

Hip Hypermobility Analysis Final Report

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Executive Summary

Joint hypermobility refers to the excessive movement of joints beyond the typical range observed in the general population. Previous research in hypermobility suggests hypermobility may be associated with greater incidence of injury which may in turn be associated with elevated psychosocial outcomes. While prior literature has made the connection between hypermobility and injury-risk, as well as the connection between physical injury and psychosocial symptoms, no research has investigated the interplay between hypermobility and psychosocial outcomes directly. This study focuses on examining the association between hypermobility (measured by Beighton Score), and various psychosocial measures, including pain catastrophizing, pain interference, and pain self-efficacy.

Data were gathered prospectively from a Baylor Scott and White hip clinic from 445 patients. The data were primarily analyzed using a multiple linear regression (MLR) with Beighton Score as the outcome variable of interest. An MLR was conducted on both complete cases and using multiple-imputation approaches to harness the full spectrum of available data. A post-hoc analysis utilizing a logistic regression was also performed on imputed data where Beighton Score was dichotomized with <4 indicating no hypermobility and ≥ 4 indicating hypermobility. The logistic regression was included since prior research often dichotomized Beighton Score when conducting regression analyses.

Contrary to initial expectations, the psychosocial variables in this data set exhibit minimal influence on hypermobility in the MLR. Instead, the MLR identifies age and gender as the primary predictors, with younger females demonstrating higher hypermobility

scores. These results hold robustly across the complete cases MLR, the MLR with multiple imputation, and the logistic regression.

This investigation, while finding no evidence of an association between hypermobility and psychosocial outcomes, must be interpreted with caution. The data were limited by substantial missingness and may not be representative of the broader population, indicating that the absence of evidence in this analysis should not be taken as definitive proof that no true association exists. Similar future research might inform more holistic diagnostic and treatment strategies that integrate both physical and psychological dimensions of patient care. Since this research uses data gathered from a single hip clinic, this population limits how broadly medical professionals can apply these findings. Future research ought to conduct surveys of a broader population who have not already reported to a clinic to more fully investigate psychosocial symptoms in hypermobile patients prior to any incidence of injury.

Keywords: Beighton Score, Hypermobility, Hip Dysplasia, Pain Catastrophizing, Pain Interference Pain Self-Efficacy

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Introduction

Joint hypermobility (JHM) is characterized by an increased range of motion in joints beyond the average limits observed in the general population. This condition arises from various anatomical factors, including the health of articular surfaces, bone structure, muscle tone, and the integrity of surrounding soft tissues such as ligaments, tendons, and entheses. The variability in range of motion is influenced by nonmodifiable factors like sex, age, and ethnicity, as well as modifiable factors including nutritional status, body weight, physical training, and history of trauma or surgery. Synonymous terms for JHM in medical literature include 'joint laxity' and 'joint hyperlaxity' (Castori et al., 2017; Micale et al., 2021).

The Beighton Score is a widely used nine-point clinical assessment for quantifying joint hypermobility (Amtmann et al., 2010). This scoring system, which evaluates hyperextensibility across multiple joints, has demonstrated substantial inter- and intra-rater reliability despite variability in test administration (Bockhorn et al. 2021). Historically, researchers and clinicians have often identified individuals as hypermobile using a Beighton Score threshold (e.g., ≥ 4) to distinguish between “hypermobile” and “non-hypermobile” groups. However, this practice of dichotomizing a naturally continuous measure has been broadly criticized within the field, as it can diminish statistical power and obscure important nuances in the data. In fact, health practitioners have suggested using this metric in conjunction with other factors rather than as a single decision assessment metric (Bukva et al., 2018; Crijns et al., 2019).

In recent years, attention has shifted towards understanding the broader clinical implications of hypermobility. Evidence suggests joint hypermobility may be associated with a heightened risk for musculoskeletal conditions, particularly among adolescents (Hampton et al., 2019; Jochimsen et al., 2021; Naal et al., 2014). Although these findings underscore the significance of structural and biomechanical factors, emerging research increasingly demonstrates that patient outcomes, including pain perception and functional limitations, may also be influenced by psychological factors. In orthopedic contexts, a growing body of literature correlates patient-reported psychological measures with clinical outcomes, yet the interplay between hypermobility and psychosocial constructs remains underexplored.

Given the scarce evidence linking Beighton-defined hypermobility to psychological components, this study aims to examine whether individuals with higher Beighton Scores—specifically those with hip dysplasia—exhibit distinct profiles in three key domains: pain catastrophizing, pain interference, and pain self-efficacy. Pain catastrophizing, commonly assessed using the Pain Catastrophizing Scale (PCS), reflects an exaggerated negative mental set related to pain perception and emotional distress (Sullivan et al., 1995). Pain interference, measured through the Patient-Reported Outcomes Measurement Information System Pain Interference (PROMIS-PI), evaluates the extent to which pain hinders engagement in social, cognitive, and physical activities (Amtmann et al., 2010). Finally, the Pain Self-Efficacy Questionnaire (PSEQ) assesses an individual's confidence in performing tasks despite pain (Nicholas, 2007).

Using data gathered from a single physician's patient panel at a Baylor Scott & White orthopedic clinic, this study aims to explore the following hypotheses:

- Patients with greater hypermobility (as indicated by higher Beighton Scores) will exhibit higher levels of pain catastrophizing (PCS) and pain interference (PROMIS-PI).
- Patients with greater hypermobility will report lower pain self-efficacy (PSEQ).

By examining these relationships, the current study seeks to fill a critical gap in the literature and offer a more comprehensive understanding of how joint hypermobility, beyond its mechanical implications, may influence psychosocial factors. This approach contributes a new perspective on patient care, potentially informing more holistic assessment strategies and tailored interventions for individuals presenting with hypermobility-related conditions.

Methodology

All data were visually explored, and assumptions were verified before completing any analyses. The participant characteristics and analyses methods are described in the subsections below. Any tools used to perform the analyses or verify assumptions are also mentioned in the corresponding subsection.

Participants

Patient data were obtained from a single specialty hip clinic. Patients completed a hypermobility test and several brief psychosocial surveys. Hypermobility was measured via a Beighton Score assigned at the completion of the test. The three main psychosocial surveys consisted of the Patient Self Efficacy Questionnaire, the Pain Catastrophizing Survey, and the Pain Interference Survey. All patient data were analyzed retrospectively. The full sample consisted of $n = 445$ individuals of which the majority (77%) were female.

Data Analysis

Because the goal of the study was to explore the relationship between hypermobility and psychosocial outcome, we utilized a multiple linear regression (MLR) model with Beighton Score treated as a continuous outcome variable. The full model included the three psychosocial scores as continuous predictor variables. Age and gender were further included in the model as covariate adjustments.

Several primary assumptions were required to justify fitting an MLR. Each of these assumptions were verified analytically or through prior research before proceeding. First, the three psychosocial scores were examined for multicollinearity using Pearson's ρ , and Variance Inflation Factor (VIF) scores were checked post-model construction to confirm the assumption of independence between the predictors. A VIF score less than 10 indicated sufficient independence (Kleinbaum et al., 1988). Second, we also assumed the normality of the error terms and verified this assumption through constructing a QQ-plot. Third, we assumed treating the Beighton Score and psychosocial outcomes as continuous would appropriately approximate their true ordinal nature. Treating an ordinal variable as continuous implies the distance between two scores is equivalent across the spectrum (i.e., the difference between a score of 1 and a score of 2 is equivalent to the difference between a score of 2 and a score of 3). This equal spacing assumption is commonly used in psychometrics and tends to hold when ordinal variables have greater than 5 categories (Rhemtulla, Brosseau-Liard, & Savalei, 2012).

Two multiple linear regression models were constructed. The first model utilized only complete cases (i.e., rows with no missing data). The second model pooled results via Rubin's Rules from a multiple imputation analysis with $m = 100$ to use the full data set. To

determine the appropriate number of imputations, the fraction of missing information (FMI) was calculated for each variable and the number of imputations was set at a level equal to or greater than the highest FMI in accordance with standard practice (White, Royston, & Wood, 2011). The regressions for both the complete case scenario and the imputation scenario can be represented by the following equation:

$$\widehat{\text{Beighton Score}} = \beta_0 + \beta_1 \text{Gender} + \beta_2 \text{Age} + \beta_3 \text{PCS} + \beta_4 \text{PROMIS.PI} + \beta_5 \text{PSEQ}$$

Because medical professionals commonly consider a Beighton Score of ≥ 4 indicative of hypermobility, an additional post-hoc analysis was also performed through dichotomizing Beighton Score into two categories (≥ 4 and < 4) and constructing a logistic regression. Similar to the multiple linear regression, the logistic regression is as follows:

$$\log(\widehat{\text{Beighton Score}} \geq 4) = \beta_0 + \beta_1 \text{Gender} + \beta_2 \text{Age} + \beta_3 \text{PCS} + \beta_4 \text{PROMIS.PI} + \beta_5 \text{PSEQ}$$

All analyses and pre-processing steps were conducted using R statistical software.

Shiny App

A Shiny application was included as a component in this analysis. A Shiny app is a web-based interface for visualizing statistical results coded in R. The app included tabs for exploratory visualizations of variable distributions and relationships, imputation comparisons, and regression results. All results reported below can also be accessed via the app. Furthermore, the app was created with the purpose of allowing users to also upload new data sets to perform new analyses if desired via an *Upload* tab.

Results

The patient cohort was predominantly female, with females comprising 77% of the sample. The mean age of participants was 40.9 years. The average Beighton Score recorded was approximately 3.8, consistent with baseline hypermobility expectations for individuals

attending a hip mobility clinic. Table 1 provides an overview of the sample's demographics and characteristics prior to any imputation.

Table 1: Patient Characteristics (N=445)

Variable	
Female n(%)	343(0.77)
Age	40.9(16.47)
Beighton Score	3.8(3.2)
Pain Catastrophizing Score	20.3(13.5)
Pain Interference Score	63.0(70.2)
Pain Self-efficacy Score	6.0(3.5)

^a All variables are mean (SD) unless otherwise noted.

Table 2 presents the correlation coefficients among the variables examined in this study. The analysis revealed minimal associations between the Beighton Score and the three pain-related measures: Pain Catastrophizing Score (PCS Total Score; $\rho = 0.005$), Pain Interference (PROMIS.PI; $\rho = 0.02$), and Pain Self-Efficacy (PSEQ; $\rho = 0.11$). In contrast, significant correlations were observed among the pain-related variables themselves. Specifically, a moderately positive correlation was identified between PCS and PROMIS.PI ($\rho = 0.51$), a slightly weaker negative correlation between PSEQ and PCS ($\rho = -0.42$), and a stronger negative correlation between PROMIS.PI and PSEQ ($\rho = -0.59$).

Table 2: Correlation Matrix

			Pain Catastrophizing Score	Pain Interference Score	Pain Self- Efficacy Score
	Age	Beighton Score			
Age	1.00	-0.30	-0.15	0.16	-0.09
Beighton Score	-0.30	1.00	0.00	0.02	0.11
Pain Catastrophizing Score	-0.15	0.00	1.00	0.51	-0.42
Pain Interference Score	0.16	0.02	0.51	1.00	-0.59
Pain Self-Efficacy Score	-0.09	0.11	-0.42	-0.59	1.00

A substantial portion of data was missing for three primary variables, with missingness rates ranging from 47% to 64% (see Table 3). No data was missing for the age, gender, or Beighton Score variables. The Fraction of Missing Information (FMI) values for the three psychosocial variables were high, between 0.68 and 0.86, indicating significant information loss necessary for accurate parameter estimation. To address the potential bias introduced by this missing data, which may not be completely random, Multiple Imputation by Chained Equations (MICE) was employed as the imputation technique.

Table 3: Missing Data Table

	n missing	Proportion missing	FMI
Pain Catastrophizing Total Score	250	0.56	0.68
Pain Interference Score	286	0.64	0.86
Pain Self-Efficacy Score	210	0.47	0.68

Three separate regressions were conducted across two datasets to evaluate the differences in Beighton Score with respect to patient age, gender, and pain-related effects using three distinct metrics as seen in Table 4.

Table 4: Regression Results

	Complete Cases	Multiple	Multiple Imputation
Term	MLR	Imputation MLR	Logistic Regression
(Intercept)	6.791	5.693	2.313
	(0.043)	(0.009)	(0.205)
Age	-0.060	-0.059	-0.054
	(<0.001)	(<0.001)	(<0.001)
GenderMale	-2.495	-3.703	-2.987
	(<0.001)	(<0.001)	(<0.001)
Pain Catastrophizing	0.001	-0.003	-0.005
Score	(0.980)	(0.833)	(0.707)

	Complete Cases	Multiple	Multiple Imputation
Term	MLR	Imputation MLR	Logistic Regression
Pain Interference	-0.011	0.021	0.014
Score	(0.829)	(0.496)	(0.610)
Pain Self-efficacy	-0.018	0.018	0.006
Score	(0.839)	(0.769)	(0.912)

^a The first row for each variable is the estimate, and the value below in parentheses is the p-value for the corresponding estimate.

Multiple linear regressions were performed on both complete cases and the imputed data set. The analyses indicated both age and gender significantly influenced the outcome variable (see Table 4). Specifically, older participants (Complete Cases MLR: $\beta_{age} = -0.060, p < 0.001$; Imputed MLR: $\beta_{age} = -0.059, p < 0.001$) and males (Complete Cases MLR: $\beta_{gender} = -2.495, p < 0.001$; Imputed MLR: $\beta_{gender} = -3.703, p < 0.001$) exhibited lower outcome scores. In contrast, psychological factors including pain catastrophizing, pain interference, and pain self-efficacy did not show significant associations with the outcome (Complete Cases MLR: $p > 0.05$; Imputed MLR: $p > 0.05$). Logistic regression of the dichotomized Beighton Score on the imputed data set revealed that age and gender were significant predictors of hypermobility (Imputed LR: $\beta_{age} = -0.0504, p < 0.001$; $\beta_{gender} = -2.987, p < 0.001$). Pain scores did not show significant associations with the outcome variable (Imputed LR: $p > 0.05$).

Discussion

When examining assumptions for the MLR, the correlation plot and VIF scores indicate multicollinearity is of little concern since all correlations are less than 0.6, and the VIF scores are less than 10. Furthermore, upon examining diagnostic plots for the regression on complete cases, there seem to be no significant leverage points. The QQ-plot (not shown) showed slightly heavy tails, but otherwise the normality assumption was appropriate. The heavy tails cause little concern given MLR is quite robust to departures from normality (Schmidt & Finan, 2018).

For the two MLRs (complete cases and multiple imputation), the results are similar to one another. Both regression outputs indicate the three psychosocial variables have a minimal effect at best on hypermobility as measured by the Beighton Score. Since all three psychosocial variables have a p-value much greater than 0.05, there is not sufficient evidence to claim there is any relationship between the psychosocial outcomes and the Beighton Score. However, both MLRs indicate age and gender do have statistically significant effects. To interpret the age and gender coefficients for the regression utilizing multiple imputation in Table 4, we are 95% confident that age and gender are related to the Beighton Scores. A 95% level of confidence means that if we conducted this same analysis multiple times on different samples of individuals, we would expect a non-zero effect to exist between age and Beighton Score as well as gender and Beighton Score 95% of the time. On average in this sample, the Beighton Score decreases by 0.06 for each one-year increase in age. Additionally, males on average have Beighton Scores 3.7 points lower than females. This indicates that younger females tend to have the highest incidence of hypermobility.

In general, the results of the multiple imputation MLR ought to be preferred over the complete cases MLR because the former utilizes all available data while the latter drops rows with missing information. Because the multiple imputation MLR considers more data, the standard errors for the coefficients are smaller which means greater confidence in the coefficient estimates and thus, greater precision. Although comparing the coefficients and standard error for the complete cases MLR versus the multiple imputation MLR (Table 4) demonstrates that there are some minor changes in the coefficient values, the most significant change occurs in the coefficient on gender. Because the gender variable has no missing rows in the original data set, the change in the coefficient post-imputation is due to the elimination of bias by including the full data set rather than any introduction in bias due to the imputation.

The logistic regression was a post-hoc analysis and thus any results ought to be treated with caution. However, the logistic regression also confirmed the results of the MLRs that psychosocial outcomes are not statistically significantly associated with Beighton Score, but age and gender are significantly associated with Beighton Score. The similarity between the logistic regression results and the previous MLR results imply that splitting the data at a Beighton Score cutoff of 4 does not significantly alter the conclusion. This similarity is helpful to keep in mind since clinicians commonly use this cutoff instead of treating Beighton Score as a continuous scale.

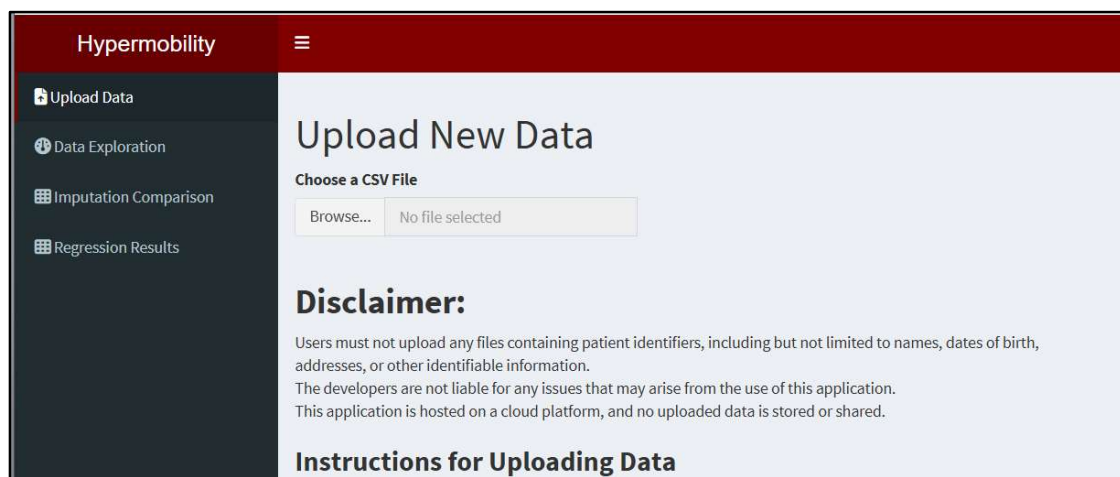
Interactive Shiny App

Results can be viewed on the interactive Shiny application at the following link: https://schneiderstats.shinyapps.io/hypermobility_app/. The app includes four tabs: an

Upload tab, a Data Exploration tab, an Imputation Comparison tab, and a Regression Results tab. Each is described in detail below.

The *Upload Data* tab (see Figure 1) enables users to obtain a full analysis of any data set without the necessity of coding. If more data is gathered regarding hypermobility after the completion of this project, the researcher can simply upload any new data (in the format specified within the instructions section of the tab) and see results for both an MLR, logistic regression, and exploratory data plots.

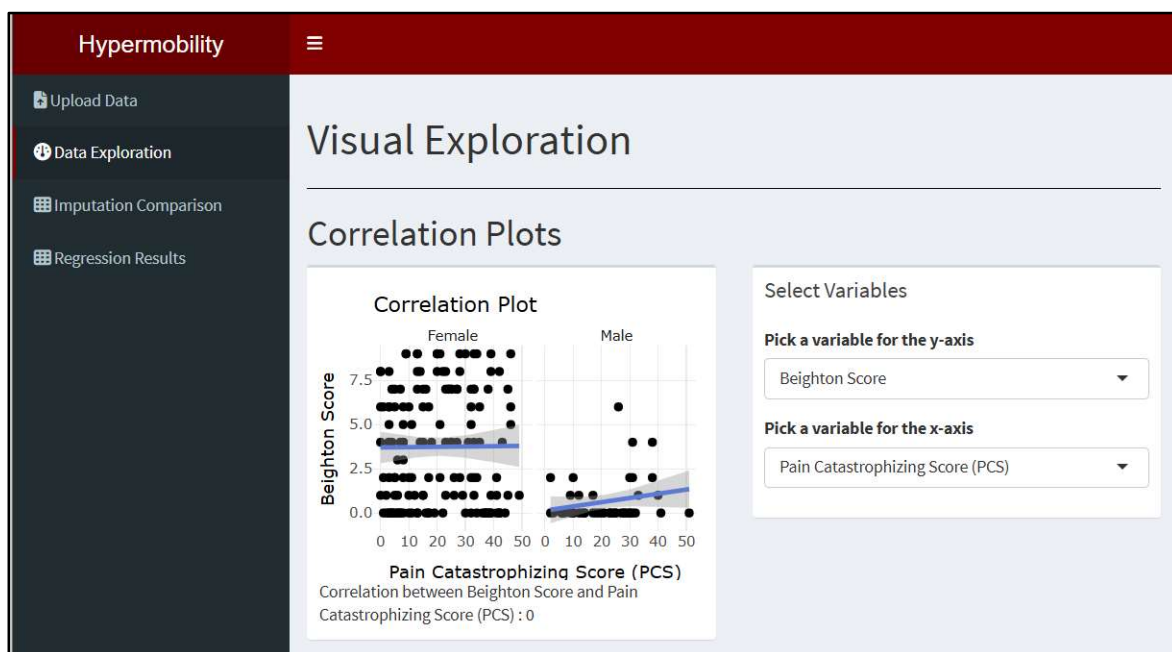
Figure 1: Upload Data Tab



The *Data Exploration* tab (see Figure 2) includes pairwise correlation plots to visualize the relationship between continuous variables and also to check assumptions of independence between the predictor variables. Within the tab, the summary statistics section includes an output of the data file and the ability to visualize the distribution of each variable via a box plot. The box plot can be split into Male and Female categories

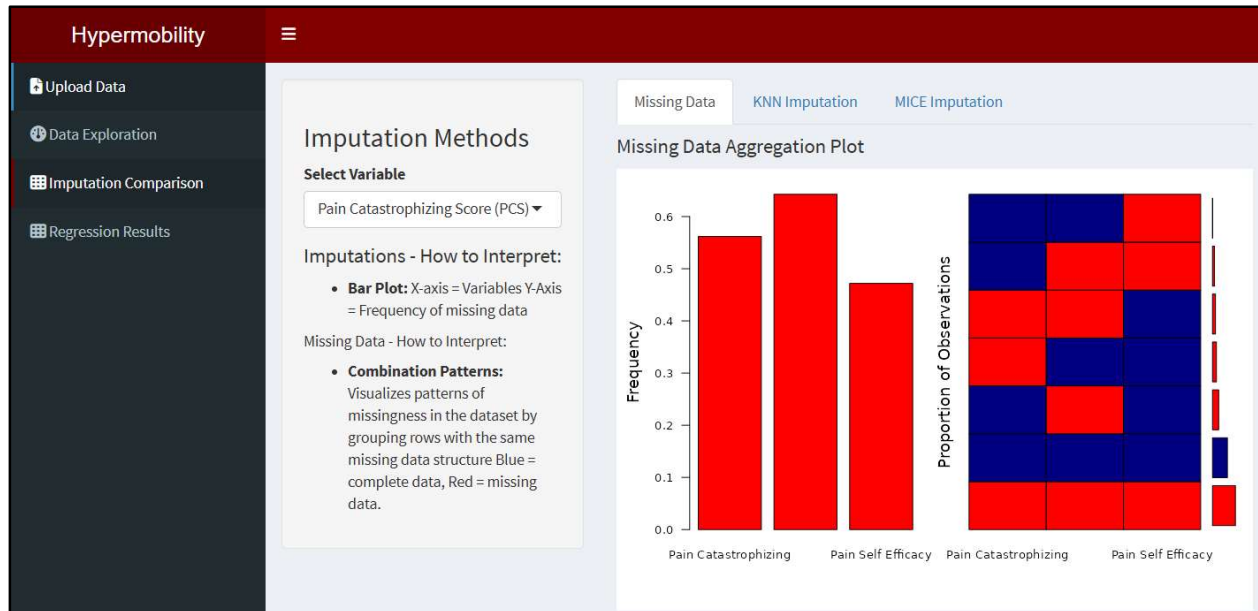
separately, if desired. Any missing values for the variable will be displayed below the box plot.

Figure 2: Data Exploration Tab



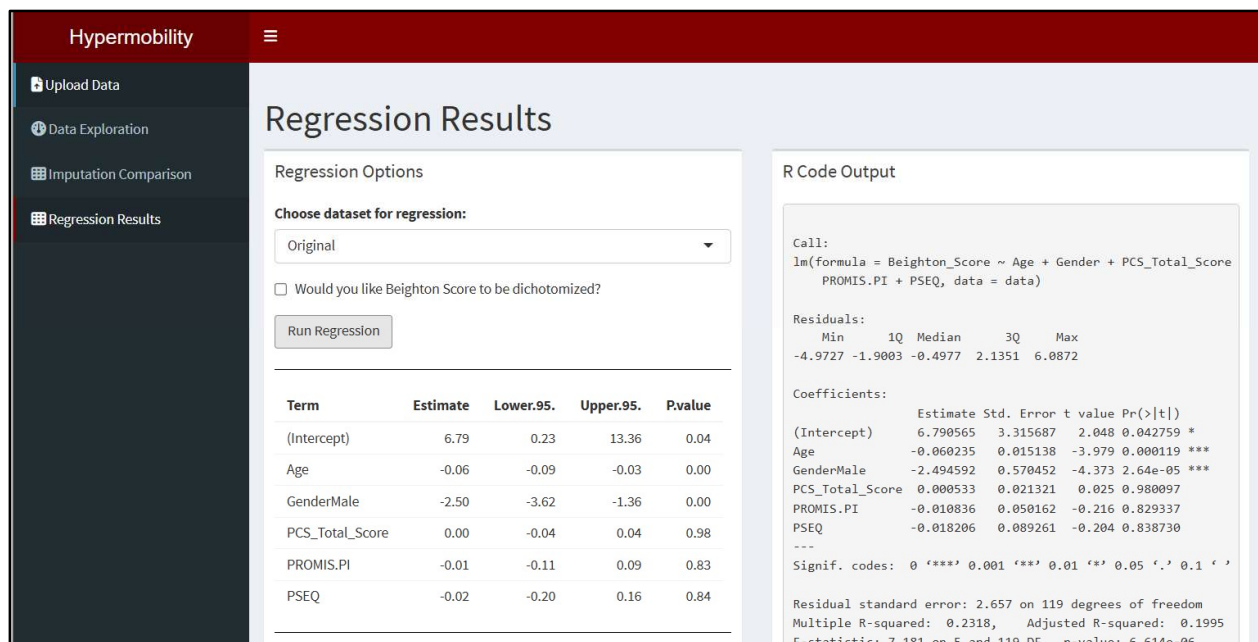
The *Imputation Comparison* tab (see Figure 3) provides a bar plot and grid plot of all missing observations within the data set. The grid plot helps the user identify any missingness patterns. For each predictor variable, the KNN Imputation and MICE Imputation sections display box plots of the imputed data which can be compared to the box plot of the original data shown in the Missing Data section. This allows the user to check how the imputation method performs and whether the distribution remains similar post-imputation.

Figure 3: Imputation Comparison Tab



Finally, the *Regression Results* tab (see Figure 4) enables users to see the output for MLR and logistic regression on both complete cases (only utilizing complete rows in the data set) and the imputed data set. To use only complete cases, the user should select “Original” from the drop-down menu. To use the imputed data set, the user should select “Imputed” from the dropdown menu. If the user selects the option to dichotomize the Beighton Score, the Beighton Score will be split into two groups (<4 and ≥ 4) and the application will conduct a logistic regression on the uploaded data. Otherwise, an MLR will be conducted. All interpretations for predictor variables can be seen by selecting a variable from the drop-down menu below the regression results. Interpretations will include an interpretation of the coefficient and the 95% confidence interval. All code output for these analyses is displayed on the right side of the screen.

Figure 4: Regression Results Tab



The app provides a user-friendly method of exploring hip hypermobility data without requiring any coding expertise. Users can check regression assumptions, visually explore each variable, conduct imputations when necessary, and view/compare various regression results. These features are useful both for compiling results for academic papers and also for explaining the data to non-subject matter experts.

Conclusion

While the findings from the data analyzed in this report indicate that there is no evidence of an association between pain self-efficacy, pain catastrophizing, pain interference and hypermobility, these findings are based upon a data set with substantial missingness from a very limited (and possibly biased) population. Thus, we cannot definitively conclude from this analysis that there is no relationship between psychosocial

variables and hypermobility. This study does replicate previous research findings that age and gender are significantly associated with hypermobility, however, further validating this result and lending credibility to this study's sample.

A major limitation of the study is the missing data for the psychosocial variables. The fraction of missing information (FMI) ranged from 68%-86%, indicating a substantial loss of information due to missingness. Furthermore, since the data were prospectively gathered, the study was not powered ahead of time which means that the sample size for this study may not be adequate to capture an effect size of interest. Due to this limitation, we cannot claim definitively that there is not an effect between the psychosocial variables and hypermobility. Thus, both the missingness and the retrospective nature of this analysis limit the validity of the findings in this report.

A second major limitation of the study which may explain the lack of any evidence of a relationship between psychosocial outcomes and hypermobility is the population from which the sample was obtained. Since the sample originated from a single hip clinic, any findings are limited in their generalizability. Patients who present to a hip clinic most probably already have some medical concern resulting in a sample that is inherently biased towards a larger representation of individuals with higher incidences of injury. Since the original hypothesis purported that hypermobility might increase physical injury incidence which in turn might impact psychosocial outcomes, drawing a sample from a population who already has an injury or medical concern might negate the marginal effects of hypermobility on elevating injury rate (thus mitigating the effects of hypermobility on psychosocial outcomes). To remedy this limitation, we recommend sampling from the

general population rather than a medical clinic to see if hypermobility increases injury and thus impacts psychosocial outcomes. We do recognize that this recommendation would probably be more costly and burdensome, however, than sampling from a single medical clinic and thus such an analysis is outside the scope of this project.

The relationship between hypermobility and psychological outcomes remains an under-researched area. This study provides some insight into the interaction of the physical and the emotional/psychological as it relates to hypermobility research, and it explores whether patients experiencing physical pain might also have a less explored psychological side effect. Though our initial findings do not indicate any major relationship, further research is necessary to explore this more fully in a broader population of hypermobile and non-hypermobile individuals and also in medical contexts beyond hypermobility. Continued research can help ensure at-risk patients are receiving not just physical medical care but also the necessary additional mental health care required for pain management.

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