Complex Sampling Design in National Health and Morbidity Survey (NHMS)

Survey Package in R

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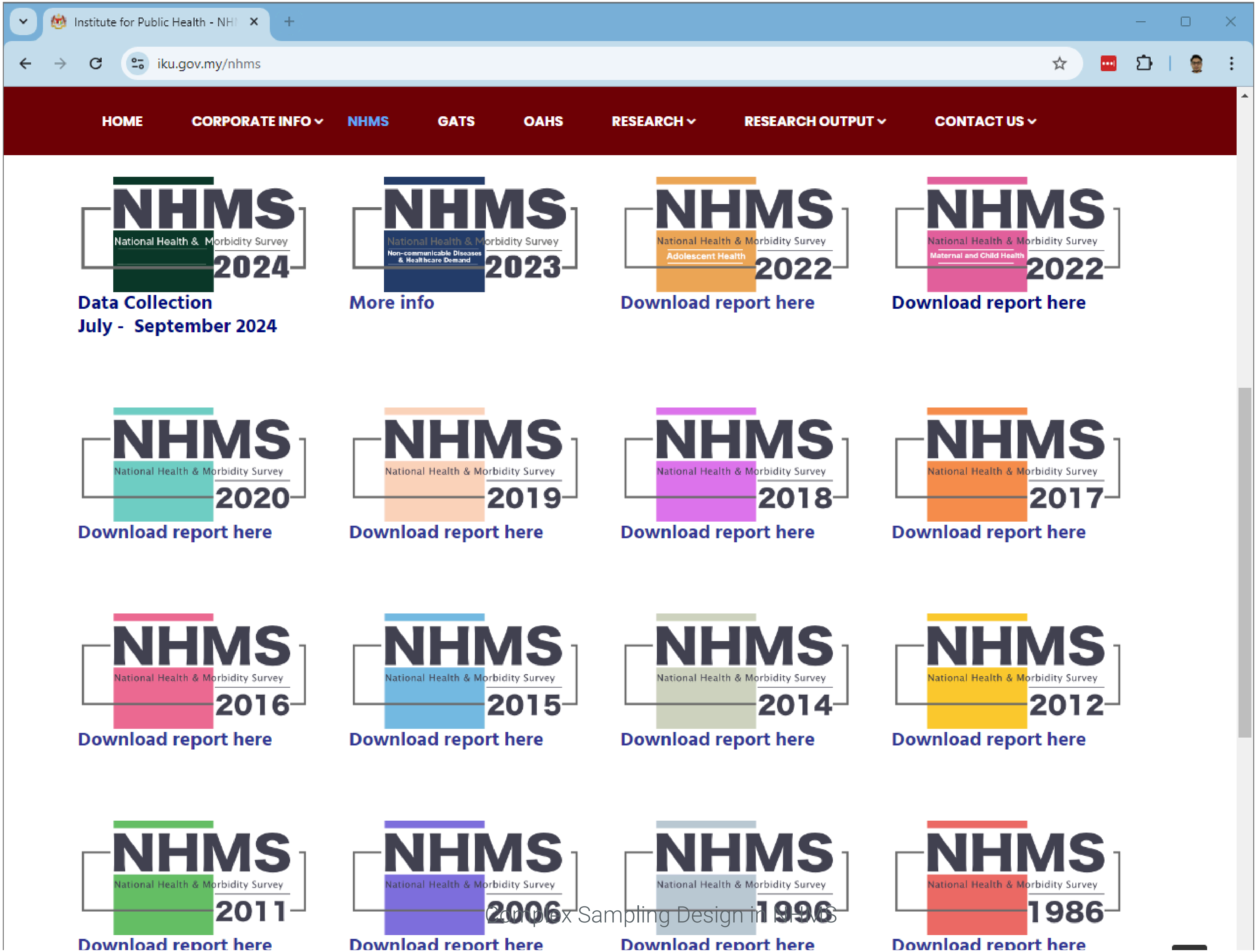
National Health and Morbidity Survey (NHMS)

Overview of NHMS

1. **Nationwide Health Survey**: Conducted by the Ministry of Health Malaysia to assess the health and healthcare needs of Malaysians.
2. **Regularly Conducted**: Since 1986, NHMS has been conducted with varying intervals, focusing on different health themes.
3. **Key Health Indicators**: Focuses on topics like Non-Communicable Diseases (NCDs), infectious diseases, and healthcare demand.
4. **Representative Sampling**: Nationally representative, covering different states, age groups, and ethnicities.
5. **Policy Impact**: NHMS findings guide national health policies and strategies.

NHMS Reports

- NHMS reports are available on the Institute for Public Health (IKU) website.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Census vs Survey

Census vs Survey

- **Census**: Collects data from every individual in a population. It's costly, time-consuming, and not feasible for large populations.
  - → e.g., DOSM conducts a Population and Housing Census every 10 years.
- **Survey**: Collects data from a sample of the population. More cost-effective and quicker but raises the question of representation.

Why Not Simple Random Sampling (SRS)?

- **Simple Random Sampling (SRS)**: Every individual theoretically has an equal chance of selection.
  - → Impractical for large, diverse populations.
  - → Assumes homogeneity, which leads to biases, especially with underrepresented groups.
- **Challenges of SRS**:
  - → Requires a complete list of the population for equal chance selection, which is often unavailable.

Simple Random Sampling (SRS) – Simulation

The Risk of Underrepresentation

- SRS may not represent minority groups adequately.
- Hypothetical Population, In a population of 1,000:
  - → 46% Malay, 33% Chinese, 25% Indian, 1% Borneo.

```r
sim_pop <- tibble(ethnicity = c(rep("Malay", 460),
                                rep("Chinese", 330),
                                rep("Indian", 250),
                                rep("Borneo", 10))) %>%
  mutate(ethnicity = fct_relevel(ethnicity, "Malay", "Chinese", "Indian"))

sim_pop %>%
  count(ethnicity) %>% mutate(pct = scales::label_percent()(n/1000))
```

```
# A tibble: 4 × 3
  ethnicity     n pct
  <fct>     <int> <chr>
1 Malay       460 46%
2 Chinese     330 33%
3 Indian      250 25%
4 Borneo       10 1%
```

The Risk of Underrepresentation

- Taking an SRS of 50 people, will the Borneo group (1%) be included?

```
sim_pop %>% sample_n(50) %>%
  count(ethnicity) %>% mutate(pct = scales::label_percent()(n/50))
```

```
# A tibble: 3 × 3
  ethnicity      n pct
  <fct>      <int> <chr>
1 Malay         21 42%
2 Chinese       13 26%
3 Indian        16 32%
```

- Let's try it again:

```
sim_pop %>% sample_n(50) %>%
  count(ethnicity) %>% mutate(pct = scales::label_percent()(n/50))
```

```
# A tibble: 3 × 3
  ethnicity      n pct
  <fct>      <int> <chr>
1 Malay         20 40%
2 Chinese       15 30%
3 Indian        15 30%
```

Key Takeaways from the Simulation

- And One More Time

```
sim_pop %>% sample_n(50) %>%
  count(ethnicity) %>% mutate(pct = scales::label_percent()(n/50))
```

```
# A tibble: 4 × 3
  ethnicity     n pct
  <fct>     <int> <chr>
1 Malay        16 32%
2 Chinese      18 36%
3 Indian       15 30%
4 Borneo        1 2%
```

- As shown in this short simulation, **Simple Random Sampling** may or may not select individuals from the **Borneo** group, which makes up only 1% of the population.
- To ensure that the **Borneo** group is properly represented in the sample, we may need to use **stratified sampling** to guarantee their inclusion.

Complex Sampling Design in NHMS

NHMS Complex Sampling

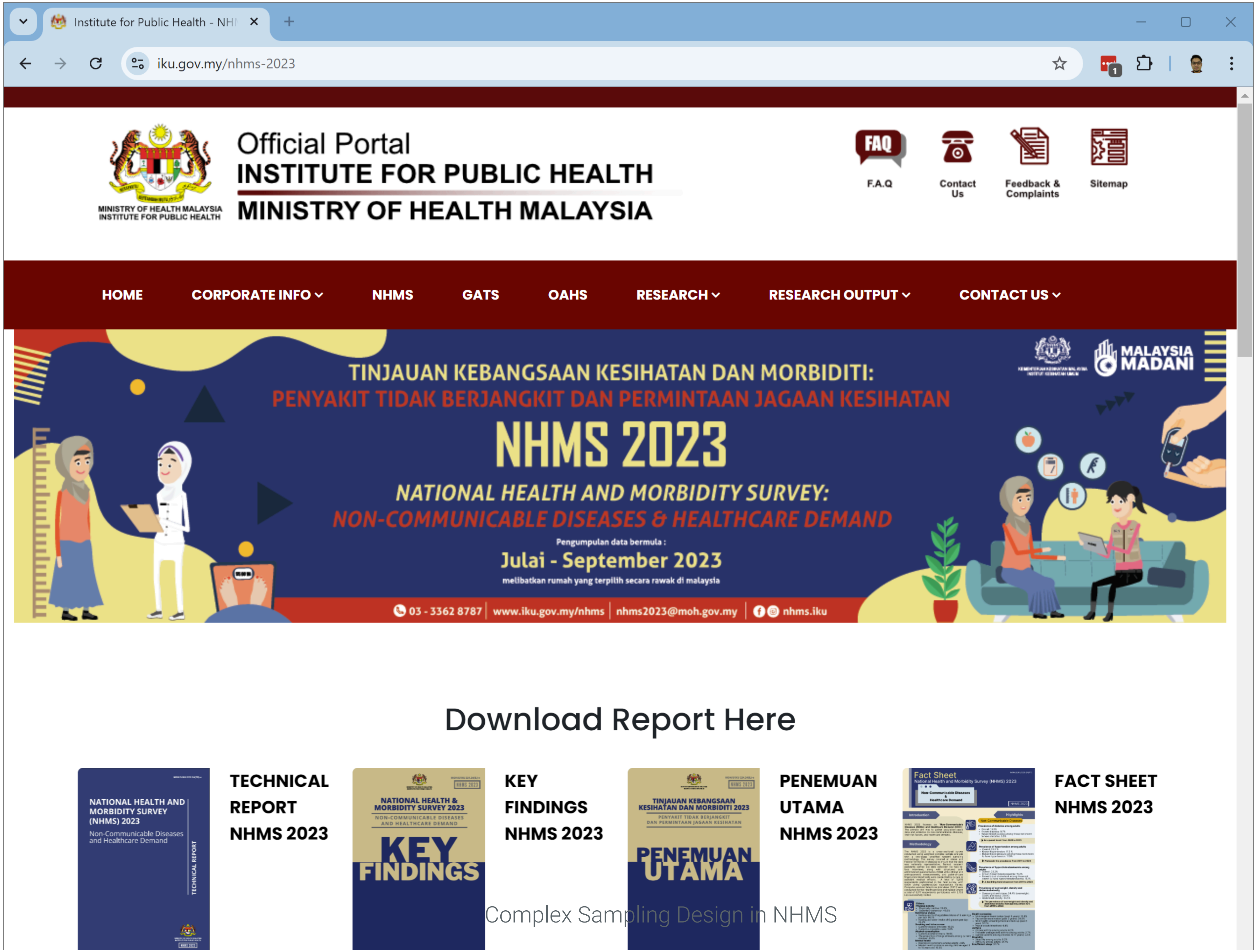
- NHMS applies stratification (State and Urban/Rural) and clustering (DOSM's enumeration blocks) to ensure representation.
- Two-stage Sampling:
  - → **Primary Sampling Unit (PSU)**: Enumeration Blocks (EBs).
  - → **Secondary Sampling Units (SSU)**: Living Quarters (LQs) within EBs.
- Impact on Sampling: Stratification and clustering affect sampling probabilities, requiring the use of sampling weights.

NHMS 2023

NHMS 2023 Overview

- Theme: **Non-communicable Diseases (NCDs) & Healthcare Demand**.
- Data collected from 11 July to 29 September 2023.
    - → 5,006 households visited.
    - → 13,616 respondents, representing the Malaysian adult population (~22 million).

NHMS 2023 Overview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Fact Sheet
FACT SHEET NHMS 2023

NHMS 2023: Findings

- NHMS 2023 included various modules focusing on **Non-Communicable Diseases (NCDs)** and **healthcare demand**.
- The **cholesterol module** was conducted using WHO's **STEPwise approach**, which is a standardized method for collecting and analysing health data.
- Among the respondents, **4,353 individuals** were identified as having **raised total cholesterol** levels.
- This represents a **33.3% prevalence** of raised cholesterol, translating to an estimated **7.6 million Malaysian adults** with high cholesterol.

Simulation and Analysis of Complex Sampling Design

Purpose of Simulation

- Objective: Demonstrate how complex sampling design is applied in practice, mimicking the National Health and Morbidity Survey (NHMS) setup.
- Population Data: We simulate data using population estimates from OpenDOSM to replicate the adult population (ages 20-59) for Malaysia.
- Disease Data: Simulated based on characteristics such as BMI, age, gender, and ethnicity to study cholesterol prevalence.

Simulating Population

- Target Population:
  - → We focus on three main ethnicities (Malay, Chinese, Indian), and simulate both male and female participants between 20-59 years of age.

Simulating Population

- OpenDOSM Population Data: Used for population distribution across states and districts, forming the basis for the simulated population.

```
library(arrow)

pop_mydist <- read_parquet("https://storage.dosm.gov.my/population/population_district.parquet'
  filter(date == dmy("01/01/23"),
         sex != "overall",
         age %in% c("20-24", "24-29", "30-34", "35-39", "40-44",
                    "45-49", "50-54", "55-59"),
         ethnicity %in% c("bumi_malay", "chinese", "indian")) %>%
  rename(gender = sex) %>%
  mutate(gender = fct_recode(gender,
                             "Male" = "male",
                             "Female" = "female"),
         ethnicity = fct_recode(ethnicity,
                                "Malay" = "bumi_malay",
                                "Chinese" = "chinese",
                                "Indian" = "indian"),
         population = population * 1000)
```

```r
pop_mydist
```

```
# A tibble: 6,720 × 7
   state district   date       gender age   ethnicity population
   <chr> <chr>      <date>     <fct>  <chr> <fct>          <dbl>
 1 Johor Batu Pahat 2023-01-01 Male   20-24 Malay          15600
 2 Johor Batu Pahat 2023-01-01 Male   30-34 Malay          13400
 3 Johor Batu Pahat 2023-01-01 Male   35-39 Malay          13300
 4 Johor Batu Pahat 2023-01-01 Male   40-44 Malay          11700
 5 Johor Batu Pahat 2023-01-01 Male   45-49 Malay           9100
 6 Johor Batu Pahat 2023-01-01 Male   50-54 Malay           8200
 7 Johor Batu Pahat 2023-01-01 Male   55-59 Malay           7500
 8 Johor Batu Pahat 2023-01-01 Female 20-24 Malay          15000
 9 Johor Batu Pahat 2023-01-01 Female 30-34 Malay          13000
10 Johor Batu Pahat 2023-01-01 Female 35-39 Malay          13000
# ℹ 6,710 more rows
```

```r
pop_mydist %>%
  summarise(population = sum(population)) %>%
  mutate(population = scales::label_comma()(population))
```

```
# A tibble: 1 × 1
  population
  <chr>
1 12,816,400
```

Simulating Population

- Stratification by Zone:
  - → Malaysia is divided into five zones (Utara, Selatan, Timur, Tengah, Borneo).
  - → For each zone, two districts are randomly selected.

```
set.seed(121)
selected_district <- pop_mydist %>%
  distinct(state, district) %>%
  mutate(zone = case_when(state %in% c("Johor", "Melaka", "Negeri Sembilan") ~ "Selatan",
                          state %in% c("Kedah", "Perak", "Perlis", "Pulau Pinang") ~ "Utara",
                          state %in% c("Kelantan", "Pahang", "Terengganu") ~ "Timur",
                          state %in% c("Selangor", "W.P. Kuala Lumpur", "W.P. Putrajaya") ~ "Ter
                          state %in% c("Sabah", "Sarawak", "W.P. Labuan") ~ "Borneo")) %>%
  group_by(zone) %>%
  slice_sample(n = 2) %>%
  ungroup() %>%
  relocate(zone, .before = 1)

selected_district
```

```
# A tibble: 10 × 3
   zone    state        district
   <chr>   <chr>        <chr>
 1 Borneo  Sarawak      Pusa
 2 Borneo  Sarawak      Asajaya
 3 Selatan Melaka       Jasin
 4 Selatan Johor        Muar
 5 Tengah  Selangor     Kuala Selangor
 6 Tengah  Selangor     Ulu Selangor
 7 Timur   Terengganu   Kuala Nerus
 8 Timur   Kelantan     Bachok
 9 Utara   Pulau Pinang Barat Daya
10 Utara   Perak        Bagan Datuk
```

Simulating Participants

- Sample Size: 40 participants are selected from each of the 10 districts.
- Variables Simulated: Variables such as gender, age, ethnicity, BMI, and hba1c are simulated to reflect realistic population characteristics.
- Disease Data: The hba1c variable is used to categorize participants as diabetic or non-diabetic.

Define Simulation (simstudy package)

```
#| eval: false

library(simstudy)

def <- defData(varname = "gender", dist = "binary", formula = 0.5,
               link = "identity") %>%
  defData(varname = "age", dist = "uniform", formula = "20;59") %>%
  defData(varname = "ethnicity", dist = "categorical",
          formula = "0.57;0.29;0.14") %>%
  defData(varname = "BMI", dist = "normal", formula = 26, variance = 2.6^2) %>%
  defData(varname = "height", dist = "normal", formula = 165, variance = 5) %>%
  defData(varname = "PAhour", dist = "uniform", formula = "2;6") %>%
  defData(varname = "hba1c", dist = "normal", variance = 1.4^2,
          formula = "2.4 + 0.05 * age + 0.1 * BMI - 0.15 * PAhour")
```

Generate Dataset (simstudy package)

```
#| eval: false

set.seed(121)
simnhmsds0 <- genData(400, def) %>%
  mutate(gender = case_when(gender == 0 ~ "Male",
                            gender == 1 ~ "Female"),
         agegp = cut(age,
                     breaks = c(19, 29, 39, 49, 59),
                     labels = c("20-29", "30-39", "40-49", "50-59")),
         ethnicity = case_when(ethnicity == 1 ~ "Malay",
                               ethnicity == 2 ~ "Chinese",
                               ethnicity == 3 ~ "Indian"),
         weight = BMI * (height/100)^2,
         across(.cols = c(hba1c, weight),
                .fns = ~ round(., 1)),
         across(.cols = c(height),
                .fns = ~ round(., 2)),
         district = rep(1:10, each = 40),
         dm_dx = cut(hba1c,
```

```r
head(simnhmsds0, 15)
```

```
# A tibble: 15 × 13
      id zone   state district gender   age agegp ethnicity height weight PAhour
   <int> <chr>  <chr> <chr>    <chr>  <int> <fct> <chr>      <int>  <dbl>  <int>
 1     1 Borneo Sara… Pusa     Male      28 20-29 Chinese      163   56.7      2
 2     2 Borneo Sara… Pusa     Female    53 50-59 Indian       164   63.2      5
 3     3 Borneo Sara… Pusa     Female    53 50-59 Chinese      164   71.1      3
 4     4 Borneo Sara… Pusa     Female    39 40-49 Malay        164   76.7      2
 5     5 Borneo Sara… Pusa     Female    32 30-39 Chinese      161   69.8      3
 6     6 Borneo Sara… Pusa     Male      28 20-29 Malay        168   71.5      5
 7     7 Borneo Sara… Pusa     Male      28 20-29 Chinese      164   63.9      3
 8     8 Borneo Sara… Pusa     Female    51 50-59 Indian       167   66.9      4
 9     9 Borneo Sara… Pusa     Male      23 20-29 Chinese      164   64.4      2
10    10 Borneo Sara… Pusa     Male      23 20-29 Malay        166   79.3      3
11    11 Borneo Sara… Pusa     Female    47 40-49 Malay        164   73.3      5
12    12 Borneo Sara… Pusa     Female    37 30-39 Malay        170   74.8      3
13    13 Borneo Sara… Pusa     Female    30 30-39 Malay        163   66.9      5
14    14 Borneo Sara… Pusa     Male      37 30-39 Chinese      164   69.5      4
15    15 Borneo Sara… Pusa     Male      30 30-39 Indian       163   73.9      5
# ℹ 2 more variables: hba1c <dbl>, dm_dx <int>
```

Simulating Non-response

- Non-response Adjustment: Different response rates are applied by zone (e.g., 36/40 for Utara), and the sampling weights are adjusted accordingly.
- Simulation of Non-response: The dataset is adjusted to reflect these response rates, ensuring the final dataset accounts for real-world data collection challenges.

Simulating Non-response

```r
sample_sizes <- list("Utara" = 36, "Selatan" = 34,
                     "Timur" = 38, "Tengah" = 32, "Borneo" = 38)

simnhmsds_split <- simnhmsds0 %>%
  group_split(zone, .keep = TRUE)

set.seed(121)
simnhmsds_final <- map(simnhmsds_split, function(data) {
  zone <- unique(data$zone)
  data %>%
    group_by(district) %>%
    slice_sample(n = sample_sizes[[zone]]) %>%
    ungroup()
}) %>%
  bind_rows() %>%
  arrange(id) %>%
  mutate(success = 1,
         .before = 1)
```

Sampling Weights Calculation

- Design Weights (W1):
  - → Calculated as the inverse probability of selecting a district within its respective zone.
  - → Ensures that smaller districts are adequately represented in the final analysis.
- Non-response Adjustment Factor (F):
  - → The inverse of the response rate for each district.
  - → Adjusts the design weight to account for missing data due to non-response.

Sampling Weights Calculation

- Post-stratification Adjustment (PS)
  - → Ensures that the sample reflects the actual population distribution by gender, age group, and ethnicity.
  - → Uses the population data to adjust for any over- or under-representation in the sample.

Design Weight (W1)

- Design Weights (W1):
  - → Calculated as the inverse probability of selecting a district within its respective zone.
  - → Ensures that smaller districts are adequately represented in the final analysis.

Design Weight (W1)

```
design_weight <- pop_mydist %>%
  distinct(state, district) %>%
  mutate(zone = case_when(state %in% c("Johor", "Melaka", "Negeri Sembilan") ~ "Selatan",
                          state %in% c("Kedah", "Perak", "Perlis", "Pulau Pinang") ~ "Utara",
                          state %in% c("Kelantan", "Pahang", "Terengganu") ~ "Timur",
                          state %in% c("Selangor", "W.P. Kuala Lumpur", "W.P. Putrajaya") ~ "Ter
                          state %in% c("Sabah", "Sarawak", "W.P. Labuan") ~ "Borneo")) %>%
  count(zone) %>%
  rename(total_district = n) %>%
  mutate(selected_district = 2,
         f1 = selected_district / total_district,
         W1 = 1/f1)

design_weight
```

```
# A tibble: 5 × 5
  zone     total_district selected_district     f1    W1
  <chr>             <int>             <dbl>  <dbl> <dbl>
1 Borneo               68                 2 0.0294  34  
2 Selatan              20                 2 0.1     10  
3 Tengah               11                 2 0.182    5.5
4 Timur                30                 2 0.0667  15  
5 Utara                31                 2 0.0645  15.5
```

Design Weight (W1)

- We use survey and srvyr package to recalculate the design weight by district

```
library(survey)
library(srvyr)

district_ws <- simnhmsds_final %>%
  left_join(.,
            design_weight %>%
              select(zone, W1),
            by = "zone") %>%
  as_survey_design(id = 1,
                   weight = W1) %>%
  group_by(district) %>%
  summarise(district_w1 = survey_total(success),
            .groups = "drop")
```

Design Weight (W1)

```
district_ws
```

```
# A tibble: 10 × 3
   district        district_w1 district_w1_se
   <chr>                 <dbl>          <dbl>
 1 Asajaya                1292          198. 
 2 Bachok                  570           87.5
 3 Bagan Datuk             558           88.3
 4 Barat Daya              558           88.3
 5 Jasin                   340           55.5
 6 Kuala Nerus             570           87.5
 7 Kuala Selangor          176           29.7
 8 Muar                    340           55.5
 9 Pusa                   1292          198. 
10 Ulu Selangor            176           29.7
```

Non-response Adjustment Factor (F)

- Non-response Adjustment Factor (F):
  - → The inverse of the response rate for each district.
  - → Adjusts the design weight to account for missing data due to non-response.

```r
nonresponse_weight <- selected_district %>%
  mutate(fnr = case_when(zone == "Utara" ~ 36/40,
                         zone == "Selatan" ~ 34/40,
                         zone == "Timur" ~ 38/40,
                         zone == "Tengah" ~ 32/40,
                         zone == "Borneo" ~ 38/40),
         Fw = 1/fnr)

nonresponse_weight
```

Non-response Adjustment Factor (F)

```
# A tibble: 10 × 5
   zone    state         district           fnr    Fw
   <chr>   <chr>         <chr>            <dbl> <dbl>
 1 Borneo  Sarawak       Pusa              0.95  1.05
 2 Borneo  Sarawak       Asajaya           0.95  1.05
 3 Selatan Melaka        Jasin             0.85  1.18
 4 Selatan Johor         Muar              0.85  1.18
 5 Tengah  Selangor      Kuala Selangor    0.8   1.25
 6 Tengah  Selangor      Ulu Selangor      0.8   1.25
 7 Timur   Terengganu    Kuala Nerus       0.95  1.05
 8 Timur   Kelantan      Bachok            0.95  1.05
 9 Utara   Pulau Pinang  Barat Daya        0.9   1.11
10 Utara   Perak         Bagan Datuk       0.9   1.11
```

Non-response Adjustment Factor (F)

- The non-response adjustment factor (F) is calculated for each district based on the response rate.

```r
district_adw <- nonresponse_weight %>%
  left_join(.,
            district_ws %>%
              select(district, district_w1),
            by = "district") %>%
  mutate(district_adw = district_w1 * Fw)

district_adw
```

```
# A tibble: 10 × 7
   zone    state         district         fnr    Fw district_w1 district_adw
   <chr>   <chr>         <chr>          <dbl> <dbl>       <dbl>        <dbl>
 1 Borneo  Sarawak       Pusa            0.95  1.05        1292         1360
 2 Borneo  Sarawak       Asajaya         0.95  1.05        1292         1360
 3 Selatan Melaka        Jasin           0.85  1.18         340          400
 4 Selatan Johor         Muar            0.85  1.18         340          400
 5 Tengah  Selangor      Kuala Selangor  0.8   1.25         176          220
 6 Tengah  Selangor      Ulu Selangor    0.8   1.25         176          220
 7 Timur   Terengganu    Kuala Nerus     0.95  1.05         570          600
 8 Timur   Kelantan      Bachok          0.95  1.05         570          600
 9 Utara   Pulau Pinang  Barat Daya      0.9   1.11         558          620
10 Utara   Perak         Bagan Datuk     0.9   1.11         558          620
```

Post-stratification Adjustment (PS)

- Post-stratification Adjustment (PS)
  - → Ensures that the sample reflects the actual population distribution by gender, age group, and ethnicity.
  - → Uses the population data to adjust for any over- or under-representation in the sample.

Total Population by Post-strat Group

```r
ps_pop <- pop_mydist %>%
  mutate(agegp = case_when(age %in% c("20-24", "24-29") ~ "20-29",
                           age %in% c("30-34", "35-39") ~ "30-39",
                           age %in% c("40-44", "45-49") ~ "40-49",
                           age %in% c("50-54", "55-59") ~ "50-59")) %>%
  group_by(gender, agegp, ethnicity) %>%
  summarise(population = sum(population),
            .groups = "drop")

ps_pop %>%
  mutate(popcoma = scales::label_comma()(population))
```

```
# A tibble: 24 × 5
   gender agegp ethnicity population popcoma
   <fct>  <chr> <fct>          <dbl> <chr>
 1 Female 20-29 Malay         777700 777,700
 2 Female 20-29 Chinese       241200 241,200
 3 Female 20-29 Indian         76800 76,800
 4 Female 30-39 Malay        1445300 1,445,300
 5 Female 30-39 Chinese       529300 529,300
 6 Female 30-39 Indian        166100 166,100
 7 Female 40-49 Malay        1101900 1,101,900
 8 Female 40-49 Chinese       515800 515,800
 9 Female 40-49 Indian        146700 146,700
10 Female 50-59 Malay         799700 799,700
# ℹ 14 more rows
```

Post-stratification Adjustment (PS)

- The adjusted weight is attached back to our dataset, and post-stratification weight is calculated using survey and srvyr package.

```
ps_weight <- simnhmsds_final %>%
  left_join(.,
            district_adw %>%
              select(district, district_adw),
            by = join_by(district)) %>%
  as_survey_design(id = 1,
                   weights = district_adw) %>%
  group_by(gender, agegp, ethnicity) %>%
  summarise(ps_adw = survey_total(success),
            .groups = "drop") %>%
  select(-ps_adw_se) %>%
  left_join(simnhmsds_final %>%
              count(gender, agegp, ethnicity),
            .,
            by = join_by(gender, agegp, ethnicity)) %>%
  left_join(.,
            ps_pop,
            by = join_by(gender, agegp, ethnicity)) %>%
  mutate(fps = population / ps_adw,
```

Post-stratification Adjustment (PS)

- The adjusted weight is attached back to our dataset, and post-stratification weight is calculated using survey and srvyr package.

```
ps_weight
```

```
# A tibble: 24 × 8
   gender agegp ethnicity     n ps_adw population   fps final_weight
   <chr>  <chr> <chr>     <int>  <dbl>      <dbl> <dbl>        <dbl>
 1 Female 20-29 Chinese      15   8220     241200  29.3      0.0341
 2 Female 20-29 Indian        6   3380      76800  22.7      0.0440
 3 Female 20-29 Malay        21  14380     777700  54.1      0.0185
 4 Female 30-39 Chinese      16  10420     529300  50.8      0.0197
 5 Female 30-39 Indian        6   4560     166100  36.4      0.0275
 6 Female 30-39 Malay        19  15420    1445300  93.7      0.0107
 7 Female 40-49 Chinese       4   1840     515800 280.       0.00357
 8 Female 40-49 Indian        8   3820     146700  38.4      0.0260
 9 Female 40-49 Malay        33  21300    1101900  51.7      0.0193
10 Female 50-59 Chinese      14   8020     428200  53.4      0.0187
# ℹ 14 more rows
```

Attaching Final Weight to Dataset

- The final weight is attached to the dataset for further analysis.

```
simnhmsds_weight <-  simnhmsds_final %>%
  left_join(.,
            ps_weight %>%
              select(gender, agegp, ethnicity, final_weight),
            by = join_by(gender, agegp, ethnicity))

simnhmsds_weight
```

```
# A tibble: 356 × 15
   success    id zone  state district gender   age agegp ethnicity height weight
     <dbl> <int> <chr> <chr> <chr>    <chr>  <int> <chr> <chr>      <int>  <dbl>
 1       1     1 Born… Sara… Pusa     Male      28 20-29 Chinese      163   56.7
 2       1     2 Born… Sara… Pusa     Female    53 50-59 Indian       164   63.2
 3       1     3 Born… Sara… Pusa     Female    53 50-59 Chinese      164   71.1
 4       1     4 Born… Sara… Pusa     Female    39 40-49 Malay        164   76.7
 5       1     6 Born… Sara… Pusa     Male      28 20-29 Malay        168   71.5
 6       1     7 Born… Sara… Pusa     Male      28 20-29 Chinese      164   63.9
 7       1     8 Born… Sara… Pusa     Female    51 50-59 Indian       167   66.9
 8       1     9 Born… Sara… Pusa     Male      23 20-29 Chinese      164   64.4
 9       1    10 Born… Sara… Pusa     Male      23 20-29 Malay        166   79.3
10       1    11 Born… Sara… Pusa     Female    47 40-49 Malay        164   73.3
# ℹ 346 more rows
# ℹ 4 more variables: PAhour <int>, hba1c <dbl>, dm_dx <int>,
#   final_weight <dbl>
```

Analyzing the Data

Survey Design Object:

- The `svydesign()` function from the survey package is used to define the complex survey design.
- We account for stratification, clustering, and weighting to accurately estimate population parameters.
- Parameters:
  - → `ids`: cluster id. ~1 if no cluster
  - → `probs` or `weights`: sampling probability or weight, use only one
  - → `strata`: strata id. NULL (or leave unspecified) if no strata
  - → `data`: dataset

Unweighted Design

```r
unwt_dsg <- svydesign(ids = ~1,
                      weights = 1,
                      data = simnhmsds_weight)

summary(unwt_dsg)
```

```
Independent Sampling design (with replacement)
svydesign(ids = ~1, weights = 1, data = simnhmsds_weight)
Probabilities:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max. 
      1       1       1       1       1       1 
Data variables:
 [1] "success"      "id"           "zone"         "state"        "district"    
 [6] "gender"       "age"          "agegp"        "ethnicity"    "height"      
[11] "weight"       "PAhour"       "hba1c"        "dm_dx"        "final_weight"
```

Weighted Design

```r
wtds_dsg <- svydesign(ids = ~district,
                      weights = ~final_weight,
                      strata = ~zone,
                      data = simnhmsds_weight)

summary(wtds_dsg)
```

```
Stratified 1 - level Cluster Sampling design (with replacement)
With (10) clusters.
svydesign(ids = ~district, weights = ~final_weight, strata = ~zone,
    data = simnhmsds_weight)
Probabilities:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
  13.48   35.83   52.25   54.56   65.99  280.33
Stratum Sizes:
           Borneo Selatan Tengah Timur Utara
obs            76      68     64    76    72
design.PSU      2       2      2     2     2
actual.PSU      2       2      2     2     2
Data variables:
 [1] "success"      "id"           "zone"         "state"        "district"
 [6] "gender"       "age"          "agegp"        "ethnicity"    "height"
[11] "weight"       "PAhour"       "hba1c"        "dm_dx"        "final_weight"
```

Estimating Population Prevalence

- We calculate estimates for key outcomes (e.g., prevalence of diabetes) using weighted data to ensure valid, representative conclusions.

```r
svymean(x = ~dm_dx,
          design = wtds_dsg,
          na.rm = T)
```

```
         mean     SE
dm_dx 0.50992 0.0373
```

Variance Estimation:

- Variance is estimated using complex sampling design techniques to ensure accurate confidence intervals for population estimates.

```r
svyciprop(formula = ~dm_dx,
          design = wtds_dsg) %>%
  attr(., "ci")
```

```
     2.5%     97.5%
0.4147657 0.6043703
```

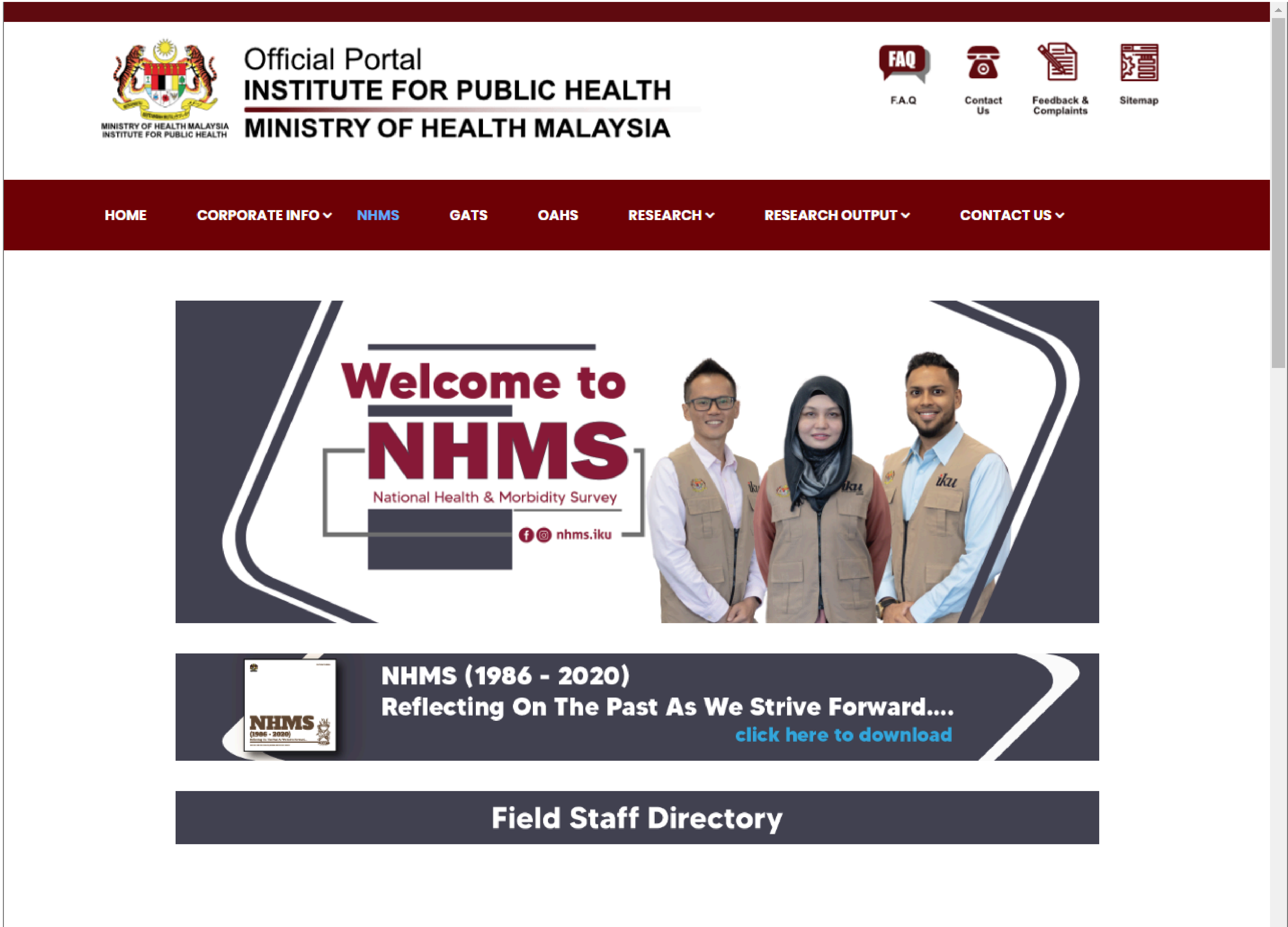
Subgroup Analysis

- For subpopulation analysis, we can use `svyby( )` function

```
svyby(formula = ~dm_dx,
      by = ~gender,
      design = wtds_dsg,
      FUN = svymean,
      na.rm = T)
```

```
       gender     dm_dx         se
Female Female 0.5350983 0.03554017
Male     Male 0.4739481 0.05523103
```

Thank you



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