

Is Ignorance Truly Bliss? Relationship between Education, Gender & Happiness

1. Project Overview and Scope



The phrase “**Ignorance is bliss**” is a perspective that most of us have come across at least once, and sometimes even found meaningful. Naturally, individuals may have developed and educated themselves regardless of their formal educational background, gaining the ability to view life from different perspectives. However, in this study, the concept of ‘ignorance’ that I aim to focus on is independent of such interpretations. Instead, it refers to the relationship between a person’s level of education and their happiness, as well as how this relationship differs between men and women.

Problem Definition: Life satisfaction among individuals may vary depending on factors such as gender and education level. Therefore, it is necessary to conduct an analysis to examine the direction and magnitude of this interaction and to observe how happiness levels change based on individuals’ gender and educational background. **The aim** of this study is to reveal whether there is a significant relationship between educational attainment, gender and happiness levels in this context.

2. Data



2.1 Data Source

In this study, data obtained from the following links conducted by the Turkish Statistical Institute (TURKSTAT) has been used.

- [Life Satisfaction Survey \[1\]](#)
- [Population Statistics Portal \[2\]](#)

2.2 General Information About Data

“**education**” dataset: This dataset contains the number of individuals by gender and educational status for each province between 2008 and 2023. A small part of the dataset is shown below.

```
#libraries
library(readxl)
library(ggplot2)
library(tidyverse)
```

```
-- Attaching core tidyverse packages ----- tidyverse 2.0.0 --
v dplyr      1.1.4      v readr      2.1.5
v forcats    1.0.0      v stringr    1.5.1
v lubridate  1.9.3      v tibble     3.2.1
v purrr      1.0.2      v tidyr      1.3.1
-- Conflicts ----- tidyverse_conflicts() --
x dplyr::filter() masks stats::filter()
```

```
x dplyr::lag()      masks stats::lag()
i Use the conflicted package (<http://conflicted.r-lib.org/>) to force all conflicts to become
```

```
library(dslabs)
library(ggthemes)
library(ggrepel)
library(dplyr)
library(gganimate)
library(sf)
```

Linking to GEOS 3.9.3, GDAL 3.5.2, PROJ 8.2.1; sf_use_s2() is TRUE

```
library(viridis)
```

Loading required package: viridisLite

```
library(broom)
library(htmlwidgets)
library(knitr)
library(gifski)
library(tidytext)
library(nortest)
library(kableExtra)
```

Attaching package: 'kableExtra'

The following object is masked from 'package:dplyr':

group_rows

```
#library(DT)
```

```
#Import education dataset
```

```
#education <- read_excel("education.xlsx")
#save(education,file = "education.RData")
load("education.RData")
head(education)
```

```
# A tibble: 6 x 8
```

	Year	Province	Educational_Status	Total	Male	Female	Percentage_Male
	<chr>	<chr>	<chr>	<dbl>	<dbl>	<dbl>	<dbl>
1	2023	ADANA	Okuma yazma bilmeyen	58357	10083	48274	1
2	2023	ADANA	Okuma yazma bilen fakat b~	219571	95506	124065	9.2
3	2023	ADANA	İlkokul	441425	190047	251378	18.4
4	2023	ADANA	Ortaokul veya dengi mesle~	384900	208582	176318	20.2
5	2023	ADANA	İlköğretim	132788	80203	52585	7.8
6	2023	ADANA	Lise veya dengi meslek ok~	484355	268172	216183	25.9

```
# i 1 more variable: Percentage_Female <dbl>
```

“**byeducation**” dataset: This dataset contains the percentages of general happiness levels by educational status between 2004 and 2024. A small part of the dataset is shown below.

```
#Import byeducation dataset
#byeducation <- read_excel("byeducation.xlsx")
#save(byeducation,file = "byeducation.RData")
load("byeducation.RData")
```

```
head(byeducation)
```

```
# A tibble: 6 x 7
  Year Happiness_Level `No School Completed` `Primary School`
  <dbl> <chr>          <dbl>          <dbl>
1  2004 Happy          54.4          57.7
2  2004 Neither happy nor unhappy  27          30.7
3  2004 Unhappy        18.6          11.6
4  2005 Happy          54          55.2
5  2005 Neither happy nor unhappy  27.8         31.8
6  2005 Unhappy        18.1          13.1
# i 3 more variables: `Primary Education or Junior High School` <dbl>,
# `High School or Equivalent` <dbl>, `Higher Education` <dbl>
```

“**bygender**” data set: This dataset contains the percentages of general happiness levels by gender between 2003 and 2024. A small part of the dataset is shown below.

```
#Import bygender dataset
#bygender <- read_excel("bygender.xlsx")
#save(bygender,file = "bygender.RData")
load("bygender.RData")
head(bygender)
```

```
# A tibble: 6 x 5
  Year Happiness_Level Total Male Female
  <dbl> <chr>          <dbl> <dbl> <dbl>
1  2003 Very happy    12    12.4  11.6
2  2003 Happy        47.6   45.7  49.4
3  2003 Neither happy nor unhappy 33.2   34.1  32.2
4  2003 Unhappy       5.6    6.2    5
5  2003 Very unhappy  1.7    1.5    1.8
6  2004 Very happy    9.3    8.4   10.2
```

2.3 Reason of Choice

Even in this century, the distinction between women and men is still evident in many areas in Turkey. Undoubtedly, educating individuals is the most effective way to change the position of women in society. And perhaps, in this way, a society that has educated itself reaches the most important value for a person: **happiness**.

2.4 Preprocessing

The datasets used in this study will be merged to facilitate the analysis and will be organized in a way that allows easy processing by the program. If needed during the later stages of the analysis, additional datasets may be incorporated into the study. Different preprocessing steps have been applied to each dataset. The specific modifications made to each dataset are listed below in bullet points.

Preprocessing for “**education**” dataset;

- The presence of missing values (NA) is examined, and necessary preprocessing steps are applied if they exist.
- The education levels (“Educational_Status”) in the “education” dataset (10 levels) were aligned with those in the ‘byeducation’ dataset (5 levels).
- Irrelevant information has been removed from the dataset to simplify it. For example, entries such as “Unknown” and “Total” in the “Educational_Status” column have been excluded.

```
#changes in education dataset
#head(education)
#str(education)

sum(is.na(education))
```

```
[1] 0
```

```
education<- education |> filter(!Educational_Status %in% c("Bilinmeyen","Toplam"))|>
mutate(Educational_Status = case_when(
  Educational_Status %in% c("Okuma yazma bilmeyen", "Okuma yazma bilen fakat bir okul bitirm
  Educational_Status== "İlkokul" ~ "Primary School",
  Educational_Status %in% c("Ortaokul veya dengi meslek okulu", "İlköğretim") ~ "Primary Edu
  Educational_Status== "Lise veya dengi meslek okulu" ~ "High School or Equivalent",
  Educational_Status %in% c("Yüksekokul veya fakülte", "Yüksek lisans ve üzeri") ~ "Higher E
  TRUE ~ as.character(Educational_Status)))

education<- education |> group_by(Year,Province,Educational_Status) |>
summarise(
  Total=sum(Total,na.rm = TRUE),
  Male=sum(Male,na.rm = TRUE),
  Female=sum(Female,na.rm = TRUE),
  Percentage_Male=sum(Percentage_Male,na.rm = TRUE),
  Percentage_Female=sum(Percentage_Female,na.rm = TRUE),
  .groups = "drop"
)

education$Educational_Status<-factor(education$Educational_Status,levels= c("No School Complet

head(education) |> kbl() |> kable_styling(full_width = 5)
```

Year	Province	Educational_Status	Total	Male	Female	Percentage_Male	Percentage_Female
2008	ADANA	High School or Equivalent	300221	163672	136549	19.6	15.8
2008	ADANA	Higher Education	100011	59440	40571	7.1	4.7
2008	ADANA	No School Completed	552668	229450	323218	27.5	37.5
2008	ADANA	Primary Education or Junior High School	275436	150951	124485	18.1	14.4
2008	ADANA	Primary School	469036	230288	238748	27.6	27.6
2008	ADIYAMAN	High School or Equivalent	62867	39780	23087	16.8	9.5

```
#datatable(education,filter = "top",options = list(pageLength = 5))
```

The variables and their corresponding value ranges in the finalized “education” dataset are defined as follows:

```
str(education)
```

```
tibble [6,480 x 8] (S3: tbl_df/tbl/data.frame)
 $ Year          : chr [1:6480] "2008" "2008" "2008" "2008" ...
 $ Province      : chr [1:6480] "ADANA" "ADANA" "ADANA" "ADANA" ...
 $ Educational_Status: Ord.factor w/ 5 levels "No School Completed"<..: 4 5 1 3 2 4 5 1 3 2 ..
 $ Total         : num [1:6480] 300221 100011 552668 275436 469036 ...
 $ Male          : num [1:6480] 163672 59440 229450 150951 230288 ...
 $ Female        : num [1:6480] 136549 40571 323218 124485 238748 ...
 $ Percentage_Male : num [1:6480] 19.6 7.1 27.5 18.1 27.6 16.8 4.4 35.5 20.1 23.3 ...
 $ Percentage_Female : num [1:6480] 15.8 4.7 37.5 14.4 27.6 9.5 1.8 52.4 15 21.5 ...
```

- Year: The year of the study (ranging from 2008 to 2023).
- Province: Name of the province (81 provinces in total).
- Educational_Status: Education level (“No School Completed,” “Primary School,” “Primary Education or Junior High School,” “High School or Equivalent,” “Higher Education”).
- Total: Total number of individuals in a given year, province, and education level.
- Male: Number of males in a given year, province, and education level.
- Female: Number of females in a given year, province, and education level.
- Percentage_Male: Percentage of males in a given year, province, and education level.
- Percentage_Female: Percentage of females in a given year, province, and education level.

Descriptive statistics for variables are presented below.

```
summary(education)
```

Year	Province
Length:6480	Length:6480
Class :character	Class :character
Mode :character	Mode :character

Educational_Status		Total
No School Completed	:1296	Min. : 681
Primary School	:1296	1st Qu.: 42114
Primary Education or Junior High School:	1296	Median : 86103
High School or Equivalent	:1296	Mean : 190227
Higher Education	:1296	3rd Qu.: 183118
		Max. : 16154476

Male	Female	Percentage_Male	Percentage_Female
Min. : 257	Min. : 424	Min. : 0.00	Min. : 0.00
1st Qu.: 21807	1st Qu.: 19350	1st Qu.:12.70	1st Qu.:11.80
Median : 43320	Median : 41185	Median :19.80	Median :18.70
Mean : 95128	Mean : 95099	Mean :19.45	Mean :19.44
3rd Qu.: 91336	3rd Qu.: 91346	3rd Qu.:25.82	3rd Qu.:25.80
Max. :7930608	Max. :8223868	Max. :54.80	Max. :79.50

Preprocessing for “byeducation” dataset;

- The presence of missing values (NA) is examined, and necessary preprocessing steps are applied if they exist.
- The “byeducation” dataset is updated to include data from 2008 to 2023, in accordance with the ‘education’ dataset, which contains information for the same years.
- The variable “Happiness_Level”, which indicates the level of happiness, is defined as a factor variable with three levels.

```
#changes in byeducation dataset
#head(byeducation)
#str(byeducation)
```

```
sum(is.na(byeducation))
```

```
[1] 0
```

```
byeducation<- byeducation |> filter(Year %in% 2008:2023)
byeducation$Happiness_Level<-factor(byeducation$Happiness_Level,levels= c("Unhappy","Neither happy nor unhappy","Happy"),
names(byeducation)[4]<-"Primary School"
```

```
head(byeducation) |> kbl() |> kable_styling(full_width = 5)
```

	Year	Happiness_Level	No School Completed	Primary School	Primary Education or Junior High School	High School or Equivalent	Higher Education
	2008	Happy	55.8	54.0	55.3	55.5	62.9
	2008	Neither happy nor unhappy	26.3	31.8	31.7	33.1	24.6
	2008	Unhappy	17.8	14.2	12.9	11.4	12.5
	2009	Happy	51.8	52.5	56.1	54.7	63.2
	2009	Neither happy nor unhappy	27.3	32.8	32.3	32.4	27.8
	2009	Unhappy	21.0	14.7	11.6	13.0	9.0

The variables and their corresponding value ranges in the finalized “byeducation” dataset are defined as follows:

```
str(byeducation)
```

```
tibble [48 x 7] (S3: tbl_df/tbl/data.frame)
 $ Year                : num [1:48] 2008 2008 2008 2009 2009 ...
 $ Happiness_Level     : Ord.factor w/ 3 levels "Unhappy"<"Neither happy nor unhappy"<"Happy"
 $ No School Completed : num [1:48] 55.8 26.3 17.8 51.8 27.3 21 56.3 28.9 1
 $ Primary School      : num [1:48] 54 31.8 14.2 52.5 32.8 14.7 60.5 29 10.
 $ Primary Education or Junior High School: num [1:48] 55.3 31.7 12.9 56.1 32.3 11.6 61.6 27.6
 $ High School or Equivalent : num [1:48] 55.5 33.1 11.4 54.7 32.4 13 62.7 27.1 1
 $ Higher Education    : num [1:48] 62.9 24.6 12.5 63.2 27.8 9 67.7 26.2 6.
```

- Year: The study year (ranging from 2008 to 2023).
- Happiness_Level: Levels of happiness (“Unhappy,” “Neither Happy nor Unhappy,” “Happy”).

- No School Completed: The percentage of individuals with no formal education for a given year and happiness level.
- Primary School: The percentage of individuals who completed primary school for a given year and happiness level.
- Primary Education or Junior High School: The percentage of individuals who completed primary education or junior high school for a given year and happiness level.
- High School or Equivalent: The percentage of individuals who completed high school or its equivalent for a given year and happiness level.
- Higher Education: The percentage of individuals who completed university or higher education for a given year and happiness level.

Descriptive statistics for the variables are as follows:

```
summary(byeducation)
```

Year	Happiness_Level	No School Completed
Min. :2008	Unhappy :16	Min. :11.66
1st Qu.:2012	Neither happy nor unhappy:16	1st Qu.:16.40
Median :2016	Happy :16	Median :28.20
Mean :2016		Mean :33.33
3rd Qu.:2019		3rd Qu.:54.37
Max. :2023		Max. :63.54
Primary School	Primary Education or Junior High School	
Min. :10.10	Min. : 7.90	
1st Qu.:14.18	1st Qu.:13.27	
Median :32.25	Median :32.47	
Mean :33.34	Mean :33.33	
3rd Qu.:52.33	3rd Qu.:52.39	
Max. :62.94	Max. :64.40	
High School or Equivalent	Higher Education	
Min. : 8.10	Min. : 6.10	
1st Qu.:13.36	1st Qu.:12.91	
Median :33.03	Median :31.32	
Mean :33.33	Mean :33.33	
3rd Qu.:50.88	3rd Qu.:51.57	
Max. :63.90	Max. :67.70	

Preprocessing for “bygender” dataset;

- The presence of missing values (NA) is examined, and necessary preprocessing steps are applied if they exist.
- The “bygender” dataset is updated to include data from 2008 to 2023, in accordance with the ‘education’ dataset, which contains information for the same years.
- Happiness levels in this dataset were originally assessed on five different levels. For the consistency of the analysis, the levels of happiness have been redefined and consolidated into three levels, similar to the categorization in the “bygender” dataset.

```
#changes in bygender dataset
#head(bygender)
#str(bygender)

sum(is.na(bygender))
```

```
[1] 0
```

```

bygender <- bygender |> filter(Year %in% 2008:2023)|>
mutate(Happiness_Level = case_when(
  Happiness_Level %in% c("Very happy", "Happy") ~ "Happy",
  Happiness_Level %in% c("Very unhappy", "Unhappy") ~ "Unhappy",
  Happiness_Level=="Neither happy nor unhappy" ~ "Neither happy nor unhappy",
  TRUE ~ as.character(Happiness_Level)))

bygender<- bygender |> group_by(Year,Happiness_Level)|>
summarise(
  Total=sum(Total,na.rm = TRUE),
  Male=sum(Male,na.rm = TRUE),
  Female=sum(Female,na.rm = TRUE),
  .groups = "drop"
)

bygender$Happiness_Level<-factor(bygender$Happiness_Level,levels= c("Unhappy","Neither happy n

head(bygender) |> kbl() |> kable_styling(full_width = 5)

```

	Year	Happiness_Level	Total	Male	Female
	2008	Happy	55.7	53.7	57.8
	2008	Neither happy nor unhappy	30.3	30.7	30.0
	2008	Unhappy	13.9	15.7	12.2
	2009	Happy	54.3	50.3	58.1
	2009	Neither happy nor unhappy	31.1	32.7	29.6
	2009	Unhappy	14.6	17.1	12.3

The variables and their corresponding value ranges in the finalized “bygender” dataset are defined as follows:

```
str(bygender)
```

```

tibble [48 x 5] (S3: tbl_df/tbl/data.frame)
 $ Year      : num [1:48] 2008 2008 2008 2009 2009 ...
 $ Happiness_Level: Ord.factor w/ 3 levels "Unhappy"<"Neither happy nor unhappy"<... 3 2 1 3 2
 $ Total      : num [1:48] 55.7 30.3 13.9 54.3 31.1 14.6 61.2 28.1 10.8 62.1 ...
 $ Male      : num [1:48] 53.7 30.7 15.7 50.3 32.7 17.1 59.6 28.9 11.5 59.5 ...
 $ Female    : num [1:48] 57.8 30 12.2 58.1 29.6 12.3 62.7 27.3 10 64.6 ...

```

- Year: The study year (ranging from 2003 to 2008).
- Happiness_Level: Levels of happiness (“Unhappy,” “Neither Happy nor Unhappy,” “Happy”).
- Total: The percentage of individuals for each year and happiness level.
- Male: The percentage of males for each year and happiness level.
- Female: The percentage of females for each year and happiness level.

Descriptive statistics for the variables are as follows:

```
summary(bygender)
```

	Year	Happiness_Level	Total
Min.	:2008	Unhappy	:16
1st Qu.:	:2012	Neither happy nor unhappy	:14.35

Median :2016	Happy	:16	Median :31.55
Mean :2016			Mean :33.33
3rd Qu.:2019			3rd Qu.:52.40
Max. :2023			Max. :62.10
Male		Female	
Min. :10.50	Min. : 9.10		
1st Qu.:16.75	1st Qu.:12.18		
Median :34.05	Median :29.70		
Mean :33.34	Mean :33.34		
3rd Qu.:48.10	3rd Qu.:55.58		
Max. :59.60	Max. :64.60		



3. Analysis

3.1 Exploratory Data Analysis

At this stage of the analysis, visualizations will be used to explore the data in more detail, aiming to gain insights into the characteristics of different variables. To ensure a more structured analysis process, the datasets will be examined one by one in sequence. For each dataset, a set of questions will be explored with the aim of gaining deeper understanding and shedding light on key patterns.

To provide a more detailed analysis of the “education” dataset, the following questions will be examined.

Examining the provinces and years with a high number of individuals holding higher education degrees or no formal education may offer meaningful insights into educational disparities. ***Question: Which are the top 10 provinces with the highest number of university graduates, and which are the top 10 provinces with the highest number of individuals who have not completed any formal education?***

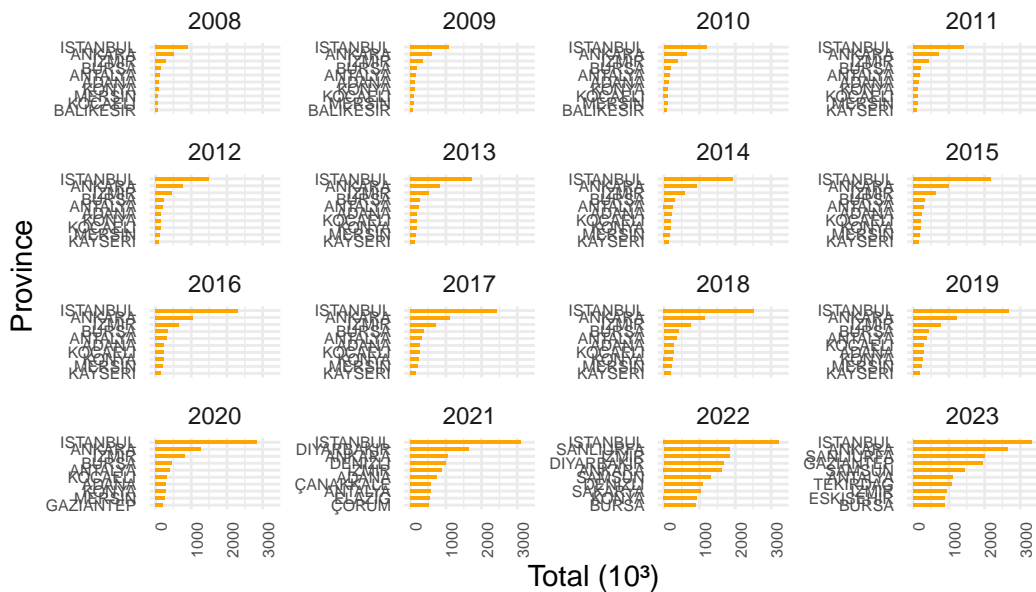
Based on the graphs presented below, the following observations can be made:

- The number of individuals with higher education has steadily **increased** over the years.
- The provinces with the highest levels of higher education attainment remain relatively consistent over time, with major cities such as **Istanbul**, **Ankara**, and **Izmir** standing out.
- This trend may be attributed to both the larger populations in these cities and the higher concentration of universities located there.

```
#Top 10 Provinces by Higher Education Attainment (Each Year)
education |>
  filter(Educational_Status == "Higher Education") |>
  group_by(Year) |>
  slice_max(order_by = Total, n = 10) |>
  ungroup() |>
  ggplot(aes(x = reorder_within(Province, Total, Year), y = Total / 1000, width = 0.5)) +
  geom_bar(stat = "identity", fill = "orange") +
  coord_flip() +
  facet_wrap(~Year, scales = "free_y") +
  scale_x_reordered() +
  labs(
    title = "Top 10 Provinces by Higher Education Attainment (Each Year)",
    x = "Province",
    y = "Total (103)"
  ) +
```

```
theme_minimal()+
theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 6),axis.text.y= element_text(
```

Top 10 Provinces by Higher Education Attainment (Each Ye

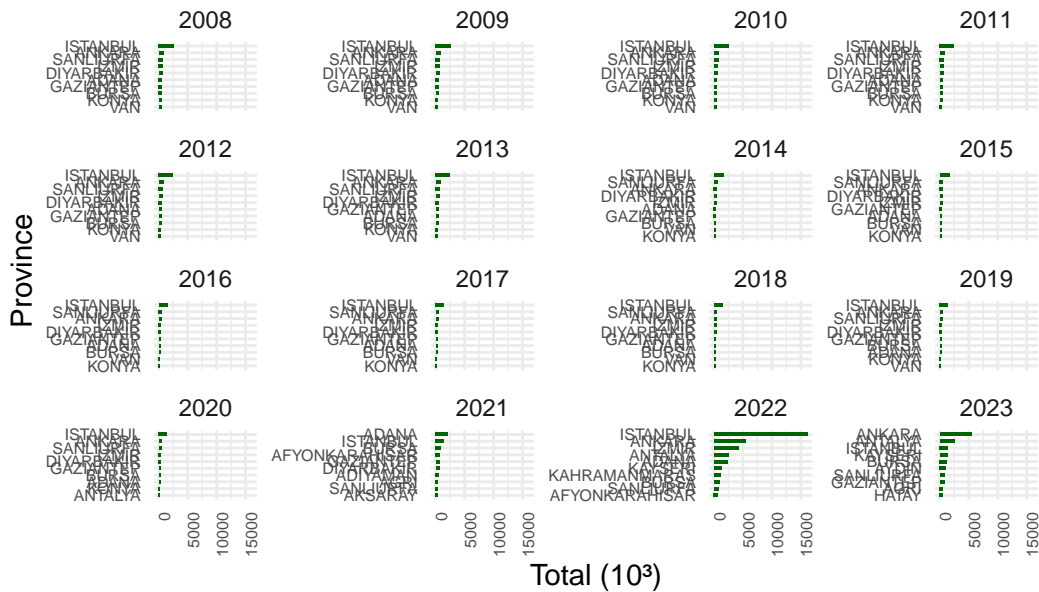


Based on the graphs presented below, several observations can be made:

- Over the years, the number of individuals with no formal education has generally increased, reaching its **peak in 2022** before starting to decline.
- The provinces appearing in the top 10 list for individuals with no education often overlap with those that also rank high in higher education attainment. A major reason for this could be the concentration of Turkey's population in these large metropolitan areas.

```
education |>
  filter(Educational_Status == "No School Completed") |>
  group_by(Year) |>
  slice_max(order_by = Total, n = 10) |>
  ungroup() |>
  ggplot(aes(x = reorder_within(Province, Total, Year), y = Total/1000 ,width = 0.5)) +
  geom_bar(stat = "identity", fill = "darkgreen") +
  coord_flip() +
  facet_wrap(~Year, scales = "free_y") +
  scale_x_reordered() +
  labs(
    title = "Top 10 Provinces by No School Attainment (Each Year)",
    x = "Province",
    y = "Total (103)"
  ) +
  theme_minimal()+
  theme(axis.text.x = element_text(angle = 90, hjust = 1, size = 6),axis.text.y= element_text(
```

Top 10 Provinces by No School Attainment (Each Year)



After examining the number of individuals with no formal education and those with higher education across provinces, the next step involves incorporating the gender dimension into the analysis. *Question: What does the comparison between female and male proportions tell us about the presumed educational disadvantage faced by women?*

Below, a series of maps illustrate the percentage of women and men with no formal education across provinces over time. The visualizations show that, in recent years, the number of **men with no education has begun to surpass that of women** in many provinces.

Does this observation indicate that the educational disadvantage has shifted over time to affect men more significantly?

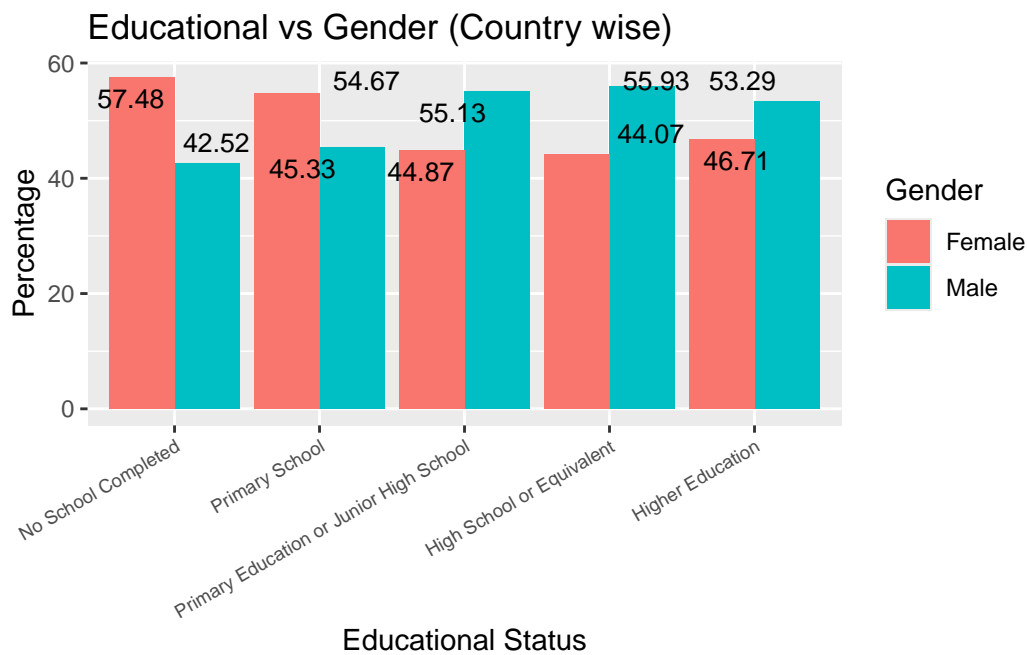
To further investigate the findings from the map above, we can examine the gender distribution across different education levels (aggregated for all years at the national level) using the chart below.

Contrary to our earlier observation, the chart reveals that **57.48%** of individuals with no formal education are **women**.

So, what do these seemingly conflicting results actually tell us?

They suggest that, overall, the number of **women who have never received any formal education is significantly higher than that of men**, even if recent trends indicate a growing number of uneducated men in certain regions.

```
education |> group_by(Educational_Status) |>
  summarise(Male = sum(Male),
            Female = sum(Female)) |> mutate(Total = Male + Female,
            Male = Male / Total * 100,
            Female = Female / Total * 100) |>
  pivot_longer(cols = c("Male", "Female"), names_to = "Gender", values_to = "Percentage") |>
  ggplot(aes(x = Educational_Status, y = Percentage, fill = Gender)) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Educational vs Gender (Country wise)", x = "Educational Status", y = "Percentage") +
  theme(axis.text.x = element_text(angle = 30, hjust = 1, size = 7))
```



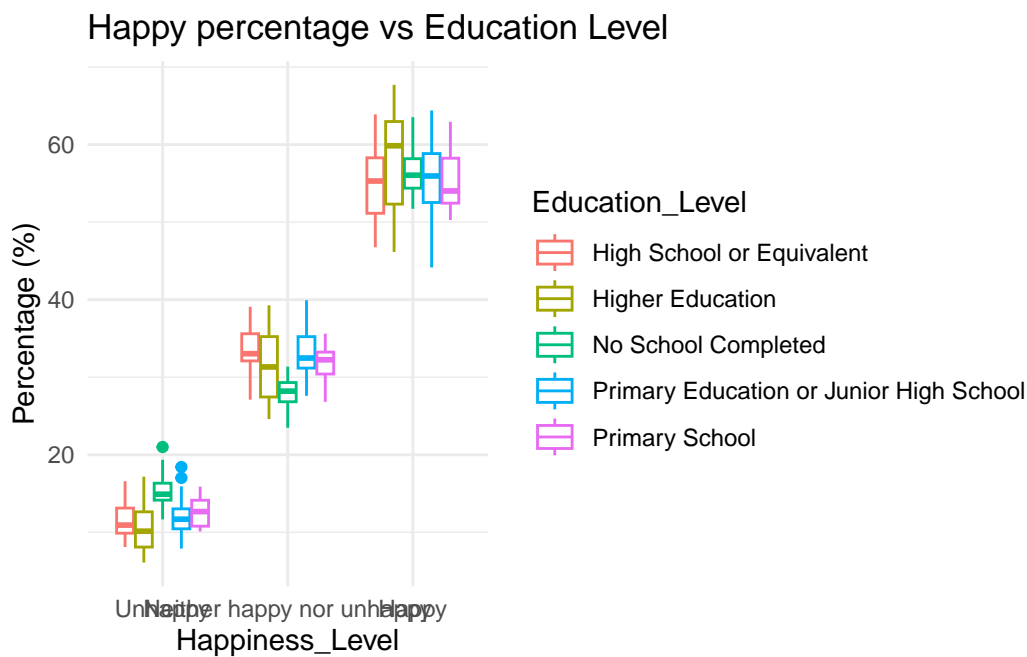
To provide a more detailed analysis of the “byeducation” dataset, the following questions will be examined.

To closely examine this dataset, the first step is to explore the relationship between education levels and life satisfaction. ***Question: Which education level group reports higher life satisfaction, and which one reports the lowest?***

Based on the results obtained, the following observations can be made:

- Within a given year, the distribution of education levels across happiness categories shows relatively similar proportions.
- Individuals with **higher education** have the **highest** average life satisfaction “Happy”, whereas those with only **primary school education** report the **lowest**.
- Among those who identify as “Unhappy,” the **largest proportion** consists of individuals with **no formal education**, while the **smallest** share belongs to those with **higher education**.
- Individuals with a high school education or with primary/junior high school education tend to display similar patterns, showing closely aligned averages across the different happiness levels.

```
byeducation |>
  select(everything()) |>
  pivot_longer(cols = c("No School Completed", "Primary School", "Primary Education or Junior Hi
  geom_boxplot() +
  labs(title = "Happy percentage vs Education Level",
        x = "Happiness_Level", y = "Percentage (%)", color = "Education_Level") +
  theme_minimal()
```



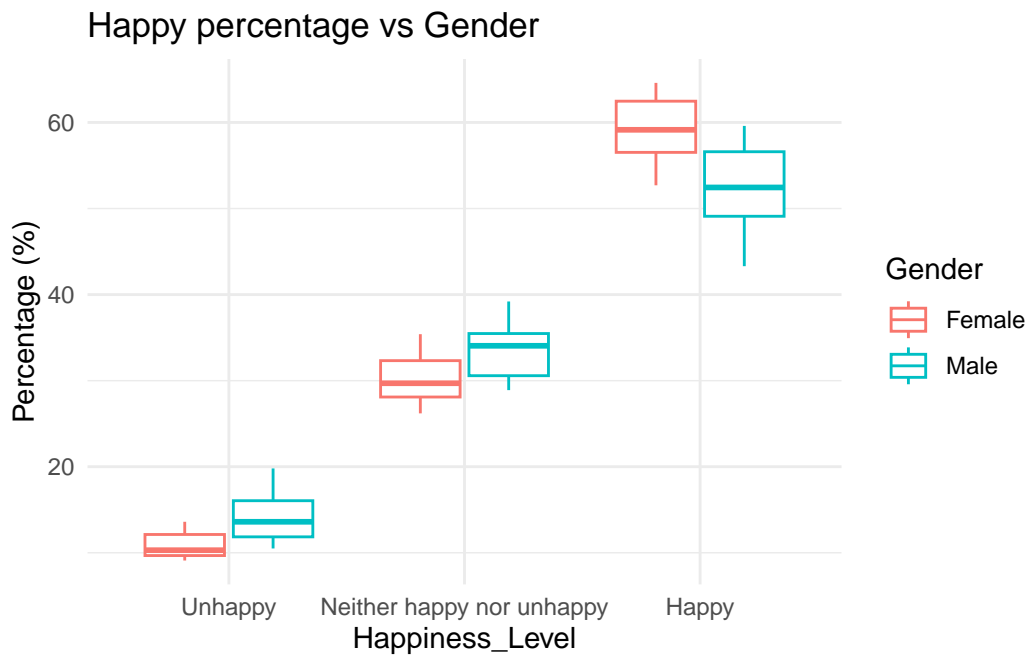
To provide a more detailed analysis of the “bygender” dataset, the following questions will be examined.

To closely examine the dataset, the first step is to explore the relationship between education levels and happiness levels. ***Question:** How does the percentage of happiness vary for each gender?*

Based on the results obtained, the following observations can be made:

- Within a given year, the distribution of happiness levels across genders shows similar proportions for both men and women.
- **Women** report the highest average life satisfaction “**Happy**”, while men tend to have the lowest average satisfaction.
- The majority of individuals who identify as “**Unhappy**” are **men**.
- There is a **notable difference** between the average happiness percentages for men and women, particularly at the “**Happy**” level.

```
bygender |>
  select( everything() ) |>
  pivot_longer(cols = c("Male", "Female"), names_to = "Gender", values_to = "Percentage") |>gg
  geom_boxplot()+
  labs(title = "Happy percentage vs Gender",
       x = "Happiness_Level", y = "Percentage (%)", color = "Gender") +
  theme_minimal()
```



3.2 Trend Analysis

In this section, the behavior of different variables within the datasets over time will be examined. As in previous sections, the datasets will be analyzed separately, and the time-dependent behavior of the variables will be explored by addressing various research questions.

Analysis for “education” dataset

In the previous sections, we examined the top 10 provinces with the highest number of university graduates over different years. As the next step in the analysis, we can investigate the provinces where the rate of university graduates has increased most rapidly. ***Question: In which provinces has the rate of university graduates increased most rapidly?***

Based on the chart below, the following observations can be made:

- Consistent with our earlier findings, provinces such as Istanbul and Ankara, which appeared in the previous analysis, are also among the provinces that have shown the fastest growth in the number of individuals with higher education. One possible explanation for this is the large population size of these cities.
- **Istanbul**, the province with the highest number of university graduates, has shown a **steady increase between 2008 and 2023**. Similarly, **Izmir** has also demonstrated consistent growth.
- A particularly noteworthy observation is the **sharp upward trend in Ankara**, especially **after 2020**, where the growth rate increased significantly. A similar observation can be made for **Konya** and **Bursa**, though the growth rate in these cities is somewhat slower. This rapid increase, particularly after 2020, may be attributed to the growth in the number of universities in these cities and the migration they have received in recent years.

```
univ_trend <- education |>
  filter(Educational_Status == "Higher Education") |>
  mutate(Total = Male + Female)

slope_by_province <- univ_trend %>%
  group_by(Province) %>%
  summarise(slope = coef(lm(Total ~ Year))[2]) %>%
  arrange(desc(slope))
```

```
head(slope_by_province, 10)
```

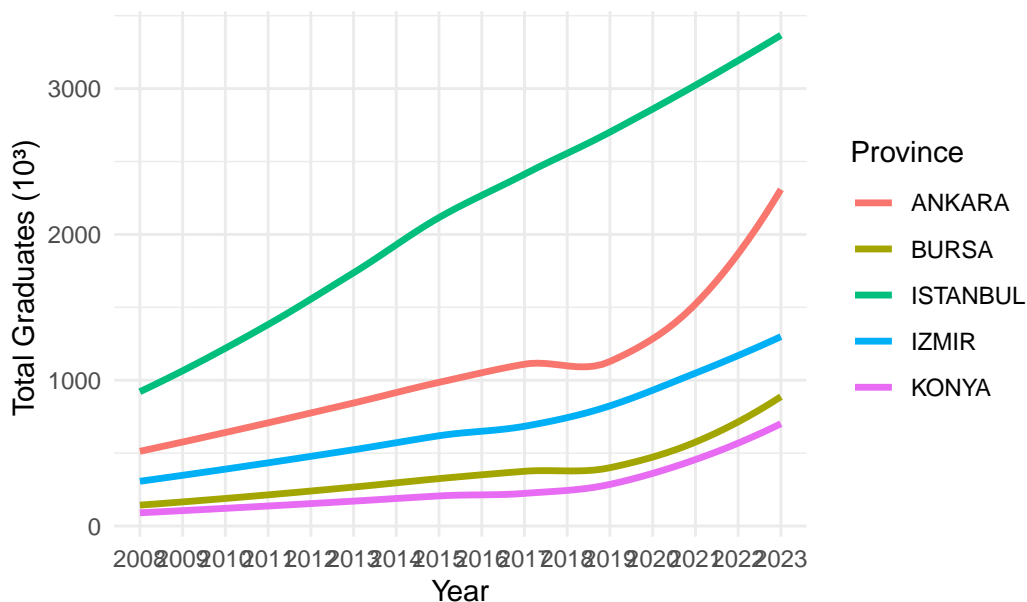
```
# A tibble: 10 x 2
  Province      slope
  <chr>        <dbl>
1 İSTANBUL 166314.
2 ANKARA    92572.
3 İZMİR     55971.
4 BURSA     29044.
5 KONYA     23179.
6 ADANA     23058.
7 KOCAELİ   22834.
8 ANTALYA   21437.
9 MERSİN    19919.
10 ESKİŞEHİR 16730.
```

```
top_provinces <- slope_by_province %>%
  slice_max(order_by = slope, n = 5) %>%
  pull(Province)
```

```
univ_trend %>%
  filter(Province %in% top_provinces) %>%
  ggplot(aes(x = Year, y = Total/1000, color = Province, group = Province)) +
  geom_smooth(method = "loess", se = FALSE, linewidth = 1.2) +
  labs(title = "Provinces which rate of university graduates increased most rapidly",
       x = "Year", y = "Total Graduates (103)") +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```

Provinces which rate of university graduates increased most



Analysis for “bygender” dataset

In the next step of our analysis, we can consider how life satisfaction has evolved over time for both men and women, based on the previously explored relationship between gender and happiness levels.

Question: *How has life satisfaction changed over time for men and women?*

Based on the chart below and in line with our earlier findings, the following observations can be made:

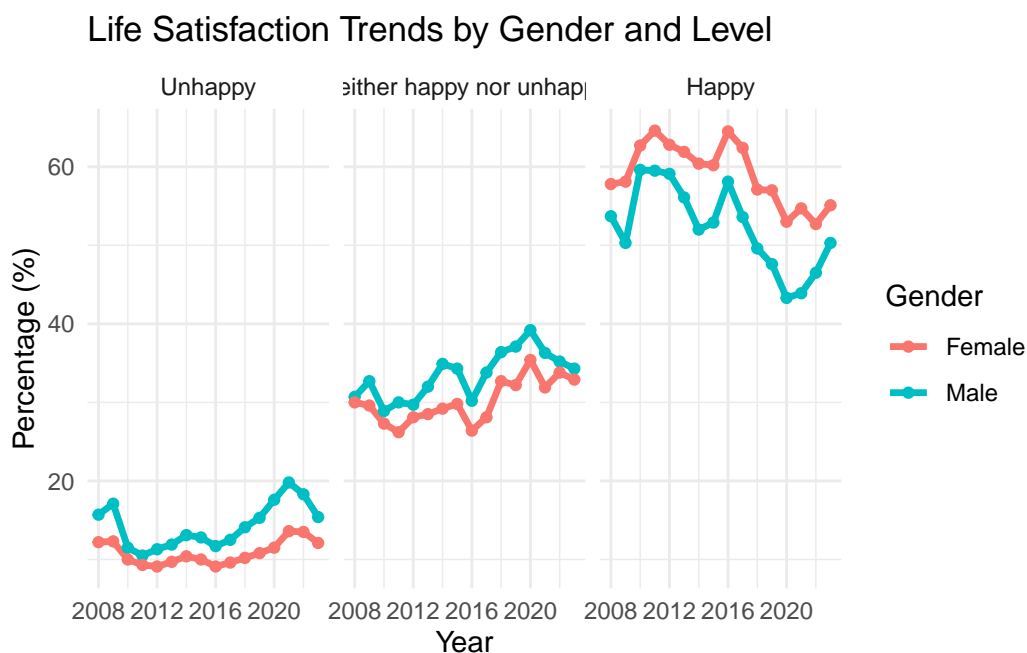
- It appears that women generally report higher levels of happiness than men, supporting the notion that men tend to be more unhappy than women.
- In **2016**, a **decrease** was observed in the percentage of individuals reporting **high life satisfaction**. This decline is mirrored by an **increase** in the percentage of individuals identifying as “unhappy” after 2016.

```
bygender_long <- bygender |>
  pivot_longer(cols = c("Male", "Female"),
               names_to = "Gender",
               values_to = "Percentage")
ggplot(bygender_long, aes(x = Year, y = Percentage, color = Gender)) +
  geom_line(size = 1.2) +
  geom_point(linewidth = 2) +
  facet_wrap(~ Happiness_Level) +
  labs(title = "Life Satisfaction Trends by Gender and Level",
       x = "Year", y = "Percentage (%)",
       color = "Gender") +
  theme_minimal()
```

Warning: Using `size` aesthetic for lines was deprecated in ggplot2 3.4.0.

i Please use `linewidth` instead.

Warning in geom_point(linewidth = 2): Ignoring unknown parameters: `linewidth`



We can conclude that there is a significant difference between men and women in terms of happiness levels. This conclusion can be further developed by examining whether the difference between men and women persists annually. *Question: Does the difference in life satisfaction between men and women persist annually?*

Based on the analysis below, the following observations can be made:

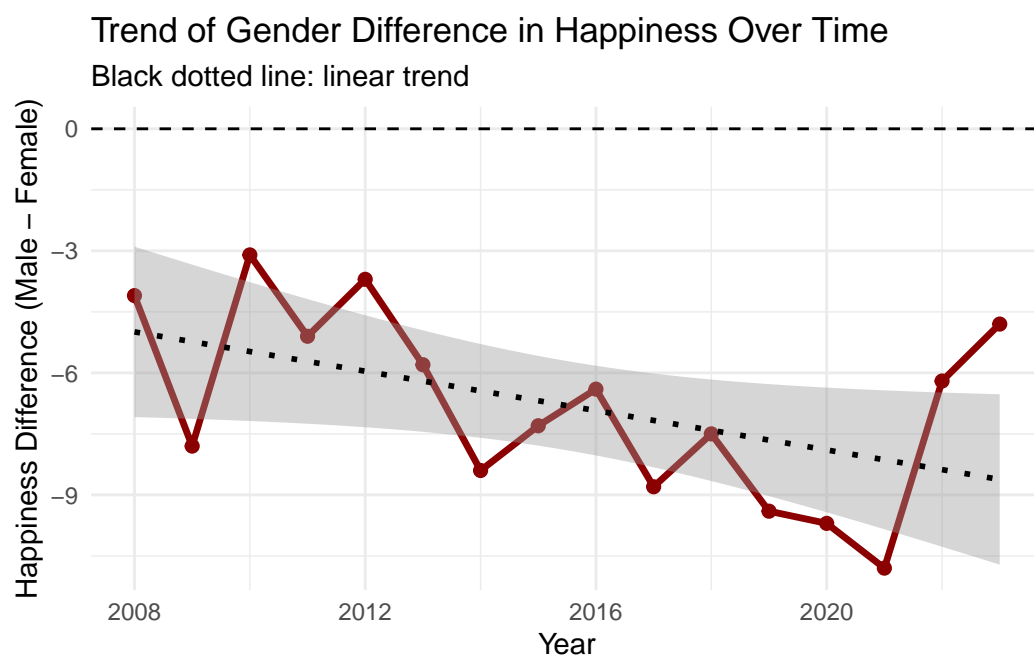
- **Negative values** indicate that **women** are generally **happier** than men.
- When examining the statistical significance of the difference (i.e., whether the **difference in happiness between men and women** shows a meaningful trend over time) through linear

regression, the **p-value = 0.046**, which is less than 0.05, indicating that the difference is statistically **significant**. On average, the difference between men and women in happiness levels **decreases by 0.24 points per year**.

```
mutlu_df <- bygender |>
  filter(Happiness_Level == "Happy") |>
  pivot_longer(cols = c(Male, Female),
               names_to = "Gender",
               values_to = "Percentage")|>
  pivot_wider(names_from = Gender, values_from = Percentage)|>
  mutate(Difference = Male - Female)

ggplot(mutlu_df, aes(x = Year, y = Difference)) +
  geom_line(color = "darkred", size = 1.2) +
  geom_point(size = 2, color = "darkred") +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dotted") +
  labs(title = "Trend of Gender Difference in Happiness Over Time",
       subtitle = "Black dotted line: linear trend",
       x = "Year", y = "Happiness Difference (Male - Female)") +
  theme_minimal()
```

`geom_smooth()` using formula = 'y ~ x'



```
model <- lm(Difference ~ Year, data = mutlu_df)
summary(model)
```

Call:

```
lm(formula = Difference ~ Year, data = mutlu_df)
```

Residuals:

Min	1Q	Median	3Q	Max
-2.6632	-1.7616	0.1562	1.2136	3.8206

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	480.7669	223.5764	2.150	0.0495 *
Year	-0.2419	0.1109	-2.181	0.0468 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.045 on 14 degrees of freedom
Multiple R-squared: 0.2536, Adjusted R-squared: 0.2003
F-statistic: 4.756 on 1 and 14 DF, p-value: 0.04675

Similarly, the difference in happiness levels between men and women at the “Unhappy” level has also been examined for statistical **significance**. According to the results, since $p = 0.0268$, which is less than 0.05, the difference is statistically significant. On average, the difference between men and women in the “Unhappy” category **increases by 0.17** points per year.

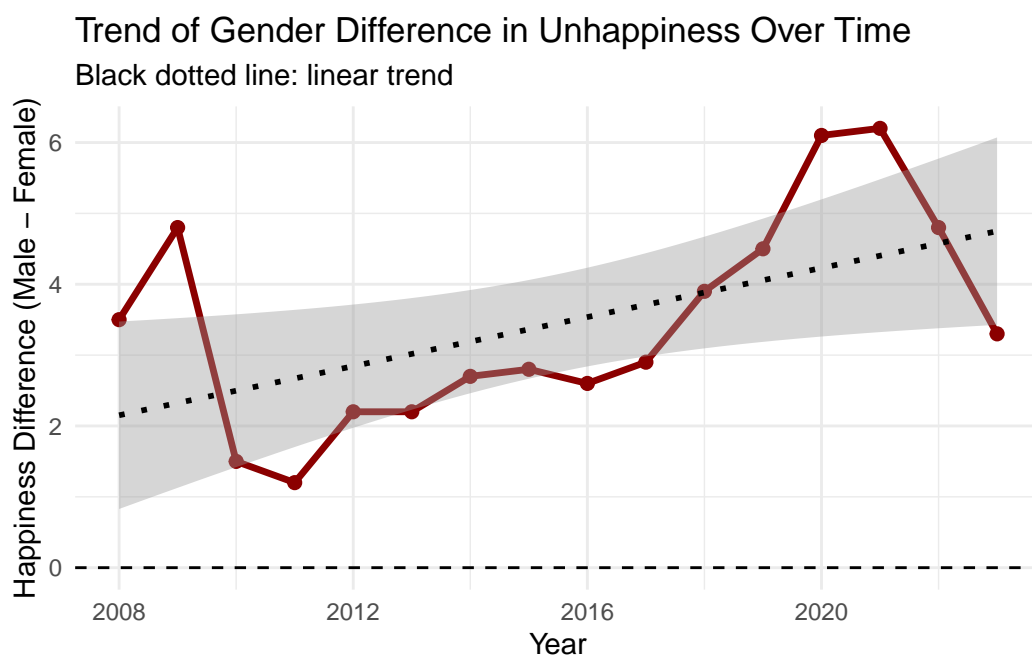
```

mutsuz_df <- bygender |>
  filter(Happiness_Level == "Unhappy") |>
  pivot_longer(cols = c(Male, Female),
               names_to = "Gender",
               values_to = "Percentage")|>
  pivot_wider(names_from = Gender, values_from = Percentage)|>
  mutate(Difference = Male - Female)

ggplot(mutsuz_df, aes(x = Year, y = Difference)) +
  geom_line(color = "darkred", size = 1.2) +
  geom_point(size = 2, color = "darkred") +
  geom_hline(yintercept = 0, linetype = "dashed") +
  geom_smooth(method = "lm", se = TRUE, color = "black", linetype = "dotted") +
  labs(title = "Trend of Gender Difference in Unhappiness Over Time",
       subtitle = "Black dotted line: linear trend",
       x = "Year", y = "Happiness Difference (Male - Female)") +
  theme_minimal()

```

`geom_smooth()` using formula = 'y ~ x'



```
model <- lm(Difference ~ Year, data = mutsuz_df)
summary(model)
```

Call:

```
lm(formula = Difference ~ Year, data = mutsuz_df)
```

Residuals:

Min	1Q	Median	3Q	Max
-1.4704	-0.8468	-0.5268	0.6701	2.4760

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-345.70574	141.18345	-2.449	0.0281 *
Year	0.17324	0.07005	2.473	0.0268 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.292 on 14 degrees of freedom

Multiple R-squared: 0.304, Adjusted R-squared: 0.2543

F-statistic: 6.116 on 1 and 14 DF, p-value: 0.02683

Analysis for “byeducation” dataset

We have previously gathered some insights regarding the relationship between education levels and happiness levels in the dataset. As the next step in this analysis, we can consider how life satisfaction has evolved over time for different education levels. ***Question: How has life satisfaction percentage changed over level of education?***

Based on the analysis provided below, the following observations can be made:

- The percentage of individuals who report being **happy** has **decreased across all education levels** over time.
- The **smallest decrease** in happiness levels has been observed among individuals **without any education**, with an average decrease of just **0.0089**, which is a very low rate.
- The education level with the **greatest decline** in life satisfaction over time is among individuals with **higher education**. For this group, the happiness percentage has decreased by an average of **1.369** points per year.

```
edu_happy <- byeducation |>
  filter(Happiness_Level=="Happy")|>pivot_longer(c(`No School Completed`,`Primary School`,`Pri
    names_to = "Educational_Status",
    values_to = "Percentage")

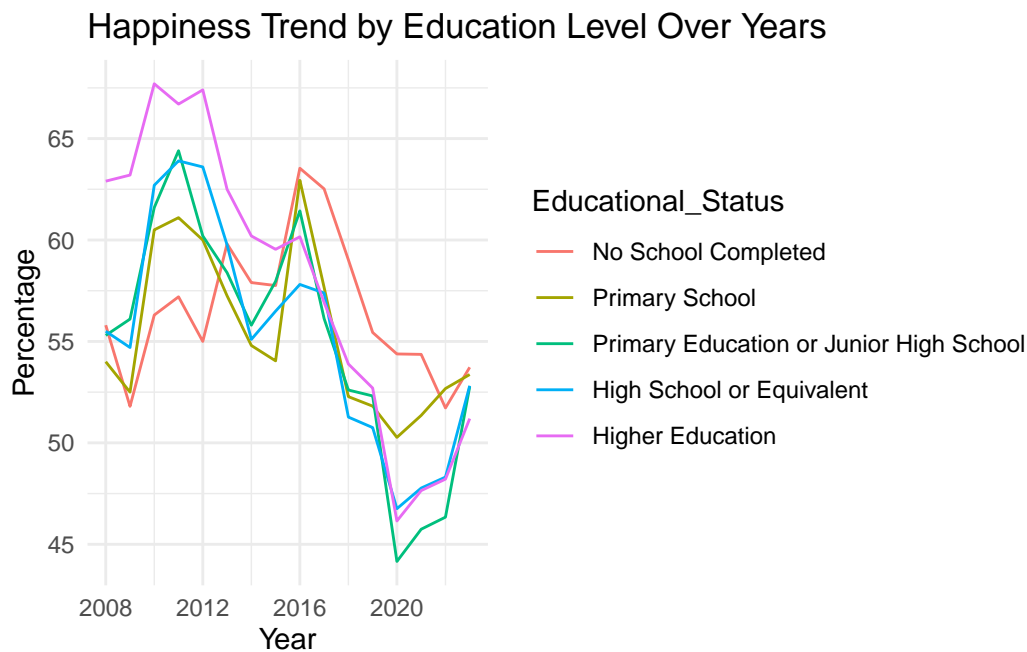
edu_happy$Educational_Status <- factor(
  edu_happy$Educational_Status,
  levels = c("No School Completed","Primary School","Primary Education or Junior High School",
)

edu_trends <- edu_happy %>%
  group_by(Educational_Status) %>%
  do(tidy(lm(Percentage ~ Year, data = .))) %>%
  filter(term == "Year") %>%
  arrange(desc(estimate))
```

Educational_Status	term	estimate	std.error	statistic	p.value
No School Completed	Year	-0.0882828	0.1888264	-0.4675341	0.6473120
Primary School	Year	-0.3969668	0.1949510	-2.0362384	0.0611031
High School or Equivalent	Year	-0.8323926	0.2130358	-3.9072905	0.0015789
Primary Education or Junior High School	Year	-0.8840392	0.2311315	-3.8248326	0.0018575
Higher Education	Year	-1.3692589	0.1712698	-7.9947499	0.0000014

```
edu_trends |> kbl() |> kable_styling()
```

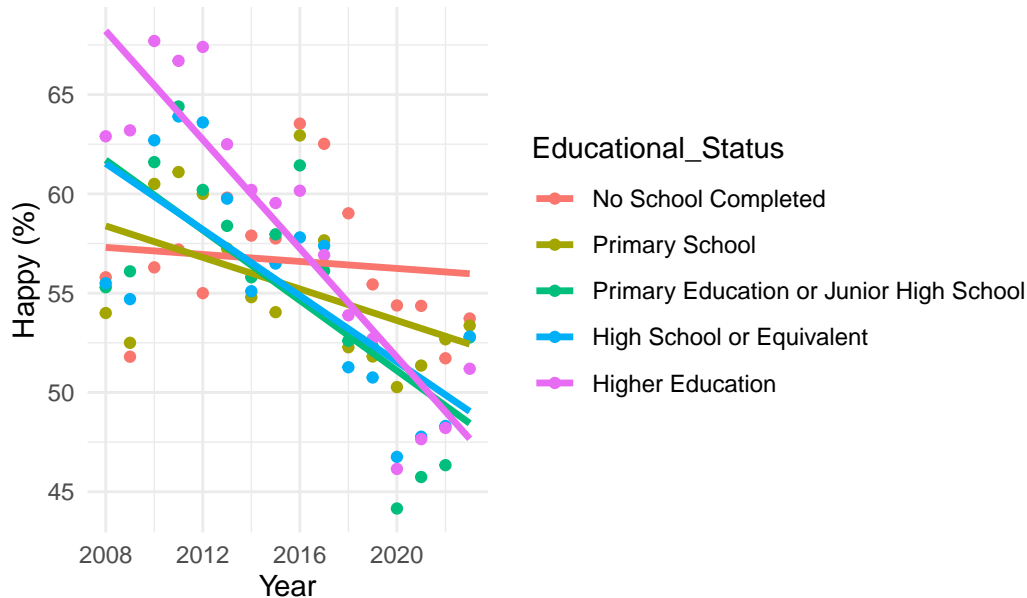
```
ggplot(edu_happy, aes(x = Year, y = Percentage, color = Educational_Status)) +
  geom_line() +
  labs(title = "Happiness Trend by Education Level Over Years")+
  theme_minimal()
```



```
ggplot(edu_happy, aes(x = Year, y = Percentage, color = Educational_Status)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE, size = 1.2) +
  labs(title = "Life satisfaction percentage changed over level of education",
       x = "Year", y = "Happy (%)") +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```

Life satisfaction percentage changed over level of education



The same analysis has been conducted for the “Unhappy” happiness level, and the following results were found:

- The percentage of individuals who identify as “**Unhappy**” has **increased** over time for all education levels, **except for those without any education**.
- For individuals **without any education**, the percentage of those who identify as “Unhappy” has decreased over time, with an average **decrease of 0.065** per year.
- The education level with the **largest increase** in the percentage of individuals who identify as “**Unhappy**” over time is **higher education**. For this group, the percentage of those who report being “Unhappy” has increased by an average of **0.45** points per year.

```
edu_unhappy <- byeducation |>
  filter(Happiness_Level=="Unhappy")|>pivot_longer(c(`No School Completed`,`Primary School`,`P
    names_to = "Educational_Status",
    values_to = "Percentage")

edu_unhappy$Educational_Status <- factor(
  edu_unhappy$Educational_Status,
  levels = c("No School Completed","Primary School","Primary Education or Junior High School",
)

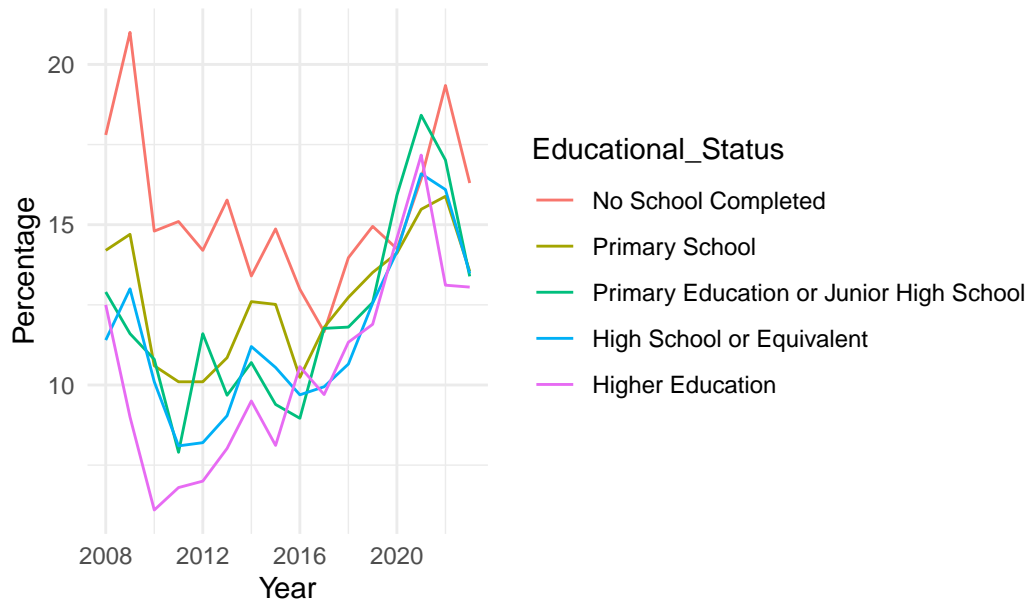
edu_trends <- edu_unhappy %>%
  group_by(Educational_Status) %>%
  do(tidy(lm(Percentage ~ Year, data = .))) %>%
  filter(term == "Year") %>%
  arrange(desc(estimate))

edu_trends |> kbl() |> kable_styling()

ggplot(edu_unhappy, aes(x = Year, y = Percentage, color = Educational_Status)) +
  geom_line() +
  labs(title = "Unhappiness Trend by Education Level Over Years")+
  theme_minimal()
```

Educational_Status	term	estimate	std.error	statistic	p.value
Higher Education	Year	0.4521631	0.1235502	3.6597527	0.0025746
Primary Education or Junior High School	Year	0.3733905	0.1286275	2.9028818	0.0115759
High School or Equivalent	Year	0.3401795	0.1121412	3.0334923	0.0089378
Primary School	Year	0.1823240	0.0966591	1.8862576	0.0801774
No School Completed	Year	-0.0656706	0.1318412	-0.4981037	0.6261441

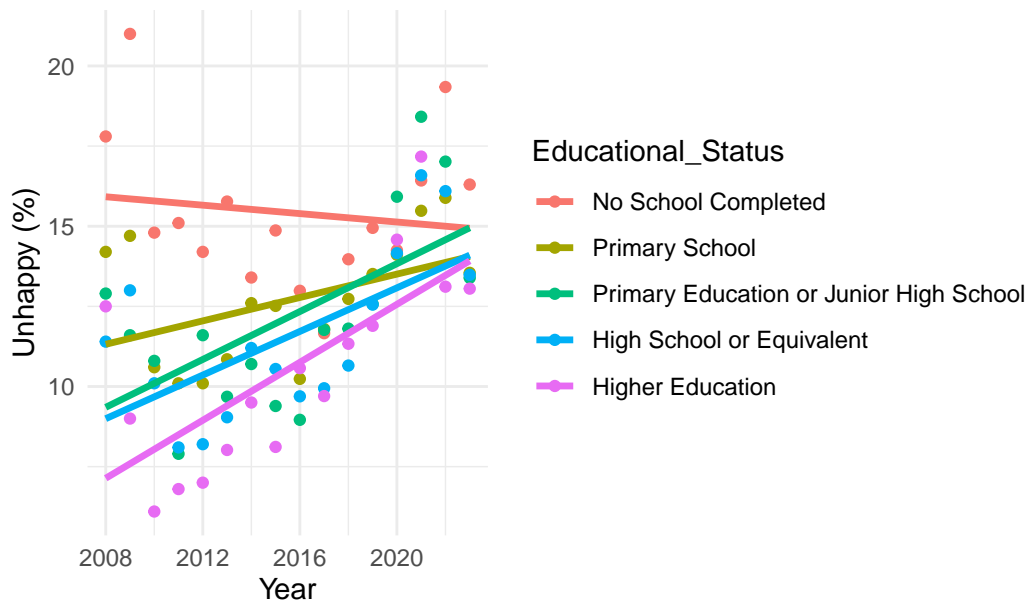
Unhappiness Trend by Education Level Over Years



```
ggplot(edu_unhappy, aes(x = Year, y = Percentage, color = Educational_Status)) +
  geom_point() +
  geom_smooth(method = "lm", se = FALSE, size = 1.2) +
  labs(title = "Life satisfaction percentage changed over level of education",
        x = "Year", y = "Unhappy (%)") +
  theme_minimal()
```

```
`geom_smooth()` using formula = 'y ~ x'
```

Life satisfaction percentage changed over level of education



3.3 Model Fitting

In this section, the primary objective of the research will be addressed by statistically examining the relationships between variables that influence individuals' happiness levels, their interconnections, and their association with happiness levels in more detail. Based on the findings, predictive models for the future will be developed. This approach will be carried out, as in previous steps, by answering key questions.

- *Question: Is there a significant difference between educational level and happiness level? (using the "byeducation" dataset)*

According to the Chi-square test[3], the **p-value is 2.2e-16**, which is less than 0.05. Therefore, it can be concluded that happiness levels are **significantly** associated with **education level**.

```
#
df<- byeducation |> pivot_longer(c(`No School Completed`,`Primary School`,`Primary Education or Junior High School`,`High School or Equivalent`,`Higher Education`),
  names_to = "Educational_Status",
  values_to = "Percentage") |>
mutate(Estimated_Count = round(Percentage * 1000 / 100))

summary_table <- df %>%
  group_by(Happiness_Level, Educational_Status) %>%
  summarise(Count = sum(Estimated_Count), .groups = "drop")

contingency_matrix <- summary_table %>%
  pivot_wider(names_from = Happiness_Level, values_from = Count) %>%
  column_to_rownames("Educational_Status") %>%
  as.matrix()
chisq.test(contingency_matrix)
```

Pearson's Chi-squared test

```
data: contingency_matrix
X-squared = 277.05, df = 8, p-value < 2.2e-16
```

- *Question: Is there a significant difference between gender and happiness level? (using the “bygender” dataset)*

According to the Chi-square test, the **p-value is 2.2e-16**, which is less than 0.05. Therefore, it can be concluded that happiness levels are **significantly** associated with **gender**.

```
#
df1<- bygender |> pivot_longer(c(Male,Female),
                               names_to = "Gender",
                               values_to = "Percentage") |>
mutate(Estimated_Count = round(Percentage * 1000 / 100))

summary_table <- df1 %>%
  group_by(Happiness_Level, Gender) %>%
  summarise(Count = sum(Estimated_Count), .groups = "drop")

contingency_matrix1 <- summary_table %>%
  pivot_wider(names_from = Happiness_Level, values_from = Count) %>%
  column_to_rownames("Gender") %>%
  as.matrix()
chisq.test(contingency_matrix1)
```

Pearson's Chi-squared test

```
data: contingency_matrix1
X-squared = 170.61, df = 2, p-value < 2.2e-16
```

- It has once again been observed that **happiness level (Happy) is influenced by both education level and gender**. In the next stage of the analysis, separate predictive models were developed to estimate happiness levels based on education and gender variables.

Education Level-Based Happiness Level Prediction Model;

A predictive model for estimating the percentage of individuals who report being happy based on education level can be constructed in three different ways:

- **Model 1** assumes that happiness is influenced solely by **education level**.
- **Model 2** includes the **effect of time (year)** in addition to education level.
- **Model 3** incorporates the **interaction** between education level and time.

Based on the results, when comparing the Akaike Information Criterion (AIC) values of the models, **Model 3** was found to have the **lowest AIC**, indicating the **best fit to the data**. This suggests that the **interaction between education level and year should be included** in the predictive model for estimating happiness levels.

Accordingly, the final model should include the statistically **significant** education levels — **Primary Education or Junior High School, High School, and Higher Education** — as well as their **interactions with the year** variable. Since the “Education_Level” variable is categorical, a reference category is selected when constructing the model, which is typically the first level. In this case, the reference category is the “No School Completed” category. The “Intercept”() value in the model output represents the average happiness percentage for “No School Completed” category, while the Other coefficients represent the difference between the average happiness percentage of the relevant education level and that of the ‘No School Completed’ category

The adequacy of the model was validated by analyzing whether the residuals conform to a normal

distribution with Q-Q Plot and Anderson-Darling Normality Test [6].

```
happy_df_byeducation <- byeducation|>
  pivot_longer(
    cols = -c(Year, Happiness_Level),
    names_to = "Education_Level",
    values_to = "Percentage"
  ) |>
  filter(Happiness_Level == "Happy")|>
mutate(Education_Level = factor(Education_Level,
                                levels = c("No School Completed","Primary School","Primary E
))

model1 <- lm(Percentage ~ Education_Level, data = happy_df_byeducation)
summary(model1)
```

Call:

```
lm(formula = Percentage ~ Education_Level, data = happy_df_byeducation)
```

Residuals:

Min	1Q	Median	3Q	Max
-11.789	-2.971	0.011	3.602	9.761

Coefficients:

	Estimate	Std. Error
(Intercept)	56.642	1.340
Education_LevelPrimary School	-1.233	1.895
Education_LevelPrimary Education or Junior High School	-1.565	1.895
Education_LevelHigh School or Equivalent	-1.353	1.895
Education_LevelHigher Education	1.296	1.895

	t value	Pr(> t)
(Intercept)	42.262	<2e-16 ***
Education_LevelPrimary School	-0.650	0.517
Education_LevelPrimary Education or Junior High School	-0.826	0.412
Education_LevelHigh School or Equivalent	-0.714	0.477
Education_LevelHigher Education	0.684	0.496

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

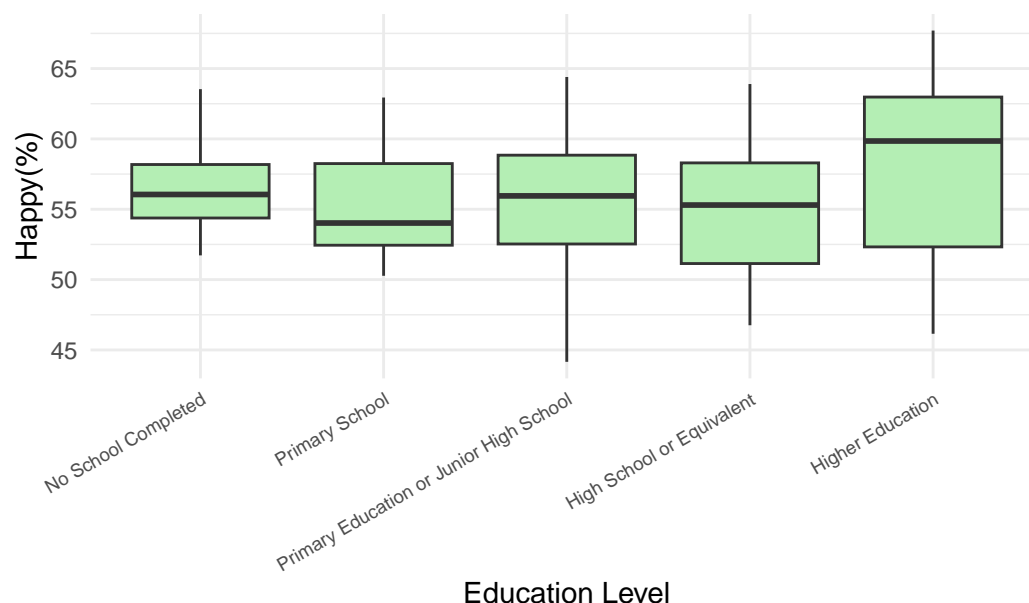
Residual standard error: 5.361 on 75 degrees of freedom

Multiple R-squared: 0.04162, Adjusted R-squared: -0.009497

F-statistic: 0.8142 on 4 and 75 DF, p-value: 0.5201

```
ggplot(happy_df_byeducation, aes(x = Education_Level, y = Percentage)) +
  geom_boxplot(fill = "darkseagreen2") +
  labs(title = "Happy Percentage vs. Education Level",
       x = "Education Level", y = "Happy(%)") +
  theme_minimal()+
  theme(axis.text.x = element_text(angle = 30, hjust = 1, size = 7))
```

Happy Percentage vs. Education Level



```
model2 <- lm(Percentage ~ Education_Level + Year, data = happy_df_byeducation)
summary(model2)
```

Call:

```
lm(formula = Percentage ~ Education_Level + Year, data = happy_df_byeducation)
```

Residuals:

Min	1Q	Median	3Q	Max
-9.4845	-2.4151	0.4029	2.6386	7.8886

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1496.0883	203.9767	7.335	2.33e-10 ***
Education_LevelPrimary School	-1.2328	1.4753	-0.836	0.406
Education_LevelPrimary Education or Junior High School	-1.5648	1.4753	-1.061	0.292
Education_LevelHigh School or Equivalent	-1.3533	1.4753	-0.917	0.362
Education_LevelHigher Education	1.2962	1.4753	0.879	0.382
Year	-0.7142	0.1012	-7.057	7.70e-10 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.173 on 74 degrees of freedom

Multiple R-squared: 0.4271, Adjusted R-squared: 0.3884

F-statistic: 11.04 on 5 and 74 DF, p-value: 5.843e-08

```
model3 <- lm(Percentage ~ Education_Level * Year, data = happy_df_byeducation)
summary(model3)
```

```
Call:
lm(formula = Percentage ~ Education_Level * Year, data = happy_df_byeducation)
```

Residuals:

Min	1Q	Median	3Q	Max
-6.9436	-2.1574	0.0044	2.6583	7.7300

Coefficients:

	Estimate	
(Intercept)	234.57621	
Education_LevelPrimary School	620.91983	
Education_LevelPrimary Education or Junior High School	1602.28219	
Education_LevelHigh School or Equivalent	1498.40007	
Education_LevelHigher Education	2583.10352	
Year	-0.08828	
Education_LevelPrimary School:Year	-0.30868	
Education_LevelPrimary Education or Junior High School:Year	-0.79576	
Education_LevelHigh School or Equivalent:Year	-0.74411	
Education_LevelHigher Education:Year	-1.28098	
	Std. Error	t value
(Intercept)	404.91157	0.579
Education_LevelPrimary School	572.63143	1.084
Education_LevelPrimary Education or Junior High School	572.63143	2.798
Education_LevelHigh School or Equivalent	572.63143	2.617
Education_LevelHigher Education	572.63143	4.511
Year	0.20090	-0.439
Education_LevelPrimary School:Year	0.28411	-1.086
Education_LevelPrimary Education or Junior High School:Year	0.28411	-2.801
Education_LevelHigh School or Equivalent:Year	0.28411	-2.619
Education_LevelHigher Education:Year	0.28411	-4.509
	Pr(> t)	
(Intercept)	0.56423	
Education_LevelPrimary School	0.28194	
Education_LevelPrimary Education or Junior High School	0.00663 **	
Education_LevelHigh School or Equivalent	0.01087 *	
Education_LevelHigher Education	2.53e-05 ***	
Year	0.66170	
Education_LevelPrimary School:Year	0.28099	
Education_LevelPrimary Education or Junior High School:Year	0.00658 **	
Education_LevelHigh School or Equivalent:Year	0.01080 *	
Education_LevelHigher Education:Year	2.56e-05 ***	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

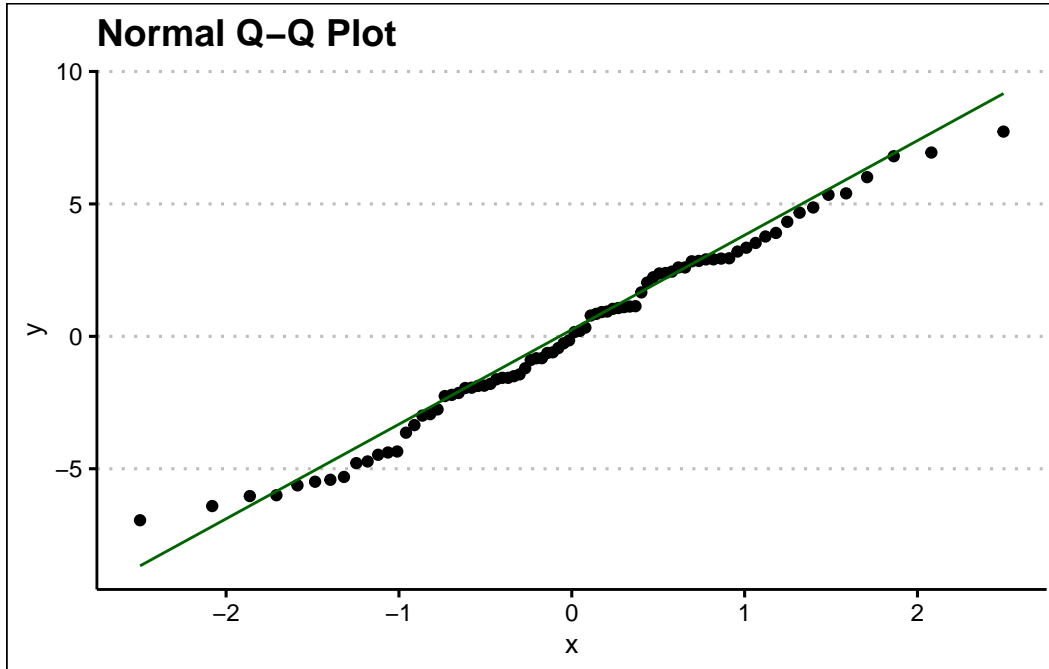
Residual standard error: 3.704 on 70 degrees of freedom
Multiple R-squared: 0.5729, Adjusted R-squared: 0.518
F-statistic: 10.43 on 9 and 70 DF, p-value: 4.852e-10

AIC(model1, model2, model3)

	df	AIC
model1	6	502.5322
model2	7	463.3631

```
model3 11 447.8703
```

```
ggplot(happy_df_byeducation, aes(sample = resid(model3))) +  
  stat_qq() +  
  stat_qq_line(color = "darkgreen") +  
  labs(title = "Normal Q-Q Plot") +  
  theme_clean()
```



```
residuals <- resid(model3)  
  
ad_test_results <- ad.test(residuals)  
print(ad_test_results)
```

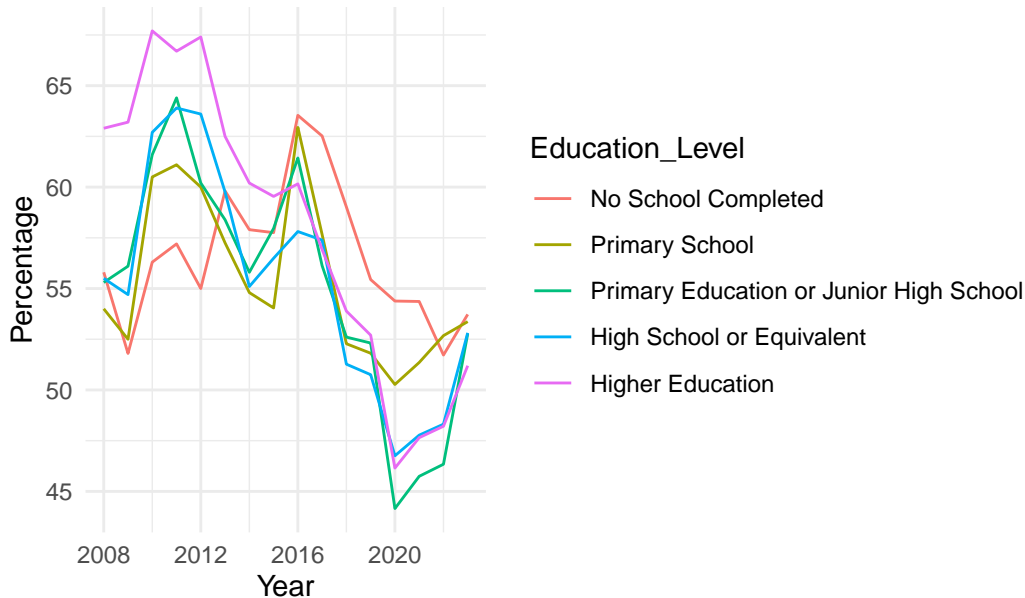
Anderson-Darling normality test

data: residuals

A = 0.31572, p-value = 0.5353

```
ornek<-data.frame(Education_Level = factor(  
  c("No School Completed",  
    "Primary School",  
    "Primary Education or Junior High School",  
    "High School or Equivalent",  
    "Higher Education"),  
  levels = levels(happy_df_byeducation$Education_Level)  
) ,Year=rep(2024:2026,each=5)  
)  
veri<-data.frame(predict(model3, newdata = ornek))  
  
ggplot(happy_df_byeducation, aes(x = Year, y = Percentage, color = Education_Level)) +  
  geom_line() +  
  labs(title = "Happiness Trend by Education Level Over Years")+  
  theme_minimal()
```

Happiness Trend by Education Level Over Years



Gender-Based Happiness Level Prediction Model;

The prediction model for happiness percentages based on gender can be established in three different ways.

- **Model 1** assumes that the happiness rate is only affected by **gender**.
- **Model 2** includes the **effect of time** in the prediction model.
- **Model 3** adds the **interaction** between gender and time to the prediction model.

Based on the results, when the AIC (Akaike Information Criterion) [4] values of the models are compared, it is observed that the model that best explains the data is **Model 2, which has the lowest AIC value**. Therefore, it can be concluded that the effect of the year should be included in the constructed prediction model.

Thus, in the prediction model for happiness percentage, the significant variables, “**GenderFemale**” (which takes a value of 0 for Male and 1 for Female) and “**Year**”, should be **included**. Since the “Gender” variable is categorical, a reference category is selected when constructing the model, which is typically the first level. In this case, the reference category is the “Male” category. The “Intercept”() value in the model output represents the average happiness percentage for males, while the “GenderFemale” coefficient indicates the difference in the average happiness percentage between females and males.

The adequacy of the model was validated by analyzing whether the residuals conform to a normal distribution with Q-Q Plot and Anderson-Darling Normality Test.

```
happy_df_bygender <- bygender|>
  pivot_longer(cols = c("Male", "Female"),
               names_to = "Gender",
               values_to = "Percentage")|>
  filter(Happiness_Level == "Happy")|>
mutate(Gender = factor(Gender, levels = c("Male", "Female")))
))

model1 <- lm(Percentage ~ Gender, data = happy_df_bygender)
summary(model1)
```

Call:

```
lm(formula = Percentage ~ Gender, data = happy_df_bygender)
```

Residuals:

Min	1Q	Median	3Q	Max
-8.9562	-2.9828	0.1938	3.6625	7.3438

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	52.256	1.171	44.619	< 2e-16 ***
GenderFemale	6.806	1.656	4.109	0.000283 ***

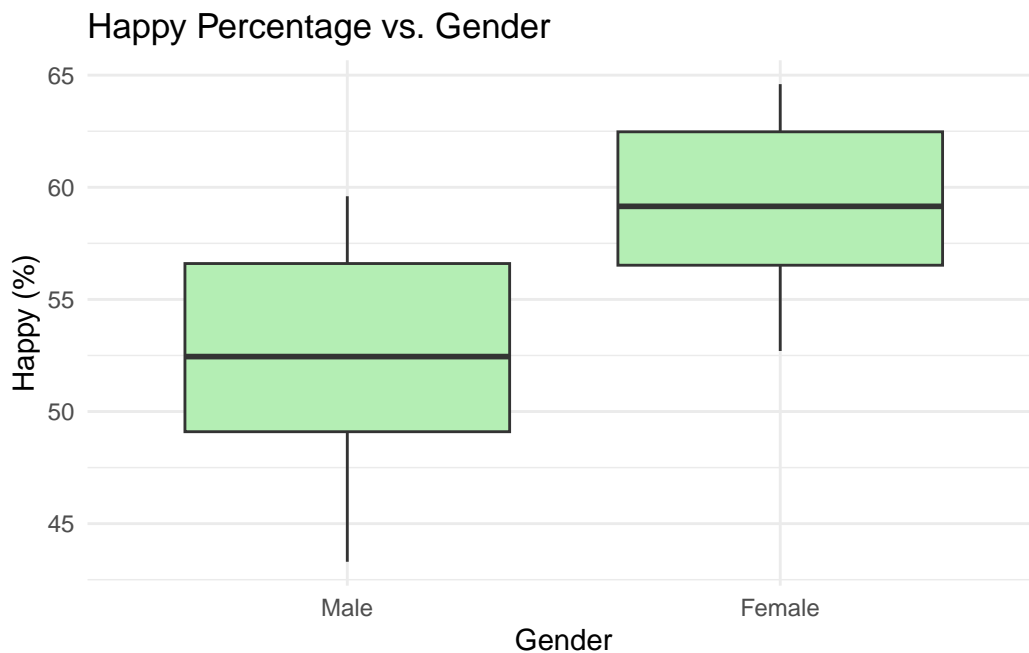
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.685 on 30 degrees of freedom

Multiple R-squared: 0.3602, Adjusted R-squared: 0.3388

F-statistic: 16.89 on 1 and 30 DF, p-value: 0.0002825

```
ggplot(happy_df_bygender, aes(x = Gender, y = Percentage)) +  
  geom_boxplot(fill = "darkseagreen2") +  
  labs(title = "Happy Percentage vs. Gender",  
       x = "Gender", y = "Happy (%)") +  
  theme_minimal()
```



```
model2 <- lm(Percentage ~ Gender+ Year, data = happy_df_bygender)  
summary(model2)
```

Call:

```
lm(formula = Percentage ~ Gender + Year, data = happy_df_bygender)
```

Residuals:

Min	1Q	Median	3Q	Max
-6.1588	-2.2183	0.2604	2.3922	6.1670

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1355.3659	277.6201	4.882	3.52e-05	***
GenderFemale	6.8063	1.2699	5.360	9.34e-06	***
Year	-0.6465	0.1377	-4.694	5.94e-05	***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.592 on 29 degrees of freedom

Multiple R-squared: 0.6364, Adjusted R-squared: 0.6113

F-statistic: 25.38 on 2 and 29 DF, p-value: 4.256e-07

```
model3 <- lm(Percentage ~ Gender * Year, data = happy_df_bygender)
summary(model3)
```

Call:

```
lm(formula = Percentage ~ Gender * Year, data = happy_df_bygender)
```

Residuals:

Min	1Q	Median	3Q	Max
-6.9450	-2.2140	0.1197	2.6519	6.2275

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	1599.1525	394.2144	4.057	0.000361	***
GenderFemale	-480.7669	557.5034	-0.862	0.395817	
Year	-0.7675	0.1956	-3.924	0.000515	***
GenderFemale:Year	0.2419	0.2766	0.875	0.389249	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.607 on 28 degrees of freedom

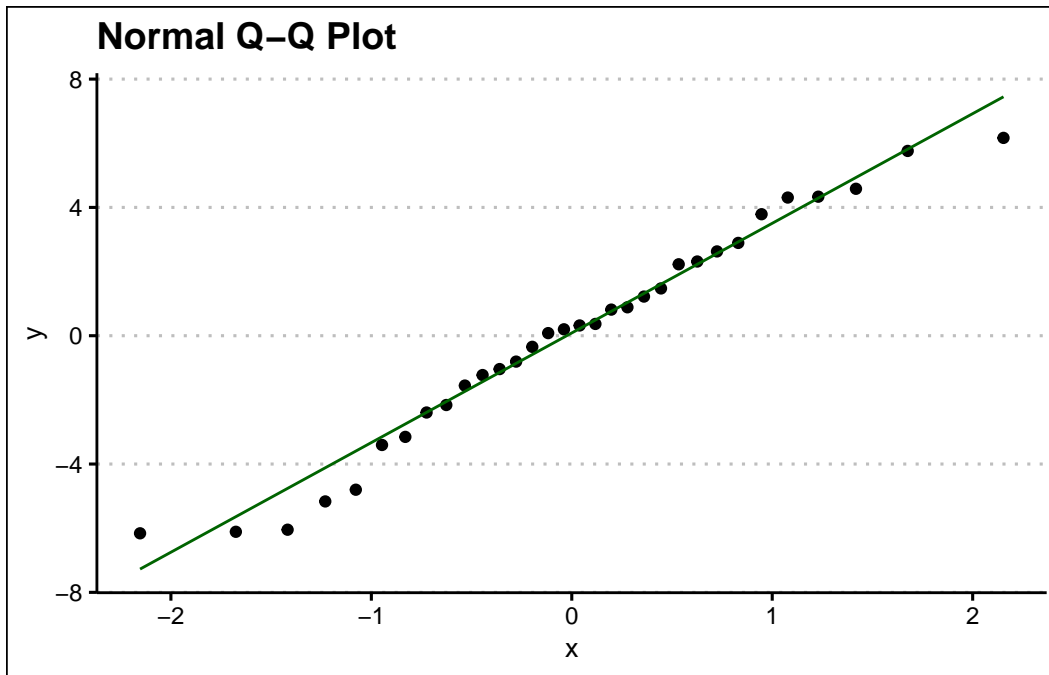
Multiple R-squared: 0.6461, Adjusted R-squared: 0.6081

F-statistic: 17.04 on 3 and 28 DF, p-value: 1.716e-06

```
AIC(model1, model2, model3)
```

	df	AIC
model1	3	193.5824
model2	4	177.4970
model3	5	178.6346

```
ggplot(happy_df_bygender, aes(sample = resid(model2))) +
  stat_qq() +
  stat_qq_line(color = "darkgreen") +
  labs(title = "Normal Q-Q Plot") +
  theme_clean()
```



```
residuals <- resid(model2)

ad_test_results <- ad.test(residuals)
print(ad_test_results)
```

Anderson-Darling normality test

data: residuals
A = 0.22885, p-value = 0.793

4. Results and Key Takeaways 📍

In this study, three different datasets were analyzed to investigate the direction and magnitude of the effects of factors such as gender and educational attainment on individuals' self-reported happiness. These datasets provide information on the total number of individuals by education level across different provinces of Turkey over the years, as well as gender distribution, and the levels of happiness individuals reported over time based on their education level and gender. The study was conducted using this information.

During the analysis phase, the first step involved examining the structure and trends of the variables to gain more detailed insight into the data. These initial observations were enriched further by exploring how the variables behaved over time. Finally, the effects of the variables on happiness percentages were discussed, and regression models based on gender and education level were developed to predict individuals' likelihood of reporting happiness.

The key findings from the analysis are summarized below:

- Over time, **Istanbul**, **Ankara**, and **Izmir** were identified as the provinces with the [greatest increase in individuals who either had no formal education or had completed university and higher education. While the increase in higher education levels in Istanbul and Izmir was more stable, **Ankara saw a rapid rise**, especially after 2020. On a national scale, the majority of individuals **without formal education or with only primary education are women**. In contrast, the opposite is true for **higher education levels, where men are in the majority**.
- Individuals who identified themselves as **happy** were mostly those with **higher education**,

whereas those who identified as **unhappy** were predominantly individuals **without any formal education**. However, the percentage of individuals reporting happiness has decreased across all education levels over time. The smallest decrease occurred among those with **no formal education** (**−0.0089**), while the largest decrease was among those with **higher education** (**−1.369**). For individuals reporting unhappiness, the percentage decreased over time only for those **without education** (**−0.065**), while it increased across all other education levels. The highest increase in unhappiness was observed among individuals with **higher education** (**+0.45**).

- Individuals who identified themselves as **happy were mostly women**, while those who reported being unhappy were mostly men. In addition, the **difference** in happiness rates between men and women who reported being happy has **decreased by an average of 0.24 points per year**. On the other hand, the difference between men and women who reported being unhappy has **increased by approximately 0.17 points annually**.
- To estimate happiness percentages, various regression models were developed based on gender and education level. Models including both main effects and interaction terms for relevant factors were compared. The best-fitting model was identified based on the Akaike Information Criterion (AIC). In the **gender-based model**, the inclusion of the time variable (year) alongside **gender improved the model fit**. In the education-level model, main effects for primary school, high school, and higher education levels, as well as their interactions with time, were included in the model specification.

According to these results, it is seen that educational disadvantage, especially in recent years, affects not only women but also men. The reasons for this should be considered from different perspectives and steps should be taken towards a solution. The level of education that individuals have creates a difference in their perspective and expectations on life and the level of happiness they define themselves in this way changes to a great extent. The fact that the percentage of people who do not receive any education feeling unhappy has increased over time, even if only slightly, has actually proven the saying that ignorance is bliss, the meaning of which we examine from a different perspective. Although women seem happier in general in the country, it should be approached with skepticism as to whether this reflects the truth in the living conditions we live in. When approached with this suspicion, the real truth is that the difference in happiness between men and women decreases over time, and women feel unhappier day by day.

*Assistance from ChatGPT was utilized at certain parts of this study.

The mini research paper related to this study can be accessed [here](#).

References

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- 3.K. Pearson, “*On the criterion that a given system of deviations from the probable in the case of a correlated system of variables is such that it can be reasonably supposed to have arisen from random sampling,*” The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science, vol. 50, no. 302, pp. 157–175, 1900.
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