#### 健康大數據 hw1

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2025-10-16

#### Introduction:

This report analyzes data from the 2021–2023 NHANES to explore the relationship between body mass index (BMI) and mean systolic blood pressure (SBP) among adults aged 20 years and older. Using R for data cleaning, visualization, and descriptive analysis, the study also examines how BMI varies by race and education level, and evaluates the consistency of blood pressure measurements across repeated trials. Through these analyses, the report aims to illustrate basic health data handling and visualization techniques using large-scale public health datasets.

#Q1. Among adults aged  $\geq 20$  years in the 2021–2023 NHANES, observe the association between BMI and mean systolic blood pressure (SBP) and does the association vary between sex?

```
# ========== Q1: BMI & SBP Cleaning and Visualization =======
# Load libraries -----
pkgs <- c("tidyverse", "haven", "janitor", "stringr", "scales", "skimr", "nan</pre>
iar")
to_install <- setdiff(pkgs, rownames(installed.packages()))</pre>
if (length(to_install)) install.packages(to_install)
invisible(lapply(pkgs, library, character.only = TRUE))
## Warning: package 'ggplot2' was built under R version 4.3.3
## Warning: package 'purrr' was built under R version 4.3.3
## Warning: package 'lubridate' was built under R version 4.3.3
## — Attaching core tidyverse packages —
                                                             - tidvve
rse 2.0.0 —
## √ dplyr
              1.1.4
                        ✓ readr
                                    2.1.5
## √ forcats
              1.0.0

√ stringr

                                    1.5.1
## √ ggplot2 3.5.2
                        √ tibble
                                    3.2.1
## ✓ lubridate 1.9.4

√ tidyr 1.3.1
```

```
## √ purrr
               1.1.0
## — Conflicts ·
                                                           - tidyverse_co
nflicts() —
## X dplyr::filter() masks stats::filter()
## X dplyr::lag()
                      masks stats::lag()
## i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to for
ce all conflicts to become errors
## Warning: package 'haven' was built under R version 4.3.3
## Warning: package 'janitor' was built under R version 4.3.3
##
## Attaching package: 'janitor'
##
## The following objects are masked from 'package:stats':
##
##
       chisq.test, fisher.test
## Warning: package 'scales' was built under R version 4.3.3
##
## Attaching package: 'scales'
##
## The following object is masked from 'package:purrr':
##
       discard
##
##
## The following object is masked from 'package:readr':
##
##
       col factor
##
##
## Attaching package: 'naniar'
## The following object is masked from 'package:skimr':
##
##
       n_complete
dir.create("outputs", showWarnings = FALSE)
data_dir <- "/Users/cindytsai/Desktop/健康大數據"
# Load data -----
demo <- read xpt(file.path(data dir, "DEMO L.xpt")) %>% clean names()
bpx <- read_xpt(file.path(data_dir,"BPXO_L.xpt")) %>% clean_names()
bmx <- read_xpt(file.path(data_dir,"BMX_L.xpt")) %>% clean_names()
skimr::skim(demo)
```

#### Data summary

Name demo Number of rows 11933 Number of columns 27

Column type frequency:

numeric 27

Group variables None

#### Variable type: numeric

skim_v ariable seqn	n_mi ssin g 0	comple te_rate 1.00	mean 1363 44.0 0	sd 344 4.90	p0 1303 78.0 0	p25 1333 61.0 0	p50 1363 44.0 0	p75 1393 27.0 0	p10 0 142 310. 0	hist
sddsrv yr	0	1.00	12.0 0	0.00	12.0 0	12.0 0	12.0 0	12.0 0	12.0	_  
ridstat r	0	1.00	1.74	0.44	1.00	1.00	2.00	2.00	2.0	_  
riagen dr	0	1.00	1.53	0.50	1.00	1.00	2.00	2.00	2.0	- 
ridage yr	0	1.00	38.3 2	25.6 0	0.00	13.0 0	37.0 0	62.0 0	80.0	<u>-</u>
ridage mn	115 56	0.03	11.6 3	6.81	0.00	6.00	11.0 0	17.0 0	24.0	
ridreth 1	0	1.00	3.10	1.08	1.00	3.00	3.00	4.00	5.0	=
ridreth 3	0	1.00	3.32	1.52	1.00	3.00	3.00	4.00	7.0	

skim_v ariable ridexm on	n_mi ssin g 307 3	comple te_rate 0.74	mean 1.52	sd 0.50	p0 1.00	p25 1.00	p50 2.00	p75 2.00	p10 0 2.0	hist —— ——
ridexa gm	914 6	0.23	121. 91	67.1 6	0.00	66.0 0	122. 00	179. 50	239. 0	┋
dmqmi liz	363 2	0.70	1.92	0.28	1.00	2.00	2.00	2.00	7.0	<b>-</b> <b>-</b> -
dmdbo rn4	19	1.00	1.16	0.36	1.00	1.00	1.00	1.00	2.0	<b>■</b> -
dmdyr usr	100 58	0.16	7.33	15.8 3	1.00	3.00	6.00	6.00	99.0	<b>=</b>  -
dmded uc2	413 9	0.65	3.80	1.15	1.00	3.00	4.00	5.00	9.0	_ <b>=</b> =- -
dmdm artz	414 1	0.65	1.78	3.10	1.00	1.00	1.00	2.00	99.0	■-  -
ridexp rg	104 30	0.13	2.24	0.49	1.00	2.00	2.00	3.00	3.0	 ■_
dmdhh siz	0	1.00	3.24	1.70	1.00	2.00	3.00	4.00	7.0	<u>-</u>
dmdhr gnd	781 8	0.34	1.56	0.50	1.00	1.00	2.00	2.00	2.0	_  
dmdhr agz	780 9	0.35	2.54	0.64	1.00	2.00	2.00	3.00	4.0	<b>■</b> <b>■</b>
dmdhr edz	818 7	0.31	2.17	0.66	1.00	2.00	2.00	3.00	3.0	<u> </u>

	n_mi									
skim_v	ssin	comple							p10	
ariable	g	te_rate	mean	sd	p0	p25	p50	p75	0	hist
dmdhr	791	0.34	1.38	0.68	1.00	1.00	1.00	2.00	3.0	<b>=</b> _
maz	3									_
dmdhs	980	0.10	2 20	0.00	1.00	2.00	2.00	2.00	2.0	_
edz	960	0.18	2.28	0.69	1.00	2.00	2.00	3.00	3.0	
euz	O									
wtint2	0	1.00	2740	194	4584	1433	2167	3383	170	
yr			4.14	49.1	.46	1.75	0.19	1.33	968.	
•				6					3	
wtmec	0	1.00	2740	279	0.00	0.00	2171	3834	227	_
2yr	U	1.00	4.14	62.9	0.00	0.00	7.85	1.15	108.	
2 y i			4.14	6			7.03	1.13	3	
_										_
sdmvs	0	1.00	179.	4.31	173.	176.	180.	184.	187.	
tra			92		00	00	00	00	0	
sdmvp	0	1.00	1.49	0.50	1.00	1.00	1.00	2.00	2.0	_
sumvp	U	1.00	1.47	0.50	1.00	1.00	1.00	2.00	2.0	_
Su										
indfm	204	0.83	2.71	1.67	0.00	1.18	2.50	4.50	5.0	
pir	1									
ckimn	ckim(h	nv l								

skimr::skim(bpx)

Data summary

Name bpx
Number of rows 7801
Number of columns 12

Column type frequency:

character 1 numeric 11

Group variables None

Variable type: character

skim_var	iabl n	_missin	complete	e_rat	mi	ma	empt	n_uniq	u wl	hitespac
e		g		e	n	X	у		e	е
bpaoarm		0		1	0	1	147		3	0
Variable	type: n	umeric								
skim_va	n_mis	complet							p10	
riable	sing	e_rate	mean	sd	p0	p25	5 p50	p75	0	hist
seqn	0	1.00	1363	344	130	133	3 136	139	142	
			49.49	9.49	378	335	382	325	310	
_										
bpaocsz	190	0.98	3.52	0.67	2	3	3 4	4	5	_=-
bpxosy	284	0.96	119.2	18.5	61	106	5 117	130	232	<b>-</b>
орхозу 1	204	0.90	9	6	01	100	) 11/	130	232	_ <b></b> _
bpxodi	284	0.96	72.75	11.9	33	64	1 72	80	142	_==
1				0						
bpxosy	296	0.96	119.0	18.5	59	106	5 116	129	233	-
2			8	7						
bpxodi 2	296	0.96	72.09	11.8 5	32	64	4 71	79	139	_
	224	0.06	1100		۲o	10/	. 116	120	222	<b></b>
bpxosy 3	321	0.96	118.9 2	18.5 0	50	106	5 116	129	232	-
bpxodi	321	0.96	71.81	11.7	24	64	¥ 71	79	136	
3	0_1	0.70	, 1.01	7					100	
bpxopls	284	0.96	72.34	12.7	35	63	3 71	80	158	_
1				2						
bpxopls	296	0.96	73.09	12.7	32	64	1 72	81	141	_
2				8						
bpxopls 3	321	0.96	73.69	12.8 9	31	65	5 73	82	154	- <b>I</b>
skimr::s	<b>kim</b> (bm)	<b>(</b> )								

Data summary

NamebmxNumber of rows8860Number of columns22

Column type frequency:

numeric 22

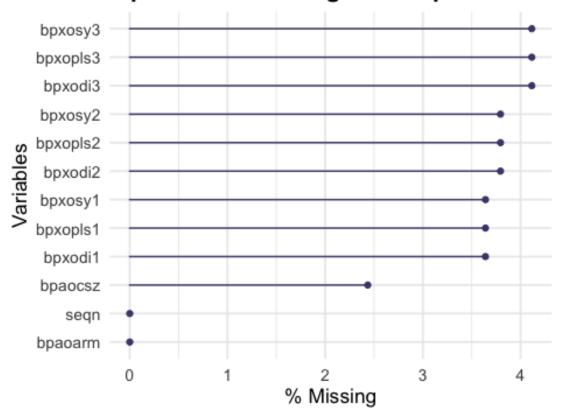
Group variables None

#### Variable type: numeric

skim_v ariable	n_mi ssing	comple te_rate	mean	sd	p0	p25	p50	p75	p10 0	hist
seqn	0	1.00	1363 45.83	345 3.78	130 378. 0	1333 19.75	136 377. 5	139 336. 2	142 310. 0	
bmdsta ts	0	1.00	1.13	0.50	1.0	1.00	1.0	1.0	4.0	<b>■</b> -
bmxwt	106	0.99	70.55	30.3	2.7	54.20	71.7	89.1	248. 2	
bmiwt	8515	0.04	2.88	0.62	1.0	3.00	3.0	3.0	4.0	 -■ -
bmxre cum	8406	0.05	84.33	14.0 6	48.5	73.48	84.7	96.1	118. 8	=======================================
bmirec um	8842	0.00	1.00	0.00	1.0	1.00	1.0	1.0	1.0	 
bmxhe ad	8790	0.01	41.93	2.80	34.4	40.20	42.4	44.0	46.5	=
bmihea d	8860	0.00	NaN	NA	NA	NA	NA	NA	NA	_
bmxht	361	0.96	159.6 6	19.8 6	79.1	154.4 0	163. 6	172. 1	200. 7	<u>.</u>
bmiht	8726	0.02	2.31	0.95	1.0	1.00	3.0	3.0	3.0	- 
bmxb mi	389	0.96	27.25	8.14	11.1	21.60	26.4	31.7	74.8	

skim_v ariable	n_mi ssing	comple te_rate	mean	sd	p0	p25	p50	p75	p10 0	hist
bmdb mic	6368	0.28	2.56	0.88	1.0	2.00	2.0	3.0	4.0	- <b>=</b>
bmxleg	1525	0.83	38.13	3.86	24.9	35.50	38.1	40.8	51.6	- 
bmileg	8464	0.04	1.00	0.00	1.0	1.00	1.0	1.0	1.0	- 
bmxar ml	292	0.97	35.11	6.18	10.0	33.60	36.5	39.0	49.2	_ 
bmiar ml	8660	0.02	1.00	0.00	1.0	1.00	1.0	1.0	1.0	-  ■-
bmxar mc	298	0.97	30.56	7.37	12.0	26.40	31.2	35.4	63.3	_ _=
bmiar mc	8655	0.02	1.00	0.00	1.0	1.00	1.0	1.0	1.0	_  <b>_</b>
bmxwa ist	670	0.92	92.12	22.0	39.8	77.50	92.7	107. 0	187. 0	_ <b>_</b> ■
bmiwa ist	8513	0.04	1.00	0.00	1.0	1.00	1.0	1.0	1.0	-  ■-
bmxhi p	2084	0.76	106.2 6	14.6 6	69.9	96.40	103. 7	113. 5	187. 1	_ _=
bmihip	8499	0.04	1.00	0.00	1.0	1.00	1.0	1.0	1.0	- 
# Plot missing proportion visually gg_miss_var(bpx, show_pct = TRUE) + theme_minimal(base_size = 13) + labs(title = "Proportion of Missing Values per Variable") + theme(plot.title = element_text(face = "bold", hjust = 0.5))										

# Proportion of Missing Values per Variable

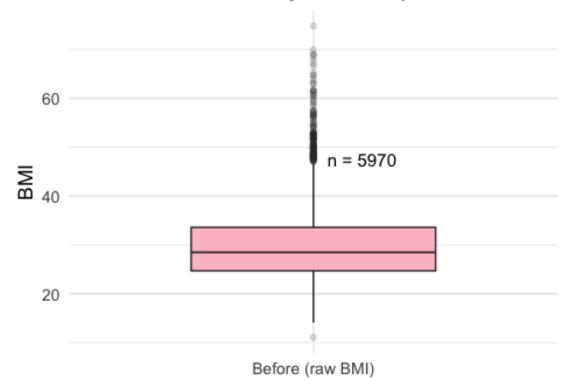


```
# Detect SBP/DBP columns ------
sbp_cols <- names(bpx)[str_detect(names(bpx), "^bpxo?sy[1-3]$")]</pre>
dbp_cols <- names(bpx)[str_detect(names(bpx), "^bpxo?di[1-3]$")]</pre>
# Build raw BMI dataset ------
bmi_raw <- bmx %>% transmute(seqn, bmi_raw = bmxbmi)
demo <- demo %>%
 mutate(riagendr = as.numeric(riagendr)) %>%
 filter(is.na(riagendr) | riagendr %in% c(1, 2))
demo_sex <- demo %>%
 transmute(seqn, age = ridageyr,
           sex = factor(riagendr, levels=c(1,2), labels=c("Male", "Fema
le")))
dat_raw <- demo_sex %>%
 left_join(bmi_raw, by="seqn") %>%
 filter(age >= 20) %>%
 mutate(bmi_raw = ifelse(is.nan(bmi_raw), NA_real_, bmi_raw))
# BEFORE boxplot -----
```

```
bmi before df <- dat raw %>% transmute(stage = "Before (raw BMI)", valu
e = bmi raw)
x <- bmi_before_df$value</pre>
qs <- quantile(x, c(.25,.75), na.rm = TRUE)
iqr \leftarrow qs[2]-qs[1]
upper_whisker <- min(max(x, na.rm = TRUE), qs[2] + 1.5*iqr)
bmi_before_label_y <- upper_whisker + 0.05*iqr</pre>
bmi_before_N <- sum(!is.na(x))</pre>
ggplot(bmi_before_df, aes(stage, value, fill = stage)) +
  geom_boxplot(width = 0.6, outlier.alpha = 0.15, fatten = 1.2) +
  geom_text(data = tibble(stage="Before (raw BMI)", y=bmi_before_label_
y, N=bmi_before_N),
            aes(stage, y, label=paste0("n = ", N)), hjust = -0.2, size
= 4) +
  scale_fill_manual(values = c("Before (raw BMI)" = "pink")) +
  labs(title = "BMI (BEFORE): Raw Distribution",
       subtitle = "Outliers and missing values not yet removed",
       x = NULL, y = "BMI") +
  theme_minimal(base_size = 13) +
  theme(legend.position = "none",
        plot.title = element_text(face="bold", hjust=0.5),
        plot.subtitle = element_text(hjust=0.5))
## Warning: Removed 1839 rows containing non-finite outside the scale r
ange
## (`stat_boxplot()`).
```

### BMI (BEFORE): Raw Distribution

Outliers and missing values not yet removed

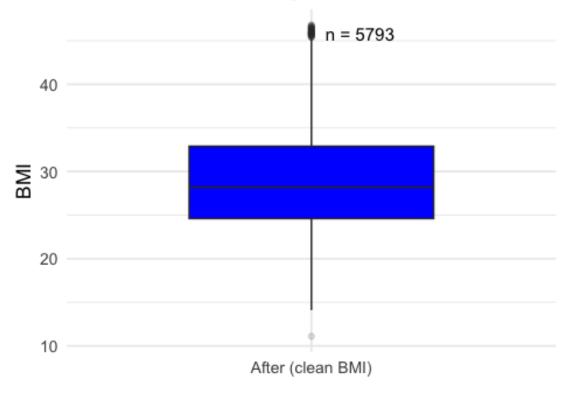


```
# Outlier cleaning ------
BMI_LO <- 10; BMI_HI <- 80
bmi_clean <- bmx %>%
 transmute(seqn, bmxbmi) %>%
 mutate(
   q1 = quantile(bmxbmi, 0.25, na.rm=TRUE),
   q3 = quantile(bmxbmi, 0.75, na.rm=TRUE),
   iqr = q3 - q1,
   lo_{iqr} = q1 - 1.5*iqr,
   hi iqr = q3 + 1.5*iqr,
   med = median(bmxbmi, na.rm=TRUE),
   madv = mad(bmxbmi, na.rm=TRUE),
   z = ifelse(madv > 0, (bmxbmi - med)/(madv*1.4826), 0),
   flag = (bmxbmi < BMI_LO | bmxbmi > BMI_HI) |
          (bmxbmi < lo iqr | bmxbmi > hi iqr) |
          (abs(z) > 3.5),
   bmxbmi_clean = ifelse(flag, NA_real_, bmxbmi)
 ) %>% select(seqn, bmxbmi_clean)
# Cleaned dataset -----
dat_clean <- demo_sex %>%
```

```
left join(bmi clean, by="seqn") %>%
  filter(age >= 20) %>%
  mutate(bmxbmi_clean = ifelse(is.nan(bmxbmi_clean), NA_real_, bmxbmi_c
lean))
# AFTER boxplot -----
bmi_after_df <- dat_clean %>% transmute(stage = "After (clean BMI)", va
lue = bmxbmi clean)
x <- bmi_after_df$value</pre>
qs <- quantile(x, c(.25,.75), na.rm = TRUE)
iqr < - qs[2] - qs[1]
upper_whisker <- min(max(x, na.rm = TRUE), qs[2] + 1.5*iqr)
bmi_after_label_y <- upper_whisker + 0.05*iqr</pre>
bmi_after_N <- sum(!is.na(x))</pre>
ggplot(bmi after df, aes(stage, value, fill = stage)) +
  geom boxplot(width = 0.6, outlier.alpha = 0.15, fatten = 1.2) +
  geom_text(data = tibble(stage="After (clean BMI)", y=bmi_after_label_
y, N=bmi_after_N),
            aes(stage, y, label=paste0("n = ", N)), hjust = -0.2, size
= 4) +
  scale fill manual(values = c("After (clean BMI)" = "blue")) +
  labs(title = "BMI (AFTER): Cleaned Distribution",
       subtitle = "Outliers removed using IQR + MAD z-score rules",
       x = NULL, y = "BMI") +
  theme minimal(base size = 13) +
  theme(legend.position = "none",
        plot.title = element text(face="bold", hjust=0.5),
        plot.subtitle = element_text(hjust=0.5))
## Warning: Removed 2016 rows containing non-finite outside the scale r
ange
## (`stat boxplot()`).
```

#### BMI (AFTER): Cleaned Distribution

Outliers removed using IQR + MAD z-score rules

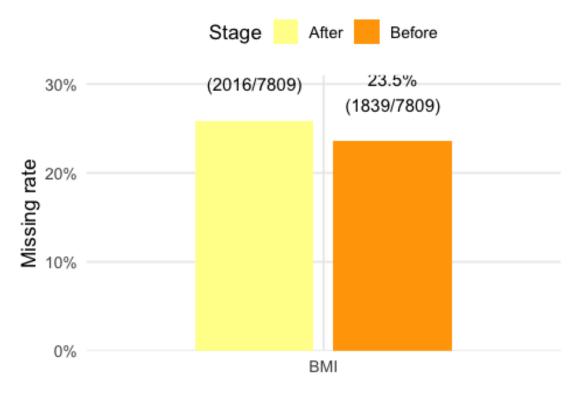


```
# Missingness comparison ------
miss_before <- tibble(</pre>
 stage = "Before",
 variable = "BMI",
 n_missing = sum(is.na(dat_raw$bmi_raw)),
 n total = nrow(dat raw)
) %>% mutate(p_missing = n_missing / n_total)
miss_after <- tibble(</pre>
 stage = "After",
 variable = "BMI",
 n missing = sum(is.na(dat clean$bmxbmi clean)),
 n_total = nrow(dat_clean)
) %>% mutate(p_missing = n_missing / n_total)
miss_long <- bind_rows(miss_before, miss_after)</pre>
pos <- position_dodge(width = 0.7)</pre>
ggplot(miss_long, aes(variable, p_missing, fill = stage)) +
 geom_col(width = 0.6, position = pos) +
 geom_text(aes(label = paste0(scales::percent(p_missing, 0.1),
                              "\n(", n_missing, "/", n_total, ")")),
```

```
position = pos, vjust = -0.8, size = 4) +
scale_y_continuous(labels = scales::percent, expand = expansion(mult
= c(0, 0.2))) +
scale_fill_manual(values = c("Before" = "orange", "After" = "#FF9"))
+
labs(title = "Missingness (NA) Before vs After Outlier Removal (BMI)"
,
    subtitle = "Slight increase due to outlier removal",
    x = NULL, y = "Missing rate", fill = "Stage") +
theme_minimal(base_size = 13) +
theme(panel.grid.minor = element_blank(),
    plot.title = element_text(face = "bold", hjust = 0.5),
    plot.subtitle = element_text(hjust = 0.5),
    legend.position = "top")
```

#### lissingness (NA) Before vs After Outlier Remova

Slight increase due to outlier removal

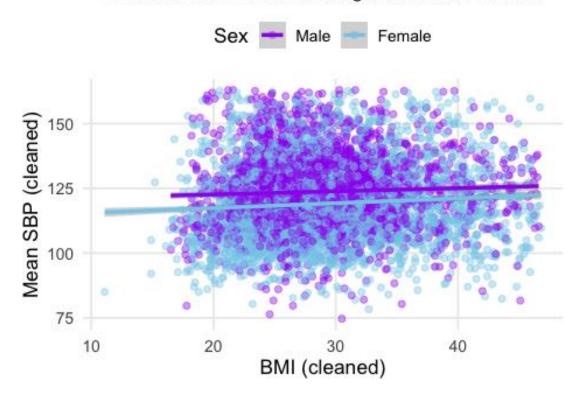


```
# SBP mean (before cleaning)
-----
sbp_raw <- bpx %>% transmute(seqn, sbp_mean_raw = rowMeans(select(., al
l_of(sbp_cols)), na.rm = TRUE))
dat_sbp_raw <- dat_raw %>%
  left_join(sbp_raw, by = "seqn") %>%
  filter(!is.na(bmi_raw) & !is.na(sbp_mean_raw))
```

```
# SBP outlier cleaning ------
SBP_LO <- 70; SBP_HI <- 260
sbp clean <- bpx %>%
 transmute(seqn, across(all_of(sbp_cols))) %>%
   sbp all = pmap dbl(across(all of(sbp cols)), ~ mean(c(...), na.rm =
TRUE)),
   q1 = quantile(sbp_all, 0.25, na.rm = TRUE),
   q3 = quantile(sbp_all, 0.75, na.rm = TRUE),
   iqr = q3 - q1,
   lo_{iqr} = q1 - 1.5 * iqr,
   hi iqr = q3 + 1.5 * iqr,
   med = median(sbp_all, na.rm = TRUE),
   madv = mad(sbp_all, na.rm = TRUE),
   z = ifelse(madv > 0, (sbp_all - med) / (madv * 1.4826), 0),
   flag = (sbp_all < SBP_LO | sbp_all > SBP_HI) |
          (sbp_all < lo_iqr | sbp_all > hi_iqr) |
          (abs(z) > 3.5),
   sbp_mean_clean = ifelse(flag, NA_real_, sbp_all)
  ) %>% select(seqn, sbp_mean_clean)
# Combine BMI + SBP clean dataset ------
dat final <- dat clean %>%
 left join(sbp clean, by = "seqn") %>%
 filter(!is.na(bmxbmi_clean) & !is.na(sbp_mean_clean))
# Scatter plot: BMI vs SBP ------
ggplot(dat_final, aes(x = bmxbmi_clean, y = sbp_mean_clean, color = sex
)) +
 geom point(alpha = 0.4, size = 1.8) +
  geom_smooth(method = "lm", se = TRUE, lwd = 1.2) +
 labs(title = "Association Between BMI and Mean SBP by Sex (Cleaned Da
ta)",
      subtitle = "Both variables cleaned using IQR & MAD criteria",
      x = "BMI (cleaned)", y = "Mean SBP (cleaned)", color = "Sex") +
 scale_color_manual(values = c("Male" = "purple", "Female" = "skyblue"
 theme minimal(base size = 13) +
 theme(panel.grid.minor = element_blank(),
       plot.title = element_text(face = "bold", hjust = 0.5),
       plot.subtitle = element text(hjust = 0.5),
       legend.position = "top")
## geom_smooth() using formula = 'y ~ x'
```

### ciation Between BMI and Mean SBP by Sex (Clea

Both variables cleaned using IQR & MAD criteria



#Q2. Among all the subjects in 2021-2023 NHANES dataset, observe the distribution of BMI in different races and education levels

```
library(knitr)
## Warning: package 'knitr' was built under R version 4.3.3
# 檢查原始教育變項
demo %>% count(dmdeduc2)
## # A tibble: 7 × 2
     dmdeduc2
##
##
        <dbl> <int>
## 1
            1
                373
## 2
            2
                666
            3
               1749
## 3
            4
               2370
## 4
## 5
            5
               2625
            9
## 6
                 11
## 7
           NA
               4139
# 重編教育變項
dat_edu <- demo %>%
transmute(
```

```
seqn,
    age = ridageyr,
    EDU = case_when(
      dmdeduc2 %in% 1:5 ~ dmdeduc2,
      TRUE ~ NA_real_
  ) %>%
  mutate(
    EDU = factor(
      EDU,
      levels = 1:5,
      labels = c("<9th grade", "9-11th grade", "High school/GED",</pre>
                 "Some college/AA", "College or above")
  ) %>%
  left_join(dat_clean %>% select(seqn, bmxbmi_clean), by = "seqn") %>%
  drop_na(EDU, bmxbmi_clean)
# 教育分布表
edu dist <- dat edu %>%
  count(EDU) %>%
  mutate(prop = n / sum(n)) %>%
  rename(category = EDU)
kable(edu_dist, digits = 3, caption = "Distribution of Educational Atta
inment (EDU)")
Distribution of Educational Attainment (EDU)
category
                   n prop
<9th grade
                 278 0.048
9–11th grade
                 457 0.079
High school/GED 1227 0.212
Some college/AA 1749 0.302
College or above
                2079 0.359
# 檢查原始種族變項
demo %>% count(ridreth3)
## # A tibble: 6 × 2
## ridreth3
##
        <dbl> <int>
## 1
            1 1117
## 2
            2 1373
## 3
            3 6217
## 4
           4 1597
```

## 5

## 6

6 681

948

7

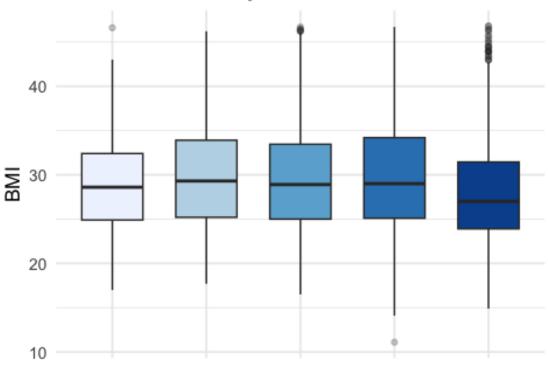
```
# 重編種族變項
dat_race <- demo %>%
 transmute(
    seqn,
    age = ridageyr,
    Race = case when(
      ridreth3 %in% 1:7 ~ ridreth3,
     TRUE ~ NA_real_
  ) %>%
 mutate(
    Race = factor(
      Race,
      levels = 1:7,
      labels = c("Mexican American", "Other Hispanic", "Non-Hispanic Wh
ite",
                 "Non-Hispanic Black", "Non-Hispanic Asian",
                 "Other Race", "Multi-Racial")
    )
  ) %>%
  left join(dat clean %>% select(seqn, bmxbmi clean), by = "seqn") %>%
  drop_na(Race, bmxbmi_clean)
# 種族分布表
race_dist <- dat_race %>%
  count(Race) %>%
 mutate(prop = n / sum(n)) %>%
  rename(category = Race)
kable(race_dist, digits = 3, caption = "Distribution of Race Categories
")
```

Distribution of Race Categories

```
category
                      n prop
Mexican American
                    390 0.067
Other Hispanic
                    593 0.102
Non-Hispanic White 3427 0.592
Non-Hispanic Black
                    689 0.119
Other Race
                    330 0.057
Multi-Racial
                    364 0.063
ggplot(dat edu, aes(x = EDU, y = bmxbmi clean, fill = EDU)) +
 geom_boxplot(outlier.alpha = 0.25, width = 0.65) +
  scale fill brewer(palette = "Blues") +
  labs(title = "BMI Distribution by Education Level",
      x = "Education Level", y = "BMI") +
```

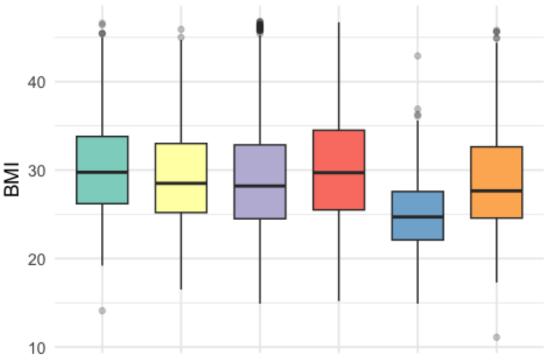
```
theme_minimal(base_size = 13) +
theme(legend.position = "none")
```

# BMI Distribution by Education Level



<9th grade 9–11th gradheigh school/@Sobne college/AvAlege or above Education Level

### BMI Distribution by Race



Mexican Am@hbaan Hishpan-idispanhio.hWHitapanic B@tbler RaceMulti-Racial Race Category

```
cat("
### Observation & Interpretation (Q2)
```

- BMI tends to increase slightly as education level decreases.
- Participants with 'College or above' education generally show lower B MI median values.
- Across race groups, Non-Hispanic Black and Hispanic groups have relatively higher BMI median compared to Non-Hispanic White and Asian participants.
- These differences might reflect socioeconomic and lifestyle factors a ffecting BMI distribution.
   ")

##
## ### Observation & Interpretation (Q2)

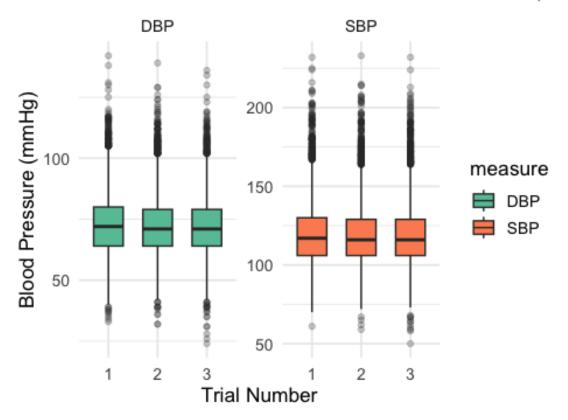
- ## BMI tends to increase slightly as education level decreases.
- ## Participants with 'College or above' education generally show lower BMI median values.
- ## Across race groups, Non-Hispanic Black and Hispanic groups have re latively higher BMI median compared to Non-Hispanic White and Asian participants.

- ## These differences might reflect socioeconomic and lifestyle factor s affecting BMI distribution.
- #Q3. Among all the subjects in 2021-2023 NHANES dataset, BPX is the data including three times of examination of blood pressure (SBP & DBP). The values were recorded in different columns (bpxosy1-3; bpxodi1-3) (Reminder: please use the "cleaned" BP data)

```
library(tidyverse)
# 偵測 SBP 與 DBP 欄位名稱
sbp cols <- names(bpx)[stringr::str detect(names(bpx), "^bpxo?sy[1-3]$"</pre>
dbp_cols <- names(bpx)[stringr::str_detect(names(bpx), "^bpxo?di[1-3]$"</pre>
)]
# 轉換為長格式 (Long format)
bpx long clean <- bpx %>%
  select(seqn, all_of(c(sbp_cols, dbp_cols))) %>%
  pivot longer(
    cols = -seqn,
    names to = c("measure", "trial"),
    names_pattern = "^bpxo?([sd]i|sy)([1-3])$",
   values to = "value"
  ) %>%
 mutate(
   measure = recode(measure, "sy" = "SBP", "di" = "DBP"),
   trial = as.integer(trial)
  )
# 檢查轉換後的資料結構
glimpse(bpx_long_clean)
## Rows: 46,806
## Columns: 4
## $ segn
            <dbl> 130378, 130378, 130378, 130378, 130378, 130378, 1303
79, 130379...
## $ measure <chr> "SBP", "SBP", "DBP", "DBP", "DBP", "BP", "SBP", "SB
P", "SBP",...
## $ trial
            <int> 1, 2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3, 1, 2, 3
, 1, 2, 3,...
## $ value
            <dbl> 135, 131, 132, 98, 96, 94, 121, 117, 113, 84, 76, 76
, 111, 112...
ggplot(bpx long clean, aes(x = factor(trial), y = value, fill = measure
)) +
 geom_boxplot(outlier.alpha = 0.25, width = 0.6) +
 facet_wrap(~ measure, scales = "free_y") +
  scale_fill_brewer(palette = "Set2") +
 labs(
```

```
title = "Distribution of SBP & DBP across 3 Trials (Cleaned Data)",
    x = "Trial Number", y = "Blood Pressure (mmHg)"
) +
    theme_minimal(base_size = 13)
## Warning: Removed 1802 rows containing non-finite outside the scale r
ange
## (`stat_boxplot()`).
```

# Distribution of SBP & DBP across 3 Trials (Cle



```
# 計算每位受試者在三次測量中的最大差值 (SBP 和 DBP 分開)

bpx_diff <- bpx_long_clean %>%
    group_by(seqn, measure) %>%
    summarise(
        diff_range = max(value, na.rm = TRUE) - min(value, na.rm = TRUE),
        .groups = "drop"
    )

## Warning: There were 1132 warnings in `summarise()`.

## The first warning was:

## i In argument: `diff_range = max(value, na.rm = TRUE) - min(value, na.rm =

## TRUE)`.

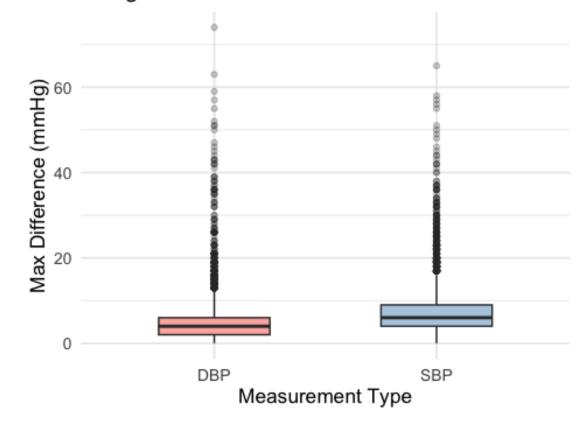
## TRUE)`.

## i In group 37: `seqn = 130401` and `measure = "DBP"`.

## Caused by warning in `max()`:
```

```
## ! no non-missing arguments to max; returning -Inf
## i Run `dplyr::last_dplyr_warnings()` to see the 1131 remaining warni
ngs.
# 取出最大差異前 5 位作為示例
head(bpx_diff[order(-bpx_diff$diff_range), ], 5)
## # A tibble: 5 × 3
      seqn measure diff_range
##
     <dbl> <chr>
                        <dbl>
                           74
## 1 141202 DBP
## 2 136053 SBP
                           65
## 3 135594 DBP
                           63
## 4 131306 DBP
                           59
## 5 141202 SBP
                           58
# 視覺化:不同測量型別的最大差值分布
ggplot(bpx diff, aes(x = measure, y = diff range, fill = measure)) +
  geom boxplot(outlier.alpha = 0.25, width = 0.5) +
  scale_fill_brewer(palette = "Pastel1") +
  labs(
    title = "Range of Blood Pressure Differences across 3 Trials",
   x = "Measurement Type", y = "Max Difference (mmHg)"
   theme minimal(base size = 13)+
  theme(legend.position = "none")
## Warning: Removed 566 rows containing non-finite outside the scale ra
nge
## (`stat_boxplot()`).
```

#### Range of Blood Pressure Differences across 3



# cat(" ### Observation & Interpretation

- Both SBP and DBP show relatively small variations across the three trials, usually within  $\pm 10~\text{mmHg}$ .
- The distributions of the 1st, 2nd, and 3rd readings are quite close, and there is no clear systematic shift.
- This pattern indicates that the three measurements were likely taken \*\*on the same day\*\*, probably within a short interval, to ensure measurement reliability.
- Larger outliers (e.g., >20 mmHg difference) may reflect temporary phy siological fluctuations or measurement error rather than time gaps.
   ")

#### ##

## ### Observation & Interpretation

##

- ## Both SBP and DBP show relatively small variations across the three trials, usually within ±10 mmHg.
- ## The distributions of the 1st, 2nd, and 3rd readings are quite close, and there is no clear systematic shift.
- ## This pattern indicates that the three measurements were likely tak en \*\*on the same day\*\*, probably within a short interval, to ensure mea

surement reliability.
## - Larger outliers (e.g., >20 mmHg difference) may reflect temporary
physiological fluctuations or measurement error rather than time gaps.

Note that the echo = FALSE parameter was added to the code chunk to prevent printing of the R code that generated the plot.

#### **Conclusion:**

In summary, higher BMI values are associated with elevated systolic blood pressure, with similar patterns observed across both sexes. Differences in BMI distribution among race and education groups suggest potential socioeconomic and lifestyle influences. The consistency across repeated SBP and DBP measurements supports the reliability of NHANES blood pressure data. Overall, this exercise demonstrates the practical application of R in managing, cleaning, and interpreting large health datasets for epidemiological research.