\ (0, \sigma)$$
$$\mu_i = a_j + \beta_j(H_i - H_{mean}) + \gamma_j(BMI_i - BMI_{mean})$$
$$\text{with } j = Male\ or\ female\ given\ i$$
$$\alpha \sim Normal\ (mean,\ 10),\ \beta \sim Normal\ (0,\ 1),\ \gamma \sim Normal\ (0,\ 1),\ \sigma \sim Uniform\ (0,\ 10)$$

The priors for all α, β and γ were normally distributed, and α was centered around the mean of the anthropometric measure of the full dataset. The model was fitted using the Markov Chain Monte Carlo (MCMC) No-U-Turn Sampler algorithm.

The male-female comparisons were done using posterior predictive distributions of the anthropometric measures. For the first comparison of *size-matched persons*, anthropometric measures were compared between a man and a woman corresponding to an average woman (height 1.61 m and BMI 24 kg/m2). For the second comparison of *average persons*, anthropometric measures were compared between an average man corresponding to height 1.75 m and BMI 25 kg/m^2 and average woman (same measurements as in the previous comparison). A contrast distribution, calculated as the difference between the male and the female posterior predictive distributions, was used to quantify the sex-difference.

III. INITIAL FINDINGS

Posterior predictive distributions of the neck circumference showed clear differences between men and women for the size-matched comparison (Fig. 1(a)) as well as for the average person comparison (Fig. 1(b)). For the neck link, the distributions did not show a distinct difference between the sexes, with the contrast distributed

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about zero (see Supplementary Material). Ninety-five percent High Density Interval for the neck circumference had small or no overlap, indicating that the female neck was smaller in both comparisons.

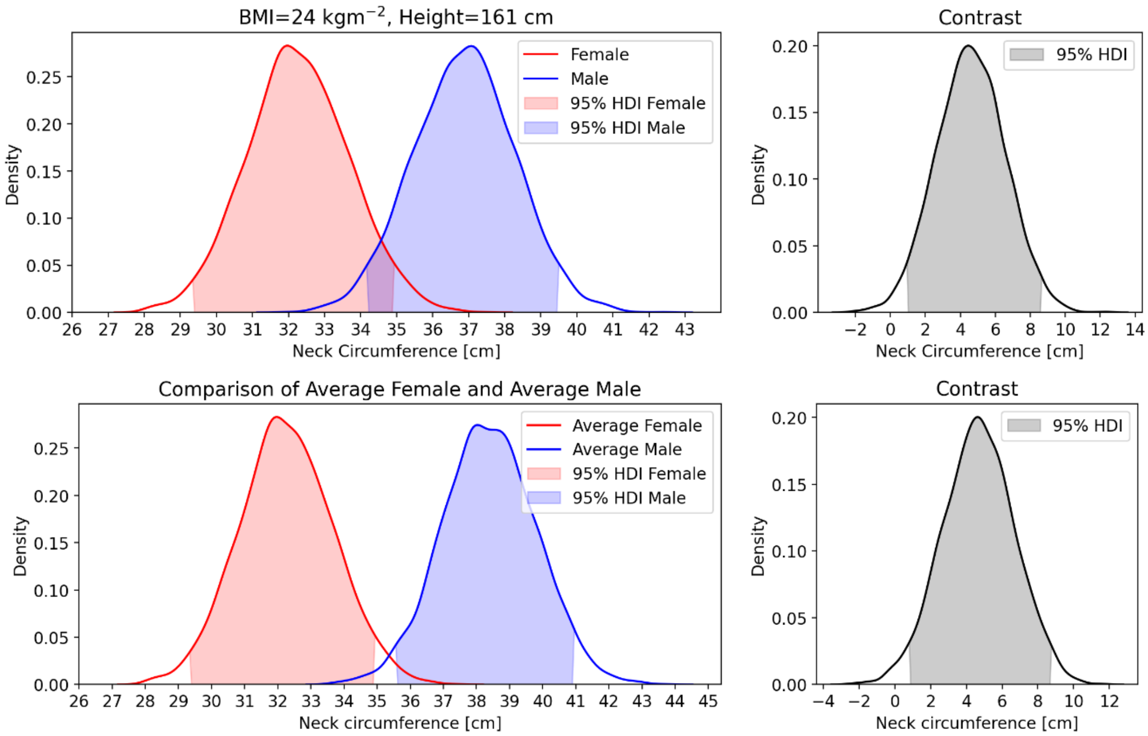

Fig. 1. Posterior predictive distribution of neck circumference. (a) Top: male and female distributions corresponding to the size of an average woman. (b) Bottom: average female and average male distributions.

IV. DISCUSSION

A Bayesian approach to modelling anthropometric data provides a straightforward method to simulate specific scenarios or to compare specific persons, especially when the data are sparse in an empirical study. For instance, in this study the anthropometric measures were compared for sizes of average male and average female as recommended for vehicle occupant safety evaluations [4]. The average male in this case would be an uncommon female and vice versa, which implies there would be limited data to make these comparisons. Bayesian regression can be effective in such scenarios, to obtain estimates of anthropometric measures along with the uncertainties involved in the predication. This information can be consecutively used in mechanistic models, such as finite element human body models (HBMs), to evaluate the role of anthropometric sex-differences in injury risks.

Neck was selected as an exemplar body region for this preliminary study as whiplash associated disorders are known to exhibit sex-differences [5]. Previous size-matched studies with a small number of samples had reported similar sex-differences in the neck circumference [6]. The differences in neck circumference would imply that male HBMs cannot be used to study neck biomechanics of women because the neck cross-section is not comparable. The contrast distributions show that neither the average male HBMs nor uniformly scaled versions of the average male can be sufficiently representative of the female neck.

V. SUPPLEMENTARY MATERIAL

Data, code and figures are available at https://github.com/chiaraf10/anthropometry-sex-differences-prestudy

VI. REFERENCES

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