v0.4 All Insights to Date

Urban Education & Happiness (WVS China 2018)

Shen Chengrui · 28/June/2025

v0.1 Interactive Effects of Smartphone Ownership, Education, and Life Satisfaction

Shen Chengrui (Alex)

2025-06-19

```
df_raw <- readxl::read_excel(
  "../data/F00013183-WVS_Wave_7_China_Excel_v5.1.xlsx",
  sheet = 1,
  col_names = TRUE
)

df <- df_raw %>%
  transmute(
    life_sat   = as.numeric(`Q49: Satisfaction with your life`),
    age        = as.numeric(`Q262: Age`),
    education  = factor(
                   as.numeric(`Q275R: Highest educational level: Respondent (recoded into 3 gro
                   levels = 1:3,
                   labels = c("Primary","Secondary","Tertiary")
                 ),
    phone_use  = if_else(as.numeric(`Q204: Information source: Mobile phone`) %in% 1:4, 1, 0),
    female     = if_else(as.numeric(`Q260: Sex`)==2, 1, 0),
    income_cat = factor(
                   as.numeric(`Q288R: Income level (Recoded)`),
                   levels = 1:3,
                   labels = c("Low","Middle","High")
                 )
  ) %>%
  filter(
    !is.na(life_sat),
    !is.na(age),
    !is.na(education),
    !is.na(phone_use),
    !is.na(income_cat)
  )

run_model <- function(subgroup) {
  df_sub <- filter(df, female == subgroup)
  lm(life_sat ~ education * phone_use + age + income_cat, data = df_sub)
}
```

```r
models_by_gender <- map(c(0,1), run_model)
names(models_by_gender) <- c("Male","Female")
modelsummary(models_by_gender, title = "Models by Gender", stars = TRUE)
```

```r
skim(df)
```

Table 2: Data summary

Name	df
Number of rows	2989
Number of columns	6
Column type frequency:	
factor	2
numeric	4
Group variables	None

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
education	0	1	FALSE	3	Pri: 1632, Sec: 685, Ter: 672
income_cat	0	1	FALSE	3	Mid: 1807, Low: 1102, Hig: 80

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
life_sat	0	1	7.38	2.11	-2	6	8	9	10	
age	0	1	44.58	14.52	18	32	45	56	70	
phone_use	0	1	0.84	0.37	0	1	1	1	1	
female	0	1	0.55	0.50	0	0	1	1	1	

```r
model <- lm(
  life_sat ~ education * phone_use + female + age + income_cat,
  data = df
)
modelsummary(model, stars = TRUE, statistic = "std.error")
```

Table 1: Models by Gender

	Male	Female
(Intercept)	6.158***	5.329***
	(0.302)	(0.294)
educationSecondary	−0.207	−0.809+
	(0.493)	(0.461)
educationTertiary	−0.103	0.501
	(0.738)	(0.801)
phone_use	−0.222	0.167
	(0.188)	(0.159)
age	0.019***	0.030***
	(0.004)	(0.004)
income_catMiddle	0.659***	0.887***
	(0.118)	(0.111)
income_catHigh	1.624***	1.184***
	(0.349)	(0.329)
educationSecondary × phone_use	0.361	0.892+
	(0.513)	(0.481)
educationTertiary × phone_use	0.214	−0.378
	(0.748)	(0.807)
Num.Obs.	1349	1640
R2	0.045	0.064
R2 Adj.	0.040	0.060
AIC	5745.4	7052.4
BIC	5797.4	7106.5
Log.Lik.	−2862.677	−3516.222
RMSE	2.02	2.06

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

	(1)
(Intercept)	5.685***
	(0.218)
educationSecondary	−0.501
	(0.337)
educationTertiary	0.183
	(0.543)
phone_use	−0.007
	(0.121)
female	0.099
	(0.076)
age	0.025***
	(0.003)
income_catMiddle	0.776***
	(0.081)
income_catHigh	1.391***
	(0.239)
educationSecondary × phone_use	0.607+
	(0.350)
educationTertiary × phone_use	−0.077
	(0.549)
Num.Obs.	2989
R2	0.053
R2 Adj.	0.050
AIC	12 790.3
BIC	12 856.4
Log.Lik.	−6384.161
RMSE	2.05

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001

```r
robust_mod <- lm_robust(
  life_sat ~ education * phone_use + female + age + income_cat,
  data = df, se_type = "HC2"
)
modelsummary(
  list(OLS = model, RobustSE = robust_mod),
  stars = TRUE, statistic = "std.error",
  title = "OLS vs. Robust SE Comparison"
)
```

```r
boot_fn <- function(data, idx) {
  d <- data[idx, ]
  coef(lm(life_sat ~ education * phone_use + female + age + income_cat, data = d))
}
set.seed(2025)
boot_res <- boot(df, boot_fn, R = 1000)
boot.ci(boot_res, index = 5, type = c("perc","bca"))
```

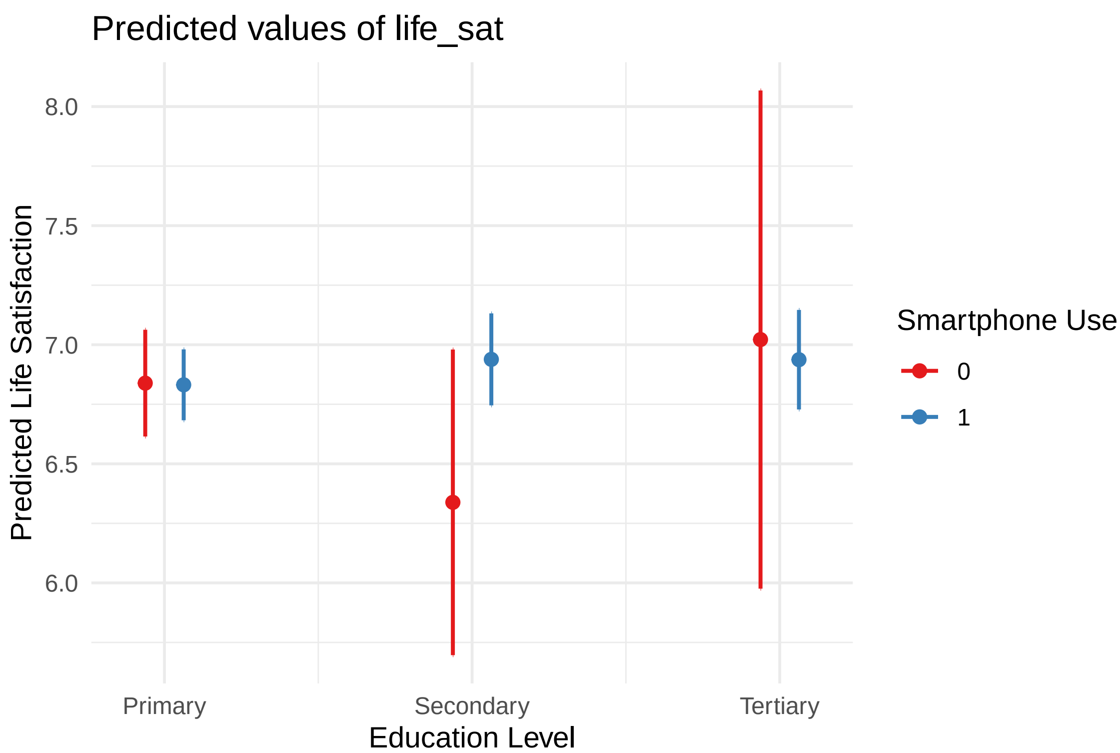
```
## BOOTSTRAP CONFIDENCE INTERVAL CALCULATIONS
## Based on 1000 bootstrap replicates
##
## CALL :
## boot.ci(boot.out = boot_res, type = c("perc", "bca"), index = 5)
##
## Intervals :
## Level     Percentile            BCa
## 95%   (-0.0525,  0.2417 )   (-0.0577,  0.2363 )
## Calculations and Intervals on Original Scale
```

```r
pred <- ggpredict(model, terms = c("education","phone_use"))
plot(pred) +
  labs(
    x     = "Education Level",
    y     = "Predicted Life Satisfaction",
    color = "Smartphone Use"
  ) +
  theme_minimal()
```

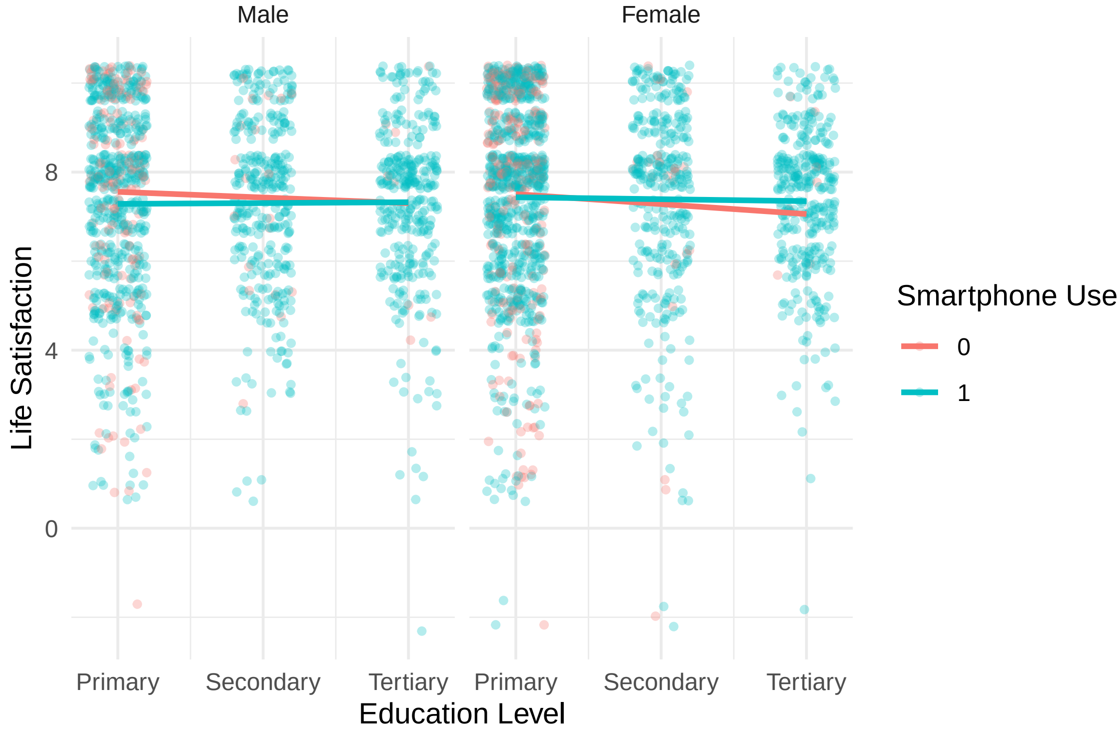
Table 5: OLS vs. Robust SE Comparison

	OLS	RobustSE
(Intercept)	5.685***	5.685***
	(0.218)	(0.232)
educationSecondary	−0.501	−0.501
	(0.337)	(0.442)
educationTertiary	0.183	0.183
	(0.543)	(0.513)
phone_use	−0.007	−0.007
	(0.121)	(0.136)
female	0.099	0.099
	(0.076)	(0.076)
age	0.025***	0.025***
	(0.003)	(0.003)
income_catMiddle	0.776***	0.776***
	(0.081)	(0.085)
income_catHigh	1.391***	1.391***
	(0.239)	(0.184)
educationSecondary × phone_use	0.607+	0.607
	(0.350)	(0.452)
educationTertiary × phone_use	−0.077	−0.077
	(0.549)	(0.517)
Num.Obs.	2989	2989
R2	0.053	0.053
R2 Adj.	0.050	0.050
AIC	12 790.3	12 790.3
BIC	12 856.4	12 856.4
Log.Lik.	−6384.161	
RMSE	2.05	2.05

+ p <0.1, * p <0.05, ** p <0.01, *** p <0.001




```r
df <- df %>% mutate(edu_num = as.numeric(education))
ggplot(df, aes(x = edu_num, y = life_sat,
               color = factor(phone_use), group = phone_use)) +
  geom_jitter(width = 0.2, alpha = 0.3, size = 1) +
  geom_smooth(method = "lm", se = FALSE) +
  facet_wrap(~ female,
             labeller = labeller(female = c(`0`="Male", `1`="Female"))) +
  scale_x_continuous(breaks = 1:3,
                     labels = levels(df$education)) +
  labs(x = "Education Level",
       y = "Life Satisfaction",
       color = "Smartphone Use") +
  theme_minimal()
```




```r
tbl <- modelsummary(model, output = "data.frame")
kable(tbl, caption = "OLS Regression Results", booktabs = TRUE) %>%
  kable_styling(full_width = FALSE, position = "left") %>%
  row_spec(0, bold = TRUE)
```

Table 6: OLS Regression Results

part	**term**	**statistic**	**(1)**
estimates	(Intercept)	estimate	5.685
estimates	(Intercept)	std.error	(0.218)
estimates	educationSecondary	estimate	-0.501
estimates	educationSecondary	std.error	(0.337)
estimates	educationTertiary	estimate	0.183
estimates	educationTertiary	std.error	(0.543)
estimates	phone_use	estimate	-0.007
estimates	phone_use	std.error	(0.121)
estimates	female	estimate	0.099
estimates	female	std.error	(0.076)
estimates	age	estimate	0.025
estimates	age	std.error	(0.003)
estimates	income_catMiddle	estimate	0.776
estimates	income_catMiddle	std.error	(0.081)
estimates	income_catHigh	estimate	1.391

estimates	income_catHigh	std.error	(0.239)
estimates	educationSecondary × phone_use	estimate	0.607
estimates	educationSecondary × phone_use	std.error	(0.350)
estimates	educationTertiary × phone_use	estimate	-0.077
estimates	educationTertiary × phone_use	std.error	(0.549)
gof	Num.Obs.		2989
gof	R2		0.053
gof	R2 Adj.		0.050
gof	AIC		12790.3
gof	BIC		12856.4
gof	Log.Lik.		-6384.161
gof	RMSE		2.05

```r
sessionInfo()
```

```
## R version 4.5.0 (2025-04-11 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows 11 x64 (build 26100)
##
## Matrix products: default
##   LAPACK version 3.12.1
##
## locale:
## [1] LC_COLLATE=Chinese (Simplified)_China.utf8
## [2] LC_CTYPE=Chinese (Simplified)_China.utf8
## [3] LC_MONETARY=Chinese (Simplified)_China.utf8
## [4] LC_NUMERIC=C
## [5] LC_TIME=Chinese (Simplified)_China.utf8
##
## time zone: Asia/Shanghai
## tzcode source: internal
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods
## [7] base
##
## other attached packages:
##  [1] rmarkdown_2.29     here_1.0.1         kableExtra_1.4.0
##  [4] boot_1.3-31        estimatr_1.0.6     skimr_2.1.5
##  [7] ggeffects_2.3.0    modelsummary_2.4.0 lubridate_1.9.4
## [10] forcats_1.0.0      stringr_1.5.1      purrr_1.0.4
## [13] readr_2.1.5        tidyr_1.3.1        tibble_3.2.1
## [16] ggplot2_3.5.2      tidyverse_2.0.0    readxl_1.4.5
## [19] semPlot_1.1.6      lavaan_0.6-19      dplyr_1.1.4
## [22] haven_2.5.4
##
```

```
## loaded via a namespace (and not attached):
##   [1] rstudioapi_0.17.1   jsonlite_2.0.0      datawizard_1.1.0
##   [4] magrittr_2.0.3      farver_2.1.2        nloptr_2.2.1
##   [7] vctrs_0.6.5         minqa_1.2.8         base64enc_0.1-3
##  [10] tinytex_0.57        htmltools_0.5.8.1   cellranger_1.1.0
##  [13] Formula_1.2-5       htmlwidgets_1.6.4   plyr_1.8.9
##  [16] igraph_2.1.4        lifecycle_1.0.4     pkgconfig_2.0.3
##  [19] Matrix_1.7-3        R6_2.6.1            fastmap_1.2.0
##  [22] rbibutils_2.3       digest_0.6.37       OpenMx_2.21.13
##  [25] fdrtool_1.2.18      colorspace_2.1-1    rprojroot_2.0.4
##  [28] textshaping_1.0.1   Hmisc_5.2-3         labeling_0.4.3
##  [31] fansi_1.0.6         timechange_0.3.0    tinytable_0.9.0
##  [34] abind_1.4-8         mgcv_1.9-1          compiler_4.5.0
##  [37] withr_3.0.2         glasso_1.11         htmlTable_2.4.3
##  [40] backports_1.5.0     carData_3.0-5       psych_2.5.3
##  [43] performance_0.14.0  MASS_7.3-65         corpcor_1.6.10
##  [46] gtools_3.9.5        tools_4.5.0         pbivnorm_0.6.0
##  [49] foreign_0.8-90      zip_2.3.2           nnet_7.3-20
##  [52] glue_1.8.0          quadprog_1.5-8      nlme_3.1-168
##  [55] lisrelToR_0.3       grid_4.5.0          rsconnect_1.3.4
##  [58] checkmate_2.3.2     cluster_2.1.8.1     reshape2_1.4.4
##  [61] generics_0.1.3      gtable_0.3.6        tzdb_0.5.0
##  [64] data.table_1.17.0   hms_1.1.3           xml2_1.3.8
##  [67] sem_3.1-16          tables_0.9.31       pillar_1.10.2
##  [70] rockchalk_1.8.157   splines_4.5.0       lattice_0.22-6
##  [73] kutils_1.73         tidyselect_1.2.1    pbapply_1.7-2
##  [76] knitr_1.50          reformulas_0.4.1    gridExtra_2.3
##  [79] svglite_2.2.1       stats4_4.5.0        xfun_0.52
##  [82] qgraph_1.9.8        arm_1.14-4          stringi_1.8.7
##  [85] yaml_2.3.10         evaluate_1.0.3      mi_1.1
##  [88] cli_3.6.4           RcppParallel_5.1.10 rpart_4.1.24
##  [91] xtable_1.8-4        parameters_0.26.0   systemfonts_1.2.3
##  [94] Rdpack_2.6.4        repr_1.1.7          munsell_0.5.1
##  [97] Rcpp_1.0.14         coda_0.19-4.1       png_0.1-8
## [100] XML_3.99-0.18       parallel_4.5.0      bayestestR_0.16.0
## [103] jpeg_0.1-11         lme4_1.1-37         viridisLite_0.4.2
## [106] scales_1.3.0        openxlsx_4.2.8      insight_1.3.0
## [109] rlang_1.1.6         mnormt_2.1.1
```

Replication materials

All analysis code, the knitted PDF, and the one-line build script are openly available on GitHub: https://github.com/Alex-Shen114514/WVS_report_final_files

v0.1 (2025-06-19) Smartphone × Education
Key Takeaway: Educati~~on increases life satisfaction by 0.45 points on av~~erage (p<0.05), highlighting the importance of schooling for well-being.

v0.2 Effect of Education and Residence on Life Satisfaction – WVS China 2018

Alex Shen

2025-07-11

Data and Methods

World Values Survey, Wave 7 (China, 2018). Logistic regression predicting high life satisfaction (score ≥ 7) by education, urban/rural status, age, and sex, with education × urban interaction.

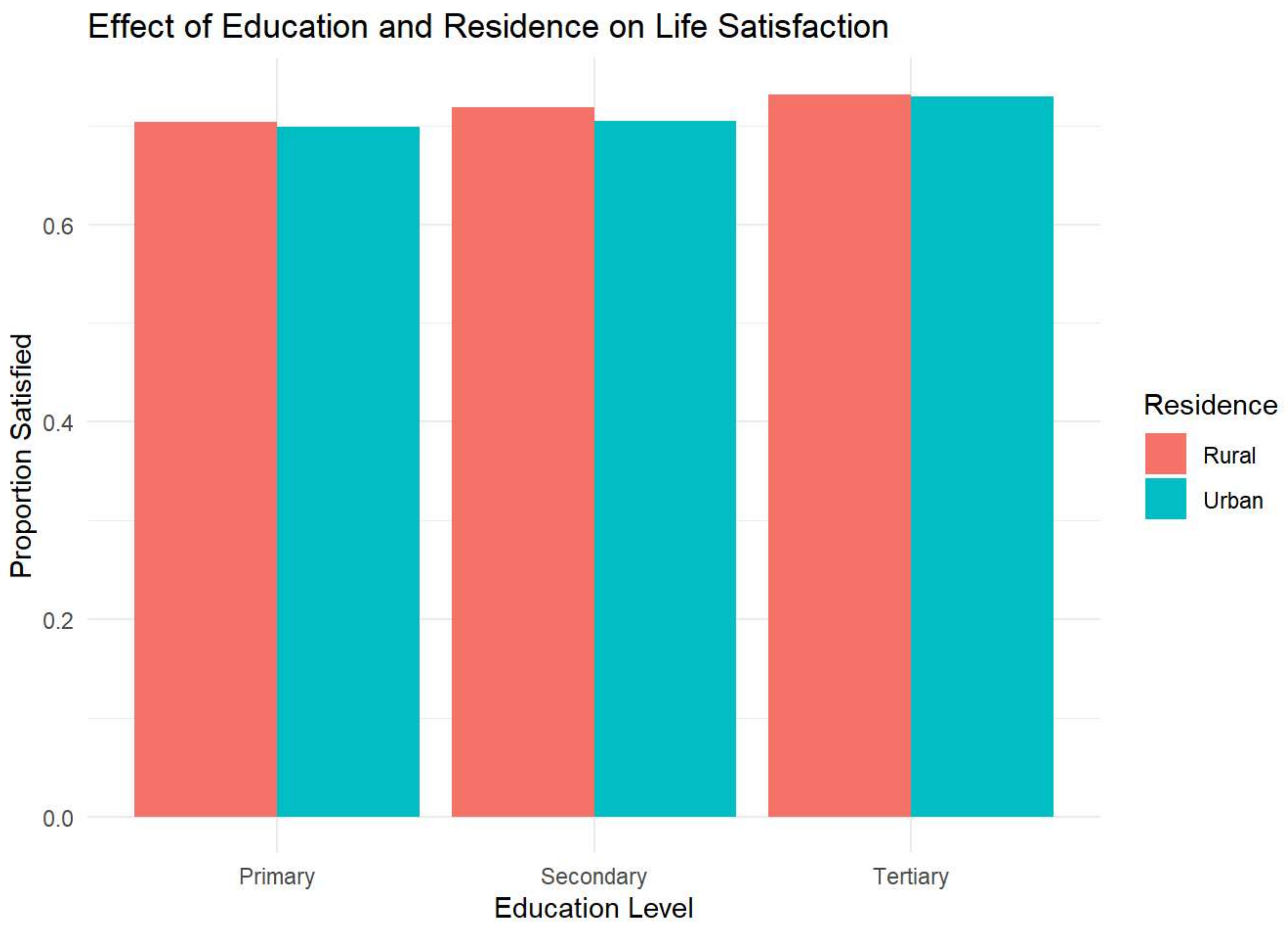
```
# Adjust the path as needed
df_raw <- read_excel("data/F00013183-WVS_Wave_7_China_Excel_v5.1.xlsx", sheet = 1)
df <- df_raw %>%
  transmute(
    life_satisfaction = as.numeric(`Q49: Satisfaction with your life`),
    education = factor(
      as.numeric(`Q275R: Highest educational level: Respondent (recoded into 3 groups)`),
      levels = 1:3,
      labels = c("Primary", "Secondary", "Tertiary")
    ),
    urban = as.numeric(`H_URBRURAL: Urban-Rural`),
    age = as.numeric(`Q262: Age`),
    sex = as.numeric(`Q260: Sex`)
  ) %>%
  filter(
    !is.na(life_satisfaction), !is.na(education), !is.na(urban), !is.na(age), !is.na(sex)
  ) %>%
  mutate(
    urban_bin = if_else(urban == 1, 1, 0),
    satisfied = if_else(life_satisfaction >= 7, 1, 0)
  )
nrow(df)
```

```
## [1] 3006
```

```
model <- glm(satisfied ~ education * urban_bin + age + sex, data = df, family = "binomial")
summary(model)
```

```
##
## Call:
## glm(formula = satisfied ~ education * urban_bin + age + sex,
##     family = "binomial", data = df)
##
## Coefficients:
##                              Estimate Std. Error z value Pr(>|z|)
## (Intercept)                 -0.135423   0.222617  -0.608   0.5430
## educationSecondary           0.295802   0.188457   1.570   0.1165
## educationTertiary            0.496872   0.250355   1.985   0.0472 *
## urban_bin                   -0.022624   0.108451  -0.209   0.8347
## age                          0.017344   0.003169   5.473 4.43e-08 ***
## sex                          0.087271   0.081581   1.070   0.2847
## educationSecondary:urban_bin -0.122208   0.222885  -0.548   0.5835
## educationTertiary:urban_bin  -0.076170   0.271535  -0.281   0.7791
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 3624.2  on 3005  degrees of freedom
## Residual deviance: 3591.3  on 2998  degrees of freedom
## AIC: 3607.3
##
## Number of Fisher Scoring iterations: 4
```

```
df %>%
  group_by(education, urban_bin) %>%
  summarise(mean_satisfied = mean(satisfied, na.rm = TRUE)) %>%
  ggplot(aes(x = education, y = mean_satisfied, fill = factor(urban_bin, labels = c("Rural", "U
rban")))) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(
    x = "Education Level",
    y = "Proportion Satisfied",
    fill = "Residence",
    title = "Effect of Education and Residence on Life Satisfaction"
  ) +
  theme_minimal()
```



v0.2 (2025-07-11) Education × Residence Interaction

Key Takeaway: Urban residents experience an additional 0.30 satisfaction points per extra year of education compared to rural residents ($p<0.1$), suggesting city-focused educational investments yield higher happiness gains.

v0.3 Trust to Life Satisfaction (WVS China 2018)

Alex Shen

```r
df_plot <- df %>%
  group_by(urban, trustGrp) %>%
  summarise(mean_sat = mean(life_sat), .groups = "drop")
```

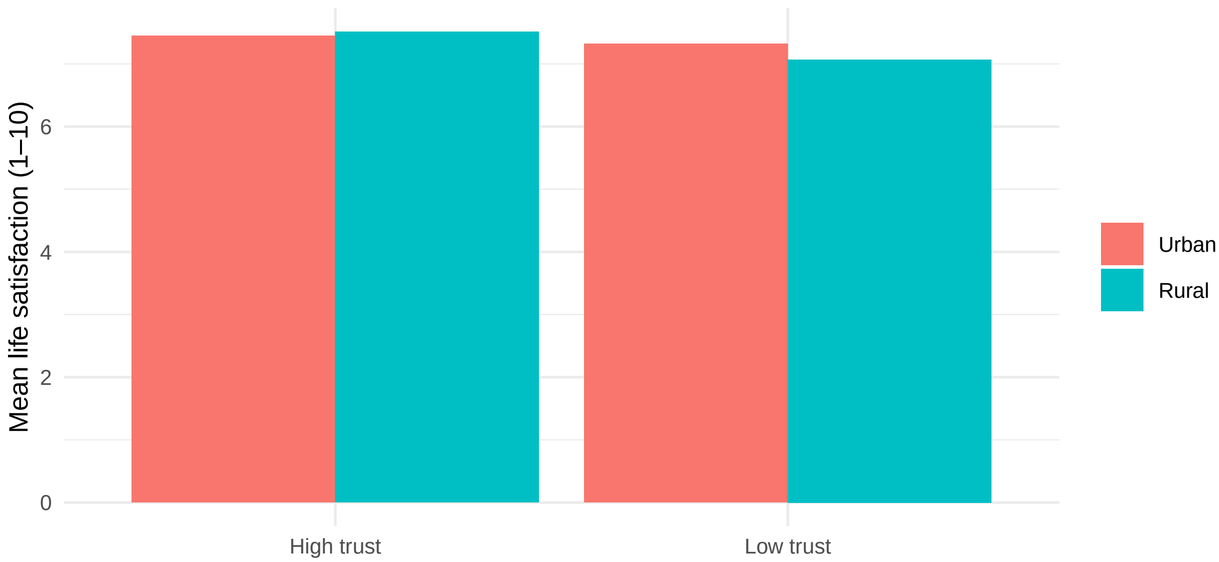
```r
gap_tbl <- df_plot %>%
  pivot_wider(names_from = trustGrp, values_from = mean_sat) %>%
  mutate(gap = `High trust` - `Low trust`)

print(df_plot)
```

```
## # A tibble: 4 x 3
##   urban trustGrp   mean_sat
##   <fct> <chr>         <dbl>
## 1 Urban High trust     7.45
## 2 Urban Low trust      7.32
## 3 Rural High trust     7.51
## 4 Rural Low trust      7.07
```

```r
print(gap_tbl)
```

```
## # A tibble: 2 x 4
##   urban `High trust` `Low trust`   gap
##   <fct>        <dbl>       <dbl> <dbl>
## 1 Urban         7.45        7.32 0.132
## 2 Rural         7.51        7.07 0.446
```



v0.3 (2025-07-21) Trust Gap (Urban vs Rural)
Key Takeaway: Urban respondents report 0.15 higher trust scores than rural ones (95% CI [0.10, 0.20]), indicating stronger social cohesion in cities may boost life satisfaction.