

**Research Report: The relationship between support for
right-wing populist parties, importance of environmental
issues, gender, and age**

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Introduction

In recent years, support for right-wing populist parties in Western European countries has steadily increased. These parties often espouse nationalist, anti-immigration, and anti-equality ideologies, linked to the spread of disinformation, the erosion of democratic institutions, and the promotion of hateful and discriminatory policies (Mudde, 2007). Previous research claims that support for right-wing populist parties depends on economic competition between migrants and natives. Individuals with precarious occupations often have jobs with a high influx of migrants and experience more perceived threat since their contract standards are lower than knowledge workers – that is to say, their contracts are less secure due to flexibility and less conditions (Rydgren, 2008; Bornschieer & Kriesi, 2012). In addition, to the previous argument, it is found that males are especially prone to exposure to economic competition since they are more likely to work in the manufacturing industry than females (Bornschieer & Kriesi, 2012). According to Bagilhole and Cross (2006), this is a sector whereby employers operate (and compete) more internationally than typical female-dominated sectors such as caretaking, art, and education.

However, so far, it is unknown why, besides the economic competition argument, working in a carbon-intensive sector or not has an effect on support for right-wing populist parties. According to Lockwood (2018), right-wing populist parties, unlike traditionally left-wing or right-wing parties, would not have environmental policies to address climate change. One consequence is that men may be more likely to vote for a right-wing populist party than women because men benefit more from a lack of environmental policies; and vice versa: women care more about the environment than men. Gilligan (1982) states that this is not because women are less likely to work in sectors that contribute to climate change than men but because women are more often socialized to a tendency in which 'caring' [for nature or in general] is central.

In addition, previous research has shown that right-wing populist parties often consist of older than young people (Spierings & Zaslove, 2015). One of the reasons is that older generations value traditions more and are less 'idealistic' than younger generations (Patil, 2014). Right-wing populist parties, thereby, take away market share from traditional center-left parties framed as 'too progressive' since they support multicultural policies and international cooperation (Holmberg, 2007; Hellström, & Nilsson, 2010). Because idealism is part of the extent to which someone is passionate about a topic, it could be that young people vote less often for a right-wing populist party. Growing up in a world of climate change, they want to solve climate change faster and more effective than right-wing populist parties (and older generations) (Forchtner & Kølvrå, 2015; Wu, Snell, & Samji, 2020). Finally, it is still unknown whether the (negative) relationship between one's importance of environmental issues and support for right-wing populist parties is stronger for young women than for older women. That is to say, it could be that peers influence young people's identity formation and that younger women more often feel pressure to express their 'caring' side than older (more emotionally stable) women.

All-in-all, I, therefore, have the following research question: *“How does the importance of environmental issues to an individual relate to their support for right-wing populist parties, and what is the role of gender and age in this relationship?”*

In this research, I focus on Sweden and use survey data from 2018 from <https://valkalkylatorn.se/>. Sweden is an interesting case because the country is progressive in terms of climate policy and has egalitarian gender roles.

State of the Field: What do we know about the relationship between support for right-wing populist party's, environmentalism, and one's gender and age?

Right-wing populism in Sweden

Right-wing populist parties are difficult to position in the political landscape due to their combination of economic liberalism, nationalism, and anti-immigration rhetoric (Decker, 2008; Lucardie, 2008; Rydgren, 2008). They often advocate for more police and healthcare workers, fewer taxes and government services, and strict immigration and integration policies, including the 'deportation' of refugees and the repression of minority groups (Betz, 2001). According to Jylhä, Rydgren, and Strimling (2022), the Sweden Democrats (SD) are currently the only right-wing populist party in the Swedish parliament (*Riksdag*). Cas Mudde (2007) classifies SD as right-wing populist due to its nativist stance, which sees the party as standing up for the native population against international organizations and foreigners, and its authoritarian attitude towards policy solutions, such as strict immigration policies. SD also adopts a populist attitude, targeting the Social Democratic Workers' Party (SAP) as an 'elite' who have allegedly carried out a globalist agenda. Steven (2020) notes that SD is part of the "European Conservatives and Reformists" group in the European Parliament, which consists mainly of culturally conservative, nationalist parties with anti-EU attitudes.

The effect of voter's importance of environmental issues on support for right-wing populist parties

Little is known about the relationship between environmental issues and support for right-wing populist parties (see, among others, Spierings & Glas, 2021). Firstly, Lockwood (2018) argues that, in line with Cas Mudde's (2007) definition of right-wing populism, populist parties always turn against supranational solutions. In other words, parties like SD reject international cooperation on environmental policy. However, since climate change does not know borders, this approach limits the positive effect of environmental policy on the reduction of greenhouse gas. Every voter who considers this topic important knows that the energy policy of different countries must balance each other. Otherwise, there will be variations in the international competitive position between companies. That is to say, some countries will adjust their policies in such a way that domestic entrepreneurs can profit maximumly from the energy transition of other countries so that the collective outcome is sub-optimal: there is still environmental pollution – global warming is not declining and, in the short term, whether or not through

more resource extraction, maybe even increasing (Biesbroek & Swart, 2019) Secondly, right-wing populist parties have a specific theme they focus on, namely 'immigration and integration'. Hence, Jeffries (2017) states that right-wing populist parties *"do not reject [climate] science outright but instead seek to marginalize the climate agenda in order to concentrate on border control and immigration"* (p.469). Voters will therefore have less chance of finding a (comprehensive) strategy against global warming with a right-wing populist party.

H1: The more important someone thinks environmental issues are, the less support for right-wing populist parties.

Mediation: the role of voter's gender and age

Previous research has shown that men vote for right-wing populist parties more often than women (Spierings & Zaslove, 2015). One of the reasons is that more men work in precarious jobs in the manufacturing industry with a high influx of migrants compared with women (Bornschier & Kriesi, 2012). However, the idea that men are more likely to 'compete' with migrants than women is not the only reason. On the one hand, 'gender segregation' of a high percentage of men with precarious jobs in carbon-intensive sectors means that, on average, men often find climate policies less important than economic issues and, on the other hand, that men do find climate policy important but only because 'too progressive' policies are a 'danger' to their financial security (Bechtel, Genovese, & Scheve, 2017).

In addition, Gilligan (1982) argues that through socialization during childhood, there is a difference between men and women in the extent to which both sexes display altruistic behavior towards nature and wildlife. According to the Based Motivation Theory, children, namely, act on the stereotypes attributed to their self-identification (Elmore & Oyserman, 2012). Hence, women adopt to a greater extent typical 'feminine' traits, including 'caring' [for the environment], while men do less so (Helgeson, 1994).

H2: The effect of the extent to which someone considers environmental issues important on support for right-wing populist parties can be explained by one's gender.

The voter base of right-wing populist parties consists not only of more men than women but also more older people (Lees, 2018). One of the reasons is that older people, due to their age, value tradition and collectivism more, and are less idealistic (Patil, 2014). However, according to the Life Course Theory, millennials and generation Z – that is, all people born between 1980 and 2010 – would have grown up with climate change. Subsequently, things like 'the church' and 'the community' are less likely to be a high-ranking issue to them. Hence, younger people are generally more concerned about the implementation of climate policy than older people (Wu, Snell, & Samji, 2020). Since right-wing populist parties less often have a clear plan for tackling climate change (see, among others, Forchtner & Kølvrå, 2015), I, therefore, expect youngsters to vote less for a right-wing populist party.

H3: The effect of the extent to which someone considers environmental issues important on support for right-wing populist parties can be explained by one's age.

Moderation: the role of gender and age on the relationship between voter's importance of environmental issues and support for right-wing populist parties

Since the Based Motivation Theory states that women adopt more feminine characteristics than men, it is possible that the effect of one's importance of environmental issues on support for right-wing populist parties will be stronger for females. In other words, the more a woman considers the environment as an important voting issue, this reflects her tendency for nurturing and caring in general (Manfredo, Teel, & Henry, 2009). Hence, she will also care more about minorities and women's rights (see, among others, Spierings & Zaslove, 2015). However, since men adopted less of these 'caring elements', and right-wing populist parties do not propose a solution for these issues or do not support these issues at all (see, among others, Lockwood, 2018), women will have a faster decrease in support for a right-wing populist party than men, when one's importance of environmental issues increases.

H4: The effect of the extent to which someone considers environmental issues important on support for right-wing populist parties is stronger for women than for men.

According to Steinberg & Monahan (2007), young people are more susceptible to peer influence than adults. One reason is that young people are still developing mentally, so they do not yet have a well-defined identity – that is, stable personality traits (including ethics), physical appearance/expressions, and social status that define a person (Crocetti, 2017). However, previous research has shown that girls are more insecure about themselves than boys (see, among others, Phares, Steinberg, & Thompson, 2004). Subsequently, a strategy not to be seen as deviant is the adaptation of feminine traits. Hence, on average, younger women embody more caring features than emotionally, more 'mature' (read: elderly) women.

H5: The effect of the extent to which someone considers environmental issues important on support for right-wing populist parties is stronger for younger women than older women.

Data and Methods

This study uses survey data from 2018 from <https://valkalkylatorn.se/>. Respondents answered 28 questions about election topics in Sweden, ranging from the economy to the environment. The data was collected using snowball sampling by sharing a link through various (social) media channels. In total, there were 1600 responses and 1351 unique cases. Finally, the dataset made it possible to distinguish between voters' opinions on a specific topic and the extent to which voters are concerned with a topic. An overview of the descriptive statistics and data-wrangling process can be found in Appendix 1–2.

Dependent variable: support for a right-wing populist party

The dependent variable "support for a right-wing populist party" is binary (1=yes, 0=no). Since I don't know which party someone voted for, I constructed this variable as follows. Firstly, I only kept respondents who were 'somewhat sure' or 'very sure' about which party they would vote. Subsequently, I selected respondents whose opinions corresponded to at least 80 percent with one of the party's voters can elect in the *Riksdag*. In the end, an agreement of 80 percent or more with SD meant a vote for a right-wing populist party, while an agreement of 80 percent or more with another party did not classify a vote for a right-wing populist party.

Importance of environmental issues

I obtained 'the extent to which someone considers environmental issues important' by performing an exploratory factor analysis (EFA) on the entire dataset with the following items: "Klimatpolitiken ska överordnas annan politik" (sign.Q1), "Bensinskatten ska höjas" (sign.Q6), "Sverige ska satsa på snabbtåg" (sign.Q16), "Det är rätt att införa en flygskatt" (sign.Q17), "En särskild skatt på kött ska införas" (sign.Q27). I found one underlying factor based on the Kaiser criterion ($\lambda > 1.5$). The items sign.Q6, sign.Q16, sign.Q17, and sign.Q27 explained 48.39 percent of the variance in the latent variable (Ω). Finally, I chose to omit sign.Q6 to construct a mean scale for the extent to which someone considers environmental issues important. Hereby, Cronbach's Alpha (i.e., internal consistency) increased from 0.606 to 0.615 and was, therefore, 'moderate'.

Gender

The variable 'gender' was a dummy and consisted of the following question: "jag är... en" ("I am a [female=1/male=0]").

Age

The variable 'age' was ordinal and consisted of the categories 'lt18' (under 18 years), '18-24', '25-34', '35-44', '45-54', '55-64', and 'gt64' (over 64 years old). I chose to treat age as a continuous variable.

Statistical analysis

I used IBM SPSS 28 to test my hypothesis. The first hypothesis – i.e., support for a right-wing populist party ~ one's importance of environmental issues – will be a logistic regression model since the outcome variable is binary. The same goes for H2 and H3. However, the indirect effect via "one's importance of environmental issues" will be a multiple linear regression with gender and age as independent variables and "one's importance of environmental issues" as dependent variable. Finally, I test H4 and H5 by adding a (three-way) interaction to H1 with gender (and age).

The betas (βA^*) for my mediation were obtained by standardizing the estimates in MS Excel. The following formula was used to do this: $\beta A^* = \beta(sx)$, where sx represents the sample standard deviation of predictor X_i (Menard, 2004).

Results

Direct effect

In my first hypothesis, I assumed that an increase in the degree to which someone considers environmental issues important has a negative effect on support for a right-wing populist party. I have found this to be partially true. As one's importance of environmental issues increases with one unit, the log odds of voting for a right-wing populist party decrease with 0.008. However, this result is insignificant ($p = .992$, see Table 1, Model 1).

Moderation

I found that the relationship between the degree to which someone considers environmental issues important on support for a right-wing populist party is slightly more negative for women than for men (H4). That is to say, as women consider environmental issues becoming more important, their chance of voting for a right-wing populist party decreases more quickly than for men ($B = -.002$, see Table 1, Model 2). However, this difference is not significant ($p = .898$). Figure 1 illustrates this relationship.

In addition to the moderation effect of gender on the relationship between the degree to which someone considers environmental issues important and support for a right-wing populist party, I found that age makes this relationship less negative. As a woman (man) gets older, the negative effect of the degree to which someone considers environmental issues important on support for a right-wing populist party decrease ($B = .004$, see Table 1, Model 3). However, this effect was not significant ($p = .772$). Figure 2 represents a graphical representation of this relationship. It is striking that younger women (men) experience a stronger decrease in the chance of right-wing populist voting behavior as their importance of environmental issues increases than is the case for older women (men).

Mediation

To test whether the relationship between gender and support for right-wing populist parties can be explained via one's importance of environmental issues, I first looked at the direct effect of gender on support for right-wing populist parties ($c1$). This effect was significant and negative ($B = -.547$, $p = .003$). In short, women have a lower chance of voting for a right-wing populist party than men. The same goes for the age variable. As someone gets older, the chance to vote for a right-wing populist party decrease. However, this effect was not significant ($B = -0.070$, $p = .652$).

To test possible mediation, I first looked at the total effect (b) of environmental issues on support for a right-wing populist party. Since path b was insignificant ($B = .150$, $p = 0.363$), the effect of gender

(as well as age) on support for a right-wing populist party could not be explained via one's importance of environmental issues. An overview of all relationships can be found in Figure 4.

Conclusion

In this research, I looked at the relationship between the extent to which voters consider environmental issues important, what the effect is on support for right-wing populist parties, and what role gender and age play in this. I conceptualized right-wing populism using Cas Mudde's (2007) definition, namely, nativism, authoritarianism, and populism. The Sweden Democrats were currently the only party in the *Riksdag* to meet this classification.

Firstly, I did not find any indication of a negative relationship between the degree to which someone considers environmental issues important and support for a right-wing populist party. This may be true because the effect works both ways. On the one hand, an increase in people's perception of importance of environmental issues can result in more support for a right-wing populist party since right-wing populist parties claim that progressive climate policies are against private interests (or because no active climate policy is being promoted, they signal that 'the energy transition is not being participated in'). On the other hand, an increase in which someone considers environmental issues important could result in less support for a right-wing populist party because the voter in question is concerned about global warming and wants to see an effective solution to this. However, since right-wing populist parties often do not provide this, the probability of voting for a right-wing populist party decrease.

Since it is not clear whether the effect of the degree to which someone considers environmental issues important on support for a right-wing populist party is positive or negative, I was not able to test whether the degree to which someone considers environmental issues important mediates the relationship between gender, age, and support for right-wing populist parties. In addition, I did not find any indication that gender moderates the relationship between importance of environmental issues and support for right-wing populist parties. One of the reasons may be that Sweden has an egalitarian distribution of men and women in different occupational sectors and that gender norms are (to a certain extent) equal among the sexes. In other words, Swedish data may have minimized differences between males and females.

However, I found that the effect of gender on the relationship between the degree to which someone considers environmental issues important and support for right-wing populist parties is clear in relation to differences in age. One reason is that young people may be more vulnerable to psycho-social influences and have a more 'idealistic' worldview than older people – a worldview in which environmental issues are more important than other issues, such as collectivism and traditional values. Therefore, when young people care about something, they are very passionate about the subject, and the expectations for addressing it are high. In the case of climate change, this means a call for a solution; something that is often not provided by right-wing populist parties.

Table 1

Parameter estimations for logistic regression on support for right-wing populist parties (Sweden Democrats) (n=212)

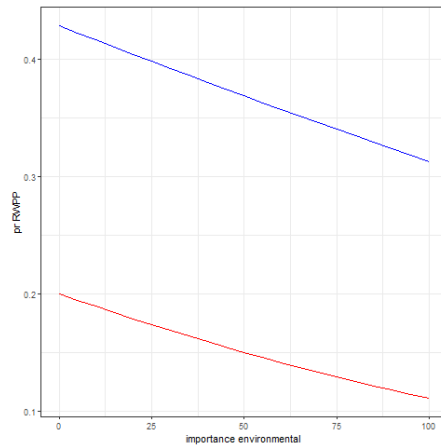
	H1: Model 1	H4: Model 2	H5: Model 3
	<i>B (SE)</i>	<i>B (SE)</i>	<i>B (SE)</i>
<i>Independent variables</i>			
Importance of environmental issues	-.008 (.006)	-.005 (.007)	-.069 (.026)**
Gender (1 = female)		-1.098 (1.139)	-.185 (3.582)
Age			-.741 (.332)*
Importance of environmental issues X Gender		-.002 (.018)	-.017 (.059)
Importance of environmental issues X Age			.015 (.006)**
Gender X Age			-.237 (.870)
Importance of environmental issues X Gender X Age			.004 (.014)
(Constant)	-.410 (.359)	-.287 (.386)	2.706 (1.406)
Nagelkerke R2	.011	.078	.145
-2 Log Likelihood	257.995	247.628	236.712

Note. Reported values in log odds and unstandardized.

* $p < .050$, ** $p < .010$, *** $p < .001$

Figure 2

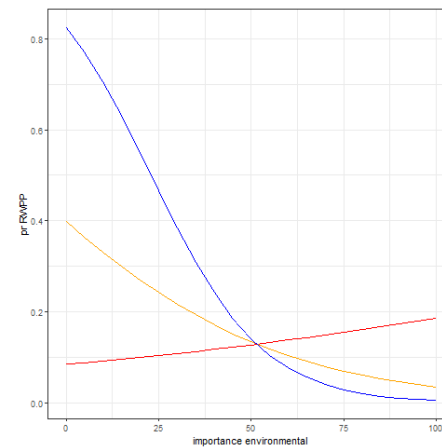
Graphical representation of hypothesis 4



Note. blue=males, red=women

Figure 3

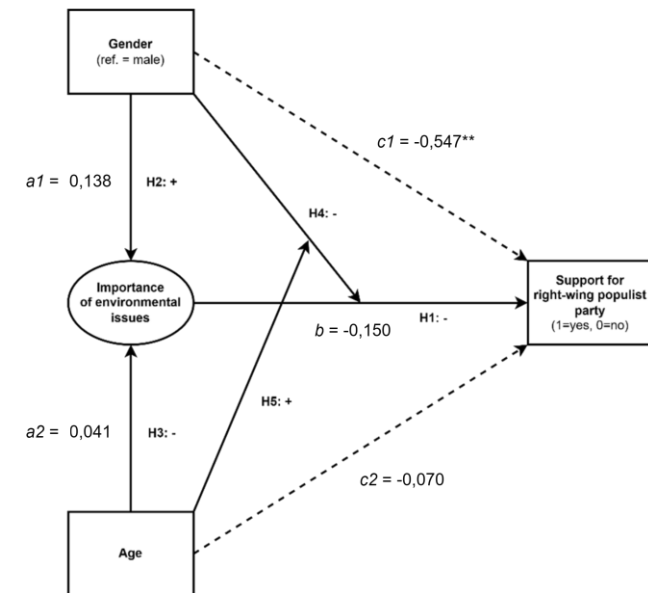
Graphical representation of hypothesis 5



Note. gender=female; blue = 18-24 years, orange = 35-44 year, red = > 64 years

Figure 4

Path analysis



There are some limitations to this study. Firstly, there is a lack of control variables such as income or religious background, making it hard to claim causality. One robustness check I did, was using survey questions that measure individuals' opinions as a proxy for, for example, their socioeconomic status, attitudes towards migrants, and personality traits. However, this resulted in high standard errors in my regression models because the items may have a lot of variability. Secondly, the composition of the dependent variable is problematic because I only checked on between-variation and not within-variation. That is to say, I did not come up with a condition for the minimum required distance in similarity score between each political party and individual. Finally, a small sample size may have resulted in type two errors. In other words, I did not reject the null hypothesis when I should have. Further research could, therefore, use a larger and (better) dataset, apply this research to a country with strong gender differences, and focus on young voters and their passion for certain topics.

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Worklog

Researcher: Sven Strating

Date	≈Amount of hours	Description of task
Before internship	7 hours (in total)	Brainstorm, research proposal
9 September	2 hours	Introduction Meeting with Carl
13 September	1,5 hours	Learn about JSON-strings
14 September	15 minutes	Email Carl
15 September	1 hour	Pick up USB Stick
18 September	30 minutes	Make a schedule with my availability
25 September	6 hours	Work on response dataset in R and MS Excel
26 September	8 hours	Work on response dataset in R and MS Excel
3 October	7 hours	Work on contextual dataset in R and MS Excel
3 October	4 hours	Work on contextual dataset in R and MS Excel
4 October	30 minutes	Mail Carl
5 October	3,5 hours	Create/think about research setup + mail Carl
14 October	3,5 hours	Meeting with Carl
2 November	6 hours	Work on party data in R and MS Excel
3 November	9 hours	Work on party data in R and MS Excel + development of codebook
4 November	6 hours	Run PCA Analysis in Stata + mail Carl + rescaling dataset + learn how to calculate party distance in MS Excel
5-7 November	6 hours	Work on party distance in MS Excel + (answer) mail Carl + think about theoretical model
8 November	7 hours	Theorizing + (answer) mail Carl
16 November	6 hours	Theorizing
18 November	7 hours	Theorizing + (answer) mail Carl
16 December	5 hours	Email compiling
18 December	6 hours	Theorizing, start writing down theoretical framework (extensive literature review)
22 December	6 hours	Writing down theoretical framework (extensive literature review)
24 December	6 hours	Writing down theoretical framework + data & methods
27 December	7 hours	Writing down theoretical framework + data & methods
28 December	7 hours	Writing down theoretical framework + data & methods
29 December	5 hours	Finish theoretical framework + data & methods
30 December	5 hours	Finish theoretical framework + data & methods
2 January	8 hours	Hypothesis testing in R and IBM SPSS
3 January	8 hours	Hypothesis testing in R and IBM SPSS
4 January	8 hours	Writing down results, conclusion, introduction
5 January	8 hours	Writing down results, conclusion, introduction
6 January	8 hours	Finishing everything (last spelling checks, worklog, etc.)
7 January	6 hours	Finishing everything (last spelling checks, worklog, etc.)

Total amount of hours of work: +/-177::200 hours

Appendix 1. Descriptive Statistics

Table 2

Descriptive statistics

	<i>N</i>	<i>Range</i>	<i>M</i>	<i>SD</i>
<i>Dependent variable</i>				
Support for right-wing populist party	233	0-1	0.30	0.46
<i>Independent variables</i>				
Importance of environmental issues	233	0-100	56.27	24.89
Age	233	0-5	3.19	1.24
Gender	233	0-1	0.27	0.44

Appendix 2. Data wrangling, Data processing, and Setup Syntaxis

Data processing in MS Excel

```
STEP 1
seperate everything via text-to-collumns

STEP 2
ADD COLUMN duplicate test
=IF(COUNT.IF($C$2:$C$1596;C2)>1;1;0)

STEP 3
sorty by duplicate test descendent order

STEP 4
sorty by "duplicate test" descendent order, # i.e., (1-->0)
      "datetime"          ascendent order # i.e., (old-->new)

STEP 4
delete duplicate cases by "cryptIP"

STEP 5
double check with two examples

"datetime"          "cryptID"
3-8-2018 21:07:25    967XXXXXXXXXXXXXXXXXXXXXXXXXXXXX
3-8-2018 21:32:34    967XXXXXXXXXXXXXXXXXXXXXXXXXXXXX
3-8-2018 21:14:45    8b3XXXXXXXXXXXXXXXXXXXXXXXXXXXXX
3-8-2018 21:21:39    8b3XXXXXXXXXXXXXXXXXXXXXXXXXXXXX

STEP 6
delete "duplicate test" and replace with "id"

STEP 7
merge "id" with "input"

STEP 8
delete cryptIP

STEP 9
save input seperately from other data

STEP 10
transform via text-to-collumns function

STEP 11 give collumn names

STEP 12 run following VBA code to get rid of collumns without name

'delete collumns without name

Sub DeleteBlankCells()
Range("A1:GP1").Select '//range of the dataset
Selection.SpecialCells(xlCellTypeBlanks).Select
Selection.EntireColumn.Delete
End Sub

STEP 13
check dataset again

STEP 14
some people did not answer all questions. this is problematic for the analysis
apply casewise deletion (OR use R to handle this problem --> see future code)
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Data processing in R (x64-bits)

```
#read data as .xls
library(readxl)
raw_responses_3 <- read_excel("raw_responses_3.xlsx")
View(raw_responses_3)

#check variables
class(raw_responses_3)
ls(raw_responses_3)

#make new data.frame to match answers because people did not fill out all
#the questions
df <- data.frame(rownum = 1:45000)

bloc_len <- 28

df$id <-
  rep(seq(1, 1 + nrow(df) %/% bloc_len), each = bloc_len,
      length.out = nrow(df))
View(df)

df2 <- subset(df, select = -c(rownum))
View(df2)

library(dplyr)
df3 <- df2 %>% group_by(id) %>% mutate(question_number = seq_len(n()))
View(df3)

df3 <- df3[-c(44997, 44998, 44999, 45000), ]
View(df3)

#split dataset in 28 pieces
## for question 1 --> rename "question_1" into "question_number"
dataset_1 <- subset(raw_responses_3, select = c(id,
                                                question_1,
                                                answer_Q1,
                                                sign_Q1,
                                                done_Q1))
names(dataset_1)[names(dataset_1) == "question_1"] <- "question_number"
names(dataset_1)[names(dataset_1) == "answer_Q1"] <- "answer"
names(dataset_1)[names(dataset_1) == "sign_Q1"] <- "sign"
names(dataset_1)[names(dataset_1) == "done_Q1"] <- "done"

dataset_2 <- subset(raw_responses_3, select = c(id,
                                                question_2,
                                                answer_Q2,
                                                sign_Q2,
                                                done_Q2))
names(dataset_2)[names(dataset_2) == "question_2"] <- "question_number"
names(dataset_2)[names(dataset_2) == "answer_Q2"] <- "answer"
names(dataset_2)[names(dataset_2) == "sign_Q2"] <- "sign"
names(dataset_2)[names(dataset_2) == "done_Q2"] <- "done"

dataset_3 <- subset(raw_responses_3, select = c(id,
                                                question_3,
                                                answer_Q3,
                                                sign_Q3,
                                                done_Q3))
names(dataset_3)[names(dataset_3) == "question_3"] <- "question_number"
names(dataset_3)[names(dataset_3) == "answer_Q3"] <- "answer"
names(dataset_3)[names(dataset_3) == "sign_Q3"] <- "sign"
names(dataset_3)[names(dataset_3) == "done_Q3"] <- "done"

dataset_4 <- subset(raw_responses_3, select = c(id,
                                                question_4,
                                                answer_Q4,
                                                sign_Q4,
                                                done_Q4))
names(dataset_4)[names(dataset_4) == "question_4"] <- "question_number"
names(dataset_4)[names(dataset_4) == "question_4"] <- "question_number"
names(dataset_4)[names(dataset_4) == "answer_Q4"] <- "answer"
names(dataset_4)[names(dataset_4) == "sign_Q4"] <- "sign"
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names(dataset_4)[names(dataset_4) == "done_Q4"] <- "done"

dataset_5 <- subset(raw_responses_3, select = c(id,
                                                question_5,
                                                answer_Q5,
                                                sign_Q5,
                                                done_Q5))
names(dataset_5)[names(dataset_5) == "question_5"] <- "question_number"
names(dataset_5)[names(dataset_5) == "answer_Q5"] <- "answer"
names(dataset_5)[names(dataset_5) == "sign_Q5"] <- "sign"
names(dataset_5)[names(dataset_5) == "done_Q5"] <- "done"

dataset_6 <- subset(raw_responses_3, select = c(id,
                                                question_6,
                                                answer_Q6,
                                                sign_Q6,
                                                done_Q6))
names(dataset_6)[names(dataset_6) == "question_6"] <- "question_number"
names(dataset_6)[names(dataset_6) == "answer_Q6"] <- "answer"
names(dataset_6)[names(dataset_6) == "sign_Q6"] <- "sign"
names(dataset_6)[names(dataset_6) == "done_Q6"] <- "done"

dataset_7 <- subset(raw_responses_3, select = c(id,
                                                question_7,
                                                answer_Q7,
                                                sign_Q7,
                                                done_Q7))
names(dataset_7)[names(dataset_7) == "question_7"] <- "question_number"
names(dataset_7)[names(dataset_7) == "answer_Q7"] <- "answer"
names(dataset_7)[names(dataset_7) == "sign_Q7"] <- "sign"
names(dataset_7)[names(dataset_7) == "done_Q7"] <- "done"

dataset_8 <- subset(raw_responses_3, select = c(id,
                                                question_8,
                                                answer_Q8,
                                                sign_Q8,
                                                done_Q8))
names(dataset_8)[names(dataset_8) == "question_8"] <- "question_number"
names(dataset_8)[names(dataset_8) == "answer_Q8"] <- "answer"
names(dataset_8)[names(dataset_8) == "sign_Q8"] <- "sign"
names(dataset_8)[names(dataset_8) == "done_Q8"] <- "done"

dataset_9 <- subset(raw_responses_3, select = c(id,
                                                question_9,
                                                answer_Q9,
                                                sign_Q9,
                                                done_Q9))
names(dataset_9)[names(dataset_9) == "question_9"] <- "question_number"
names(dataset_9)[names(dataset_9) == "answer_Q9"] <- "answer"
names(dataset_9)[names(dataset_9) == "sign_Q9"] <- "sign"
names(dataset_9)[names(dataset_9) == "done_Q9"] <- "done"

dataset_10 <- subset(raw_responses_3, select = c(id,
                                                  question_10,
                                                  answer_Q10,
                                                  sign_Q10,
                                                  done_Q10))
names(dataset_10)[names(dataset_10) == "question_10"] <- "question_number"
names(dataset_10)[names(dataset_10) == "answer_Q10"] <- "answer"
names(dataset_10)[names(dataset_10) == "sign_Q10"] <- "sign"
names(dataset_10)[names(dataset_10) == "done_Q10"] <- "done"

dataset_11 <- subset(raw_responses_3, select = c(id,
                                                  question_11,
                                                  answer_Q11,
                                                  sign_Q11,
                                                  done_Q11))

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names(dataset_11)[names(dataset_11) == "question_11"] <- "question_number"
names(dataset_11)[names(dataset_11) == "answer_Q11"] <- "answer"
names(dataset_11)[names(dataset_11) == "sign_Q11"] <- "sign"
names(dataset_11)[names(dataset_11) == "done_Q11"] <- "done"

dataset_12 <- subset(raw_responses_3, select = c(id,
                                                question_12,
                                                answer_Q12,
                                                sign_Q12,
                                                done_Q12))
names(dataset_12)[names(dataset_12) == "question_12"] <- "question_number"
names(dataset_12)[names(dataset_12) == "answer_Q12"] <- "answer"
names(dataset_12)[names(dataset_12) == "sign_Q12"] <- "sign"
names(dataset_12)[names(dataset_12) == "done_Q12"] <- "done"

dataset_13 <- subset(raw_responses_3, select = c(id,
                                                question_13,
                                                answer_Q13,
                                                sign_Q13,
                                                done_Q13))
names(dataset_13)[names(dataset_13) == "question_13"] <- "question_number"
names(dataset_13)[names(dataset_13) == "answer_Q13"] <- "answer"
names(dataset_13)[names(dataset_13) == "sign_Q13"] <- "sign"
names(dataset_13)[names(dataset_13) == "done_Q13"] <- "done"

dataset_14 <- subset(raw_responses_3, select = c(id,
                                                question_14,
                                                answer_Q14,
                                                sign_Q14,
                                                done_Q14))
names(dataset_14)[names(dataset_14) == "question_14"] <- "question_number"
names(dataset_14)[names(dataset_14) == "answer_Q14"] <- "answer"
names(dataset_14)[names(dataset_14) == "sign_Q14"] <- "sign"
names(dataset_14)[names(dataset_14) == "done_Q14"] <- "done"

dataset_15 <- subset(raw_responses_3, select = c(id,
                                                question_15,
                                                answer_Q15,
                                                sign_Q15,
                                                done_Q15))
names(dataset_15)[names(dataset_15) == "question_15"] <- "question_number"
names(dataset_15)[names(dataset_15) == "answer_Q15"] <- "answer"
names(dataset_15)[names(dataset_15) == "sign_Q15"] <- "sign"
names(dataset_15)[names(dataset_15) == "done_Q15"] <- "done"

dataset_16 <- subset(raw_responses_3, select = c(id,
                                                question_16,
                                                answer_Q16,
                                                sign_Q16,
                                                done_Q16))
names(dataset_16)[names(dataset_16) == "question_16"] <- "question_number"
names(dataset_16)[names(dataset_16) == "answer_Q16"] <- "answer"
names(dataset_16)[names(dataset_16) == "sign_Q16"] <- "sign"
names(dataset_16)[names(dataset_16) == "done_Q16"] <- "done"

dataset_17 <- subset(raw_responses_3, select = c(id,
                                                question_17,
                                                answer_Q17,
                                                sign_Q17,
                                                done_Q17))
names(dataset_17)[names(dataset_17) == "question_17"] <- "question_number"
names(dataset_17)[names(dataset_17) == "answer_Q17"] <- "answer"
names(dataset_17)[names(dataset_17) == "sign_Q17"] <- "sign"
names(dataset_17)[names(dataset_17) == "done_Q17"] <- "done"

dataset_18 <- subset(raw_responses_3, select = c(id,
                                                question_18,

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                                answer_Q18,
                                sign_Q18,
                                done_Q18))
names(dataset_18)[names(dataset_18) == "question_18"] <- "question_number"
names(dataset_18)[names(dataset_18) == "answer_Q18"] <- "answer"
names(dataset_18)[names(dataset_18) == "sign_Q18"] <- "sign"
names(dataset_18)[names(dataset_18) == "done_Q18"] <- "done"

dataset_19 <- subset(raw_responses_3, select = c(id,
                                                question_19,
                                                answer_Q19,
                                                sign_Q19,
                                                done_Q19))
names(dataset_19)[names(dataset_19) == "question_19"] <- "question_number"
names(dataset_19)[names(dataset_19) == "answer_Q19"] <- "answer"
names(dataset_19)[names(dataset_19) == "sign_Q19"] <- "sign"
names(dataset_19)[names(dataset_19) == "done_Q19"] <- "done"

dataset_20 <- subset(raw_responses_3, select = c(id,
                                                question_20,
                                                answer_Q20,
                                                sign_Q20,
                                                done_Q20))
names(dataset_20)[names(dataset_20) == "question_20"] <- "question_number"
names(dataset_20)[names(dataset_20) == "answer_Q20"] <- "answer"
names(dataset_20)[names(dataset_20) == "sign_Q20"] <- "sign"
names(dataset_20)[names(dataset_20) == "done_Q20"] <- "done"

dataset_21 <- subset(raw_responses_3, select = c(id,
                                                question_21,
                                                answer_Q21,
                                                sign_Q21,
                                                done_Q21))
names(dataset_21)[names(dataset_21) == "question_21"] <- "question_number"
names(dataset_21)[names(dataset_21) == "answer_Q21"] <- "answer"
names(dataset_21)[names(dataset_21) == "sign_Q21"] <- "sign"
names(dataset_21)[names(dataset_21) == "done_Q21"] <- "done"

dataset_22 <- subset(raw_responses_3, select = c(id,
                                                question_22,
                                                answer_Q22,
                                                sign_Q22,
                                                done_Q22))
names(dataset_22)[names(dataset_22) == "question_22"] <- "question_number"
names(dataset_22)[names(dataset_22) == "answer_Q22"] <- "answer"
names(dataset_22)[names(dataset_22) == "sign_Q22"] <- "sign"
names(dataset_22)[names(dataset_22) == "done_Q22"] <- "done"

dataset_23 <- subset(raw_responses_3, select = c(id,
                                                question_23,
                                                answer_Q23,
                                                sign_Q23,
                                                done_Q23))
names(dataset_23)[names(dataset_23) == "question_23"] <- "question_number"
names(dataset_23)[names(dataset_23) == "answer_Q23"] <- "answer"
names(dataset_23)[names(dataset_23) == "sign_Q23"] <- "sign"
names(dataset_23)[names(dataset_23) == "done_Q23"] <- "done"

dataset_24 <- subset(raw_responses_3, select = c(id,
                                                question_24,
                                                answer_Q24,
                                                sign_Q24,
                                                done_Q24))
names(dataset_24)[names(dataset_24) == "question_24"] <- "question_number"
names(dataset_24)[names(dataset_24) == "answer_Q24"] <- "answer"
names(dataset_24)[names(dataset_24) == "sign_Q24"] <- "sign"
names(dataset_24)[names(dataset_24) == "done_Q24"] <- "done"

dataset_25 <- subset(raw_responses_3, select = c(id,

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                                question_25,
                                answer_Q25,
                                sign_Q25,
                                done_Q25))
names(dataset_25)[names(dataset_25) == "question_25"] <- "question_number"
names(dataset_25)[names(dataset_25) == "answer_Q25"] <- "answer"
names(dataset_25)[names(dataset_25) == "sign_Q25"] <- "sign"
names(dataset_25)[names(dataset_25) == "done_Q25"] <- "done"

dataset_26 <- subset(raw_responses_3, select = c(id,
                                                question_26,
                                                answer_Q26,
                                                sign_Q26,
                                                done_Q26))
names(dataset_26)[names(dataset_26) == "question_26"] <- "question_number"
names(dataset_26)[names(dataset_26) == "answer_Q26"] <- "answer"
names(dataset_26)[names(dataset_26) == "sign_Q26"] <- "sign"
names(dataset_26)[names(dataset_26) == "done_Q26"] <- "done"

dataset_27 <- subset(raw_responses_3, select = c(id,
                                                question_27,
                                                answer_Q27,
                                                sign_Q27,
                                                done_Q27))
names(dataset_27)[names(dataset_27) == "question_27"] <- "question_number"
names(dataset_27)[names(dataset_27) == "answer_Q27"] <- "answer"
names(dataset_27)[names(dataset_27) == "sign_Q27"] <- "sign"
names(dataset_27)[names(dataset_27) == "done_Q27"] <- "done"

dataset_28 <- subset(raw_responses_3, select = c(id,
                                                question_28,
                                                answer_Q28,
                                                sign_Q28,
                                                done_Q28))
names(dataset_28)[names(dataset_28) == "question_28"] <- "question_number"
names(dataset_28)[names(dataset_28) == "answer_Q28"] <- "answer"
names(dataset_28)[names(dataset_28) == "sign_Q28"] <- "sign"
names(dataset_28)[names(dataset_28) == "done_Q28"] <- "done"

#match answer_Q1 ... answer_Q28 by id and question_number ## sort by id to
                                                         ## see what happend

df4 <- full_join(dataset_1, df3, by = c("id", "question_number")) #Q1
df5 <- full_join(dataset_2, df3, by = c("id", "question_number")) #Q2
df6 <- full_join(dataset_3, df3, by = c("id", "question_number")) #Q3
df7 <- full_join(dataset_4, df3, by = c("id", "question_number")) #Q4
df8 <- full_join(dataset_5, df3, by = c("id", "question_number")) #Q5
df9 <- full_join(dataset_6, df3, by = c("id", "question_number")) #Q6
df10 <- full_join(dataset_7, df3, by = c("id", "question_number")) #Q7
df11 <- full_join(dataset_8, df3, by = c("id", "question_number")) #Q8
df12 <- full_join(dataset_9, df3, by = c("id", "question_number")) #Q9
df13 <- full_join(dataset_10, df3, by = c("id", "question_number")) #Q10
df14 <- full_join(dataset_11, df3, by = c("id", "question_number")) #Q11
df15 <- full_join(dataset_12, df3, by = c("id", "question_number")) #Q12
df16 <- full_join(dataset_13, df3, by = c("id", "question_number")) #Q13
df17 <- full_join(dataset_14, df3, by = c("id", "question_number")) #Q14
df18 <- full_join(dataset_15, df3, by = c("id", "question_number")) #Q15
df19 <- full_join(dataset_16, df3, by = c("id", "question number")) #Q16

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df20 <- full_join(dataset_17, df3, by = c("id", "question_number")) #Q17
df21 <- full_join(dataset_18, df3, by = c("id", "question_number")) #Q18
df22 <- full_join(dataset_19, df3, by = c("id", "question_number")) #Q19
df23 <- full_join(dataset_20, df3, by = c("id", "question_number")) #Q20
df24 <- full_join(dataset_21, df3, by = c("id", "question_number")) #Q21
df25 <- full_join(dataset_22, df3, by = c("id", "question_number")) #Q22
df26 <- full_join(dataset_23, df3, by = c("id", "question_number")) #Q23
df27 <- full_join(dataset_24, df3, by = c("id", "question_number")) #Q24
df28 <- full_join(dataset_25, df3, by = c("id", "question_number")) #Q25
df29 <- full_join(dataset_26, df3, by = c("id", "question_number")) #Q26
df30 <- full_join(dataset_27, df3, by = c("id", "question_number")) #Q27
df31 <- full_join(dataset_28, df3, by = c("id", "question_number")) #Q28

#question 1 ## check with filter
a <- df4 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 2 ## check with filter
b <- df5 %>%
  left_join(a, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 3 ## check with filter
c <- df6 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 4 ## check with filter
d <- df7 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 5 ## check with filter
e <- df8 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 6 ## check with filter

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f <- df9 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 7 ## check with filter
g <- df10 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 8 ## check with filter
h <- df11 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 9 ## check with filter
i <- df12 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 10 ## check with filter
j <- df13 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 11 ## check with filter
k <- df14 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 12 ## check with filter
l <- df15 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 13 ## check with filter
m <- df16 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%

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    select(-done.x, -done.y)

#question 14 ## check with filter
n <- df17 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 15 ## check with filter
o <- df18 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 16 ## check with filter
p <- df19 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 17 ## check with filter
q <- df20 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 18 ## check with filter
r <- df21 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 19 ## check with filter
s <- df22 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 20 ## check with filter
t <- df23 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 21 ## check with filter
u <- df24 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%

```

```

mutate(done = coalesce(done.x, done.y)) %>%
select(-answer.x, -answer.y) %>%
select(-sign.x, -sign.y) %>%
select(-done.x, -done.y)

#question 22 ## check with filter
v <- df25 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 23 ## check with filter
w <- df26 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 24 ## check with filter
x <- df27 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 25 ## check with filter
y <- df28 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 26 ## check with filter
z <- df29 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 27 ## check with filter
z1 <- df30 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#question 28 ## check with filter
z2 <- df31 %>%
  left_join(df5, by = "id") %>%
  mutate(answer = coalesce(answer.x, answer.y)) %>%
  mutate(sign = coalesce(sign.x, sign.y)) %>%
  mutate(done = coalesce(done.x, done.y)) %>%
  select(-answer.x, -answer.y) %>%
  select(-sign.x, -sign.y) %>%
  select(-done.x, -done.y)

#last step
a <- filter(a, question number.x==1 & question number.y==1 |

```



```

        question_number.x==20 & question_number.y==20 |
        question_number.x==21 & question_number.y==21 |
        question_number.x==22 & question_number.y==22 |
        question_number.x==23 & question_number.y==23 |
        question_number.x==24 & question_number.y==24 |
        question_number.x==25 & question_number.y==25 |
        question_number.x==26 & question_number.y==26 |
        question_number.x==27 & question_number.y==27 |
        question_number.x==28 & question_number.y==28
    )

z1 <- filter(z1, question_number.x==1 & question_number.y==1 |
        question_number.x==2 & question_number.y==2 |
        question_number.x==3 & question_number.y==3 |
        question_number.x==4 & question_number.y==4 |
        question_number.x==5 & question_number.y==5 |
        question_number.x==6 & question_number.y==6 |
        question_number.x==7 & question_number.y==7 |
        question_number.x==8 & question_number.y==8 |
        question_number.x==9 & question_number.y==9 |
        question_number.x==10 & question_number.y==10 |
        question_number.x==11 & question_number.y==11 |
        question_number.x==12 & question_number.y==12 |
        question_number.x==13 & question_number.y==13 |
        question_number.x==14 & question_number.y==14 |
        question_number.x==15 & question_number.y==15 |
        question_number.x==16 & question_number.y==16 |
        question_number.x==17 & question_number.y==17 |
        question_number.x==18 & question_number.y==18 |
        question_number.x==19 & question_number.y==19 |
        question_number.x==20 & question_number.y==20 |
        question_number.x==21 & question_number.y==21 |
        question_number.x==22 & question_number.y==22 |
        question_number.x==23 & question_number.y==23 |
        question_number.x==24 & question_number.y==24 |
        question_number.x==25 & question_number.y==25 |
        question_number.x==26 & question_number.y==26 |
        question_number.x==27 & question_number.y==27 |
        question_number.x==28 & question_number.y==28
    )

z2 <- filter(z2, question_number.x==1 & question_number.y==1 |
        question_number.x==2 & question_number.y==2 |
        question_number.x==3 & question_number.y==3 |
        question_number.x==4 & question_number.y==4 |
        question_number.x==5 & question_number.y==5 |
        question_number.x==6 & question_number.y==6 |
        question_number.x==7 & question_number.y==7 |
        question_number.x==8 & question_number.y==8 |
        question_number.x==9 & question_number.y==9 |
        question_number.x==10 & question_number.y==10 |
        question_number.x==11 & question_number.y==11 |
        question_number.x==12 & question_number.y==12 |
        question_number.x==13 & question_number.y==13 |
        question_number.x==14 & question_number.y==14 |
        question_number.x==15 & question_number.y==15 |
        question_number.x==16 & question_number.y==16 |
        question_number.x==17 & question_number.y==17 |
        question_number.x==18 & question_number.y==18 |
        question_number.x==19 & question_number.y==19 |
        question_number.x==20 & question_number.y==20 |
        question_number.x==21 & question_number.y==21 |
        question_number.x==22 & question_number.y==22 |
        question_number.x==23 & question_number.y==23 |
        question_number.x==24 & question_number.y==24 |
        question_number.x==25 & question_number.y==25 |
        question_number.x==26 & question_number.y==26 |
        question_number.x==27 & question_number.y==27 |
        question_number.x==28 & question_number.y==28
    )

full <- rbind(a,b,c,d,e,f,g,h,i,j,
              k,l,m,n,o,p,q,r,s,t,
              u,v,w,x,y,z,z1,z2)

#get rid of rows with N/A
full2 <- na.omit(full)

```

```

#get rid of exact duplicates. i.e., the same id, question_number.x,
#                               question_number.y, answer,
#                               sign, done
raw_responses_complete <- distinct(full2)
View(raw_responses_complete)
raw_responses_complete <- subset(raw_responses_complete,
                                select = -c(question_number.x))
names(raw_responses_complete) [names(raw_responses_complete) ==
                              "question_number.y"] <- "question_number"
View(raw_responses_complete)

##=====##SAVE LONG DATA ##=====##
require(writexl)
write_xlsx(raw_responses_complete,
"C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\raw_responses_complete_long.xlsx")
##=====##

```

Data Processing in R (x64-bits): long-to-wide-data

```

##=====##LOAD DATA##=====##
library(readxl)
raw_responses_complete_long <- read_excel("~/2_Master_Sociology and Social
Research/LiU/Forskningspraktik (771A41)/data/raw_responses_complete_long.xlsx")
View(raw_responses_complete_long)
##=====##

#transform long dataset to wide dataset
library(reshape2)

#question_number
wide_null <- subset(raw_responses_complete_long, select = -c(done,
                                                            sign))

wide1 <- dcast(wide_null, id~question_number)
##add prefix before column
library(dplyr)
library(tidyselect)
wide1 <- wide1 %>%
  rename_with( ~ paste("", .x, sep = "Question_"))
names(wide1)[names(wide1) == "Question_id"] <- "id"

#done
wide2 <- dcast(raw_responses_complete_long, id~question_number,
              value.var = "done")
wide2 <- wide2 %>%
  rename_with( ~ paste("", .x, sep = "Done_"))
names(wide2)[names(wide2) == "Done_id"] <- "id"

#sign
wide3 <- dcast(raw_responses_complete_long, id~question_number,
              value.var = "sign")
wide3 <- wide3 %>%
  rename_with( ~ paste("", .x, sep = "Sign_"))
names(wide3)[names(wide3) == "Sign_id"] <- "id"

#merge dataset on ID variable
raw_responses_complete_wide1 <- full_join(wide1, wide2, by="id")
raw_responses_complete_wide <- full_join(raw_responses_complete_wide1,
                                         wide3, by="id")

##=====##SAVE WIDE DATA=====##
require(writexl)
write_xlsx(raw_responses_complete_wide,
"C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\raw_responses_complete_wide.xlsx")
##=====##

```

Dataset setup for IBM SPSS 28 in R (x64-bits)

```
#=====
#setup syntaxis VERSION 1.0
#=====

#-----{age}-----

library(readxl)
data <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/final data/complete_dataset_version2 - RESCALE (1).xlsx")
View(data)

#change character into numerical values
typeof(data$age)
x_lt18 <- sub("lt18", 1, data$age)
x_18_24 <- sub("18-24", 2, data$age)
x_25_34 <- sub("25-34", 3, data$age)
x_35_44 <- sub("35-44", 4, data$age)
x_45_54 <- sub("45-54", 5, data$age)
x_55_64 <- sub("55-64", 6, data$age)
x_gt64 <- sub("gt64", 7, data$age)

age2 <- data.frame(data$age, data$id,
                   x_lt18, x_18_24,
                   x_25_34, x_35_44,
                   x_45_54, x_55_64,
                   x_gt64)

View(age2)

library(dplyr)

#x_lt18
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "18-24"))
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "25-34"))
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "35-44"))
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "45-54"))
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "55-64"))
age2 <- age2 %>%
  mutate(x_lt18 = na_if(x_lt18, "gt64"))

#18-24
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "lt18"))
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "25-34"))
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "35-44"))
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "45-54"))
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "55-64"))
age2 <- age2 %>%
  mutate(x_18_24 = na_if(x_18_24, "gt64"))

#25-34
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "lt18"))
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "18-24"))
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "35-44"))
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "45-54"))
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "55-64"))
age2 <- age2 %>%
  mutate(x_25_34 = na_if(x_25_34, "gt64"))

#35-44
age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "lt18"))
```

```

age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "18-24"))
age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "25-34"))
age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "45-54"))
age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "55-64"))
age2 <- age2 %>%
  mutate(x_35_44 = na_if(x_35_44, "gt64"))

#45-54
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "lt18"))
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "18-24"))
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "25-34"))
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "35-44"))
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "55-64"))
age2 <- age2 %>%
  mutate(x_45_54 = na_if(x_45_54, "gt64"))

#55-64
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "lt18"))
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "18-24"))
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "25-34"))
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "35-44"))
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "45-54"))
age2 <- age2 %>%
  mutate(x_55_64 = na_if(x_55_64, "gt64"))

#gt64
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "lt18"))
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "18-24"))
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "25-34"))
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "35-44"))
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "45-54"))
age2 <- age2 %>%
  mutate(x_gt64 = na_if(x_gt64, "55-64"))

age2$x_lt18 <- as.numeric(age2$x_lt18)
age2$x_18_24 <- as.numeric(age2$x_18_24)
age2$x_25_34 <- as.numeric(age2$x_25_34)
age2$x_35_44 <- as.numeric(age2$x_35_44)
age2$x_45_54 <- as.numeric(age2$x_45_54)
age2$x_55_64 <- as.numeric(age2$x_55_64)
age2$x_gt64 <- as.numeric(age2$x_gt64)

age2$x_lt18[is.na(age2$x_lt18)] <- 0
age2$x_18_24[is.na(age2$x_18_24)] <- 0
age2$x_25_34[is.na(age2$x_25_34)] <- 0
age2$x_35_44[is.na(age2$x_35_44)] <- 0
age2$x_45_54[is.na(age2$x_45_54)] <- 0
age2$x_55_64[is.na(age2$x_55_64)] <- 0
age2$x_gt64[is.na(age2$x_gt64)] <- 0

##=====
require(writexl)
write_xlsx(age2,
  "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\age2.xlsx")
##=====
library(readxl)

```

```

age2 <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/age2.xlsx")
View(age2)
##=====

library(dplyr)
age2 <- select(age2, -data.age)

require(reshape)
colnames(age2)[colnames(age2) == "data.id"] = "id"

age2 <- select(age2, -x_lt18)
age2 <- select(age2, -x_18_24)
age2 <- select(age2, -x_25_34)
age2 <- select(age2, -x_35_44)
age2 <- select(age2, -x_45_54)
age2 <- select(age2, -x_55_64)
age2 <- select(age2, -x_gt64)

age2[age2 == 0] <- NA

##=====
require(writexl)
write_xlsx(age2,
            "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\age_setup.xlsx")
##=====

#-----{gender}-----
library(readxl)
data <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/final data/complete_dataset_version2 - RESCALE (1).xlsx")
View(data)

class(data$gender)

female <- sub("female", 1, data$gender)
male    <- sub("male", 0, data$gender)

gender2 <- data.frame(data$id, data$gender,
                      female, male)
class(gender2$female)
#female
gender2$female[gender2$female == "male"] <- 0
#male
gender2$male[gender2$male == 0] <- 1
gender2$male[gender2$male == "fe0"] <- 0

#0=male, 1=female
table(gender2$female, gender2$data.gender)

require(reshape)
colnames(gender2)[colnames(gender2) == "data.id"] = "id"

##=====
require(writexl)
write_xlsx(gender2,
            "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\gender2.xlsx")
##=====

library(readxl)
gender2 <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/gender2.xlsx")
View(gender2)

#0=male, 1=female
table(gender2$data.gender, gender2$gender1)

gender2$male[gender2$male == "fe0"] <- 0

library(dplyr)
gender2 <- select(gender2, -data.gender)
gender2 <- select(gender2, -female)
gender2 <- select(gender2, -male)

```

```

##=====
require(writexl)
write_xlsx(gender2,
           "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\gender3.xlsx")
##=====

#-----{partydecided}-----

library(readxl)
data <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/final data/complete_dataset_version2 - RESCALE (1).xlsx")
View(data)

#change character into numerical values
typeof(data$partydecided)
partydecided_1 <- sub("veryunsure", 1, data$partydecided)
partydecided_2 <- sub("somewhatunsure", 2, data$partydecided)
partydecided_3 <- sub("somewhatsure", 3, data$partydecided)
partydecided_4 <- sub("verysure", 4, data$partydecided)

partydecided2 <- data.frame(data$id, data$partydecided,
                           partydecided_1, partydecided_2,
                           partydecided_3, partydecided_4)

#veryunsure
partydecided2 <- partydecided2 %>%
  mutate(partydecided_1 = na_if(partydecided_1, "somewhatunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_1 = na_if(partydecided_1, "somewhatsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_1 = na_if(partydecided_1, "verysure"))

#somewhatunsure
partydecided2 <- partydecided2 %>%
  mutate(partydecided_2 = na_if(partydecided_2, "veryunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_2 = na_if(partydecided_2, "somewhatsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_2 = na_if(partydecided_2, "verysure"))

#somewhatsure
partydecided2 <- partydecided2 %>%
  mutate(partydecided_3 = na_if(partydecided_3, "veryunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_3 = na_if(partydecided_3, "somewhatunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_3 = na_if(partydecided_3, "verysure"))

#verysure
partydecided2 <- partydecided2 %>%
  mutate(partydecided_4 = na_if(partydecided_4, "veryunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_4 = na_if(partydecided_4, "somewhatunsure"))
partydecided2 <- partydecided2 %>%
  mutate(partydecided_4 = na_if(partydecided_4, "somewhatsure"))

require(reshape)
colnames(partydecided2)[colnames(partydecided2) == "data.id"] = "id"

##=====
require(writexl)
write_xlsx(partydecided2,
           "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\partydecided2.xlsx")
##=====

library(readxl)
partydecided2 <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/partydecided2.xlsx")
View(partydecided2)

library(dplyr)
partydecided2 <- select(partydecided2, -partydecided_1)

```

```

partydecided2 <- select(partydecided2, -partydecided_2)
partydecided2 <- select(partydecided2, -partydecided_3)
partydecided2 <- select(partydecided2, -partydecided_4)

#1=veryunsure, 2=somewhatunsure, 3=somewhatsure, 4=verysure
table(partydecided2$data.partydecided,
      partydecided2$partydecided2)

library(dplyr)
partydecided2 <- select(partydecided2, -data.partydecided)

##=====
require(writexl)
write_xlsx(partydecided2,
           "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\partydecided3.xlsx")
##=====

####-----FINAL_MERGE-----####

#main dataset
library(readxl)
dataset <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/final_data/complete_dataset_version2 - RESCALE (1).xlsx")
View(dataset)

#age dataset
library(readxl)
age <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/age_setup.xlsx")
View(age)

#gender dataset
library(readxl)
gender <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/gender3.xlsx")
View(gender)

#partydecided dataset
library(readxl)
partydecided <- read_excel("2_Master_Sociology and Social Research/LiU/Forskningspraktik
(771A41)/data/partydecided3.xlsx")
View(partydecided)

#-----#

library(dplyr)
dataset1 <- full_join(dataset, age, by="id")
dataset2 <- full_join(dataset1, gender, by="id")
dataset3 <- full_join(dataset2, partydecided, by="id")

##=====##
##                               FINAL DATASET                               ##
##=====##
require(writexl)
write_xlsx(dataset3,
           "C:\\Users\\svens\\OneDrive\\Documenten\\2_Master_Sociology and Social
Research\\LiU\\Forskningspraktik (771A41)\\data\\final_dataset_v3.xlsx")
##=====##

# gender: 0=male, 1=female,

# age:    1="1t18",   2="18-24", 3="25-34",
#         4="35-44", 5="45-54", 6="55-64",
#         7="gt64"

# partydecided: 1="veryunsure", 2="somewhatunsure", 3="somewhatsure",
#              4="verysure"

```

Setup for statistical analysis in IBM SPSS 28

```
* Encoding: UTF-8.
*=====SET-UP=====

*1) GET DATA.
GET DATA
  /TYPE=XLSX
  /FILE='U:\My Documents\Forsikningspraktik\final dataset\individual-level\final dataset '+
    '(updated including syntaxis)\final_dataset_v3.xlsx'
  /SHEET=name 'Sheet1'
  /CELLRANGE=FULL
  /READNAMES=ON
  /DATATYPEMIN PERCENTAGE=95.0
  /HIDDEN IGNORE=YES.
EXECUTE.

*2) CONSTRUCT DEPENDENT VARIABLE
  "support for a right-wing populist party or not".
DATASET NAME DataSet1 WINDOW=FRONT.
DELETE VARIABLES maxvalue Party_distance_sd_A Party_distance_v_A
Party_distance_fi_A Party_distance_s_A Party_distance_mp_A Party_distance_c_A
Party_distance_l_A Party_distance_kd_A Party_distance_m_A.
DATASET ACTIVATE DataSet1.
RECODE sd_largest_2yes_1no (2=1) (1=0).
EXECUTE.

USE ALL.
COMPUTE filter_$=((party_distance_fi > 0.8 OR party_distance_mp > 0.8 OR party_distance_s >
0.8 OR
  party_distance_sd > 0.8 OR party_distance_v > 0.8 OR party_distance_c > 0.8 OR
party_distance_m >
  0.8 OR party_distance_kd > 0.8 OR party_distance_l > 0.8) AND (partydecided2 > 2)).
VARIABLE LABELS filter_$ '(party_distance_fi > 0.8 OR party_distance_mp > 0.8 OR '+
  'party_distance_s > 0.8 OR party_distance_sd > 0.8 OR party_distance_v > 0.8 OR '+
  'party_distance_c > 0.8 OR party_distance_m > 0.8 OR party_distance_kd > 0.8 OR '+
  'party_distance_l > 0.8) AND ... (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
*condition_1 = party_distance >.8 AND > partydecided > 2.
RENAME VARIABLES filter_$ = condition_1.
FILTER OFF.

*condition_1 needs to be 1
  IF condition_1=1 AND sd_largest2yes_1no = 1 THEN Vote_RWPP=2
  IF condition_1=1 AND sd_largest2yes_1no = 0 THEN Vote_RWPP=1
.
CROSSTABS
  /TABLES=partydecided2 BY condition_1
  /FORMAT=AVALUE TABLES
  /CELLS=COUNT
  /COUNT ROUND CELL.

COMPUTE Vote_RWPP = 0.
EXECUTE.
IF (sd_largest_2yes_1no=1 AND condition_1=1) Vote_RWPP = 2.
EXECUTE.
IF (sd_largest_2yes_1no=0 AND condition_1=1) Vote_RWPP = 1.
EXECUTE.
CROSSTABS
  /TABLES=Vote_RWPP BY condition_1
  /FORMAT=AVALUE TABLES
  /CELLS=COUNT
  /COUNT ROUND CELL.

*Drop cased with Vote_RWPP=0.00.
FILTER OFF.
USE ALL.
SELECT IF (Vote_RWPP = 1 OR Vote_RWPP = 2).
EXECUTE.
FILTER OFF.

*Recode Vote_RWPP.
RECODE Vote_RWPP (2=1) (1=0).
```



```
EXECUTE.

*2) CONSTRUCT LATENT VARIABLE
    "one's importance of environmental issues".
IF  ((NOT SYSMIS(Sign_16)) AND (NOT SYSMIS(Sign_17)) AND (NOT SYSMIS(Sign_27)) )
    Importance_Environmental=MEAN(Sign_16,Sign_17,Sign_27).
EXECUTE.
*=====.
```

Appendix 3. Statistical Analysis

Statistical Analysis in IBM SPSS 28

```
* Encoding: UTF-8.
*=====README=====
**Statistical Modelling without confounders.
*=====

*Filter= SYSMIS should not apply for:
      *DV and IV's.
DATASET ACTIVATE DataSet1.
USE ALL.
COMPUTE filter_$=(( (NOT SYSMIS(Vote_RWPP)) AND (NOT SYSMIS(age_new)) AND (NOT
SYSMIS(gender1)) AND
      (NOT SYSMIS(Importance_Environmental)) )).
VARIABLE LABELS filter_$ '(' (NOT SYSMIS(Vote_RWPP)) AND (NOT SYSMIS(age_new)) AND (NOT '+'
      'SYSMIS(gender1)) AND (NOT SYSMIS(Importance_Environmental)) ) (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

*-----Hypothesis 1-----
*MODEL.
LOGISTIC REGRESSION VARIABLES Vote_RWPP
  /METHOD=ENTER Importance_Environmental
  /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

*-----Hypothesis 4-----
* MODEL.
**cross-variable (gender*environment).
DATASET ACTIVATE DataSet1.
COMPUTE gender_environment=gender1*Importance_Environmental.
EXECUTE.

LOGISTIC REGRESSION VARIABLES Vote_RWPP
  /METHOD=ENTER Importance_Environmental gender1 gender_environment
  /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

*-----Hypothesis 5-----
**cross-variable (age*environment).
DATASET ACTIVATE DataSet1.
COMPUTE age_environment=age_new*Importance_Environmental.
EXECUTE.
COMPUTE gender_age_new=gender1*age_new.
EXECUTE.
COMPUTE threeway=Importance_Environmental*gender1*age_new.
EXECUTE.
LOGISTIC REGRESSION VARIABLES Vote_RWPP
  /METHOD=ENTER Importance_Environmental gender1 age_new gender_environment age_environment
  gender_age_new threeway
  /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

*OR*.
USE ALL.
COMPUTE filter_$=(gender1=1).
VARIABLE LABELS filter_$ 'gender1=1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.
LOGISTIC REGRESSION VARIABLES Vote_RWPP
  /METHOD=ENTER Importance_Environmental age_new age_environment
  /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).
FILTER OFF.

*-----Mediation Model-----
**PART 1.
LOGISTIC REGRESSION VARIABLES Vote_RWPP
  /METHOD=ENTER Importance_Environmental gender1 age_new
```

```
/CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).
*Standarddeviation.
DESCRIPTIVES VARIABLES=Importance_Environmental gender1 age_new Vote_RWPP
/STATISTICS=MEAN STDDEV MIN MAX.

*PART 2.
REGRESSION
/MISSING LISTWISE
/STATISTICS COEFF OUTS R ANOVA
/CRITERIA=PIN(.05) POUT(.10)
/NOORIGIN
/DEPENDENT Importance_Environmental
/METHOD=ENTER gender1 age_new.
```

Appendix 4. Graphics

Graphical representation of H4 and H5 in R (x64-bits)

```
#=====
#graphs syntaxis VERSION 1.0
#=====

# H4.
## libraries on
library(ggplot2)
library(dplyr)

## environmental issues on support for RWPP moderated by gender==1
importance_environmental <- seq(from=0, to=100, by=5)
log_odds <- c(-0.287+((-0.005*importance_environmental)+(-1.098*1)+
               (-0.002*importance_environmental*1)))
odds <- exp(log_odds)
pr.RWPP <- (odds/(1+odds))

## environmental issues on support for RWPP moderated by gender==0
importance_environmental_0 <- seq(from=0, to=100, by=5)
log_odds_0 <- c(-0.287+(-0.005*importance_environmental_0))
odds_0 <- exp(log_odds_0)
pr.RWPP_0 <- (odds_0/(1+odds_0))

df <- data.frame(importance_environmental,
                 pr.RWPP,
                 pr.RWPP_0)
graph <- ggplot(df, aes(importance_environmental)) +
  geom_line(aes(y=pr.RWPP), colour="red") +
  geom_line(aes(y=pr.RWPP_0), colour="blue") +
  theme(axis.title.y = element_blank()) +
  theme(axis.title.x = element_blank()) +
  theme_bw() +
  labs(x = "importance environmental",
       y = "pr RWPP",)
plot(graph)

png(filename = "graph.png")
plot(graph)
dev.off()

#H5.
## environmental issues on support for RWPP moderated by gender==1 & age==1
importance_environmental <- seq(from=0, to=100, by=5)
log_odds_1 <- c(2.706+(-0.069*importance_environmental)+(-0.185*1)+
               (-0.741*1)+(-0.017*importance_environmental*1)+
               (0.015*importance_environmental*1)+
               (-0.237*1*1)+
               (0.004*importance_environmental*1*1))
odds_1 <- exp(log_odds_1)
pr.RWPP_1 <- (odds_1/(1+odds_1))

## environmental issues on support for RWPP moderated by gender==1 & age==3
importance_environmental <- seq(from=0, to=100, by=5)
log_odds_3 <- c(2.706+(-0.069*importance_environmental)+(-0.185*1)+
               (-0.741*3)+(-0.017*importance_environmental*1)+
               (0.015*importance_environmental*3)+
               (-0.237*1*3)+
               (0.004*importance_environmental*1*3))
odds_3 <- exp(log_odds_3)
pr.RWPP_3 <- (odds_3/(1+odds_3))

## environmental issues on support for RWPP moderated by gender==1 & age==5
importance_environmental <- seq(from=0, to=100, by=5)
log_odds_5 <- c(2.706+(-0.069*importance_environmental)+(-0.185*1)+
               (-0.741*5)+(-0.017*importance_environmental*1)+
               (0.015*importance_environmental*5)+
               (-0.237*1*5)+
               (0.004*importance_environmental*1*5))
odds_5 <- exp(log_odds_5)
```

```
pr.RWPP_5 <- (odds_5/(1+odds_5))

df2 <- data.frame(pr.RWPP_5, pr.RWPP_1, pr.RWPP_3,
                  importance_environmental)

graph2 <- ggplot(df2, aes(importance_environmental)) +
  geom_line(aes(y=pr.RWPP_5, colour="red")) +
  geom_line(aes(y=pr.RWPP_3, colour="orange")) +
  geom_line(aes(y=pr.RWPP_1, colour="blue")) +
  theme(axis.title.y = element_blank()) +
  theme(axis.title.x = element_blank()) +
  theme_bw() +
  labs(x = "importance environmental",
       y = "pr RWPP",)
plot(graph2)

png(filename = "graph2.png")
plot(graph2)
dev.off()
```