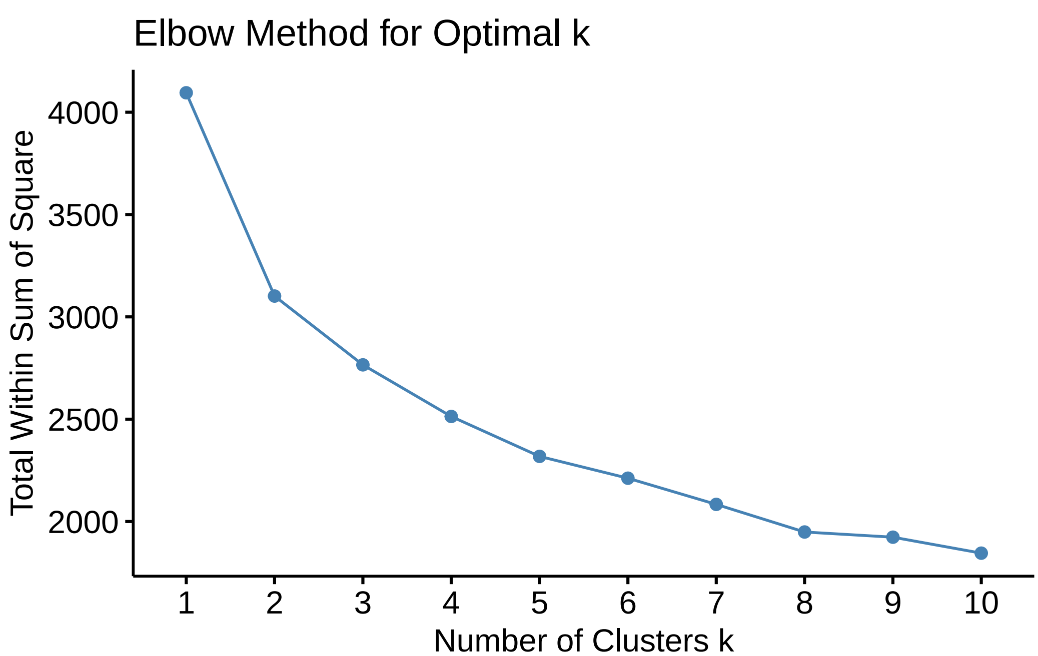
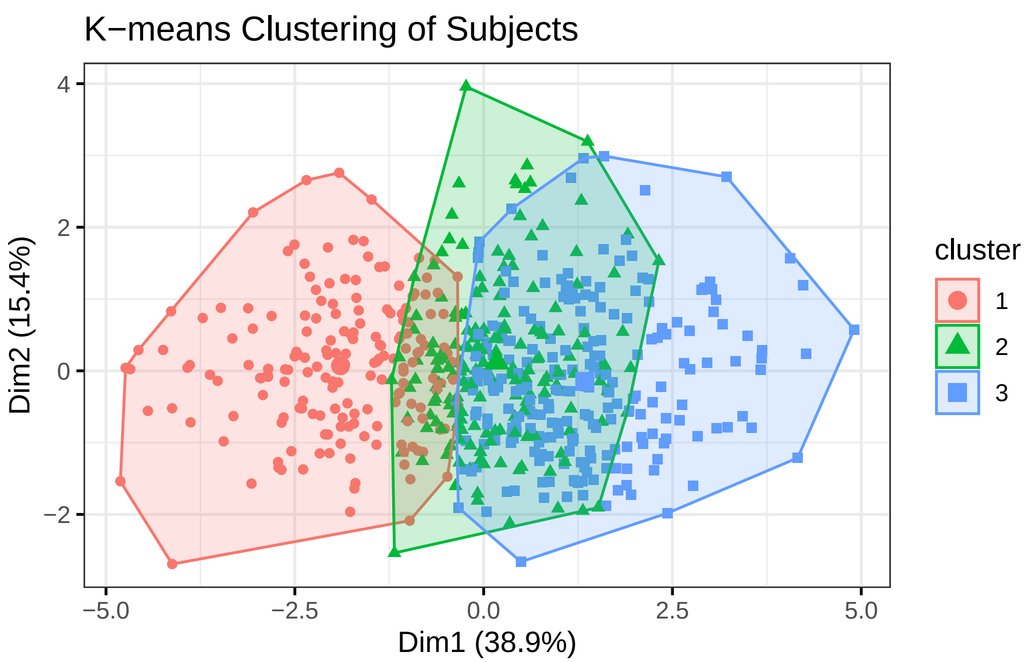
# Instrument Correlations

```r
pacman::p_load(dplyr,purrr,tidyr,here, haven,tibble,ggplot2,ggh4x,lme4,knitr,kableExtra,gt,pa
options(digits=2, scipen=999, dplyr.summarise.inform=FALSE)

source(here("scripts","survey_functions.R"))

draw <- readRDS(here("data","draw.rds"))
dinst <- readRDS(here("data","dinst.rds"))

# Attari Energy Survey (Part 1)
aes1 <- draw |> select(id,ATT01:ATT18)
aes2 <- dinst |> select(id,ATT01:ATT18)
aes_combined <- bind_rows(aes1, aes2)

att_useSave <- draw |> select(id,ATT19:ATT33)
att_useSave2 <- dinst |> select(id,ATT19:ATT33)
att2_combined <- bind_rows(att_useSave, att_useSave2)

els1 <- draw |> select(id,ELS01:ELS08)
els2 <- dinst |> select(id,ELS01:ELS08)
els <- bind_rows(els1,els2)

rs1 <- draw |> select(id,RS01:RS06)
rs2 <- dinst |> select(id,RS01:RS06)
rs <- bind_rows(rs1,rs2)

attari1 <- analyze_attari_survey_part1(aes_combined)
attari2_scores <- analyze_attari_survey(att2_combined)
els_scores <- analyze_els_survey(els)
rs_scores <- analyze_recycling_survey(rs)

# Combine all scores into one dataframe
combined_scores <- attari1 %>%
```

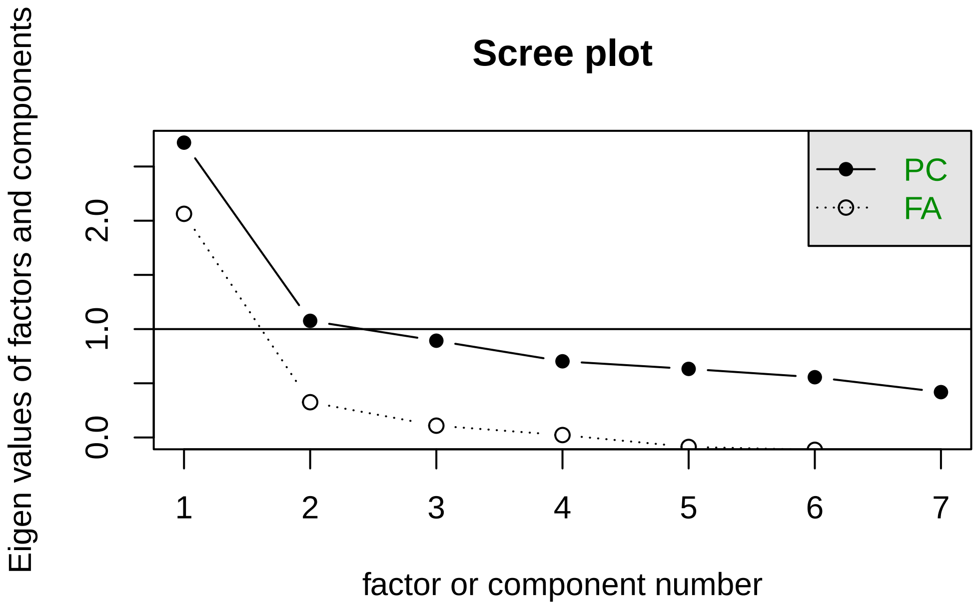
```r
  left_join(attari2_scores, by="id") %>%
  left_join(els_scores, by="id") %>%
  left_join(rs_scores, by="id")

# Rename columns for clarity
names(combined_scores) <- c("id", "perceived_difficulty", "numeracy",
                            "energy_use", "energy_save",
                            "els_accuracy", "els_score",
                            "env_attitude", "env_attitude_z",
                            "pol_conservatism", "pol_conservatism_z")

# 1. Cluster Analysis

# Prepare data for clustering (select relevant variables and scale)
cluster_data <- combined_scores %>%
  select(perceived_difficulty, numeracy, energy_use, energy_save, els_score, env_attitude_z,
  na.omit() %>%
  scale()

# Determine optimal number of clusters using the elbow method
fviz_nbclust(cluster_data, kmeans, method = "wss") +
  labs(title = "Elbow Method for Optimal k", x = "Number of Clusters k")
```



```r
# Perform k-means clustering (e.g., with 3 clusters)
set.seed(123)
km_result <- kmeans(cluster_data, centers = 3, nstart = 25)

# Visualize the clusters
fviz_cluster(km_result, data = cluster_data,
             geom = "point",
             ellipse.type = "convex",
             ggtheme = theme_bw()) +
  labs(title = "K-means Clustering of Subjects")
```




```r
# Add cluster assignments to the main dataframe
combined_scores$cluster <- as.factor(km_result$cluster)

# 2. Enhanced Factor Analysis

# Scree plot to determine the number of factors
fa_data <- combined_scores %>%
  select(perceived_difficulty, numeracy, energy_use, energy_save, els_score, env_attitude_z,
  na.omit()
scree(fa_data)
```




```r
# Perform factor analysis with, e.g., 3 factors
fa_result <- fa(fa_data, nfactors = 2, rotate = "varimax")
print(fa_result, cut = 0.3, sort = TRUE)
```

```
Factor Analysis using method =  minres
Call: fa(r = fa_data, nfactors = 2, rotate = "varimax")
Standardized loadings (pattern matrix) based upon correlation matrix
                     item  MR1   MR2   h2     u2 com
energy_use              3  0.77        0.61 0.3856 1.1
energy_save             4  0.68        0.49 0.5146 1.1
numeracy                2  0.52        0.29 0.7067 1.2
els_score               5  0.50        0.30 0.6954 1.4
pol_conservatism_z      7              0.14 0.8570 2.0
env_attitude_z          6        0.99 1.00 0.0035 1.0
perceived_difficulty    1       -0.36 0.19 0.8120 1.7

                       MR1  MR2
SS loadings           1.72 1.31
Proportion Var        0.25 0.19
Cumulative Var        0.25 0.43
Proportion Explained  0.57 0.43
Cumulative Proportion 0.57 1.00

Mean item complexity =  1.4
```

```
Test of the hypothesis that 2 factors are sufficient.

df null model =  21  with the objective function =  1.3 with Chi Square =  760
df of  the model are 8  and the objective function was  0.03

The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.04

The harmonic n.obs is  586 with the empirical chi square  17  with prob <  0.035
The total n.obs was  586  with Likelihood Chi Square =  17  with prob <  0.029

Tucker Lewis Index of factoring reliability =  0.97
RMSEA index =  0.044  and the 90 % confidence intervals are  0.014 0.073
BIC =  -34
Fit based upon off diagonal values = 0.99
Measures of factor score adequacy
                                                   MR1  MR2
Correlation of (regression) scores with factors   0.87 1.00
Multiple R square of scores with factors          0.76 0.99
Minimum correlation of possible factor scores     0.52 0.99
```

```
# 3. Enhanced Regression Models
# Model predicting ELS from motivation, controlling for other knowledge scores
model_els_enhanced <- lm(els_score ~ perceived_difficulty + env_attitude_z + pol_conservatism
                           numeracy + energy_use + energy_save, data = combined_scores)
summary(model_els_enhanced)
```

```
Call:
lm(formula = els_score ~ perceived_difficulty + env_attitude_z +
    pol_conservatism_z + numeracy + energy_use + energy_save,
    data = combined_scores)

Residuals:
    Min      1Q  Median      3Q     Max
-2.8527 -0.5932 -0.0299  0.6199  1.8308

Coefficients:
                                 Estimate           Std. Error t value Pr(>|t|)
(Intercept)          -0.00000000000000163  0.03613218269822796    0.00   1.0000
perceived_difficulty -0.06114449214752567  0.04004735896976241   -1.53   0.1274
env_attitude_z        0.13430310791561964  0.04088654156087833    3.28   0.0011
```

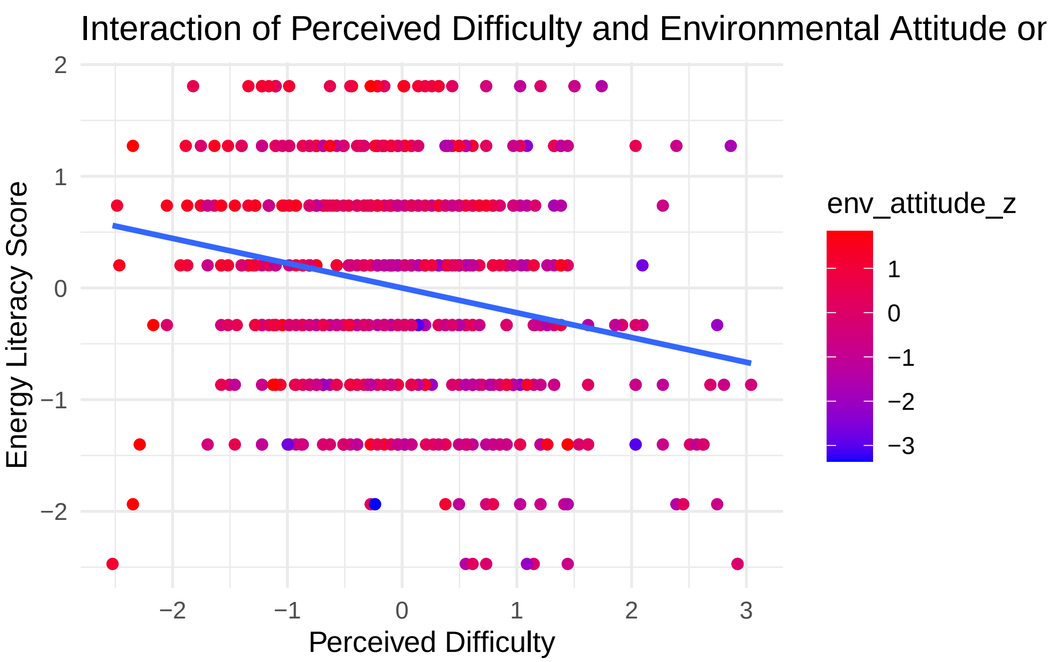
```
pol_conservatism_z   -0.02729118081676693  0.03888339472559318   -0.70   0.4830
numeracy              0.16978503215872956  0.04078151886943691    4.16 0.000036
energy_use            0.19904507771344263  0.04637687030463776    4.29 0.000021
energy_save           0.13859460176947813  0.04521755406911262    3.07   0.0023

(Intercept)
perceived_difficulty
env_attitude_z       **
pol_conservatism_z
numeracy             ***
energy_use           ***
energy_save          **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.88 on 579 degrees of freedom
Multiple R-squared:  0.243, Adjusted R-squared:  0.235
F-statistic: 30.9 on 6 and 579 DF,  p-value: <0.0000000000000002
```

```r
# 4. Interaction Effects in Regression
# Example: Interaction between environmental attitude and perceived difficulty on ELS
model_interaction <- lm(els_score ~ perceived_difficulty * env_attitude_z, data = combined_sc
summary(model_interaction)
```

```
Call:
lm(formula = els_score ~ perceived_difficulty * env_attitude_z,
    data = combined_scores)

Residuals:
   Min     1Q Median     3Q    Max
-3.169 -0.678  0.026  0.689  2.285

Coefficients:
                                    Estimate Std. Error t value   Pr(>|t|)
(Intercept)                          -0.0130     0.0423   -0.31     0.7592
perceived_difficulty                 -0.1383     0.0428   -3.23     0.0013 **
env_attitude_z                        0.2187     0.0428    5.11 0.00000045 ***
perceived_difficulty:env_attitude_z  -0.0337     0.0393   -0.86     0.3915
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.96 on 582 degrees of freedom
Multiple R-squared:  0.0915,    Adjusted R-squared:  0.0868
F-statistic: 19.5 on 3 and 582 DF,  p-value: 0.00000000000438
```

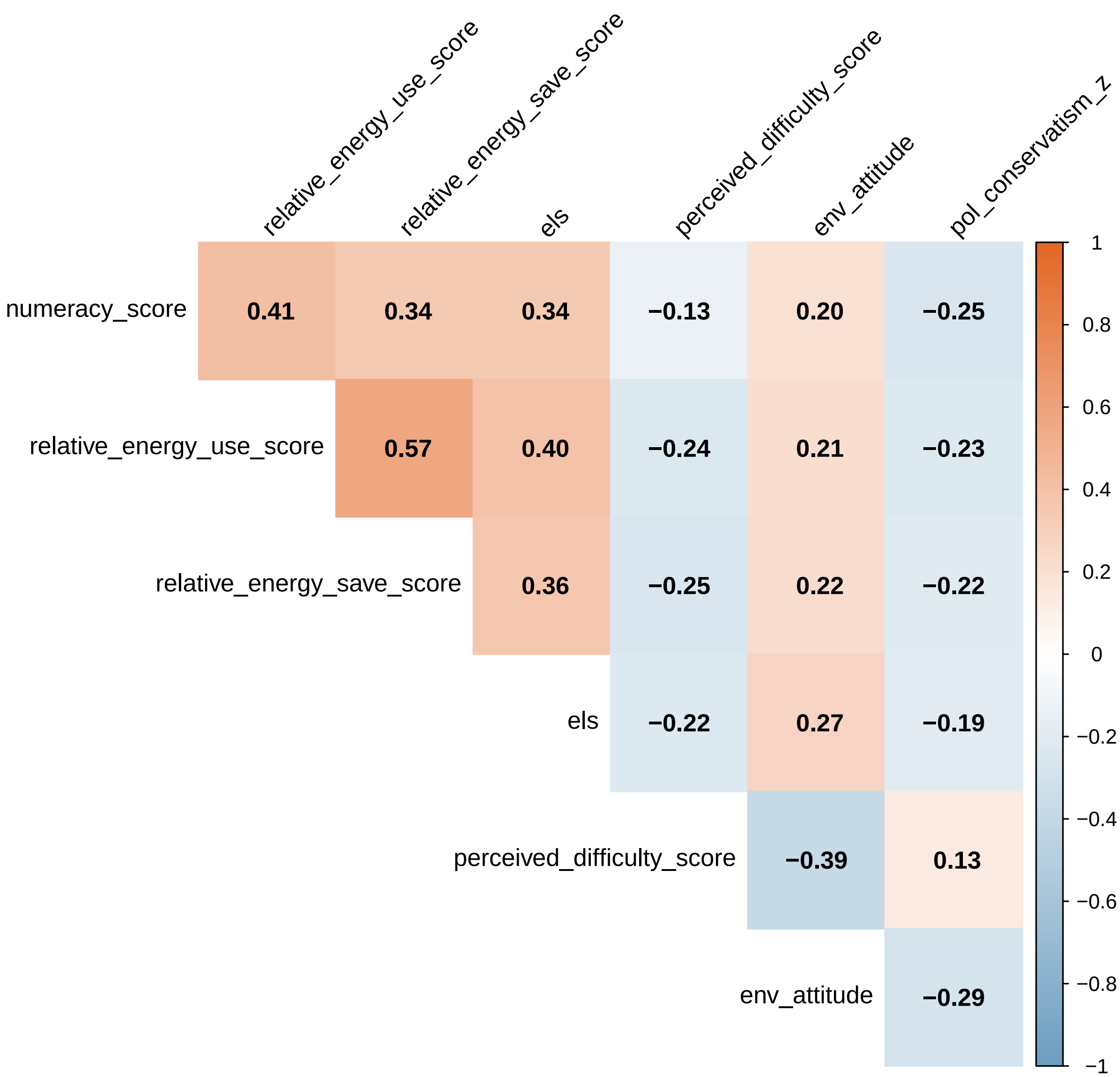
```r
# Visualize the interaction (example)
ggplot(combined_scores, aes(x = perceived_difficulty, y = els_score, color = env_attitude_z)
  geom_point() +
  geom_smooth(method = "lm", se = FALSE) +
  scale_color_gradient(low = "blue", high = "red") +
  labs(title = "Interaction of Perceived Difficulty and Environmental Attitude on ELS",
       x = "Perceived Difficulty",
       y = "Energy Literacy Score") +
  theme_minimal()
```



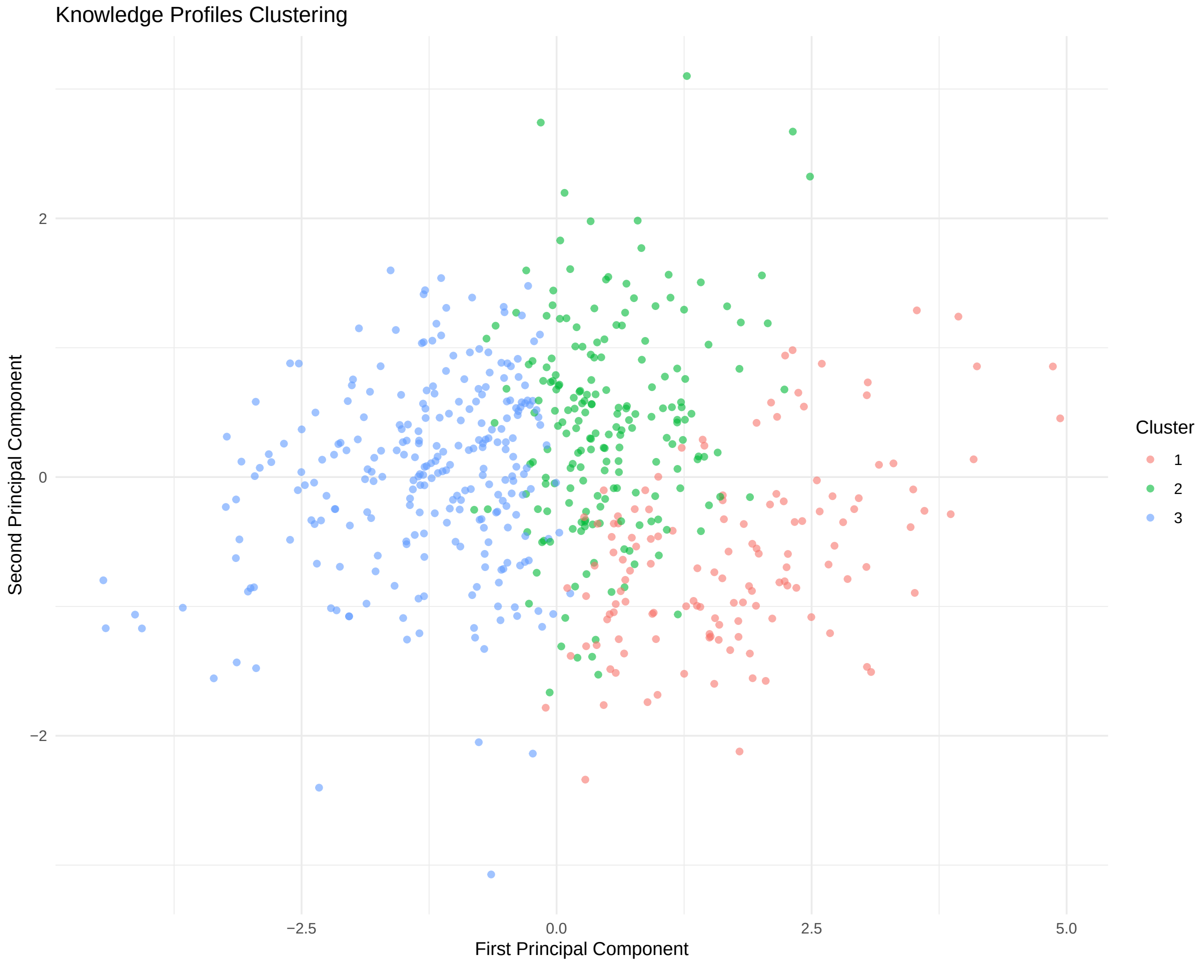

```r
combined_df <- attari1 %>%
  full_join(attari2_scores, by = "id") %>%
  full_join(els_scores,        by = "id") %>%
  full_join(rs_scores,         by = "id")


# 1. Create knowledge profiles using cluster analysis
knowledge_vars <- combined_df %>%
  select(numeracy_score, relative_energy_use_score,
```

```
        relative_energy_save_score, els)

set.seed(123)
clusters <- kmeans(scale(knowledge_vars), centers=3)

# Add cluster membership to data
combined_df$knowledge_cluster <- as.factor(clusters$cluster)

# Compare motivation scores across clusters
cluster_comparison <- combined_df %>%
  group_by(knowledge_cluster) %>%
  summarise(
    mean_env_attitude = mean(env_attitude, na.rm=TRUE),
    mean_difficulty = mean(perceived_difficulty_score, na.rm=TRUE)
  )

# 2. Test for non-linear relationships
library(mgcv)
gam_model <- gam(els ~ s(env_attitude) + s(perceived_difficulty_score),
                 data=combined_df)

# 3. Create interaction model between knowledge and motivation
interaction_model <- lm(els ~ env_attitude * perceived_difficulty_score +
                         numeracy_score, data=combined_df)




library(gridExtra)
library(factoextra)
library(mgcv)
library(corrplot)

# 1. Enhanced Correlation Plot
cor_matrix <- combined_df %>%
  select(numeracy_score, relative_energy_use_score,
         relative_energy_save_score, els,
         perceived_difficulty_score, env_attitude,
         pol_conservatism_z) %>%
  cor(use = "pairwise.complete.obs")

corrplot(cor_matrix,
```

```
         method = "color",
         type = "upper",
         addCoef.col = "black",
         tl.col = "black",
         tl.srt = 45,
         diag = FALSE,
         col = colorRampPalette(c("#6D9EC1", "white", "#E46726"))(200))
```



```r
# 2. Knowledge Profile Clustering
# Standardize knowledge variables
knowledge_vars <- combined_df %>%
  select(numeracy_score, relative_energy_use_score,
         relative_energy_save_score, els) %>%
  scale()

# Determine optimal number of clusters
set.seed(123)
wss <- sapply(1:10, function(k) {
  kmeans(knowledge_vars, centers=k)$tot.withinss
})

# Perform k-means clustering
k <- 3  # Based on elbow plot inspection
clusters <- kmeans(knowledge_vars, centers=k)

# Add cluster membership to data
combined_df$knowledge_cluster <- as.factor(clusters$cluster)

# Visualize clusters
pca_result <- prcomp(knowledge_vars)
cluster_df <- data.frame(
  PC1 = pca_result$x[,1],
  PC2 = pca_result$x[,2],
  Cluster = combined_df$knowledge_cluster
)

# Create cluster visualization
p_clusters <- ggplot(cluster_df, aes(x=PC1, y=PC2, color=Cluster)) +
  geom_point(alpha=0.6) +
  theme_minimal() +
  labs(title="Knowledge Profiles Clustering",
       x="First Principal Component",
       y="Second Principal Component")
p_clusters
```




```r
# 3. Non-linear GAM Analysis
gam_model <- gam(els ~ s(env_attitude) + s(perceived_difficulty_score),
                 data=combined_df)

# Create prediction grid for GAM visualization
env_grid <- seq(min(combined_df$env_attitude, na.rm=TRUE),
                max(combined_df$env_attitude, na.rm=TRUE),
                length.out=100)
diff_grid <- seq(min(combined_df$perceived_difficulty_score, na.rm=TRUE),
                 max(combined_df$perceived_difficulty_score, na.rm=TRUE),
                 length.out=100)

# Predict ELS scores
pred_env <- predict(gam_model,
                   newdata=data.frame(env_attitude=env_grid,
```

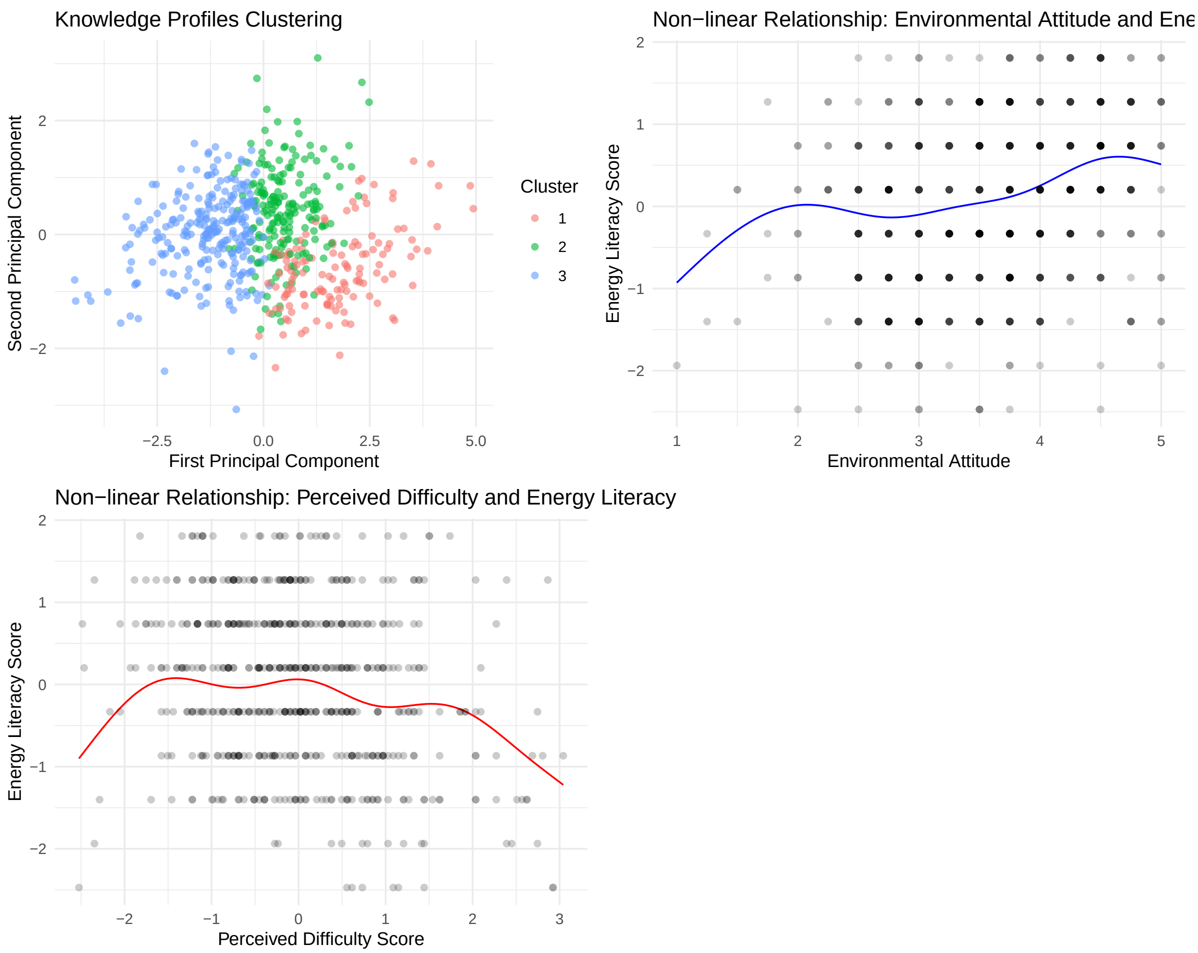
```
                                    perceived_difficulty_score=mean(combined_df$perceived_di
pred_diff <- predict(gam_model,
                    newdata=data.frame(perceived_difficulty_score=diff_grid,
                                     env_attitude=mean(combined_df$env_attitude, na.rm=TRUE)

# Create GAM plots
p_gam_env <- ggplot() +
  geom_line(aes(x=env_grid, y=pred_env), color="blue") +
  geom_point(data=combined_df, aes(x=env_attitude, y=els), alpha=0.2) +
  theme_minimal() +
  labs(title="Non-linear Relationship: Environmental Attitude and Energy Literacy",
       x="Environmental Attitude",
       y="Energy Literacy Score")

p_gam_diff <- ggplot() +
  geom_line(aes(x=diff_grid, y=pred_diff), color="red") +
  geom_point(data=combined_df, aes(x=perceived_difficulty_score, y=els), alpha=0.2) +
  theme_minimal() +
  labs(title="Non-linear Relationship: Perceived Difficulty and Energy Literacy",
       x="Perceived Difficulty Score",
       y="Energy Literacy Score")

#p_gam_diff


# 4. Knowledge-Motivation Interaction Analysis
interaction_model <- lm(els ~ env_attitude * perceived_difficulty_score +
                         numeracy_score, data=combined_df)

summary(interaction_model)
```

```

Call:
lm(formula = els ~ env_attitude * perceived_difficulty_score +
    numeracy_score, data = combined_df)

Residuals:
    Min      1Q  Median      3Q     Max
-3.0152 -0.6285  0.0088  0.6599  2.2174

Coefficients:
                                        Estimate Std. Error t value
```

```
(Intercept)                              -0.7906     0.1966   -4.02
env_attitude                              0.2192     0.0538    4.07
perceived_difficulty_score               -0.0550     0.1782   -0.31
numeracy_score                            0.2909     0.0387    7.52
env_attitude:perceived_difficulty_score  -0.0177     0.0488   -0.36
                                                Pr(>|t|)
(Intercept)                             0.00006570557947 ***
env_attitude                            0.00005257587373 ***
perceived_difficulty_score                          0.76
numeracy_score                          0.00000000000021 ***
env_attitude:perceived_difficulty_score             0.72
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.91 on 581 degrees of freedom
Multiple R-squared:  0.172, Adjusted R-squared:  0.166
F-statistic: 30.2 on 4 and 581 DF,  p-value: <0.0000000000000002
```

```r
# Create interaction plot data
env_levels <- quantile(combined_df$env_attitude, probs=c(0.25, 0.75), na.rm=TRUE)
diff_seq <- seq(min(combined_df$perceived_difficulty_score, na.rm=TRUE),
                max(combined_df$perceived_difficulty_score, na.rm=TRUE),
                length.out=100)

# pred_data <- expand.grid(
#   perceived_difficulty_score = diff_seq,
#   env_attitude = levels(factor(combined_df$env_attitude)),
#   numeracy_score = mean(combined_df$numeracy_score, na.rm=TRUE)
# )

# pred_data$predicted_els <- predict(interaction_model, newdata=pred_data)

# p_interaction <- ggplot(pred_data, aes(x=perceived_difficulty_score, y=predicted_els,
#                                        color=factor(env_attitude))) +
#   geom_line() +
#   theme_minimal() +
#   labs(title="Interaction between Environmental Attitude and Perceived Difficulty",
#        x="Perceived Difficulty Score",
#        y="Predicted Energy Literacy Score",
#        color="Environmental\nAttitude Level")

# Arrange all plots
```

```r
grid.arrange(p_clusters, p_gam_env, p_gam_diff, ncol=2)
```




```r
# Print statistical summaries
summary(gam_model)
```

```
Family: gaussian
Link function: identity

Formula:
els ~ s(env_attitude) + s(perceived_difficulty_score)

Parametric coefficients:
                        Estimate          Std. Error t value Pr(>|t|)
```

```
(Intercept) 0.00000000000000488 0.03867979305614088       0        1

Approximate significance of smooth terms:
                               edf Ref.df    F   p-value
s(env_attitude)               5.44   6.52 6.19 0.0000016 ***
s(perceived_difficulty_score) 6.28   7.42 3.76   0.00043 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

R-sq.(adj) =  0.123   Deviance explained = 14.1%
GCV = 0.89618  Scale est. = 0.87673   n = 586
```

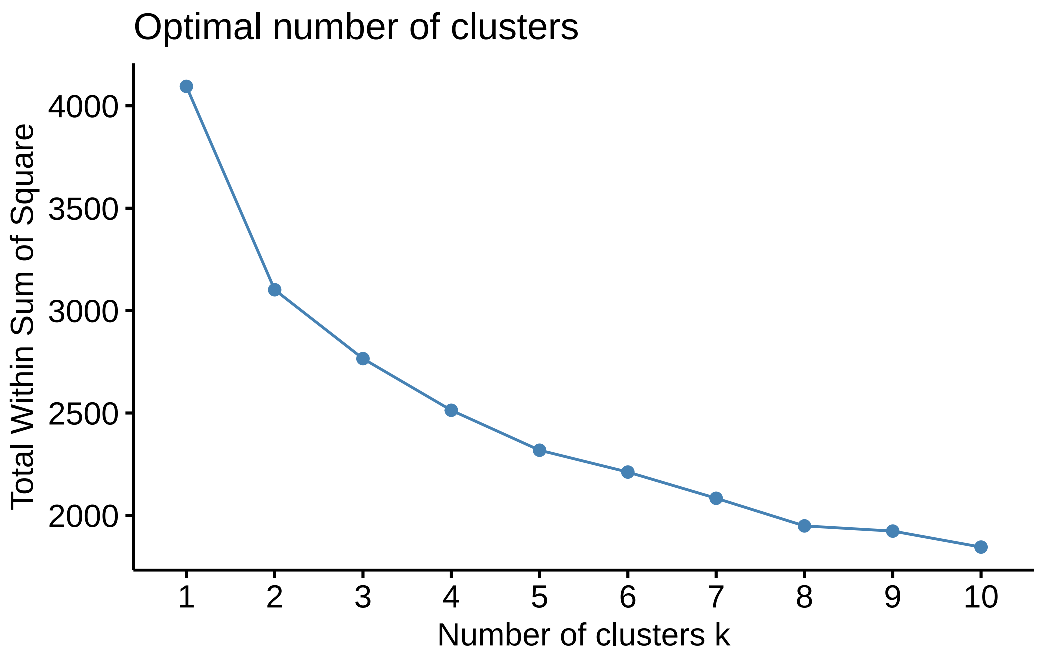
```
summary(interaction_model)
```

```
Call:
lm(formula = els ~ env_attitude * perceived_difficulty_score +
    numeracy_score, data = combined_df)

Residuals:
    Min      1Q  Median      3Q     Max
-3.0152 -0.6285  0.0088  0.6599  2.2174

Coefficients:
                                        Estimate Std. Error t value
(Intercept)                              -0.7906     0.1966   -4.02
env_attitude                              0.2192     0.0538    4.07
perceived_difficulty_score               -0.0550     0.1782   -0.31
numeracy_score                            0.2909     0.0387    7.52
env_attitude:perceived_difficulty_score  -0.0177     0.0488   -0.36
                                                Pr(>|t|)
(Intercept)                             0.00006570557947 ***
env_attitude                            0.00005257587373 ***
perceived_difficulty_score                          0.76
numeracy_score                          0.00000000000021 ***
env_attitude:perceived_difficulty_score             0.72
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.91 on 581 degrees of freedom
Multiple R-squared:  0.172, Adjusted R-squared:  0.166
F-statistic: 30.2 on 4 and 581 DF,  p-value: <0.0000000000000002
```

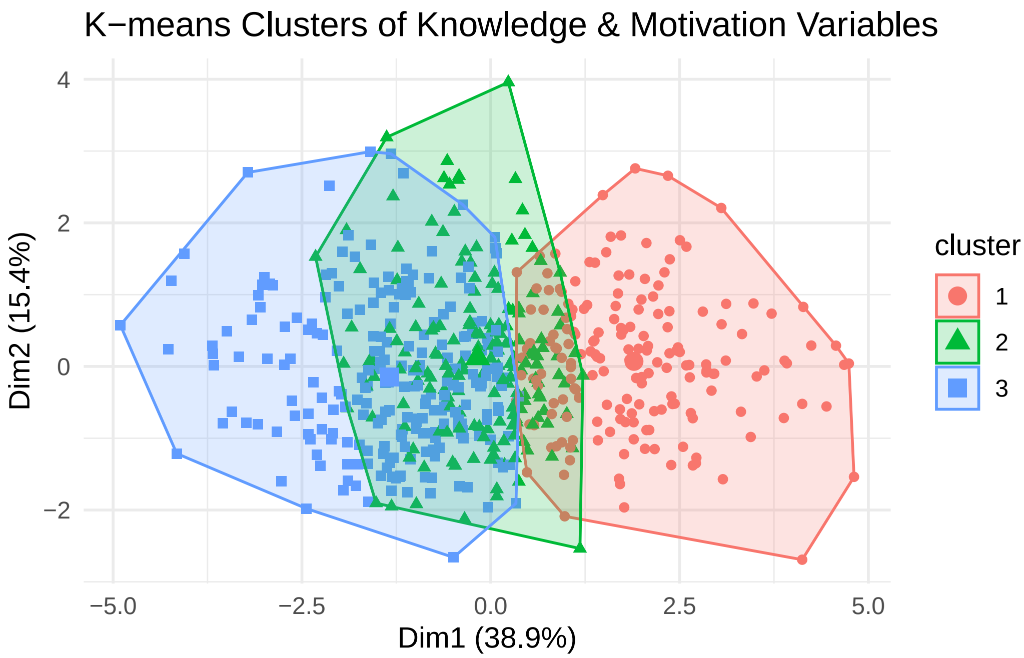
```r
# Cluster profile analysis
cluster_profiles <- combined_df %>%
  group_by(knowledge_cluster) %>%
  summarise(
    mean_numeracy = mean(numeracy_score, na.rm=TRUE),
    mean_energy_use = mean(relative_energy_use_score, na.rm=TRUE),
    mean_energy_save = mean(relative_energy_save_score, na.rm=TRUE),
    mean_els = mean(els, na.rm=TRUE),
    mean_env_attitude = mean(env_attitude, na.rm=TRUE),
    mean_difficulty = mean(perceived_difficulty_score, na.rm=TRUE),
    n = n()
  )

print(cluster_profiles)
```

```
# A tibble: 3 x 8
  knowledge_cluster mean_numeracy mean_energy_use mean_energy_save mean_els
  <fct>                     <dbl>           <dbl>            <dbl>    <dbl>
1 1                        -1.43           -0.670           -0.679   -0.790
2 2                         0.361          -0.386           -0.470   -0.463
3 3                         0.459           0.635            0.705    0.756
# i 3 more variables: mean_env_attitude <dbl>, mean_difficulty <dbl>, n <int>
```

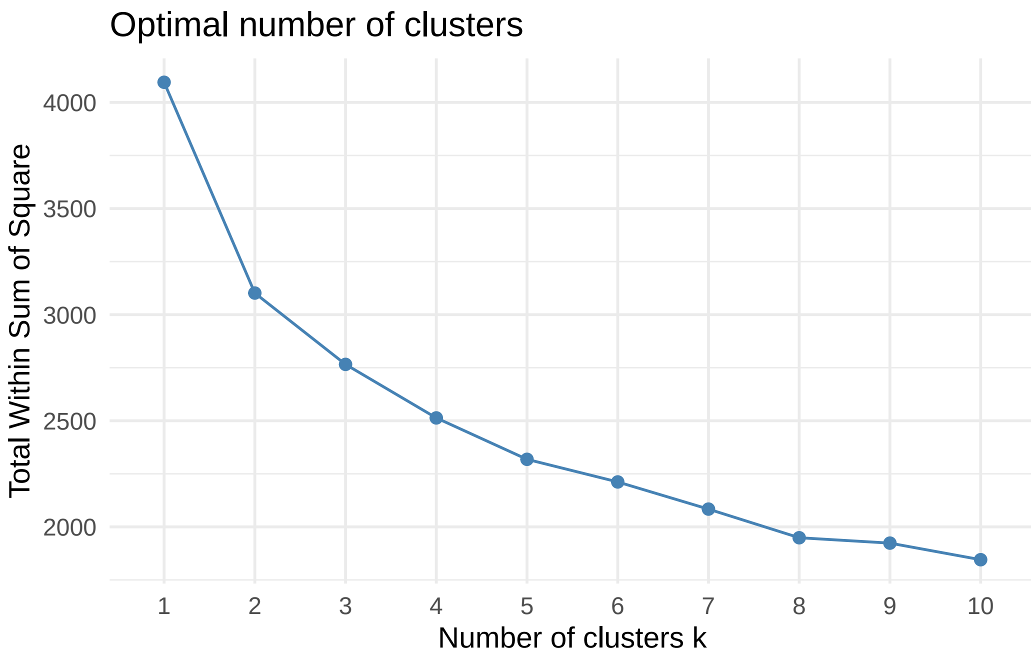
```r
# Example: K-means clustering on knowledge + motivation
library(dplyr)
library(factoextra)   # for visualization of clusters

# Subset your knowledge & motivation columns
cluster_data <- combined_df %>%
  select(numeracy_score, relative_energy_use_score, relative_energy_save_score,
         els, perceived_difficulty_score, env_attitude, pol_conservatism) %>%
  na.omit()

# Scale them
cluster_data_scaled <- scale(cluster_data)

# Decide on number of clusters (e.g. 2-5) - use e.g. Elbow method
fviz_nbclust(cluster_data_scaled, kmeans, method = "wss")
```



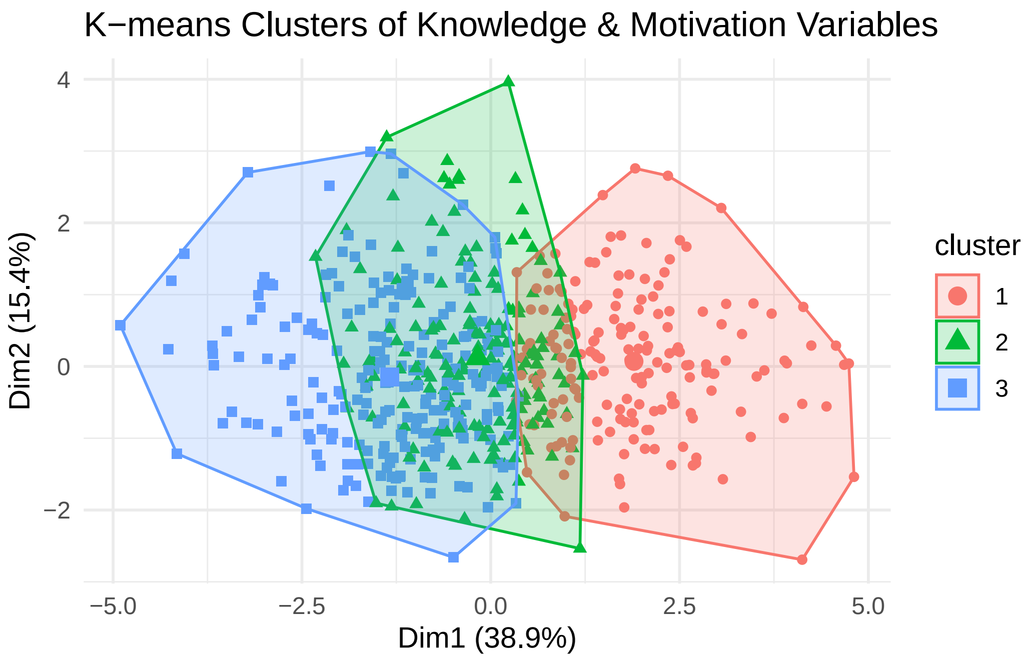

```
# Suppose we choose 3 clusters as a demonstration
set.seed(123)
km_result <- kmeans(cluster_data_scaled, centers = 3, nstart = 25)

# Add cluster membership back into the original data
cluster_data$cluster <- factor(km_result$cluster)

# Visualize clusters in 2D (using PCA behind the scenes)
fviz_cluster(km_result, data = cluster_data_scaled,
             geom = "point", ellipse.type = "convex") +
  theme_minimal() +
  labs(title = "K-means Clusters of Knowledge & Motivation Variables")
```




```
# 1. Grab relevant variables
cluster_data <- combined_df %>%
  select(numeracy_score, relative_energy_use_score, relative_energy_save_score,
         els, perceived_difficulty_score, env_attitude, pol_conservatism) %>%
  na.omit()

# 2. Standardize/scale them
cluster_data_scaled <- scale(cluster_data)

# 3. Determine the optimal number of clusters (Elbow or Silhouette methods)
fviz_nbclust(cluster_data_scaled, kmeans, method = "wss") +
  theme_minimal()
```



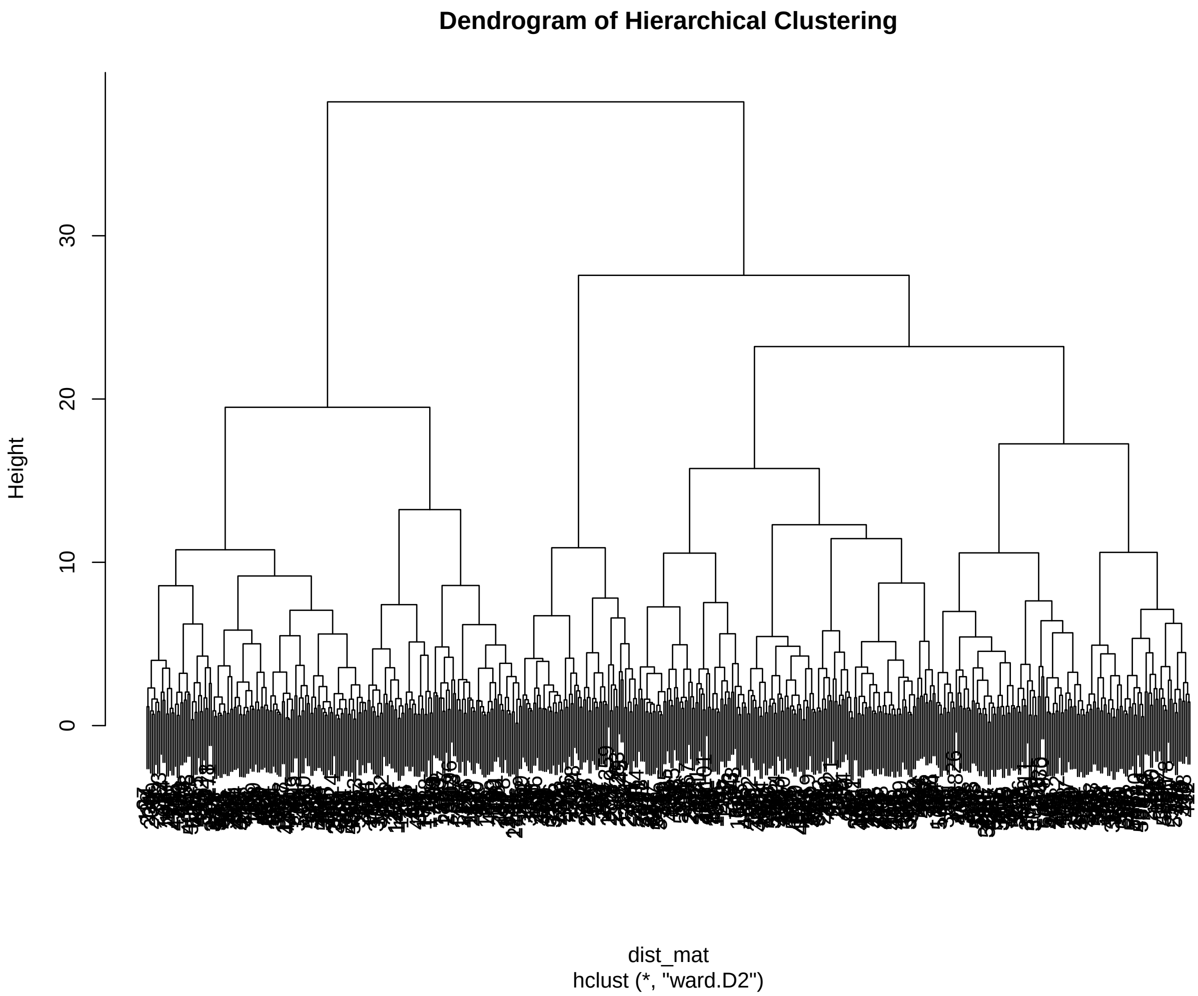

```
# 4. Run k-means with your chosen number of clusters (say k = 3)
set.seed(123)
km_res <- kmeans(cluster_data_scaled, centers = 3, nstart = 25)

# 5. Visualize
fviz_cluster(km_res, data = cluster_data_scaled,
             geom = "point", ellipse.type = "convex") +
  theme_minimal() +
  labs(title = "K-means Clusters of Knowledge & Motivation Variables")
```




```r
# 6. Inspect cluster means
cluster_centers <- as.data.frame(km_res$centers)
colnames(cluster_centers) <- colnames(cluster_data)
cluster_centers
```

```
  numeracy_score relative_energy_use_score relative_energy_save_score   els
1          -0.80                     -0.74                      -0.76 -0.89
2           0.19                      0.12                       0.13  0.33
3           0.48                      0.48                       0.49  0.44
  perceived_difficulty_score env_attitude pol_conservatism
1                       0.69      -0.6788             0.41
2                      -0.35       0.0008             0.84
3                      -0.27       0.5253            -0.96
```

```r
# Example of hierarchical clustering if that is preferred
dist_mat <- dist(cluster_data_scaled, method = "euclidean")
hc_res <- hclust(dist_mat, method = "ward.D2")
plot(hc_res, main = "Dendrogram of Hierarchical Clustering")
```




```r
# Cut tree at chosen k
clusters <- cutree(hc_res, k = 3)
table(clusters)
```

```
clusters
  1   2   3
211  65 310
```

```r
# Example mediation: knowledge -> perceived_difficulty -> env_attitude
library(lavaan)

model_mediation <- '
  # direct effect
  env_attitude ~ c*els
```

```r
  # mediator
  perceived_difficulty_score ~ a*els
  env_attitude ~ b*perceived_difficulty_score
  # indirect effect
  ab := a*b
  # total effect
  total := c + (a*b)
'

fit_mediation <- sem(model_mediation, data = combined_df, missing="fiml")
summary(fit_mediation, fit.measures=TRUE, standardized=TRUE, rsquare=TRUE)
```

```
lavaan 0.6-19 ended normally after 1 iteration

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                         7

  Number of observations                           586
  Number of missing patterns                         1

Model Test User Model:

  Test statistic                                 0.000
  Degrees of freedom                                 0

Model Test Baseline Model:

  Test statistic                               149.690
  Degrees of freedom                                 3
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    1.000
  Tucker-Lewis Index (TLI)                       1.000

  Robust Comparative Fit Index (CFI)             1.000
  Robust Tucker-Lewis Index (TLI)                1.000

Loglikelihood and Information Criteria:
```

```
  Loglikelihood user model (H0)              -1434.548
  Loglikelihood unrestricted model (H1)      -1434.548

  Akaike (AIC)                                2883.095
  Bayesian (BIC)                              2913.709
  Sample-size adjusted Bayesian (SABIC)       2891.486

Root Mean Square Error of Approximation:

  RMSEA                                          0.000
  90 Percent confidence interval - lower         0.000
  90 Percent confidence interval - upper         0.000
  P-value H_0: RMSEA <= 0.050                       NA
  P-value H_0: RMSEA >= 0.080                       NA

  Robust RMSEA                                   0.000
  90 Percent confidence interval - lower         0.000
  90 Percent confidence interval - upper         0.000
  P-value H_0: Robust RMSEA <= 0.050                NA
  P-value H_0: Robust RMSEA >= 0.080                NA

Standardized Root Mean Square Residual:

  SRMR                                           0.000

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Observed
  Observed information based on                Hessian

Regressions:
                             Estimate  Std.Err  z-value  P(>|z|)   Std.lv
  env_attitude ~
    els        (c)              0.152    0.029    5.151    0.000    0.152
  perceived_difficulty_score ~
    els        (a)             -0.222    0.040   -5.506    0.000   -0.222
  env_attitude ~
    prcvd_dff_ (b)             -0.263    0.029   -8.934    0.000   -0.263
  Std.all

    0.197
```

```
   -0.222

   -0.342

Intercepts:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .env_attitude      3.583    0.029  124.796    0.000    3.583    4.653
   .prcvd_dffclty_    0.000    0.040    0.000    1.000    0.000    0.000

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .env_attitude      0.483    0.028   17.117    0.000    0.483    0.815
   .prcvd_dffclty_    0.949    0.055   17.117    0.000    0.949    0.951

R-Square:
                   Estimate
    env_attitude      0.185
    prcvd_dffclty_    0.049

Defined Parameters:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
    ab                0.058    0.012    4.687    0.000    0.058    0.076
    total             0.210    0.031    6.862    0.000    0.210    0.273
```

---

```
combined_scores <- combined_df %>%
  mutate(
    # Example composite for knowledge: average of (z-scored) numeracy,
    # energy_use, energy_save, ELS.
    # (You can also sum them, but average is convenient.)
    composite_knowledge = rowMeans(
      cbind(numeracy_score, relative_energy_use_score,
            relative_energy_save_score, els),
      na.rm = FALSE  # If a row has missing for any item, result = NA
    ),

    # Example composite for motivation:
    # env_attitude might be already in a favorable direction, but if
    # perceived_difficulty is "difficulty," consider reversing so that
    # higher = "less difficulty" = "higher motivation."
    # For example: reverse_diff = (-1)*perceived_difficulty_score
```

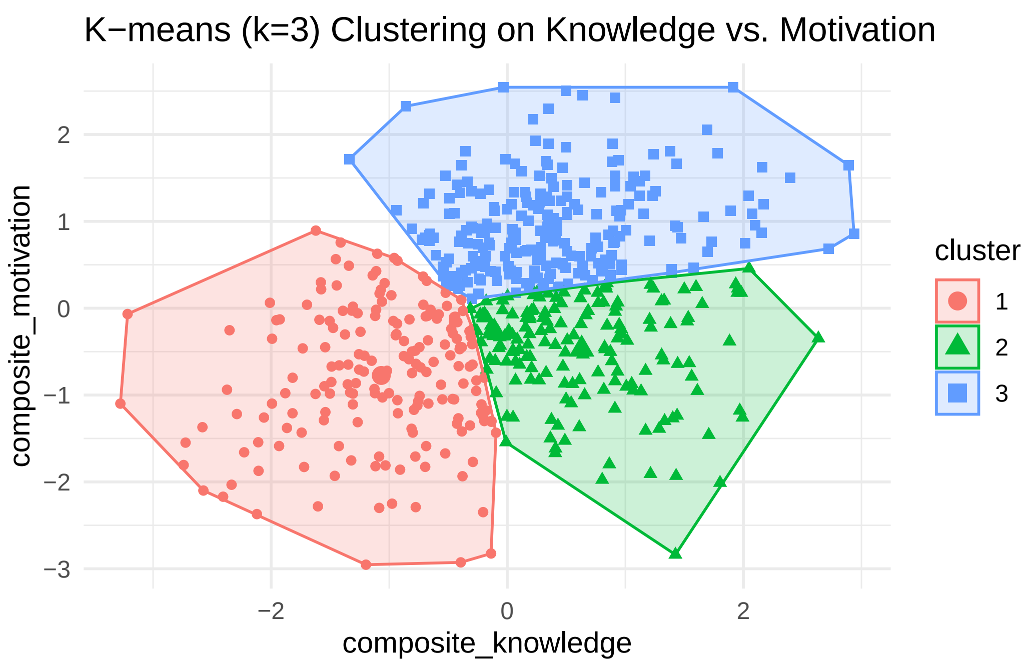
```
    # Then average with env_attitude (if you want them combined).
    # If you are including pol_conservatism as well, you must decide
    # how to handle that in the composite. Possibly reverse-coded
    # so that higher # = more liberal or more "pro-environment" stance.
    # (It's your theoretical call.)

    # For now, let's do a small composite with environmental attitude
    # and reversed difficulty:
    reverse_diff = -1 * perceived_difficulty_score,

    composite_motivation = rowMeans(
      cbind(env_attitude, reverse_diff),
      na.rm = FALSE
    )
  )
```

```
library(factoextra)  # for nice cluster visualizations

# We'll create a small data frame with just the two composites,
# removing any incomplete cases
cluster_data <- combined_scores %>%
  select(composite_knowledge, composite_motivation) %>%
  na.omit()

# Decide on number of clusters "k". Let's try k = 3:
set.seed(123)
km3 <- kmeans(cluster_data, centers = 3, nstart = 25)

# Inspect results
km3
```

```
K-means clustering with 3 clusters of sizes 184, 167, 235

Cluster means:
  composite_knowledge composite_motivation
1               -0.79                  1.2
2                0.47                  1.4
3                0.29                  2.5

Clustering vector:
```

```
  [1] 2 3 1 3 2 3 3 1 2 3 3 3 1 3 1 1 1 1 1 3 3 2 1 3 3 3 2 3 1 1 2 2 2 3 2 2 2
 [38] 1 3 2 1 3 2 1 2 3 3 1 1 1 2 2 3 1 3 2 3 3 1 3 2 3 1 2 3 2 1 3 1 3 3 1 3 2
 [75] 2 3 1 3 1 3 3 3 3 2 2 2 1 2 3 1 2 3 3 3 2 3 1 3 2 3 3 3 3 2 2 2 3 3 3 3 2
[112] 3 2 3 3 1 3 3 2 2 2 1 3 3 2 2 3 3 2 2 3 3 3 3 1 1 3 3 3 1 3 1 3 2 3 3 2 2
[149] 2 3 3 2 2 1 3 3 1 2 2 1 2 3 3 2 3 1 3 3 2 2 3 2 2 1 2 3 1 3 2 2 2 3 3 1 2
[186] 1 2 2 3 3 3 2 1 2 2 2 3 2 3 2 3 2 3 1 1 1 3 3 3 2 1 2 3 1 2 1 3 2 2 3 2 2
[223] 3 1 3 1 2 2 3 2 1 1 2 2 3 2 1 3 1 1 1 2 2 1 1 1 3 1 3 1 3 1 1 2 1 2 1 1 1
[260] 3 1 3 1 3 3 1 1 1 3 1 1 1 1 1 3 3 1 2 1 1 1 1 1 1 1 3 1 3 2 1 1 3 1 2 2 2
[297] 2 3 2 2 3 2 1 3 3 1 2 1 1 1 1 2 2 3 2 1 3 1 1 2 3 3 2 2 3 3 1 1 1 2 2 1 3
[334] 1 3 3 3 1 1 1 2 2 2 1 3 3 3 1 1 3 1 2 2 3 2 2 1 1 1 1 1 3 3 1 2 3 3 2 1 3
[371] 1 2 3 3 3 2 1 3 2 3 3 3 3 2 1 3 2 3 3 3 1 1 1 1 2 2 1 3 3 3 3 2 3 1 1 3 1
[408] 3 2 2 2 1 2 2 3 1 2 3 3 2 3 1 2 3 1 1 3 3 1 1 3 2 2 1 3 1 3 2 2 3 2 3 1 1
[445] 2 1 1 2 3 3 2 1 3 1 2 2 2 2 3 1 1 2 2 3 3 2 3 3 1 3 2 3 1 3 3 1 2 3 3 1 3
[482] 3 3 2 3 3 2 2 3 1 1 1 2 1 3 1 1 3 1 1 3 1 3 3 3 1 3 3 3 3 3 3 1 2 2 3 3 1
[519] 3 1 2 3 2 1 2 2 1 2 3 3 3 3 3 3 1 3 3 3 3 1 3 1 3 2 1 1 2 3 3 1 2 1 3 1 1
[556] 2 1 1 1 1 3 1 3 2 1 3 3 2 2 3 3 3 2 1 3 3 1 1 1 3 3 2 3 3 3 2

Within cluster sum of squares by cluster:
[1] 103  67 108
 (between_SS / total_SS =  57.0 %)

Available components:

[1] "cluster"      "centers"      "totss"        "withinss"     "tot.withinss"
[6] "betweenss"    "size"         "iter"         "ifault"
```

```
# Visualize
fviz_cluster(km3, data = cluster_data,
             geom = "point", ellipse.type = "convex") +
  theme_minimal() +
  labs(title = "K-means (k=3) Clustering on Knowledge vs. Motivation")
```



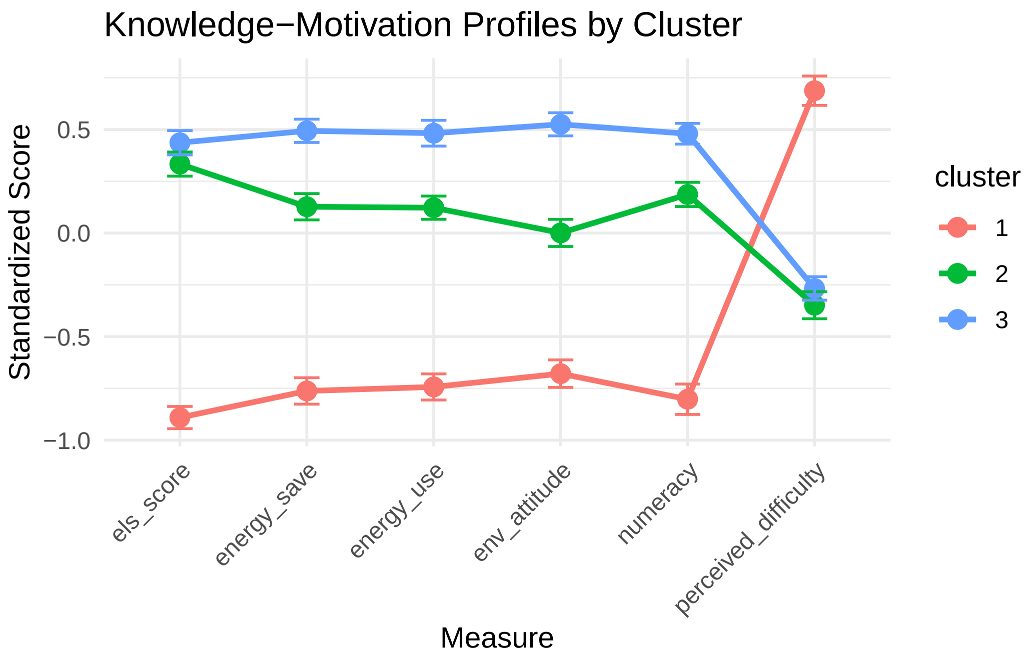

```
combined_scores$cluster <- factor(km3$cluster)

# Compare mean knowledge & motivation by cluster
combined_scores %>%
  group_by(cluster) %>%
  summarize(
    n = n(),
    mean_knowledge = mean(composite_knowledge, na.rm = TRUE),
    mean_motivation = mean(composite_motivation, na.rm = TRUE)
  )
```

```
# A tibble: 3 x 4
  cluster     n mean_knowledge mean_motivation
  <fct>   <int>          <dbl>           <dbl>
1 1         184         -0.794            1.22
2 2         167          0.469            1.44
3 3         235          0.288            2.49
```

---

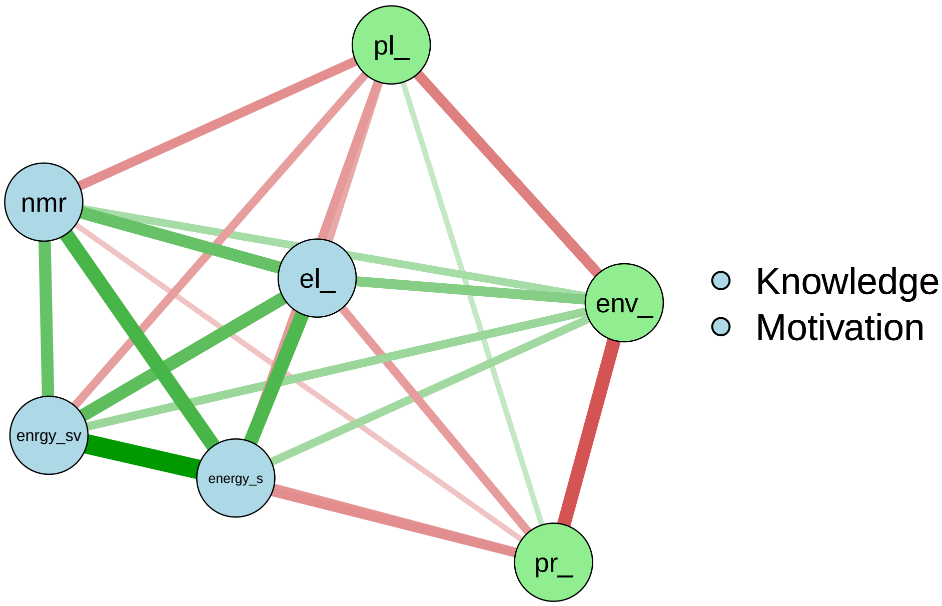
#1b

```r
combined_scores <- attari1 %>%
  left_join(attari2_scores, by="id") %>%
  left_join(els_scores, by="id") %>%
  left_join(rs_scores, by="id")

# Rename columns for clarity
names(combined_scores) <- c("id", "perceived_difficulty", "numeracy",
                            "energy_use", "energy_save",
                            "els_accuracy", "els_score",
                            "env_attitude", "env_attitude_z",
                            "pol_conservatism", "pol_conservatism_z")

combined_scores$cluster <- as.factor(km_result$cluster)

# Create composite knowledge score
combined_scores$composite_knowledge <- rowMeans(combined_scores[, c("numeracy", "energy_use"

# Create standardized scores for profile analysis
profile_data <- combined_scores %>%
  select(id, cluster, numeracy, energy_use, energy_save,
         els_score, env_attitude, perceived_difficulty) %>%
  gather(measure, value, -id, -cluster) %>%
  group_by(measure) %>%
  mutate(z_score = scale(value)[,1]) %>%
  ungroup()

# Create profile plot
ggplot(profile_data, aes(x = measure, y = z_score, color = cluster, group = cluster)) +
  stat_summary(fun = mean, geom = "line", size = 1) +
  stat_summary(fun = mean, geom = "point", size = 3) +
  stat_summary(fun.data = mean_se, geom = "errorbar", width = 0.2) +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1)) +
  labs(title = "Knowledge-Motivation Profiles by Cluster",
       x = "Measure", y = "Standardized Score")
```




```
# 2. Canonical Correlation Analysis between Knowledge and Motivation Sets
library(CCA)

select <- dplyr::select

# Prepare matrices
knowledge_vars <- combined_scores %>% select(numeracy, energy_use, energy_save, els_score) %>%
  as.matrix()

motivation_vars <- combined_scores %>%
  select(env_attitude, perceived_difficulty, pol_conservatism) %>%
  as.matrix()

# Perform CCA
cc_result <- cancor(knowledge_vars, motivation_vars)

# 3. Network Analysis to Visualize Variable Relationships
library(qgraph)

# Create correlation matrix
cor_matrix <- cor(combined_scores %>%
                    select(numeracy, energy_use, energy_save, els_score,
                           env_attitude, perceived_difficulty, pol_conservatism),
                  use = "pairwise.complete.obs")
```

```r
# Create network plot
qgraph(cor_matrix,
       layout = "spring",
       groups = list(Knowledge = 1:4, Motivation = 5:7),
       color = c(rep("lightblue", 4), rep("lightgreen", 3)))
```




```r
# 4. Mixed Effects Model to Account for Potential Group-Level Effects
library(lme4)

mixed_model <- lmer(els_score ~ env_attitude + perceived_difficulty +
                      (1|cluster), data = combined_scores)
summary(mixed_model)
```

```
Linear mixed model fit by REML ['lmerMod']
Formula: els_score ~ env_attitude + perceived_difficulty + (1 | cluster)
   Data: combined_scores

REML criterion at convergence: 1432

Scaled residuals:
   Min     1Q Median     3Q    Max
-3.446 -0.743  0.019  0.716  2.054
```

```
Random effects:
 Groups   Name        Variance Std.Dev.
 cluster  (Intercept) 0.583    0.763
 Residual             0.650    0.806
Number of obs: 586, groups:  cluster, 3

Fixed effects:
                     Estimate Std. Error t value
(Intercept)           -0.1027     0.4782   -0.21
env_attitude           0.0172     0.0515    0.33
perceived_difficulty   0.0600     0.0386    1.55

Correlation of Fixed Effects:
            (Intr) env_tt
env_attitud -0.382
prcvd_dffcl -0.095  0.244
```

```r
# 5. Structural Equation Model for Path Analysis
library(lavaan)

# Define model
model <- '
  # Measurement model
  knowledge =~ numeracy + energy_use + energy_save + els_score
  motivation =~ env_attitude + perceived_difficulty + pol_conservatism

  # Structural model
  knowledge ~ motivation
'

# Fit model
fit <- sem(model, data = combined_scores)
summary(fit, standardized = TRUE, fit.measures = TRUE)
```

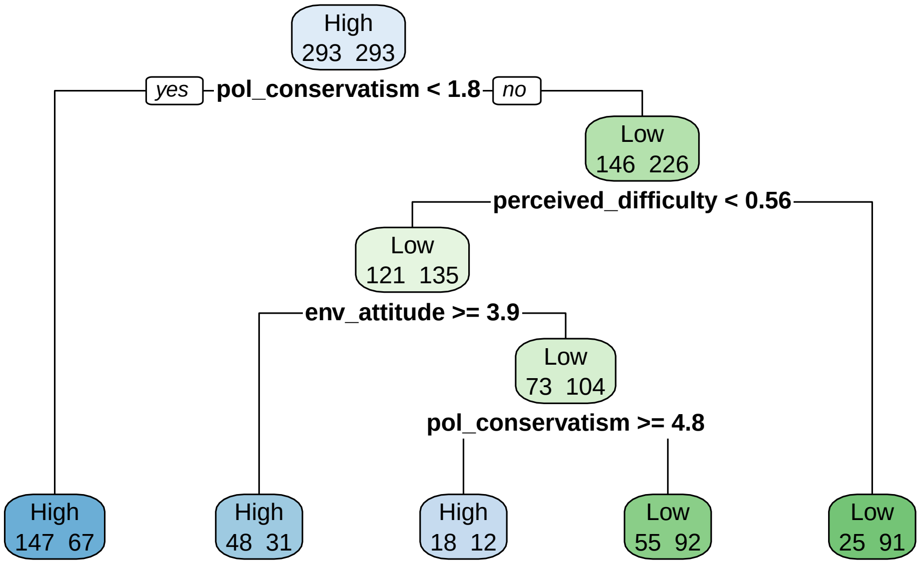
```
lavaan 0.6-19 ended normally after 36 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        15

  Number of observations                           586
```

```
Model Test User Model:

  Test statistic                                48.061
  Degrees of freedom                                13
  P-value (Chi-square)                           0.000

Model Test Baseline Model:

  Test statistic                               765.733
  Degrees of freedom                                21
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.953
  Tucker-Lewis Index (TLI)                       0.924

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5510.805
  Loglikelihood unrestricted model (H1)      -5486.775

  Akaike (AIC)                               11051.610
  Bayesian (BIC)                             11117.210
  Sample-size adjusted Bayesian (SABIC)      11069.590

Root Mean Square Error of Approximation:

  RMSEA                                          0.068
  90 Percent confidence interval - lower         0.048
  90 Percent confidence interval - upper         0.089
  P-value H_0: RMSEA <= 0.050                    0.068
  P-value H_0: RMSEA >= 0.080                    0.180

Standardized Root Mean Square Residual:

  SRMR                                           0.045

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured
```

```
Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  knowledge =~
    numeracy          1.000                               0.534    0.534
    energy_use        1.441    0.131   10.978    0.000    0.769    0.769
    energy_save       1.331    0.123   10.786    0.000    0.710    0.711
    els_score         1.024    0.109    9.393    0.000    0.546    0.547
  motivation =~
    env_attitude      1.000                               0.506    0.657
    percvd_dffclty   -1.068    0.142   -7.515    0.000   -0.540   -0.541
    pol_conservtsm   -1.159    0.175   -6.635    0.000   -0.586   -0.413

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  knowledge ~
    motivation        0.609    0.094    6.497    0.000    0.577    0.577

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .numeracy          0.714    0.047   15.120    0.000    0.714    0.715
   .energy_use        0.408    0.042    9.619    0.000    0.408    0.408
   .energy_save       0.494    0.042   11.665    0.000    0.494    0.495
   .els_score         0.700    0.047   14.976    0.000    0.700    0.701
   .env_attitude      0.337    0.037    9.074    0.000    0.337    0.569
   .percvd_dffclty    0.706    0.056   12.591    0.000    0.706    0.708
   .pol_conservtsm    1.668    0.111   14.976    0.000    1.668    0.829
   .knowledge         0.190    0.034    5.553    0.000    0.667    0.667
    motivation        0.256    0.042    6.021    0.000    1.000    1.000
```

```r
# 6. Classification Tree for Predicting Knowledge Levels
library(rpart)
library(rpart.plot)

# Create binary knowledge indicator (high/low) based on median split
combined_scores$knowledge_level <- factor(ifelse(combined_scores$composite_knowledge >
                                               median(combined_scores$composite_knowledge, na
                                               "High", "Low"))

# Fit tree
tree_model <- rpart(knowledge_level ~ env_attitude + perceived_difficulty +
                    pol_conservatism, data = combined_scores)
```

```r
# Plot tree
rpart.plot(tree_model, extra = 1)
```



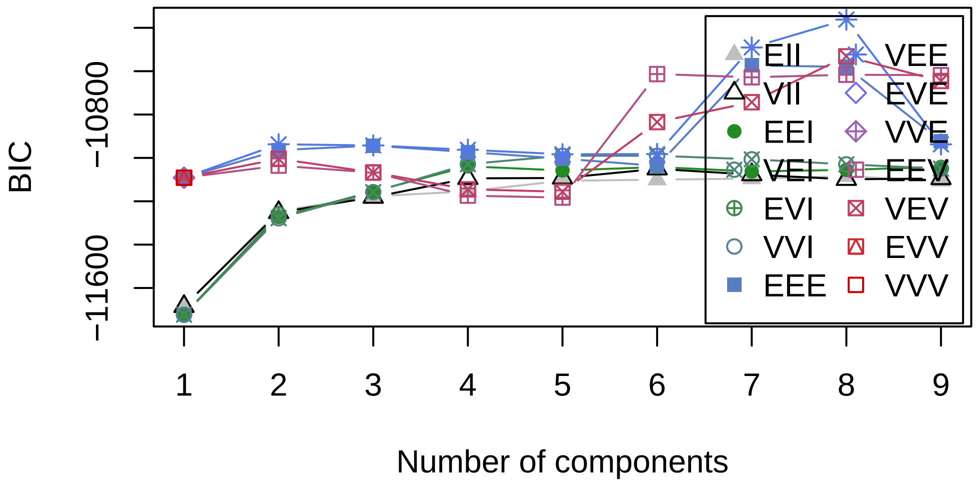

---

## 2b

```r
library(mclust)
lpa_model <- Mclust(cluster_data_scaled)
summary(lpa_model)
```

```
----------------------------------------------------
Gaussian finite mixture model fitted by EM algorithm
----------------------------------------------------

Mclust VEE (ellipsoidal, equal shape and orientation) model with 8 components:

 log-likelihood   n df    BIC    ICL
          -4869 586 98 -10362 -10419

Clustering table:
  1   2   3   4   5   6   7   8
 54 123 115  30  81  68  83  32
```

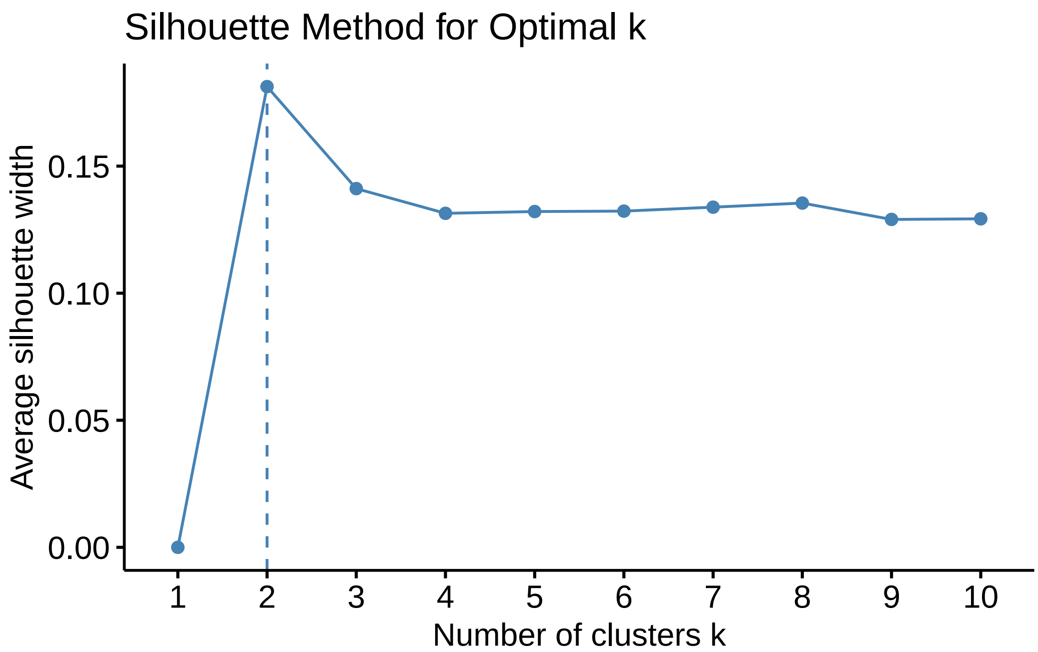
```r
plot(lpa_model, "BIC")
```




```r
can_cor <- cancor(select(combined_scores, numeracy, energy_use, energy_save),
                  select(combined_scores, env_attitude_z, perceived_difficulty))
print(can_cor$cor)
```

```
[1] 0.324 0.084
```

```r
fviz_nbclust(cluster_data_scaled, cluster::pam, method = "silhouette") +
  labs(title = "Silhouette Method for Optimal k")
```




```
sem_model <- '
  knowledge =~ numeracy + energy_use + energy_save + els_accuracy
  motivation =~ env_attitude_z + perceived_difficulty
  knowledge ~ motivation
'
fit <- sem(sem_model, data = combined_scores)
summary(fit, standardized = TRUE)
```

```
lavaan 0.6-19 ended normally after 34 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        13

  Number of observations                           586

Model Test User Model:

  Test statistic                                23.012
  Degrees of freedom                                 8
  P-value (Chi-square)                           0.003

Parameter Estimates:
```

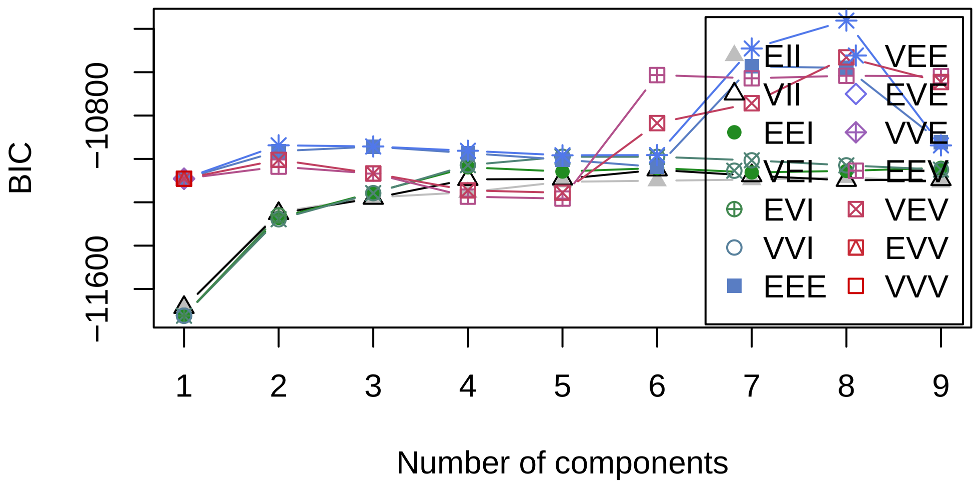
```
  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  knowledge =~
    numeracy          1.000                               0.527    0.527
    energy_use        1.469    0.136   10.825    0.000    0.774    0.774
    energy_save       1.352    0.127   10.662    0.000    0.712    0.713
    els_accuracy      1.925    0.208    9.263    0.000    1.014    0.543
  motivation =~
    env_attitude_z    1.000                               0.618    0.619
    percvd_dffclty   -1.006    0.160   -6.283    0.000   -0.622   -0.623

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  knowledge ~
    motivation        0.450    0.076    5.903    0.000    0.529    0.529

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .numeracy          0.721    0.047   15.176    0.000    0.721    0.722
   .energy_use        0.400    0.043    9.282    0.000    0.400    0.400
   .energy_save       0.491    0.043   11.489    0.000    0.491    0.492
   .els_accuracy      2.463    0.164   15.004    0.000    2.463    0.705
   .env_attitude_z    0.616    0.070    8.860    0.000    0.616    0.617
   .percvd_dffclty    0.611    0.070    8.726    0.000    0.611    0.612
   .knowledge         0.200    0.036    5.586    0.000    0.721    0.721
    motivation        0.382    0.075    5.087    0.000    1.000    1.000
```

```r
combined_scores %>%
  group_by(cluster) %>%
  summarise(across(c(numeracy, env_attitude_z),
                   list(mean = mean, sd = sd)))
```

```
# A tibble: 3 x 5
  cluster numeracy_mean numeracy_sd env_attitude_z_mean env_attitude_z_sd
  <fct>           <dbl>       <dbl>               <dbl>             <dbl>
1 1              -0.802       0.983           -0.679                0.890
2 2               0.187       0.774            0.000799             0.869
```

```
3 3                  0.480        0.761            0.525                 0.848
```

```r
plot(lpa_model, "BIC") # Visualize model selection
```




```r
lpa_3class <- Mclust(cluster_data_scaled, G=3) # Force 3-class solution
summary(lpa_3class, parameters=TRUE)
```

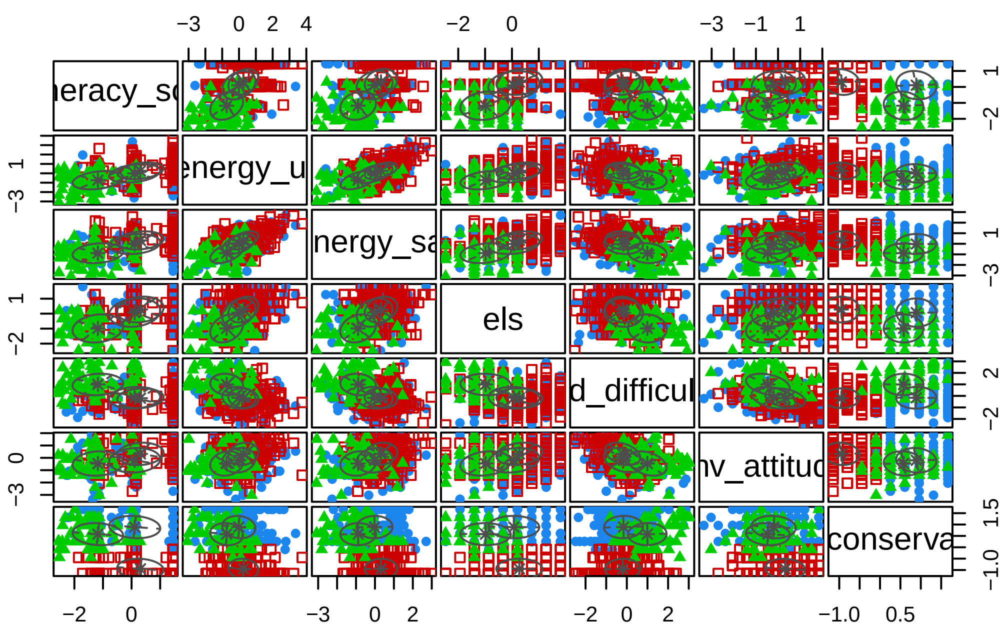
```
----------------------------------------------------
Gaussian finite mixture model fitted by EM algorithm
----------------------------------------------------

Mclust VEE (ellipsoidal, equal shape and orientation) model with 3 components:

 log-likelihood   n df    BIC    ICL
          -5302 586 53 -10943 -11055

Clustering table:
  1   2   3
236 270  80

Mixing probabilities:
   1    2    3
0.39 0.46 0.16

Means:
                             [,1]  [,2]  [,3]
numeracy_score              0.108  0.31 -1.18
```

```
relative_energy_use_score  -0.010  0.26 -0.74
relative_energy_save_score -0.021  0.32 -0.89
els                         0.069  0.28 -0.98
perceived_difficulty_score -0.163 -0.20  0.99
env_attitude               -0.196  0.32 -0.46
pol_conservatism            0.889 -0.95  0.58

Variances:
[,,1]
                           numeracy_score relative_energy_use_score
numeracy_score                      0.800                      0.27
relative_energy_use_score           0.266                      0.97
relative_energy_save_score          0.151                      0.47
els                                 0.127                      0.27
perceived_difficulty_score          0.087                     -0.11
env_attitude                        0.088                      0.13
pol_conservatism                   -0.051                     -0.05
                           relative_energy_save_score     els
numeracy_score                                 0.1511  0.1272
relative_energy_use_score                      0.4697  0.2750
relative_energy_save_score                     0.9038  0.2033
els                                            0.2033  0.8974
perceived_difficulty_score                    -0.0940 -0.0432
env_attitude                                   0.1237  0.1850
pol_conservatism                               0.0079 -0.0076
                           perceived_difficulty_score env_attitude
numeracy_score                                  0.087        0.088
relative_energy_use_score                      -0.108        0.133
relative_energy_save_score                     -0.094        0.124
els                                            -0.043        0.185
perceived_difficulty_score                      0.890       -0.326
env_attitude                                   -0.326        0.996
pol_conservatism                                0.014       -0.044
                           pol_conservatism
numeracy_score                      -0.0507
relative_energy_use_score           -0.0504
relative_energy_save_score           0.0079
els                                 -0.0076
perceived_difficulty_score           0.0139
env_attitude                        -0.0441
pol_conservatism                     0.2415
[,,2]
                           numeracy_score relative_energy_use_score
```

```
numeracy_score                        0.658                    0.219
relative_energy_use_score             0.219                    0.798
relative_energy_save_score            0.124                    0.386
els                                   0.105                    0.226
perceived_difficulty_score            0.071                   -0.089
env_attitude                          0.073                    0.109
pol_conservatism                     -0.042                   -0.041
                           relative_energy_save_score     els
numeracy_score                                 0.1243  0.1046
relative_energy_use_score                      0.3863  0.2262
relative_energy_save_score                     0.7434  0.1672
els                                            0.1672  0.7381
perceived_difficulty_score                    -0.0773 -0.0355
env_attitude                                   0.1018  0.1522
pol_conservatism                               0.0065 -0.0063
                           perceived_difficulty_score env_attitude
numeracy_score                                  0.071        0.073
relative_energy_use_score                      -0.089        0.109
relative_energy_save_score                     -0.077        0.102
els                                            -0.036        0.152
perceived_difficulty_score                      0.732       -0.268
env_attitude                                   -0.268        0.819
pol_conservatism                                0.011       -0.036
                           pol_conservatism
numeracy_score                      -0.0417
relative_energy_use_score           -0.0415
relative_energy_save_score           0.0065
els                                 -0.0063
perceived_difficulty_score           0.0114
env_attitude                        -0.0363
pol_conservatism                     0.1987
[,,3]
                           numeracy_score relative_energy_use_score
numeracy_score                      0.785                    0.261
relative_energy_use_score           0.261                    0.952
relative_energy_save_score          0.148                    0.461
els                                 0.125                    0.270
perceived_difficulty_score          0.085                   -0.106
env_attitude                        0.087                    0.130
pol_conservatism                   -0.050                   -0.049
                           relative_energy_save_score     els
numeracy_score                                 0.1483  0.1248
relative_energy_use_score                      0.4608  0.2698
```

```
relative_energy_save_score                           0.8868  0.1994
els                                                  0.1994  0.8806
perceived_difficulty_score                          -0.0922 -0.0424
env_attitude                                         0.1214  0.1816
pol_conservatism                                     0.0078 -0.0075
                           perceived_difficulty_score env_attitude
numeracy_score                                     0.085        0.087
relative_energy_use_score                         -0.106        0.130
relative_energy_save_score                        -0.092        0.121
els                                               -0.042        0.182
perceived_difficulty_score                         0.874       -0.320
env_attitude                                      -0.320        0.977
pol_conservatism                                   0.014       -0.043
                           pol_conservatism
numeracy_score                      -0.0498
relative_energy_use_score           -0.0494
relative_energy_save_score           0.0078
els                                 -0.0075
perceived_difficulty_score           0.0136
env_attitude                        -0.0432
pol_conservatism                     0.2370
```

```
plot(lpa_3class, what="classification") # Visualize classification
```



```r
# 2. Interpret canonical variables
cancor_loadings <- can_cor$xcoef %>%
  as.data.frame() %>%
  rownames_to_column("variable") %>%
  rename(Dimension1=V1, Dimension2=V2, Dimension3=V3)
print(cancor_loadings)
```

```
     variable Dimension1 Dimension2 Dimension3
1    numeracy      0.010      0.045    0.00041
2  energy_use      0.017     -0.019    0.04573
3 energy_save      0.023     -0.012   -0.04353
```

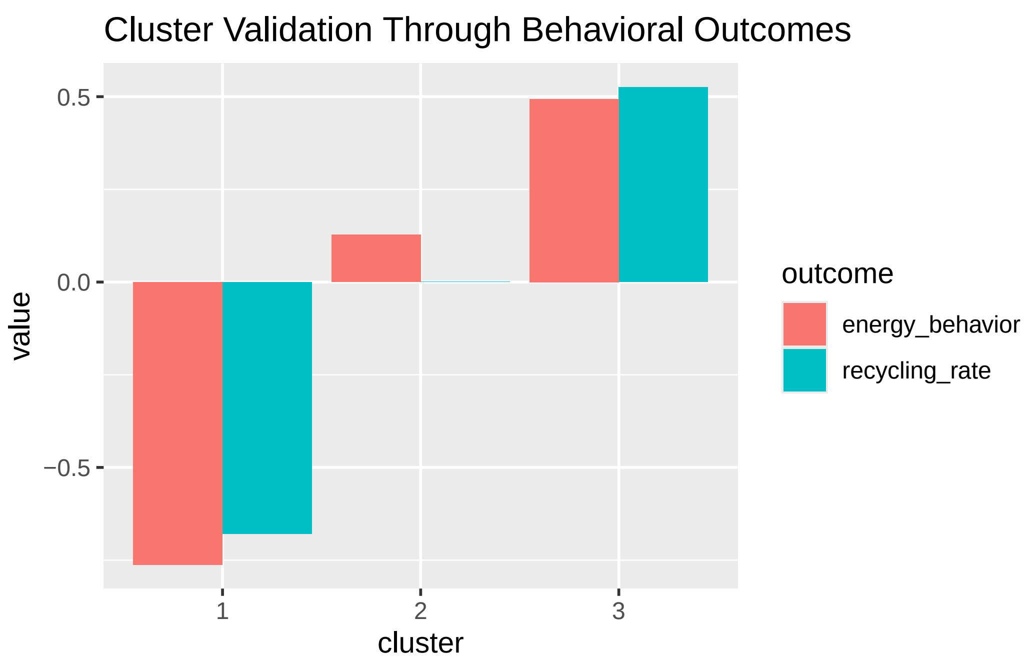
```r
# 3. Improve SEM specification
sem_improved <- '
  knowledge =~ numeracy + energy_use + energy_save + els_accuracy
  motivation =~ env_attitude_z + perceived_difficulty
  knowledge ~ motivation
  els_accuracy ~~ energy_use # Add residual covariance
'
fit_improved <- sem(sem_improved, data=combined_scores)
summary(fit_improved, fit.measures=TRUE)
```

```
lavaan 0.6-19 ended normally after 37 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        14

  Number of observations                           586

Model Test User Model:

  Test statistic                                19.280
  Degrees of freedom                                 7
  P-value (Chi-square)                           0.007

Model Test Baseline Model:

  Test statistic                               680.231
  Degrees of freedom                                15
  P-value                                        0.000
```

```
User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.982
  Tucker-Lewis Index (TLI)                       0.960

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -5022.340
  Loglikelihood unrestricted model (H1)      -5012.700

  Akaike (AIC)                               10072.681
  Bayesian (BIC)                             10133.907
  Sample-size adjusted Bayesian (SABIC)      10089.462

Root Mean Square Error of Approximation:

  RMSEA                                          0.055
  90 Percent confidence interval - lower         0.026
  90 Percent confidence interval - upper         0.085
  P-value H_0: RMSEA <= 0.050                    0.350
  P-value H_0: RMSEA >= 0.080                    0.085

Standardized Root Mean Square Residual:

  SRMR                                           0.029

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)
  knowledge =~
    numeracy          1.000
    energy_use        1.551    0.154   10.076    0.000
    energy_save       1.312    0.122   10.768    0.000
    els_accuracy      2.123    0.248    8.545    0.000
  motivation =~
    env_attitude_z    1.000
    percvd_dffclty   -0.999    0.158   -6.311    0.000
```

```
Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)
  knowledge ~
    motivation        0.436    0.075    5.812    0.000

Covariances:
                   Estimate  Std.Err  z-value  P(>|z|)
 .energy_use ~~
   .els_accuracy     -0.150    0.077   -1.946    0.052

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)
   .numeracy          0.727    0.048   15.278    0.000
   .energy_use        0.346    0.054    6.423    0.000
   .energy_save       0.531    0.046   11.596    0.000
   .els_accuracy      2.269    0.189   11.994    0.000
   .env_attitude_z    0.613    0.070    8.811    0.000
   .percvd_dffclty    0.614    0.069    8.836    0.000
   .knowledge         0.198    0.035    5.650    0.000
    motivation        0.385    0.075    5.111    0.000
```

```r
# 4. Validate clusters with outcomes
combined_scores %>%
  group_by(cluster) %>%
  summarise(recycling_rate = mean(env_attitude_z, na.rm=TRUE),
            energy_behavior = mean(energy_save, na.rm=TRUE)) %>%
  pivot_longer(-cluster, names_to="outcome") %>%
  ggplot(aes(x=cluster, y=value, fill=outcome)) +
  geom_col(position="dodge") +
  labs(title="Cluster Validation Through Behavioral Outcomes")
```




## 3b

```r
# Combine all items into a single dataframe
all_items <- full_join(aes_combined, att2_combined, by = "id") %>%
  full_join(els, by = "id") %>%
  full_join(rs, by = "id")

# Select only item columns for factor analysis
item_columns <- setdiff(names(all_items), "id")
item_data <- all_items[, item_columns]

# Perform factor analysis
fa_items <- fa(item_data, nfactors = 5, rotate = "varimax")  # Adjust nfactors as needed
print(fa_items, cut = 0.3, sort = TRUE)
```

```
Factor Analysis using method =  minres
Call: fa(r = item_data, nfactors = 5, rotate = "varimax")
Standardized loadings (pattern matrix) based upon correlation matrix
      item  MR1   MR2   MR5   MR3   MR4    h2    u2 com
ATT25   25  0.94                          0.903 0.097 1.0
ATT23   23  0.90                          0.865 0.135 1.1
```

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ATT27 | 27 | 0.89 | | | | | 0.804 | 0.196 | 1.0 |
| ATT26 | 26 | 0.89 | | | | | 0.810 | 0.190 | 1.0 |
| ATT24 | 24 | 0.82 | | | | | 0.767 | 0.233 | 1.3 |
| ATT33 | 33 | 0.70 | | | | | 0.622 | 0.378 | 1.5 |
| ATT32 | 32 | 0.61 | | | | | 0.424 | 0.576 | 1.3 |
| ATT30 | 30 | 0.56 | | 0.40 | | | 0.572 | 0.428 | 2.6 |
| ATT31 | 31 | 0.42 | | | | | 0.258 | 0.742 | 1.9 |
| ELS08 | 41 | | | | | | 0.026 | 0.974 | 3.2 |
| ATT10 | 10 | | 0.63 | | | | 0.455 | 0.545 | 1.3 |
| ATT15 | 15 | | 0.63 | | -0.37 | | 0.537 | 0.463 | 1.7 |
| ATT09 | 9 | | 0.62 | | | | 0.456 | 0.544 | 1.3 |
| ATT14 | 14 | | 0.62 | | -0.34 | | 0.516 | 0.484 | 1.6 |
| ATT06 | 6 | | 0.61 | | | | 0.401 | 0.599 | 1.2 |
| ATT07 | 7 | | 0.56 | | | | 0.337 | 0.663 | 1.1 |
| ATT08 | 8 | | 0.55 | | | | 0.313 | 0.687 | 1.0 |
| ATT13 | 13 | | 0.54 | | | | 0.317 | 0.683 | 1.2 |
| ATT03 | 3 | | 0.49 | | 0.36 | | 0.367 | 0.633 | 1.9 |
| ATT12 | 12 | | 0.48 | | | | 0.256 | 0.744 | 1.2 |
| ATT05 | 5 | | 0.48 | | 0.37 | | 0.362 | 0.638 | 1.9 |
| ATT04 | 4 | | 0.47 | | | | 0.235 | 0.765 | 1.1 |
| ATT01 | 1 | | 0.42 | | 0.31 | | 0.275 | 0.725 | 1.9 |
| RS01 | 42 | | -0.40 | | | | 0.248 | 0.752 | 2.0 |
| RS02 | 43 | | | | | | 0.083 | 0.917 | 1.2 |
| ATT11 | 11 | | | | | | 0.070 | 0.930 | 1.5 |
| ELS01 | 34 | | | | | | 0.037 | 0.963 | 2.8 |
| ATT20 | 20 | | | 0.92 | | | 0.915 | 0.085 | 1.2 |
| ATT21 | 21 | 0.35 | | 0.79 | | | 0.759 | 0.241 | 1.4 |
| ATT22 | 22 | | | 0.73 | | | 0.610 | 0.390 | 1.3 |
| RS03 | 44 | | -0.37 | | 0.59 | | 0.503 | 0.497 | 1.8 |
| RS04 | 45 | | | | 0.46 | | 0.256 | 0.744 | 1.5 |
| RS05 | 46 | | | | 0.44 | | 0.212 | 0.788 | 1.2 |
| RS06 | 47 | | | | 0.38 | | 0.158 | 0.842 | 1.2 |
| ATT17 | 17 | | | | -0.36 | | 0.166 | 0.834 | 1.5 |
| ELS02 | 35 | | | | 0.34 | | 0.132 | 0.868 | 1.2 |
| ATT18 | 18 | | | | | | 0.139 | 0.861 | 2.6 |
| ELS03 | 36 | | | | | | 0.073 | 0.927 | 1.4 |
| ATT02 | 2 | | | | | | 0.111 | 0.889 | 2.2 |
| ELS04 | 37 | | | | | | 0.038 | 0.962 | 1.3 |
| ELS07 | 40 | | | | | | 0.039 | 0.961 | 1.9 |
| ATT19 | 19 | | | | | | 0.028 | 0.972 | 1.1 |
| ELS05 | 38 | | | | | | 0.022 | 0.978 | 1.4 |
| ATT28 | 28 | | | | | 0.94 | 0.888 | 0.112 | 1.0 |
| ATT29 | 29 | | | | | 0.90 | 0.827 | 0.173 | 1.0 |

```
ATT16   16                              0.024 0.976 1.1
ELS06   39                              0.027 0.973 4.0

                       MR1  MR2  MR5  MR3  MR4
SS loadings           5.69 4.67 2.52 2.38 1.98
Proportion Var        0.12 0.10 0.05 0.05 0.04
Cumulative Var        0.12 0.22 0.27 0.32 0.37
Proportion Explained  0.33 0.27 0.15 0.14 0.11
Cumulative Proportion 0.33 0.60 0.75 0.89 1.00

Mean item complexity =  1.6
Test of the hypothesis that 5 factors are sufficient.

df null model =  1081  with the objective function =  27 with Chi Square =  15130
df of  the model are 856  and the objective function was  8.8

The root mean square of the residuals (RMSR) is  0.05
The df corrected root mean square of the residuals is  0.06

The harmonic n.obs is  586 with the empirical chi square  3813  with prob <  0
The total n.obs was  586  with Likelihood Chi Square =  4950  with prob <  0

Tucker Lewis Index of factoring reliability =  0.63
RMSEA index =  0.09  and the 90 % confidence intervals are  0.088 0.093
BIC =  -506
Fit based upon off diagonal values = 0.91
Measures of factor score adequacy
                                                   MR1  MR2  MR5  MR3  MR4
Correlation of (regression) scores with factors   0.98 0.93 0.97 0.87 0.97
Multiple R square of scores with factors          0.97 0.87 0.94 0.76 0.93
Minimum correlation of possible factor scores     0.94 0.75 0.88 0.52 0.87
```

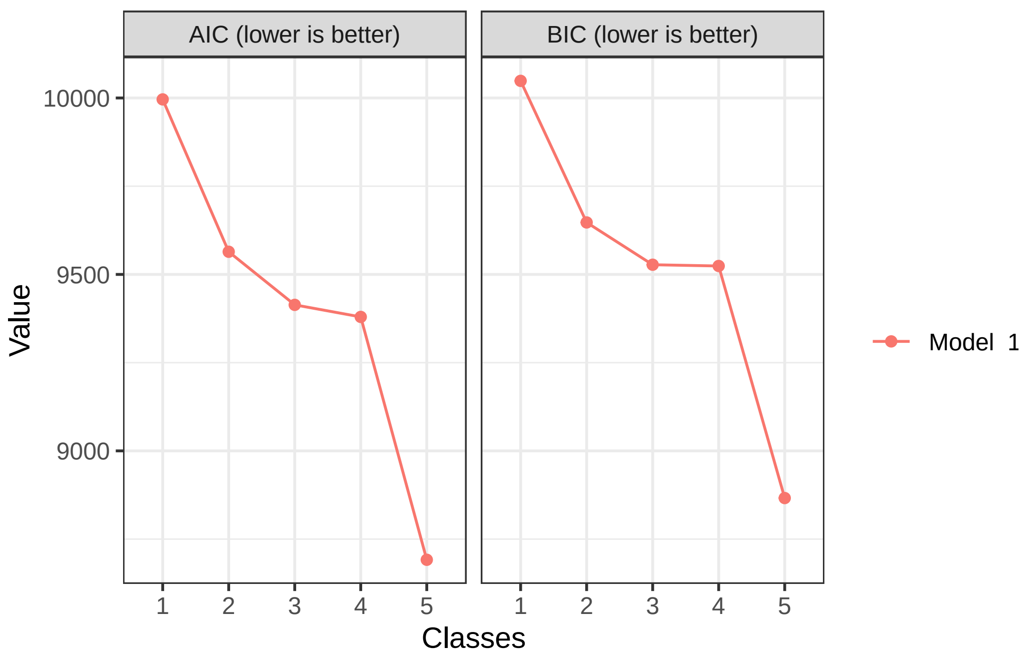
```r
# Example SEM model (using lavaan)
library(lavaan)

model <- '
  # Measurement model
  Knowledge =~ numeracy + energy_use + energy_save + els_score
  Motivation =~ env_attitude_z + perceived_difficulty

  # Structural model
  Knowledge ~ Motivation
```

```r
'

fit <- sem(model, data = combined_scores)
summary(fit, fit.measures = TRUE, standardized = TRUE)
```

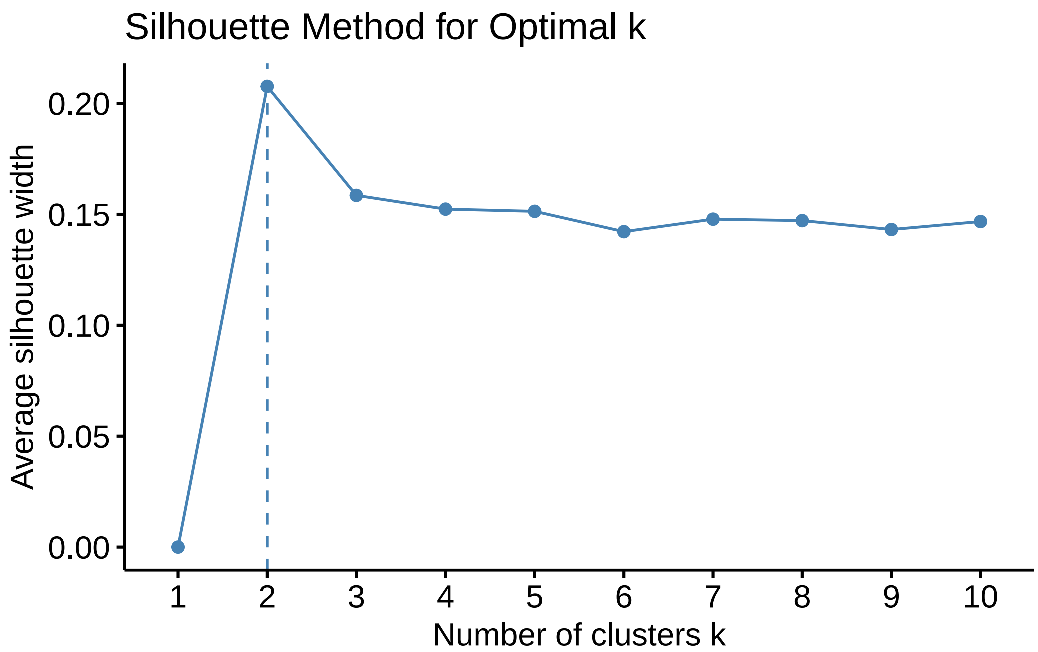
```
lavaan 0.6-19 ended normally after 32 iterations

  Estimator                                         ML
  Optimization method                           NLMINB
  Number of model parameters                        13

  Number of observations                           586

Model Test User Model:

  Test statistic                                23.012
  Degrees of freedom                                 8
  P-value (Chi-square)                           0.003

Model Test Baseline Model:

  Test statistic                               680.231
  Degrees of freedom                                15
  P-value                                        0.000

User Model versus Baseline Model:

  Comparative Fit Index (CFI)                    0.977
  Tucker-Lewis Index (TLI)                       0.958

Loglikelihood and Information Criteria:

  Loglikelihood user model (H0)              -4657.376
  Loglikelihood unrestricted model (H1)      -4645.870

  Akaike (AIC)                                9340.753
  Bayesian (BIC)                              9397.606
  Sample-size adjusted Bayesian (SABIC)       9356.335

Root Mean Square Error of Approximation:

  RMSEA                                          0.057
```

```
  90 Percent confidence interval - lower         0.030
  90 Percent confidence interval - upper         0.084
  P-value H_0: RMSEA <= 0.050                    0.305
  P-value H_0: RMSEA >= 0.080                    0.086

Standardized Root Mean Square Residual:

  SRMR                                           0.032

Parameter Estimates:

  Standard errors                             Standard
  Information                                 Expected
  Information saturated (h1) model          Structured

Latent Variables:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Knowledge =~
    numeracy          1.000                                0.527    0.527
    energy_use        1.469    0.136   10.825    0.000    0.774    0.774
    energy_save       1.352    0.127   10.662    0.000    0.712    0.713
    els_score         1.029    0.111    9.263    0.000    0.542    0.543
  Motivation =~
    env_attitude_z    1.000                                0.618    0.619
    percvd_dffclty   -1.006    0.160   -6.283    0.000   -0.622   -0.623

Regressions:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
  Knowledge ~
    Motivation        0.450    0.076    5.903    0.000    0.529    0.529

Variances:
                   Estimate  Std.Err  z-value  P(>|z|)   Std.lv  Std.all
   .numeracy          0.721    0.047   15.176    0.000    0.721    0.722
   .energy_use        0.400    0.043    9.282    0.000    0.400    0.400
   .energy_save       0.491    0.043   11.489    0.000    0.491    0.492
   .els_score         0.704    0.047   15.004    0.000    0.704    0.705
   .env_attitude_z    0.616    0.070    8.860    0.000    0.616    0.617
   .percvd_dffclty    0.611    0.070    8.726    0.000    0.611    0.612
   .Knowledge         0.200    0.036    5.586    0.000    0.721    0.721
    Motivation        0.382    0.075    5.087    0.000    1.000    1.000
```

```r
# Example LPA (using tidyLPA)
library(tidyLPA)

lpa_data <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score, env_attitude_z, perceived_difficulty)
  na.omit() |>
  # convert all to numeric
    mutate_all(as.numeric)

lpa_results <- lpa_data %>%
  estimate_profiles(n_profiles = 1:5) %>% # Estimate models with 1-5 profiles
  compare_solutions(statistics = c("AIC", "BIC"))

plot(lpa_results)
```




```r
# Determine optimal k using silhouette method
fviz_nbclust(cluster_data_scaled, kmeans, method = "silhouette") +
  labs(title = "Silhouette Method for Optimal k")
```




```r
# Example of cluster stability assessment (using fpc package)
library(fpc)

clusterboot_result <- clusterboot(cluster_data_scaled, B = 100,
                                  bootmethod = "boot", clustermethod = kmeansCBI,
                                  krange = 3, seed = 123)
```

```
boot 1
boot 2
boot 3
boot 4
boot 5
boot 6
boot 7
boot 8
boot 9
boot 10
boot 11
boot 12
boot 13
boot 14
boot 15
boot 16
```

```
boot 17
boot 18
boot 19
boot 20
boot 21
boot 22
boot 23
boot 24
boot 25
boot 26
boot 27
boot 28
boot 29
boot 30
boot 31
boot 32
boot 33
boot 34
boot 35
boot 36
boot 37
boot 38
boot 39
boot 40
boot 41
boot 42
boot 43
boot 44
boot 45
boot 46
boot 47
boot 48
boot 49
boot 50
boot 51
boot 52
boot 53
boot 54
boot 55
boot 56
boot 57
boot 58
boot 59
```

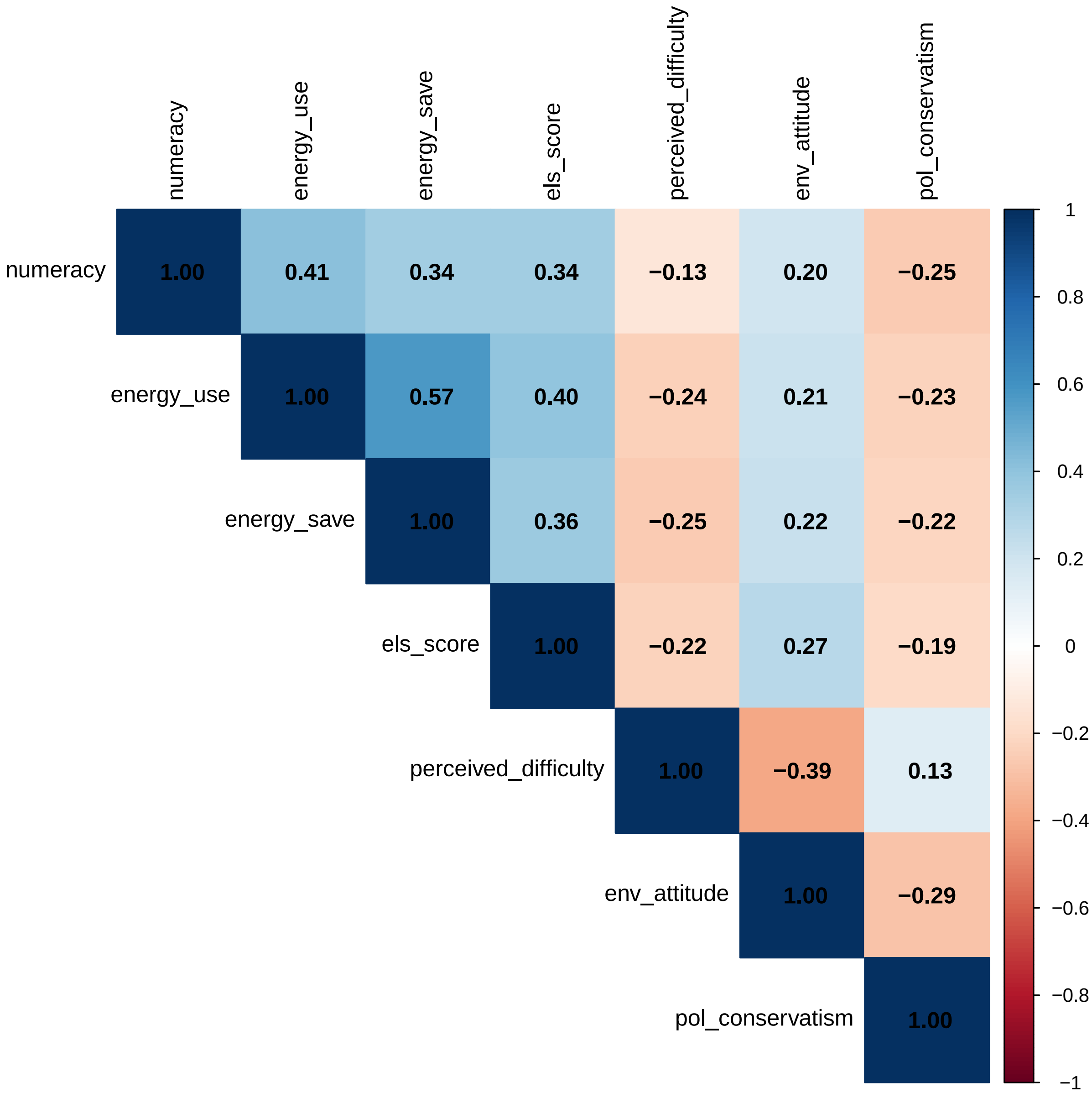
```
boot 60
boot 61
boot 62
boot 63
boot 64
boot 65
boot 66
boot 67
boot 68
boot 69
boot 70
boot 71
boot 72
boot 73
boot 74
boot 75
boot 76
boot 77
boot 78
boot 79
boot 80
boot 81
boot 82
boot 83
boot 84
boot 85
boot 86
boot 87
boot 88
boot 89
boot 90
boot 91
boot 92
boot 93
boot 94
boot 95
boot 96
boot 97
boot 98
boot 99
boot 100
```

```r
print(clusterboot_result)
```

```
* Cluster stability assessment *
Cluster method:  kmeans
Full clustering results are given as parameter result
of the clusterboot object, which also provides further statistics
of the resampling results.
Number of resampling runs:  100

Number of clusters found in data:  3

 Clusterwise Jaccard bootstrap (omitting multiple points) mean:
[1] 0.82 0.68 0.74
dissolved:
[1]  0 26 16
recovered:
[1] 68 45 57
```

---

```r
# 1) Create a correlation matrix of the key knowledge & motivation subscales
#    ensuring no duplicates (e.g., pick either 'env_attitude' or 'env_attitude_z').

cor_vars <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score,
         perceived_difficulty, env_attitude, pol_conservatism)

# 2) Compute correlations
cor_matrix <- cor(cor_vars, use = "pairwise.complete.obs")

# 3) Visualize
corrplot::corrplot(cor_matrix, method = "color", type="upper",
                   tl.col="black", addCoef.col="black")
```




```
library(psych)

fa_data <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score,
         perceived_difficulty, env_attitude, pol_conservatism) %>%
  na.omit()

fa_result <- fa(fa_data, nfactors = 2, rotate = "varimax", fm = "ml")
```

```r
print(fa_result, cut=0.3, sort=TRUE)
```

```
Factor Analysis using method =  ml
Call: fa(r = fa_data, nfactors = 2, rotate = "varimax", fm = "ml")
Standardized loadings (pattern matrix) based upon correlation matrix
                     item   ML2   ML1   h2    u2 com
energy_use              2  0.78        0.63 0.374 1.1
energy_save             3  0.69        0.50 0.497 1.1
numeracy                1  0.51        0.28 0.720 1.2
els_score               4  0.49        0.29 0.709 1.4
pol_conservatism        7              0.14 0.860 2.0
env_attitude            6        0.99 1.00 0.005 1.0
perceived_difficulty    5       -0.37 0.19 0.807 1.7

                       ML2  ML1
SS loadings           1.71 1.31
Proportion Var        0.24 0.19
Cumulative Var        0.24 0.43
Proportion Explained  0.57 0.43
Cumulative Proportion 0.57 1.00

Mean item complexity =  1.4
Test of the hypothesis that 2 factors are sufficient.

df null model =  21  with the objective function =  1.3 with Chi Square =  760
df of  the model are 8  and the objective function was  0.03

The root mean square of the residuals (RMSR) is  0.03
The df corrected root mean square of the residuals is  0.04

The harmonic n.obs is  586 with the empirical chi square  18  with prob <  0.025
The total n.obs was  586  with Likelihood Chi Square =  16  with prob <  0.036

Tucker Lewis Index of factoring reliability =  0.97
RMSEA index =  0.042  and the 90 % confidence intervals are  0.01 0.072
BIC =  -35
Fit based upon off diagonal values = 0.99
Measures of factor score adequacy
                                                   ML2  ML1
Correlation of (regression) scores with factors   0.87 1.00
Multiple R square of scores with factors          0.77 0.99
Minimum correlation of possible factor scores     0.53 0.99
```

```r
model_motivation <- lm(env_attitude ~ els_score + numeracy + pol_conservatism,
                       data=combined_scores)
summary(model_motivation)
```

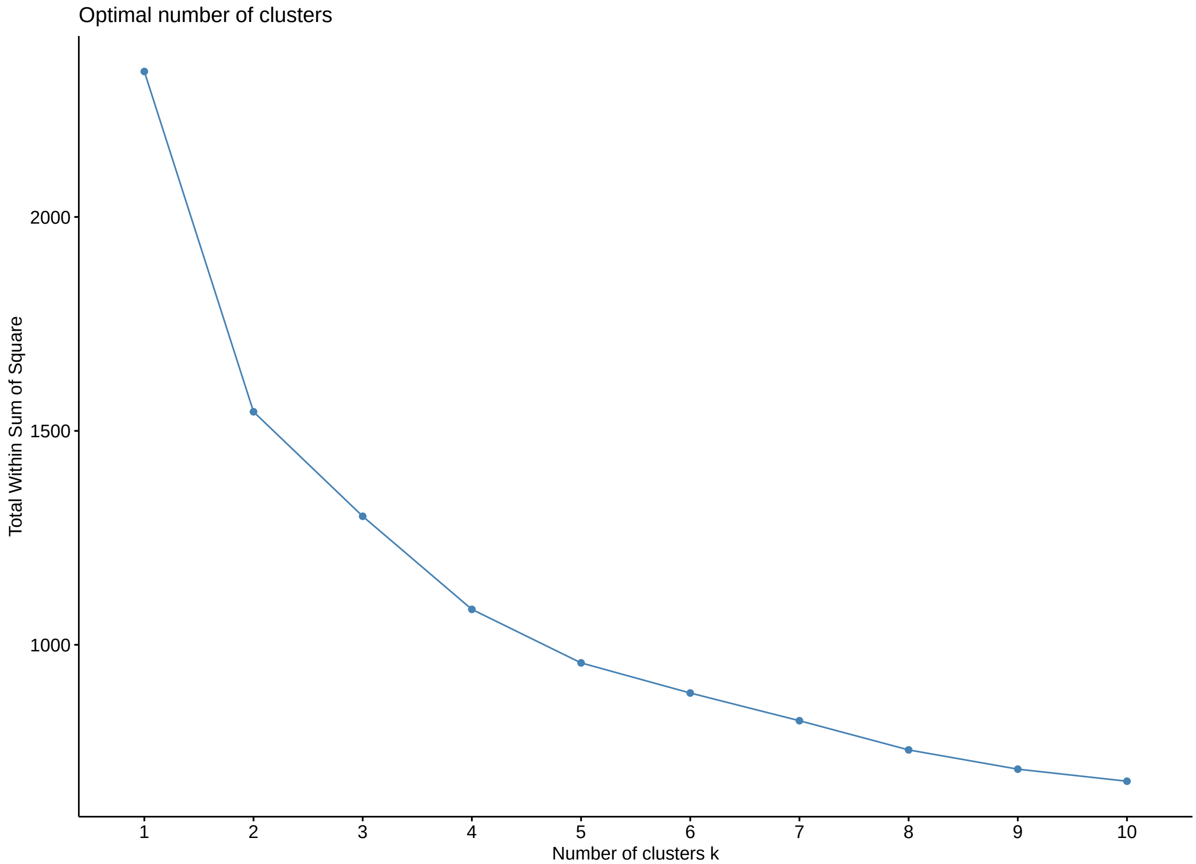
```

Call:
lm(formula = env_attitude ~ els_score + numeracy + pol_conservatism,
    data = combined_scores)

Residuals:
   Min     1Q Median     3Q    Max
-2.320 -0.486  0.020  0.514  1.944

Coefficients:
                 Estimate Std. Error t value             Pr(>|t|)
(Intercept)        3.9098     0.0646   60.48 < 0.0000000000000002 ***
els_score          0.1575     0.0318    4.95           0.00000098 ***
numeracy           0.0555     0.0323    1.72                0.086 .
pol_conservatism  -0.1239     0.0218   -5.69           0.00000002 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.72 on 582 degrees of freedom
Multiple R-squared:  0.135, Adjusted R-squared:  0.131
F-statistic: 30.3 on 3 and 582 DF,  p-value: <0.0000000000000002
```

```r
model_knowledge <- lm(els_score ~ perceived_difficulty + env_attitude + pol_conservatism,
                      data=combined_scores)
summary(model_knowledge)
```

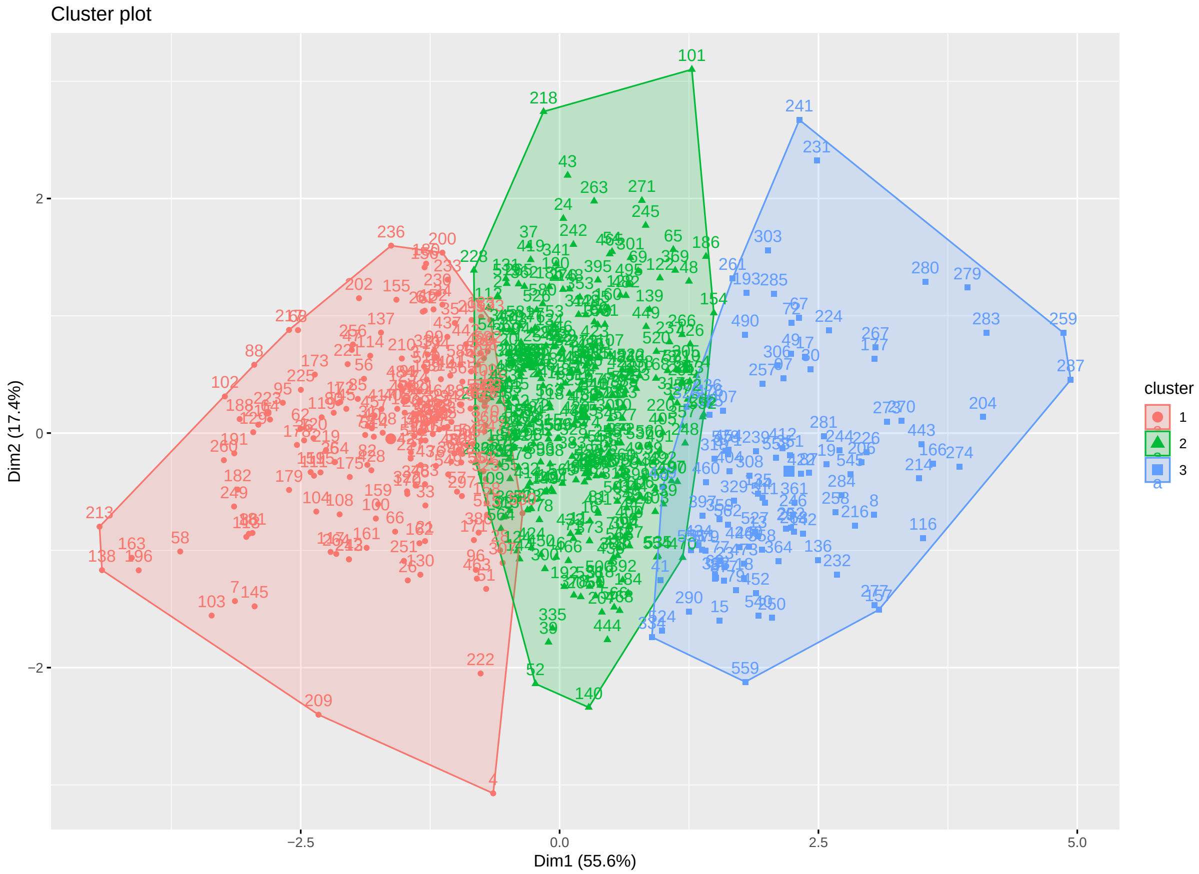
```

Call:
lm(formula = els_score ~ perceived_difficulty + env_attitude +
    pol_conservatism, data = combined_scores)

Residuals:
   Min     1Q Median     3Q    Max
-3.171 -0.646 -0.004  0.716  2.333

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
```

```
(Intercept)           -0.6422     0.2390   -2.69   0.0074 **
perceived_difficulty  -0.1338     0.0425   -3.15   0.0017 **
env_attitude           0.2421     0.0571    4.24 0.000026 ***
pol_conservatism      -0.0854     0.0289   -2.96   0.0032 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.95 on 582 degrees of freedom
Multiple R-squared:  0.104, Adjusted R-squared:  0.0992
F-statistic: 22.5 on 3 and 582 DF,  p-value: 0.0000000000000872
```

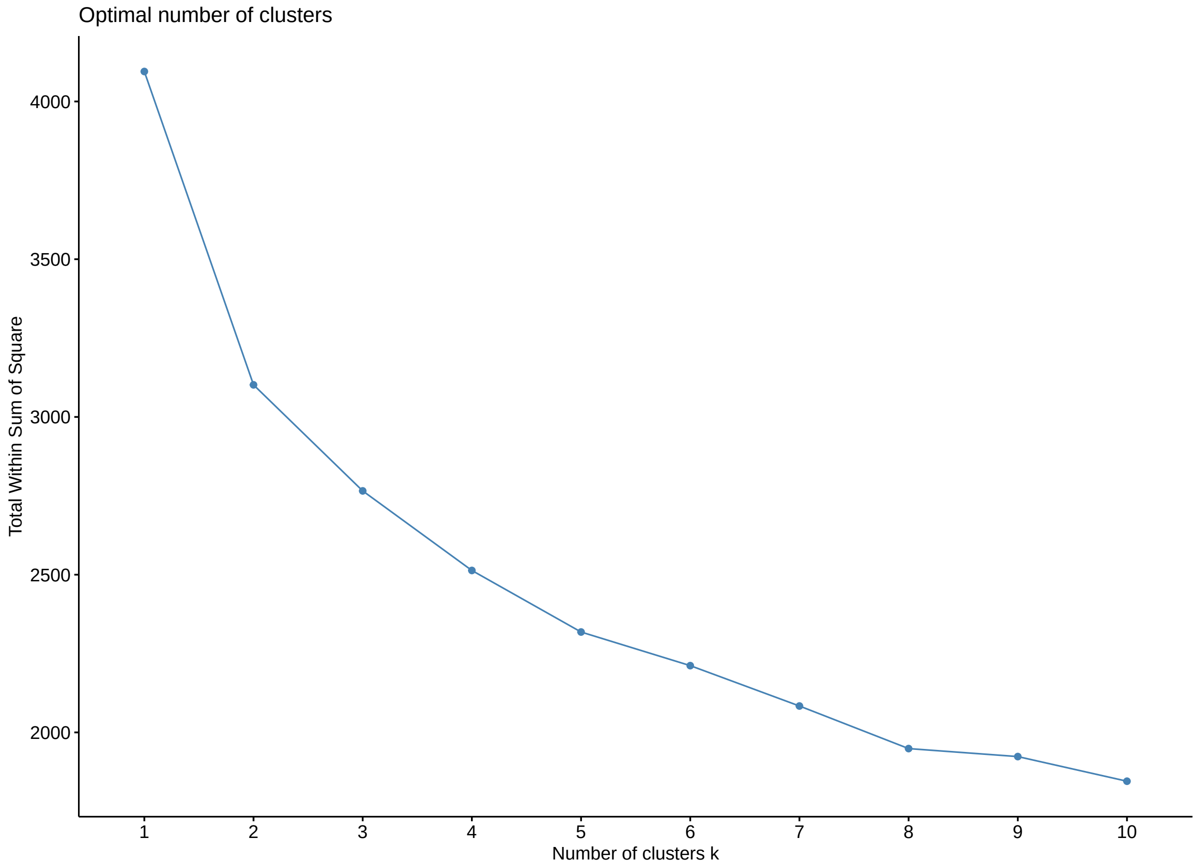
```
library(factoextra)

knowledge_only <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score) %>%
  na.omit() %>%
  scale()

set.seed(123)
# Decide k with elbow or silhouette
fviz_nbclust(knowledge_only, kmeans, method="wss")
```



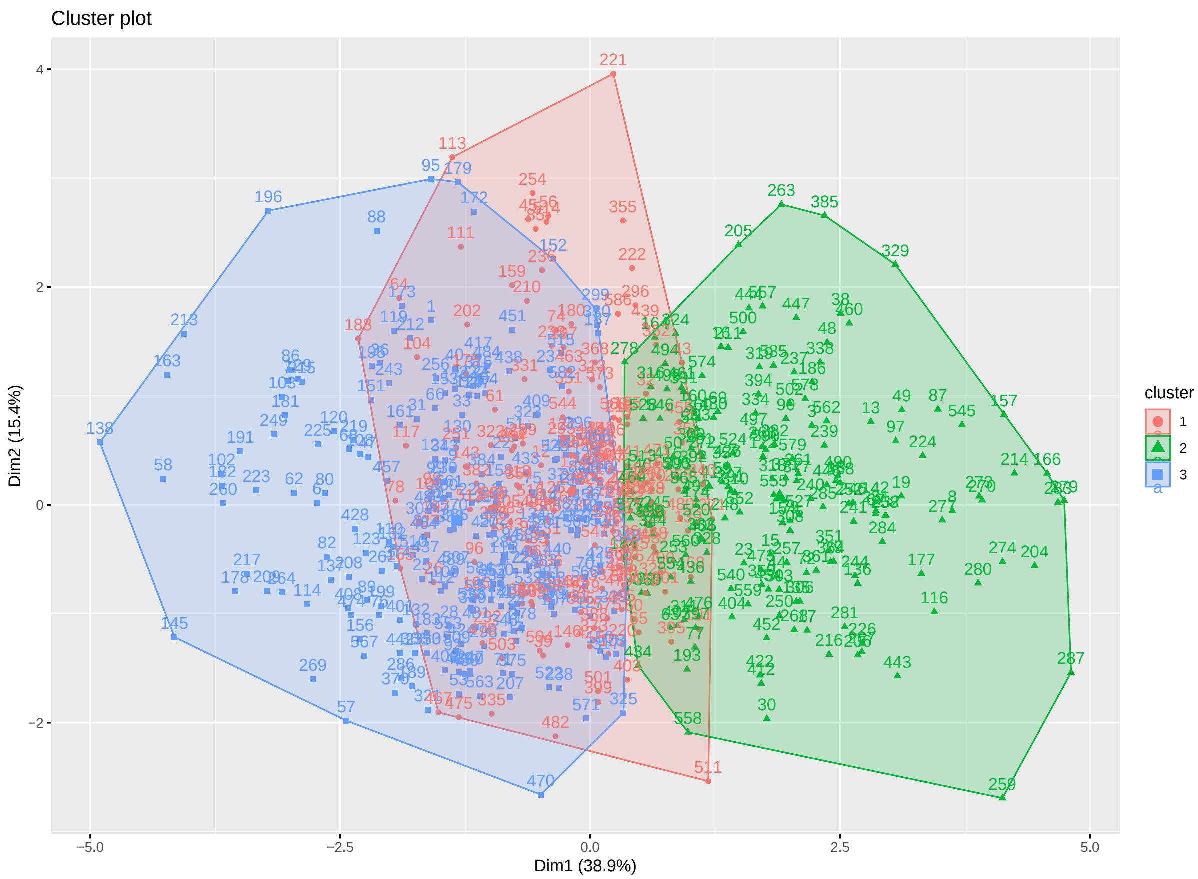

```
km_knowl <- kmeans(knowledge_only, centers=3, nstart=25)
fviz_cluster(km_knowl, data = knowledge_only)
```




```r
all_vars <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score,
         perceived_difficulty, env_attitude, pol_conservatism) %>%
  na.omit() %>%
  scale()

set.seed(123)
fviz_nbclust(all_vars, kmeans, method="wss")
```




```
km_all <- kmeans(all_vars, centers=3, nstart=25)
fviz_cluster(km_all, data=all_vars)
```




```r
# 1. Summarize clusters on an extra measure
combined_scores %>%
  group_by(cluster) %>%
  summarise(
    mean_recycling = mean(env_attitude_z, na.rm=TRUE),
    sd_recycling   = sd(env_attitude_z, na.rm=TRUE),
    n = n()
  ) %>%
  arrange(cluster)
```

```
# A tibble: 3 x 4
  cluster mean_recycling sd_recycling     n
  <fct>            <dbl>        <dbl> <int>
1 1            -0.679           0.890   179
2 2             0.000799        0.869   176
3 3             0.525           0.848   231
```

```r
# 2. ANOVA to test whether clusters differ significantly
anova_result <- aov(env_attitude_z ~ cluster, data = combined_scores)
summary(anova_result)
```

```
             Df Sum Sq Mean Sq F value              Pr(>F)    
cluster       2    146    73.1    97.1 <0.0000000000000002 ***
Residuals   583    439     0.8                                
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# 3. Pairwise comparisons if ANOVA is significant
TukeyHSD(anova_result)
```

```
  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = env_attitude_z ~ cluster, data = combined_scores)

$cluster
    diff  lwr  upr p adj
2-1 0.68 0.46 0.90     0
3-1 1.20 1.00 1.41     0
3-2 0.52 0.32 0.73     0
```

```r
library(mclust)

# Subset data to knowledge & motivation variables
lpa_data <- combined_scores %>%
  select(numeracy, energy_use, energy_save, els_score,
         perceived_difficulty, env_attitude, pol_conservatism) %>%
  na.omit() %>%
  scale()

# Model-based clustering
lpa_model <- Mclust(lpa_data)
summary(lpa_model)  # Tells you how many clusters & the type of covariance structure
```

```
----------------------------------------------------
Gaussian finite mixture model fitted by EM algorithm
----------------------------------------------------
```

```
Mclust VEE (ellipsoidal, equal shape and orientation) model with 8 components:

 log-likelihood   n df    BIC    ICL
          -4869 586 98 -10362 -10419

Clustering table:
  1   2   3   4   5   6   7   8
 54 123 115  30  81  68  83  32
```

```r
# Extract membership
combined_scores$LPA_cluster <- as.factor(lpa_model$classification)
table(combined_scores$LPA_cluster)
```

```
  1   2   3   4   5   6   7   8
 54 123 115  30  81  68  83  32
```

```r
# Compare means across the new LPA-based clusters
combined_scores %>%
  group_by(LPA_cluster) %>%
  summarise(
    across(numeracy:pol_conservatism, mean, na.rm=TRUE)
  )
```

```
# A tibble: 8 x 9
  LPA_cluster numeracy energy_use energy_save els_accuracy els_score
  <fct>          <dbl>      <dbl>       <dbl>        <dbl>     <dbl>
1 1             1.45       0.453      0.258          5.04    0.222
2 2             0.106      0.0661     0.146          4.84    0.116
3 3            -1.50      -0.687     -0.671          3.17   -0.774
4 4            -1.17       0.146      0.239          4.37   -0.136
5 5             0.117     -0.130     -0.193          4.79    0.0903
6 6             1.43       0.785      0.659          5.18    0.297
7 7             0.0666    -0.0178     0.00612        4.67    0.0286
8 8             0.133      0.0197     0.261          6.78    1.16
# i 3 more variables: env_attitude <dbl>, env_attitude_z <dbl>,
#   pol_conservatism <dbl>
```