Flow Profiles GD

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2023-06-29

##Prepare the library and import the data

```
library(haven)
library(tidyverse)
library(tidyLPA)
library(ggplot2)
library(psych)
library(dplyr)
library(tidyr)
library(broom)
library(officer)
library(flextable)
library(ggpubr)
library(AICcmodavg)

data<-read_sav("C:/[redacted]
```

##Describe the Data

```
DataDes<-describe(data)
DS<-summary(data)
flextable(DataDes)
```

vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
1	565	283.0000000	163.2457248	283	283.0000000	209.0466	1	565	564	0.00000000	-1.20637353	6.86779926
2	565	0.4884956	0.5003106	0	0.4856512	0.0000	0	1	1	0.04590774	-2.00142543	0.02104822
3	565	1.6212389	0.8842045	1	1.4988962	0.0000	1	7	6	2.94881441	12.26498039	0.03719876
4	561	2.2638146	0.7961463	2	2.2383073	0.0000	1	4	3	0.36302287	-0.21990259	0.03361332
5	561	2.4135472	0.8430991	2	2.3919822	1.4826	1	4	3	0.17393439	-0.55723792	0.03559567
6	561	2.2335116	0.9471857	2	2.1670379	1.4826	1	4	3	0.50322736	-0.61070102	0.03999021
7	560	1.7892857	0.6938726	2	1.7098214	0.0000	1	4	3	0.69153033	0.65334168	0.02932147
8	561	2.3689840	1.0493368	2	2.3028953	1.4826	1	5	4	0.37064010	-0.54138393	0.04430303
9	561	1.8377897	0.9202473	2	1.7238307	1.4826	1	5	4	0.86042289	-0.02278532	0.03885287
10	560	1.9142857	0.9900089	2	1.7857143	1.4826	1	5	4	0.87827259	0.06986347	0.04183551
11	561	1.6844920	0.8895776	1	1.5345212	0.0000	1	5	4	1.26625741	1.08711317	0.03755800
12	561	2.0962567	1.0697147	2	1.9844098	1.4826	1	5	4	0.54238453	-0.82877399	0.04516339
13	561	1.6292335	0.8933090	1	1.4721604	0.0000	1	5	4	1.31942516	0.97304036	0.03771554
14	561	1.4081996	0.7482387	1	1.2338530	0.0000	1	5	4	1.80803464	2.57428036	0.03159066
15	561	2.9500891	1.2222655	3	2.9376392	1.4826	1	5	4	-0.10998259	-0.85393690	0.05160409
16	561	1.2959002	0.6448707	1	1.1358575	0.0000	1	5	4	2.34461067	5.42993432	0.02722646
17	523	2.8699809	1.3569452	3	2.8377088	1.4826	1	5	4	0.15768772	-1.22266233	0.05933507
18	514	3.8171206	1.3556677	4	3.9854369	1.4826	1	5	4	-0.75868657	-0.84374091	0.05979594
19	553	4.1555154	1.0431155	4	4.3408578	1.4826	1	5	4	-1.13485474	0.42378124	0.04435778
20	552	3.7409420	1.2109263	4	3.8755656	1.4826	1	5	4	-0.71364826	-0.49567671	0.05154045
21	553	2.1482821	1.2567505	2	2.0022573	1.4826	1	5	4	0.70910278	-0.75059939	0.05344247
22	290	1.9965517	0.9131802	2	1.9181034	1.4826	1	4	3	0.49581447	-0.72642758	0.05362379
23	290	2.1862069	0.9842089	2	2.1163793	1.4826	1	4	3	0.20885848	-1.11694111	0.05779474
24	290	2.0103448	1.0272565	2	1.8922414	1.4826	1	4	3	0.51384516	-1.03637830	0.06032258
25	290	1.3827586	0.6563868	1	1.2500000	0.0000	1	4	3	1.75293672	2.78137262	0.03854436
26	290	2.2586207	1.0549003	2	2.1637931	1.4826	1	5	4	0.53009982	-0.39378159	0.06194588

vars	n	mean	sd	median	trimmed	mad	min	max	range	skew	kurtosis	se
27	290	1.7551724	0.9143554	1	1.6293103	0.0000	1	5	4	1.01367235	0.29119580	0.05369280
28	290	1.8896552	0.9956114	2	1.7543103	1.4826	1	5	4	0.91272521	0.07544752	0.05846432
29	290	1.6275862	0.9032416	1	1.4655172	0.0000	1	5	4	1.41505608	1.45895916	0.05304017
30	290	1.9344828	1.0452648	2	1.7974138	1.4826	1	5	4	0.78246307	-0.38640814	0.06138006
31	290	1.4862069	0.8244634	1	1.3017241	0.0000	1	5	4	1.74209972	2.42953247	0.04841416
32	290	1.2793103	0.6969431	1	1.0948276	0.0000	1	5	4	2.80175741	7.76025507	0.04092591
33	290	2.9206897	1.2214573	3	2.9008621	1.4826	1	5	4	-0.13295585	-0.80886770	0.07172644
34	290	1.2482759	0.6116633	1	1.0905172	0.0000	1	4	3	2.69765107	7.12782728	0.03591810
35	290	2.6344828	1.3064323	2	2.5431034	1.4826	1	5	4	0.42534356	-0.99054904	0.07671635
36	290	3.8068966	1.2494791	4	3.9482759	1.4826	1	5	4	-0.75753260	-0.64915348	0.07337194
37	290	4.2482759	0.9228438	4	4.4137931	1.4826	1	5	4	-1.29764004	1.26743243	0.05419125
38	290	3.7344828	1.2063201	4	3.8750000	1.4826	1	5	4	-0.74365107	-0.39528414	0.07083756
39	290	1.9724138	1.2251394	1	1.7715517	0.0000	1	5	4	1.07618163	0.01733145	0.07194266
40	560	8.7446429	2.7235421	8	8.6361607	2.9652	4	19	15	0.50443412	0.55297667	0.11509066
41	560	17.1910714	5.7248408	16	16.6361607	5.9304	9	38	29	0.88991710	0.57624239	0.24191868
42	509	16.8015717	3.9962972	17	16.9486553	4.4478	5	25	20	-0.27986237	-0.49072506	0.17713276
43	290	7.6137931	3.0963450	7	7.3103448	2.9652	4	16	12	0.61761290	-0.45702211	0.18182364
44	290	16.4000000	5.7986993	15	15.7715517	5.9304	9	36	27	0.97757337	0.75342870	0.34051135
45	290	16.3965517	3.9060757	17	16.5129310	4.4478	7	25	18	-0.22326784	-0.23502503	0.22937266

```
DS
```

```
##       ID            AttritionW1W2       Gender         GD_Q1_W1    
##  Length:565         Min.   :0.0000   Min.   :1.000   Min.   :1.000  
##  Class :character   1st Qu.:0.0000   1st Qu.:1.000   1st Qu.:2.000  
##  Mode  :character   Median :0.0000   Median :1.000   Median :2.000  
##                     Mean   :0.4885   Mean   :1.621   Mean   :2.264  
##                     3rd Qu.:1.0000   3rd Qu.:2.000   3rd Qu.:3.000  
##                     Max.   :1.0000   Max.   :7.000   Max.   :4.000  
##                                                      NA's   :4      
##     GD_Q2_W1        GD_Q3_W1        GD_Q4_W1       IGD9_Q1_W1   
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:2.000   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:2.000  
##  Median :2.000   Median :2.000   Median :2.000   Median :2.000  
##  Mean   :2.414   Mean   :2.234   Mean   :1.789   Mean   :2.369  
##  3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:2.000   3rd Qu.:3.000  
##  Max.   :4.000   Max.   :4.000   Max.   :4.000   Max.   :5.000  
##  NA's   :4       NA's   :4       NA's   :5       NA's   :4      
##    IGD9_Q2_W1      IGD9_Q3_W1      IGD9_Q4_W1      IGD9_Q5_W1   
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000  
##  Median :2.000   Median :2.000   Median :1.000   Median :2.000  
##  Mean   :1.838   Mean   :1.914   Mean   :1.684   Mean   :2.096  
##  3rd Qu.:2.000   3rd Qu.:3.000   3rd Qu.:2.000   3rd Qu.:3.000  
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
##  NA's   :4       NA's   :5       NA's   :4       NA's   :4      
##    IGD9_Q6_W1      IGD9_Q7_W1      IGD9_Q8_W1     IGD9_Q9_W1      FlowQ1_W1   
##  Min.   :1.000   Min.   :1.000   Min.   :1.00   Min.   :1.000   Min.   :1.00  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:2.00   1st Qu.:1.000   1st Qu.:2.00  
##  Median :1.000   Median :1.000   Median :3.00   Median :1.000   Median :3.00  
##  Mean   :1.629   Mean   :1.408   Mean   :2.95   Mean   :1.296   Mean   :2.87  
##  3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:4.00   3rd Qu.:1.000   3rd Qu.:4.00  
##  Max.   :5.000   Max.   :5.000   Max.   :5.00   Max.   :5.000   Max.   :5.00  
##  NA's   :4       NA's   :4       NA's   :4      NA's   :4       NA's   :42    
##    FlowQ2_W1       FlowQ3_W1       FlowQ4_W1       FlowQ5_W1    
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:3.000   1st Qu.:4.000   1st Qu.:3.000   1st Qu.:1.000  
##  Median :4.000   Median :4.000   Median :4.000   Median :2.000  
##  Mean   :3.817   Mean   :4.156   Mean   :3.741   Mean   :2.148  
##  3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:3.000  
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
##  NA's   :51      NA's   :12      NA's   :13      NA's   :12     
##     GD_Q1_W2        GD_Q2_W2        GD_Q3_W2       GD_Q4_W2       IGD9_Q1_W2   
##  Min.   :1.000   Min.   :1.000   Min.   :1.00   Min.   :1.000   Min.   :1.000  
##  1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.00   1st Qu.:1.000   1st Qu.:1.000  
##  Median :2.000   Median :2.000   Median :2.00   Median :1.000   Median :2.000  
##  Mean   :1.997   Mean   :2.186   Mean   :2.01   Mean   :1.383   Mean   :2.259  
##  3rd Qu.:3.000   3rd Qu.:3.000   3rd Qu.:3.00   3rd Qu.:2.000   3rd Qu.:3.000  
##  Max.   :4.000   Max.   :4.000   Max.   :4.00   Max.   :4.000   Max.   :5.000  
##  NA's   :275     NA's   :275     NA's   :275    NA's   :275     NA's   :275    
##    IGD9_Q2_W2      IGD9_Q3_W2     IGD9_Q4_W2      IGD9_Q5_W2      IGD9_Q6_W2   
##  Min.   :1.000   Min.   :1.00   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:1.000   1st Qu.:1.00   1st Qu.:1.000   1st Qu.:1.000   1st Qu.:1.000  
##  Median :1.000   Median :2.00   Median :1.000   Median :2.000   Median :1.000  
##  Mean   :1.755   Mean   :1.89   Mean   :1.628   Mean   :1.934   Mean   :1.486  
##  3rd Qu.:2.000   3rd Qu.:3.00   3rd Qu.:2.000   3rd Qu.:3.000   3rd Qu.:2.000  
##  Max.   :5.000   Max.   :5.00   Max.   :5.000   Max.   :5.000   Max.   :5.000  
##  NA's   :275     NA's   :275    NA's   :275     NA's   :275     NA's   :275    
##    IGD9_Q7_W2      IGD9_Q8_W2      IGD9_Q9_W2      FlowQ1_W2    
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:1.000   1st Qu.:2.000   1st Qu.:1.000   1st Qu.:2.000  
##  Median :1.000   Median :3.000   Median :1.000   Median :2.000  
##  Mean   :1.279   Mean   :2.921   Mean   :1.248   Mean   :2.634  
##  3rd Qu.:1.000   3rd Qu.:4.000   3rd Qu.:1.000   3rd Qu.:4.000  
##  Max.   :5.000   Max.   :5.000   Max.   :4.000   Max.   :5.000  
##  NA's   :275     NA's   :275     NA's   :275     NA's   :275    
##    FlowQ2_W2       FlowQ3_W2       FlowQ4_W2       FlowQ5_W2    
##  Min.   :1.000   Min.   :1.000   Min.   :1.000   Min.   :1.000  
##  1st Qu.:3.000   1st Qu.:4.000   1st Qu.:3.000   1st Qu.:1.000  
##  Median :4.000   Median :4.000   Median :4.000   Median :1.000  
##  Mean   :3.807   Mean   :4.248   Mean   :3.734   Mean   :1.972  
##  3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:5.000   3rd Qu.:3.000  
##  Max.   :5.000   Max.   :5.000   Max.   :5.000   Max.   :5.000  
##  NA's   :275     NA's   :275     NA's   :275     NA's   :275    
##    GD1_total        IGD1_total     Flow1_total     GD2_total    
```

```
##  Min.   : 4.000   Min.   : 9.00   Min.   : 5.0   Min.   : 4.000
##  1st Qu.: 7.000   1st Qu.:13.00   1st Qu.:14.0   1st Qu.: 5.000
##  Median : 8.000   Median :16.00   Median :17.0   Median : 7.000
##  Mean   : 8.745   Mean   :17.19   Mean   :16.8   Mean   : 7.614
##  3rd Qu.:10.000   3rd Qu.:21.00   3rd Qu.:20.0   3rd Qu.:10.000
##  Max.   :19.000   Max.   :38.00   Max.   :25.0   Max.   :16.000
##  NA's   :5        NA's   :5       NA's   :56     NA's   :275
##    IGD2_total    Flow2_total
##  Min.   : 9.0   Min.   : 7.0
##  1st Qu.:12.0   1st Qu.:14.0
##  Median :15.0   Median :17.0
##  Mean   :16.4   Mean   :16.4
##  3rd Qu.:19.0   3rd Qu.:19.0
##  Max.   :36.0   Max.   :25.0
##  NA's   :275    NA's   :275
```

LPA with Online Flow, IGD and GD

```
###################################################################################
#################### Models cheat sheet ##########################################
###################################################################################
#Model 1 is Equal variances and covariances fixed to 0 (CIDP)
#Model 2 is Varying variances and covariances fixed to 0 (CVDP)
#Model 3 is Equal variances and equal covariances (CIRP)
#Model 4 and 5 are not able to fit Mclust
#Model 6 is Varying variances and Varying covariances (CVUP)
###################################################################################
###################################################################################

## Initial model fit
set.seed(123)
data%>%
  select("FlowQ1_W1","FlowQ2_W1","FlowQ3_W1","FlowQ4_W1","FlowQ5_W1")%>%
  single_imputation()%>%
  estimate_profiles(2:5, variances = c("equal", "varying", "equal", "varying"),
                    covariances = c("zero", "zero", "equal", "varying"))%>%
  compare_solutions(statistics = c("AIC","BIC","AWE", "CLC", "KIC"))
```

```
## Compare tidyLPA solutions:
##
##  Model Classes AIC      BIC      AWE      CLC      KIC      Warnings
##  1     2       8836.830 8906.219 9054.004 8806.435 8855.830
##  1     3       8688.450 8783.860 8987.670 8646.050 8713.450
##  1     4       8659.179 8780.610 9040.566 8604.655 8690.179
##  1     5       8495.218 8642.671 8958.502 8428.839 8532.218
##  2     2                                                    Warning
##  2     3                                                    Warning
##  2     4                                                    Warning
##  2     5                                                    Warning
##  3     2       8589.304 8702.061 8942.998 8539.125 8618.304
##  3     3       8586.102 8724.880 9022.247 8523.513 8621.102
##  3     4       8543.683 8708.483 9061.828 8469.137 8584.683
##  3     5       8477.206 8668.026 9077.376 8390.677 8524.206
##  6     2                                                    Warning
##  6     3                                                    Warning
##  6     4                                                    Warning
##  6     5                                                    Warning
##
## Best model according to AIC is Model 3 with 5 classes.
## Best model according to BIC is Model 1 with 5 classes.
## Best model according to AWE is Model 3 with 2 classes.
## Best model according to CLC is Model 3 with 5 classes.
## Best model according to KIC is Model 3 with 5 classes.
##
## An analytic hierarchy process, based on the fit indices AIC, AWE, BIC, CLC, and KIC (Akogul & Erisoglu, 2017), suggests t
he best solution is Model 1 with 5 classes.
```

Selecting best model

```
## Filtering model
set.seed(125)
CIDP2 <- data%>%
  select("FlowQ1_W1","FlowQ2_W1","FlowQ3_W1","FlowQ4_W1","FlowQ5_W1")%>%
  single_imputation()%>%
  estimate_profiles(2, variances="equal",covariances="zero")

set.seed(126)
CIDP3 <- data%>%
  select("FlowQ1_W1","FlowQ2_W1","FlowQ3_W1","FlowQ4_W1","FlowQ5_W1")%>%
  single_imputation()%>%
  estimate_profiles(3, variances="equal",covariances="zero")

set.seed(127)
CIDP4 <- data%>%
  select("FlowQ1_W1","FlowQ2_W1","FlowQ3_W1","FlowQ4_W1","FlowQ5_W1")%>%
  single_imputation()%>%
  estimate_profiles(4, variances="equal",covariances="zero")

set.seed(128)
CIDP5 <- data%>%
  select("FlowQ1_W1","FlowQ2_W1","FlowQ3_W1","FlowQ4_W1","FlowQ5_W1")%>%
  single_imputation()%>%
  estimate_profiles(5, variances="equal",covariances="zero")

as_tibble(rbind(CIDP2[["model_1_class_2"]][["fit"]],CIDP3[["model_1_class_3"]][["fit"]],
                CIDP4[["model_1_class_4"]][["fit"]], CIDP5[["model_1_class_5"]][["fit"]])) %>%
  select(Model,Classes,LogLik,AIC,BIC,Entropy,n_min,BLRT_p)
```

```
## # A tibble: 4 x 8
##   Model Classes LogLik   AIC   BIC Entropy n_min  BLRT_p
##   <dbl>   <dbl>  <dbl> <dbl> <dbl>   <dbl> <dbl>   <dbl>
## 1     1       2 -4386. 8804. 8873.   0.798 0.324 0.00990
## 2     1       3 -4345. 8734. 8829.   0.789 0.216 0.00990
## 3     1       4 -4299. 8653. 8775.   0.728 0.193 0.00990
## 4     1       5 -4212. 8493. 8640.   0.796 0.119 0.00990
```

Proportion of participants en each profile

```
## Prep data
lpa <- get_data(CIDP5)
summary(lpa)
```

```
##   model_number classes_number   FlowQ1_W1        FlowQ2_W1        FlowQ3_W1
##  Min.   :1     Min.   :5      Min.   :0.4147   Min.   :0.4903   Min.   :1.000
##  1st Qu.:1     1st Qu.:5      1st Qu.:2.0000   1st Qu.:2.9471   1st Qu.:4.000
##  Median :1     Median :5      Median :3.0000   Median :4.0000   Median :4.000
##  Mean   :1     Mean   :5      Mean   :2.8612   Mean   :3.7687   Mean   :4.149
##  3rd Qu.:1     3rd Qu.:5      3rd Qu.:4.0000   3rd Qu.:5.0000   3rd Qu.:5.000
##  Max.   :1     Max.   :5      Max.   :5.7848   Max.   :7.3207   Max.   :6.630
##    FlowQ4_W1       FlowQ5_W1          CPROB1              CPROB2
##  Min.   :1.000   Min.   :0.6092   Min.   :0.0000000   Min.   :0.0000000
##  1st Qu.:3.000   1st Qu.:1.0000   1st Qu.:0.0000038   1st Qu.:0.0000000
##  Median :4.000   Median :2.0000   Median :0.0056680   Median :0.0000001
##  Mean   :3.733   Mean   :2.1411   Mean   :0.1431326   Mean   :0.1168504
##  3rd Qu.:5.000   3rd Qu.:3.0000   3rd Qu.:0.1072252   3rd Qu.:0.0005382
##  Max.   :6.477   Max.   :5.0000   Max.   :0.9887378   Max.   :1.0000000
##      CPROB3              CPROB4             CPROB5              Class
##  Min.   :0.0000000   Min.   :0.000000   Min.   :0.0000000   Min.   :1.000
##  1st Qu.:0.0001929   1st Qu.:0.000259   1st Qu.:0.0000016   1st Qu.:2.000
##  Median :0.1322607   Median :0.001756   Median :0.0000514   Median :3.000
##  Mean   :0.3548926   Mean   :0.190534   Mean   :0.1945905   Mean   :3.177
##  3rd Qu.:0.7960212   3rd Qu.:0.231760   3rd Qu.:0.0283557   3rd Qu.:4.000
##  Max.   :0.9942265   Max.   :0.999896   Max.   :0.9999995   Max.   :5.000
```

```
view(lpa)

lpas <- data%>%
  add_column(lpa$Class)%>%
  rename(Class = "lpa$Class")%>%
  mutate(FlowQ1_W1 = scale(FlowQ1_W1)) %>%
  mutate(FlowQ2_W1 = scale(FlowQ2_W1)) %>%
  mutate(FlowQ3_W1 = scale(FlowQ3_W1)) %>%
  mutate(FlowQ4_W1 = scale(FlowQ4_W1)) %>%
  mutate(FlowQ5_W1 = scale(FlowQ5_W1))

view(lpas)


lpa$Class <- as.factor(lpa$Class)
## Proportion of participants
lpa%>%
  group_by(Class)%>%
  count(Class)%>%
  mutate(Perc = (n/565)*100)
```

```
## # A tibble: 5 x 3
## # Groups:   Class [5]
##   Class     n  Perc
##   <fct> <int> <dbl>
## 1 1        79  14.0
## 2 2        67  11.9
## 3 3       207  36.6
## 4 4        99  17.5
## 5 5       113  20
```

Raw and Std values

```
## Raw Values
describe(lpa)
```

```
##                 vars   n mean   sd median trimmed  mad  min  max range  skew
## model_number       1 565 1.00 0.00   1.00    1.00 0.00 1.00 1.00  0.00   NaN
## classes_number     2 565 5.00 0.00   5.00    5.00 0.00 5.00 5.00  0.00   NaN
## FlowQ1_W1          3 565 2.86 1.36   3.00    2.83 1.48 0.41 5.78  5.37  0.17
## FlowQ2_W1          4 565 3.77 1.37   4.00    3.92 1.48 0.49 7.32  6.83 -0.66
## FlowQ3_W1          5 565 4.15 1.05   4.00    4.33 1.48 1.00 6.63  5.63 -1.09
## FlowQ4_W1          6 565 3.73 1.21   4.00    3.86 1.48 1.00 6.48  5.48 -0.67
## FlowQ5_W1          7 565 2.14 1.25   2.00    2.00 1.48 0.61 5.00  4.39  0.72
## CPROB1             8 565 0.14 0.28   0.01    0.07 0.01 0.00 0.99  0.99  2.02
## CPROB2             9 565 0.12 0.31   0.00    0.02 0.00 0.00 1.00  1.00  2.37
## CPROB3            10 565 0.35 0.40   0.13    0.32 0.20 0.00 0.99  0.99  0.55
## CPROB4            11 565 0.19 0.33   0.00    0.12 0.00 0.00 1.00  1.00  1.55
## CPROB5            12 565 0.19 0.37   0.00    0.12 0.00 0.00 1.00  1.00  1.53
## Class*            13 565 3.18 1.27   3.00    3.22 1.48 1.00 5.00  4.00 -0.16
##                 kurtosis   se
## model_number         NaN 0.00
## classes_number       NaN 0.00
## FlowQ1_W1          -1.17 0.06
## FlowQ2_W1          -0.86 0.06
## FlowQ3_W1           0.38 0.04
## FlowQ4_W1          -0.51 0.05
## FlowQ5_W1          -0.73 0.05
## CPROB1              2.73 0.01
## CPROB2              3.77 0.01
## CPROB3             -1.42 0.02
## CPROB4              0.79 0.01
## CPROB5              0.49 0.02
## Class*             -0.86 0.05
```

```
ClassProp<-lpa%>%
  select(Class,FlowQ1_W1,FlowQ2_W1,FlowQ3_W1,FlowQ4_W1,FlowQ5_W1) %>%
  group_by(Class) %>%
  summarise(FlowQ1_W1=mean(FlowQ1_W1),
            FlowQ2_W1=mean(FlowQ2_W1),
            FlowQ3_W1=mean(FlowQ3_W1),
            FlowQ4_W1=mean(FlowQ4_W1),
            FlowQ5_W1=mean(FlowQ5_W1)) %>%
  na.omit()
as_flextable(ClassProp)
```

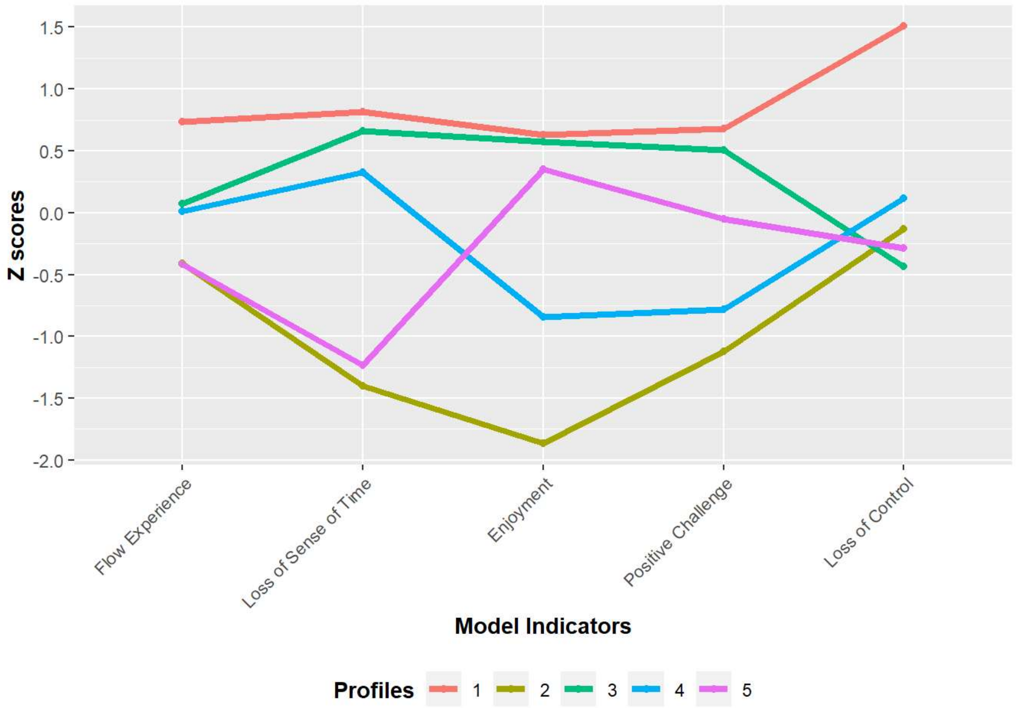
Class	FlowQ1_W1	FlowQ2_W1	FlowQ3_W1	FlowQ4_W1	FlowQ5_W1
factor	numeric	numeric	numeric	numeric	numeric
1	3.9	4.9	4.8	4.6	4.0
2	2.3	1.9	2.2	2.4	2.0
3	3.0	4.7	4.8	4.3	1.6
4	2.9	4.2	3.3	2.8	2.3
5	2.3	2.1	4.5	3.7	1.8

```
# Std Values
  ClassProps<-lpa%>%
  select(Class,FlowQ1_W1,FlowQ2_W1,FlowQ3_W1,FlowQ4_W1,FlowQ5_W1) %>%
  mutate(FlowQ1_W1 = scale(FlowQ1_W1)) %>%
  mutate(FlowQ2_W1 = scale(FlowQ2_W1)) %>%
  mutate(FlowQ3_W1 = scale(FlowQ3_W1)) %>%
  mutate(FlowQ4_W1 = scale(FlowQ4_W1)) %>%
  mutate(FlowQ5_W1 = scale(FlowQ5_W1)) %>%
  group_by(Class) %>%
  summarise(FlowQ1_W1=mean(FlowQ1_W1),
            FlowQ2_W1=mean(FlowQ2_W1),
            FlowQ3_W1=mean(FlowQ3_W1),
            FlowQ4_W1=mean(FlowQ4_W1),
            FlowQ5_W1=mean(FlowQ5_W1)) %>%
  na.omit()
as_flextable(ClassProps)
```

Class	FlowQ1_W1	FlowQ2_W1	FlowQ3_W1	FlowQ4_W1	FlowQ5_W1
factor	numeric	numeric	numeric	numeric	numeric
1	0.7	0.8	0.6	0.7	1.5
2	-0.4	-1.4	-1.9	-1.1	-0.1
3	0.1	0.7	0.6	0.5	-0.4
4	0.0	0.3	-0.8	-0.8	0.1
5	-0.4	-1.2	0.4	-0.0	-0.3

Plot

```
ClassProps%>%
  select(Class,FlowQ1_W1,FlowQ2_W1,FlowQ3_W1,FlowQ4_W1,FlowQ5_W1) %>%
  group_by(Class) %>%
  summarise(FlowQ1_W1=mean(FlowQ1_W1),
            FlowQ2_W1=mean(FlowQ2_W1),
            FlowQ3_W1=mean(FlowQ3_W1),
            FlowQ4_W1=mean(FlowQ4_W1),
            FlowQ5_W1=mean(FlowQ5_W1)) %>%
  na.omit() %>%
  pivot_longer(cols=c(FlowQ1_W1,FlowQ2_W1,FlowQ3_W1,FlowQ4_W1,FlowQ5_W1),
             names_to="Model_Indicators",
             values_to="Z_Scores") %>%
  ggplot(aes(x=Model_Indicators, y=Z_Scores, group=Class, color=Class)) +
  geom_point(size = 1.5) + geom_line(size = 1.5) +
  labs(x= "Model Indicators", y = "Z scores", color = "Profiles") +
  theme(axis.title.x = element_text(face = "bold"),
        axis.text.x = element_text(angle = 45, hjust = 1.0),
        axis.title.y = element_text(face = "bold"),
        legend.title = element_text(face = "bold"),
        legend.position="bottom") +
  scale_y_continuous(breaks=seq(-2.0, 2.0, by = 0.5)) +
  scale_x_discrete(labels=c("FlowQ1_W1"="Flow Experience",
                            "FlowQ2_W1"="Loss of Sense of Time", "FlowQ3_W1"="Enjoyment", "FlowQ4_W1"="Positive Challeng
e","FlowQ5_W1"="Loss of Control"))
```



#IGD Wave 1 Anova

```
one.way1 <- aov(IGD1_total ~ Class, data = lpas)

summary(one.way1)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Class         1    694   694.1   21.97 3.48e-06 ***
## Residuals   558  17626    31.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 5 observations deleted due to missingness
```

```
posthoc_bonferroni1 <- pairwise.t.test(lpas$IGD1_total, lpa$Class, p.adjust.method = "bonferroni")
print(posthoc_bonferroni1)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  lpas$IGD1_total and lpa$Class
##
##   1       2       3       4
## 2 7.4e-13 -       -       -
## 3 7.8e-06 0.00015 -       -
## 4 6.5e-07 0.05604 1.00000 -
## 5 3.4e-10 0.69254 0.04775 1.00000
##
## P value adjustment method: bonferroni
```

#IGD Wave 2 Anova

```
one.way2 <- aov(IGD2_total ~ Class, data = lpas)

summary(one.way2)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Class         1    488   487.8   15.22 0.000119 ***
## Residuals   288   9230    32.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 275 observations deleted due to missingness
```

```
posthoc_bonferroni2 <- pairwise.t.test(lpas$IGD2_total, lpa$Class, p.adjust.method = "bonferroni")
print(posthoc_bonferroni2)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  lpas$IGD2_total and lpa$Class
##
##   1       2       3       4
## 2 0.00019 -       -       -
## 3 0.00465 0.52216 -       -
## 4 0.00265 1.00000 1.00000 -
## 5 2e-05   1.00000 0.37632 1.00000
##
## P value adjustment method: bonferroni
```

#Gaming Disorder Test Wave 1 Anova

```
one.way3 <- aov(GD1_total ~ Class, data = lpas)

summary(one.way3)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Class         1    180  179.52   25.25 6.78e-07 ***
## Residuals   558   3967    7.11
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 5 observations deleted due to missingness
```

```
posthoc_bonferroni3 <- pairwise.t.test(lpas$GD1_total, lpa$Class, p.adjust.method = "bonferroni")
print(posthoc_bonferroni3)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  lpas$GD1_total and lpa$Class
##
##   1       2     3     4
## 2 2.0e-08 -     -     -
## 3 7.8e-05 0.031 -     -
## 4 3.7e-05 0.535 1.000 -
## 5 9.9e-10 1.000 0.016 0.608
##
## P value adjustment method: bonferroni
```

#Gaming Disorder Test Wave 2

```
one.way4 <- aov(GD2_total ~ Class, data = lpas)

summary(one.way4)
```

```
##              Df Sum Sq Mean Sq F value   Pr(>F)
## Class         1  139.8  139.80    15.3 0.000114 ***
## Residuals   288 2630.9    9.14
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 275 observations deleted due to missingness
```

```
posthoc_bonferroni4 <- pairwise.t.test(lpas$GD2_total, lpa$Class, p.adjust.method = "bonferroni")
print(posthoc_bonferroni4)
```

```
##
##  Pairwise comparisons using t tests with pooled SD
##
## data:  lpas$GD2_total and lpa$Class
##
##   1       2     3     4
## 2 0.016   -     -     -
## 3 0.013   1.000 -     -
## 4 0.022   1.000 1.000 -
## 5 8.9e-05 1.000 0.444 1.000
##
## P value adjustment method: bonferroni
```