

Multivariate statistics: Assignment 1

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1 Task 1

1.1 CFA to construct a measurement model for the Attitude items

There are 9 attitude items that are scored on a five-point Likert scale. To conduct CFA on the attitude items using the covariance matrix, we first center the data.

1.1.1 A simple 3-factor model

We first conduct a simple confirmatory factor analysis, assuming each item only has a loading on the concept it aims to measure (organic, packaging, and cruelty free). We will assume the three latent variables are correlated and the factor loading of the first indicator of each latent variable is fixed to 1. We fit the model on standardized data. The first columns in Table 3 shows several performance measures for the model. It shows that the currently proposed 3-factor model is not a good fit. The chi-squared goodness of fit tests indicate that the constraints imposed by the model are not supported ($p < 0.001$). The cutoff for a good model for CFI and TLI (cutoff > 0.95) and for RMSEA and SRMR (cutoff < 0.08) are also not satisfied. On the other hand, composite reliability measures the reliability of the factor scores. We can see that the composite reliability values are high (Table 1), therefore, the factors are measured in a reliable way. Figure 1 in the appendix shows a graphical representation of the model, including all loadings, correlations and variances.

In the standardized solution, the standardized loadings represent correlations between a variable and a factor (Table 1). All standardized loadings are above 0.7. Therefore, the squared loadings are higher than 0.5. This reflects a sufficient reliability of the indicator variables. Since all the standardized loadings are positive and significant, there is convergent validity.

and the error variances indicate the proportion of the variance in a variable that cannot be explained by the model (Table 1).

```
#We first standardize the variables
cosmetics_std <- scale(cosmetics, center = TRUE, scale = FALSE)
covmat1 <- cov(cosmetics_std[,1:9])
simplemodel1 <-
'organic = ~1*A_organic1 + A_organic2 + A_organic3
 packaging = ~1*A_packaging1 + A_packaging2 + A_packaging3
 crueltyfree = ~1*A_crueltyfree1 + A_crueltyfree2 + A_crueltyfree3
 organic ~~ organic
 packaging ~~ packaging
 crueltyfree ~~ crueltyfree
 organic ~~ packaging
 organic ~~ crueltyfree
 packaging ~~ crueltyfree'
fit1 <- cfa(simplemodel1, sample.cov = covmat1, sample.nobs = nrow(cosmetics))
sum_fit1 <- summary(fit1, fit.measure = T)
sum_fit1_std <- standardizedSolution(fit1)
```

Table 1: The solution of the simple model for the attitudes.

std_loading		value
organic \sim A_organic1		0.87 (0.80, 0.94)***
organic \sim A_organic2		0.73 (0.63, 0.82)***
organic \sim A_organic3		0.72 (0.62, 0.81)***
packaging \sim A_packaging1		0.84 (0.78, 0.91)***
packaging \sim A_packaging2		0.79 (0.72, 0.87)***
packaging \sim A_packaging3		0.80 (0.73, 0.88)***
crueltyfree \sim A_crueltyfree1		0.91 (0.87, 0.96)***
crueltyfree \sim A_crueltyfree2		0.79 (0.72, 0.86)***
crueltyfree \sim A_crueltyfree3		0.86 (0.81, 0.92)***

	std_error.variance	value	factor	reliability
10	organic \sim organic	1.00 (1.00, 1.00)	organic	0.817
11	packaging \sim packaging	1.00 (1.00, 1.00)	packaging	0.855
12	crueltyfree \sim crueltyfree	1.00 (1.00, 1.00)	crueltyfree	0.892
13	organic \sim packaging	0.74 (0.63, 0.84)***		
14	organic \sim crueltyfree	0.60 (0.48, 0.73)***		
15	packaging \sim crueltyfree	0.72 (0.63, 0.82)***		
16	A_organic1 \sim A_organic1	0.24 (0.12, 0.36)***		
17	A_organic2 \sim A_organic2	0.47 (0.34, 0.61)***		
18	A_organic3 \sim A_organic3	0.48 (0.35, 0.62)***		
19	A_packaging1 \sim A_packaging1	0.29 (0.18, 0.40)***		
20	A_packaging2 \sim A_packaging2	0.37 (0.25, 0.49)***		
21	A_packaging3 \sim A_packaging3	0.35 (0.24, 0.47)***		
22	A_crueltyfree1 \sim A_crueltyfree1	0.17 (0.08, 0.25)***		
23	A_crueltyfree2 \sim A_crueltyfree2	0.38 (0.26, 0.49)***		
24	A_crueltyfree3 \sim A_crueltyfree3	0.25 (0.16, 0.35)***		

1.1.2 A 3-factor model with correlated error terms

Since the simple 3-factor model does not seem to perform well, we alter the model by including correlated error terms for all pairs of items that focus on the same aspect. We also impose equal residual correlations for all pairs of items that focus on the same aspect.

```
corrmodel1 <-  
'organic = ~1*A_organic1 + A_organic2 + A_organic3  
  packaging = ~1*A_packaging1 + A_packaging2 + A_packaging3  
  crueltyfree = ~1*A_crueltyfree1 + A_crueltyfree2 + A_crueltyfree3  
  A_organic1 ~~c*A_packaging1  
  A_organic1 ~~c*A_crueltyfree1  
  A_packaging1 ~~c*A_crueltyfree1  
  
  A_organic2 ~~d*A_packaging2  
  A_organic2 ~~d*A_crueltyfree2  
  A_packaging2 ~~d*A_crueltyfree2  
  
  A_organic3 ~~e*A_packaging3  
  A_organic3 ~~e*A_crueltyfree3  
  A_packaging3 ~~e*A_crueltyfree3  
  
  organic ~~ organic  
  packaging ~~ packaging  
  crueltyfree ~~ crueltyfree  
  
  organic ~~ packaging  
  organic ~~ crueltyfree  
  packaging ~~ crueltyfree  
'  
fit1corr <- cfa(corrmodel1, sample.cov = covmat1, sample.nobs = nrow(cosmetics))  
sum_fit1corr <- summary(fit1corr, fit.measure = T)  
sum_fit1_std_corr <- standardizedSolution(fit1corr)
```

1.1.3 Conclusion

An anova test between the two models shows that the model with correlated error terms is significantly better (p-value < 0.001).

Since, however, the performance measures (second column in Table 3) shows less-than-perfect fit, we look at the residual correlations in the model with correlated error terms for all pairs of attitude items that focus on the same aspect and notice that 7 (19.44%) of all correlations are larger than 0.05 or smaller than -0.05 (this was 27.7% in the simple model). Three of the largest residual correlations involved the correlations between A_organic3, A_packaging3, and A_crueltyfree3 which leads us to believe that the assumption that these correlations are equal does not hold. Indeed, a model that relaxes this assumption has a good TLI (0.967), CFI (0.983), RMSEA (0.073), and SRMR (0.031). The Chi-square goodness of fit test still has a p-value of 0.018.

1.2 CFA to construct a measurement model for the Behavior-Intention items

There are 9 behavior-intention items that are scored on a five-point Likert scale. As with the attitude items, we fit a CFA on the covariance matrix of the centered dataset.

1.2.1 A simple 3-factor model

Table 3 shows, in the third column) that all performance metrics, except for SRMSR, indicate that this simple model does not fit the data well. Nevertheless, composite reliability (Table 2) is high for all three latent variables.

```
#We first standardize the variables
covmat1 <- cov(cosmetics_std[,10:18])
simplemodel1 <-
'organic = ~1*BI_organic1 + BI_organic2 + BI_organic3
 packaging = ~1*BI_packaging1 + BI_packaging2 + BI_packaging3
 crueltyfree = ~1*BI_crueltyfree1 + BI_crueltyfree2 + BI_crueltyfree3
 organic ~~ organic
 packaging ~~ packaging
 crueltyfree ~~ crueltyfree
 organic ~~ packaging
 organic ~~ crueltyfree
 packaging ~~ crueltyfree'
fit1 <- cfa(simplemodel1, sample.cov = covmat1, sample.nobs = nrow(cosmetics))
sum_fit1 <- summary(fit1, fit.measure = T)
sum_fit1_std <- standardizedSolution(fit1)
```

1.2.2 A 3-factor model with correlated error terms

Since the simple 3-factor model does not seem to perform well, we alter the model by including correlated error terms for all pairs of items that focus on the same aspect. We also impose equal residual residual correlations for all pairs of items that focus on the same aspect.

```
corrmodel1 <-
'organic = ~1*BI_organic1 + BI_organic2 + BI_organic3
 packaging = ~1*BI_packaging1 + BI_packaging2 + BI_packaging3
 crueltyfree = ~1*BI_crueltyfree1 + BI_crueltyfree2 + BI_crueltyfree3

BI_organic1 ~~c*BI_packaging1
BI_organic1 ~~c*BI_crueltyfree1
BI_packaging1 ~~c*BI_crueltyfree1

BI_organic2 ~~d*BI_packaging2
BI_organic2 ~~d*BI_crueltyfree2
BI_packaging2 ~~d*BI_crueltyfree2

BI_organic3 ~~e*BI_packaging3
BI_organic3 ~~e*BI_crueltyfree3
BI_packaging3 ~~e*BI_crueltyfree3

organic ~~ organic
packaging ~~ packaging
crueltyfree ~~ crueltyfree
organic ~~ packaging
organic ~~ crueltyfree
packaging ~~ crueltyfree
'
fit1corr <- cfa(corrmodel1, sample.cov = covmat1, sample.nobs = nrow(cosmetics))
sum_fit1corr <- summary(fit1corr, fit.measure = T)
```

Table 2: The standardized solution of the simple model for the behavior-intent items.

std_loading		value		
organic =~ BI_organic1		0.89 (0.84, 0.93)***		
organic =~ BI_organic2		0.90 (0.85, 0.94)***		
organic =~ BI_organic3		0.84 (0.79, 0.90)***		
packaging =~ BI_packaging1		0.88 (0.83, 0.92)***		
packaging =~ BI_packaging2		0.89 (0.85, 0.93)***		
packaging =~ BI_packaging3		0.87 (0.82, 0.91)***		
crueltyfree =~ BI_crueltyfree1		0.92 (0.88, 0.95)***		
crueltyfree =~ BI_crueltyfree2		0.92 (0.89, 0.95)***		
crueltyfree =~ BI_crueltyfree3		0.94 (0.91, 0.97)***		
std_error.variance	value	factor	reliability	
10 organic~~organic	1.00 (1.00, 1.00)	organic	0.908	
11 packaging~~packaging	1.00 (1.00, 1.00)	packaging	0.910	
12 crueltyfree~~crueltyfree	1.00 (1.00, 1.00)	crueltyfree	0.946	
13 organic~~packaging	0.88 (0.82, 0.93)***			
14 organic~~crueltyfree	0.78 (0.71, 0.86)***			
15 packaging~~crueltyfree	0.83 (0.77, 0.90)***			
16 BI_organic1~~BI_organic1	0.22 (0.14, 0.29)***			
17 BI_organic2~~BI_organic2	0.20 (0.12, 0.27)***			
18 BI_organic3~~BI_organic3	0.29 (0.20, 0.38)***			
19 BI_packaging1~~BI_packaging1	0.23 (0.15, 0.31)***			
20 BI_packaging2~~BI_packaging2	0.21 (0.13, 0.28)***			
21 BI_packaging3~~BI_packaging3	0.25 (0.17, 0.33)***			
22 BI_crueltyfree1~~BI_crueltyfree1	0.16 (0.10, 0.22)***			
23 BI_crueltyfree2~~BI_crueltyfree2	0.16 (0.10, 0.22)***			
24 BI_crueltyfree3~~BI_crueltyfree3	0.12 (0.07, 0.17)***			

Table 3: Performance measure for the different models

parameter	Attitudes		Behavior-intention	
	simple model	with correlated error terms	simple model	with correlated error terms
user model Chisq. (df)	120.89 (24)***	56.74 (21)***	147.81 (24)***	26.78 (21)
baseline model Chisq. (df)	906.01 (36) ***	906.01 (36) ***	1478.43 (36) ***	1478.43 (36) ***
comparative fit index (CFI)	0.889	0.959	0.914	0.996
Tucker-Lewis index (TLI)	0.833	0.93	0.871	0.993
RMSEA (ll,ul)	0.16 (0.14, 0.19)***	0.11 (0.07, 0.14)**	0.19 (0.16, 0.21)***	0.04 (0.00, 0.09)
Standardized root mean square residual	0.057	0.042	0.033	0.02

```
sum_fit1_std_corr <- standardizedSolution(fit1corr)
```

1.2.3 Conclusion

An anova test between the two models shows that the model with correlated error terms for all pairs of Behavior-Intention items that focus on the same aspect is significantly better (p-value < 0.001).

The performance measures (column 3 and 4 in Table 3) show a good fit and all residual correlations are between -0.05 and 0.05 (the simpler model had 0 (0%) residual correlations between -0.05 and 0.05). For the simple model We shall thus keep this model as the final model.

1.3 Structural equation model to evaluate the impact of attitude on behavior intention

We first fit a structural equation model on the covariance matrix of all items.

- A_organic, A_packaging, and A_crueltyfree are related to the attitude items with a model with correlated error terms for pairs of items that focus on the same aspects. For statements that focus on “the right thing to do” or “pleasant”, there are equal correlations. As discussed in section 1.1.3, we relax the constraint of equal residual correlations for items that focus on the fact that purchasing sustainable cosmetics is “a must”.
- BI_organic, BI_packaging, and BI_crueltyfree are related to the attitude items with a model with correlated error terms for pairs of items that focus on the same aspects. As discussed in section 1.2.3, a model that imposes the constraint of equal residual correlations for all pairs of items that focus on the same aspect has a good fit and will be used here.

Structural relations are added to assess the effect of (1) Att_organic on BI_organic, (2) Att_packaging on BI_packaging and (3) Att_crueltyfree on BI_crueltyfree.

```
cormat <- cov(cosmetics_std)
sem1 <- 'BI_organic = ~1*BI_organic1 + BI_organic2 + BI_organic3
BI_packaging = ~1*BI_packaging1 + BI_packaging2 + BI_packaging3
BI_crueltyfree = ~1*BI_crueltyfree1 + BI_crueltyfree2 + BI_crueltyfree3

BI_organic1 ~~c*BI_packaging1
```

```

BI_organic1 ~~c*BI_crueltyfree1
BI_packaging1 ~~c*BI_crueltyfree1

BI_organic2 ~~d*BI_packaging2
BI_organic2 ~~d*BI_crueltyfree2
BI_packaging2 ~~d*BI_crueltyfree2

BI_organic3 ~~e*BI_packaging3
BI_organic3 ~~e*BI_crueltyfree3
BI_packaging3 ~~e*BI_crueltyfree3

BI_organic ~~ BI_organic
BI_packaging ~~ BI_packaging
BI_crueltyfree ~~ BI_crueltyfree
BI_organic ~~ BI_packaging
BI_organic ~~ BI_crueltyfree
BI_packaging ~~ BI_crueltyfree

A_organic = ~NA*A_organic1 + A_organic2 + A_organic3
A_packaging = ~NA*A_packaging1 + A_packaging2 + A_packaging3
A_crueltyfree = ~NA*A_crueltyfree1 + A_crueltyfree2 + A_crueltyfree3
A_organic1 ~~a*A_packaging1
A_organic1 ~~a*A_crueltyfree1
A_packaging1 ~~a*A_crueltyfree1

A_organic2 ~~b*A_packaging2
A_organic2 ~~b*A_crueltyfree2
A_packaging2 ~~b*A_crueltyfree2

A_organic3 ~~A_packaging3
A_organic3 ~~A_crueltyfree3
A_packaging3 ~~A_crueltyfree3

A_organic ~~ 1*A_organic
A_packaging ~~ 1*A_packaging
A_crueltyfree ~~ 1*A_crueltyfree

A_organic ~~ A_packaging
A_organic ~~ A_crueltyfree
A_packaging ~~ A_crueltyfree

#structural model
BI_organic ~A_organic
BI_packaging ~A_packaging
BI_crueltyfree ~A_crueltyfree
'

fitsem1 <-sem(sem1,sample.cov=cormat, sample.nobs = nrow(cosmetics))
sum_sem1 <- summary(fitsem1)
sum_sem1_std <- standardizedSolution(fitsem1)

```

With a test statistics of 145.01 with 118 degrees of freedom, the chi-square p-value is 0.0462742 which means we

cannot reject the null hypothesis that the model fits well.

The structural equation model shows that all correlations between latent variables are positive and highly significant.

- an increase of one unit in attitude_organic increases the behavior intention with 0.68.
- an increase of one unit in attitude_packaging increases the behavior intention with 0.684.
- an increase of one unit in attitude_crueltyfree increases the behavior intention with 0.716.

These population regression coefficients are quite similar so we next test a model that imposes that all three regression coefficients are the same.

1.3.1 Equal population regression coefficients

```
sem2 <- 'BI_organic = ~1*BI_organic1 + BI_organic2 + BI_organic3
BI_packaging = ~1*BI_packaging1 + BI_packaging2 + BI_packaging3
BI_crueltyfree = ~1*BI_crueltyfree1 + BI_crueltyfree2 + BI_crueltyfree3

BI_organic1 ~~c*BI_packaging1
BI_organic1 ~~c*BI_crueltyfree1
BI_packaging1 ~~c*BI_crueltyfree1
BI_organic2 ~~d*BI_packaging2
BI_organic2 ~~d*BI_crueltyfree2
BI_packaging2 ~~d*BI_crueltyfree2
BI_organic3 ~~e*BI_packaging3
BI_organic3 ~~e*BI_crueltyfree3
BI_packaging3 ~~e*BI_crueltyfree3
BI_organic ~~ BI_organic
BI_packaging ~~ BI_packaging
BI_crueltyfree ~~ BI_crueltyfree
BI_organic ~~ BI_packaging
BI_organic ~~ BI_crueltyfree
BI_packaging ~~ BI_crueltyfree

A_organic = ~NA*A_organic1 + A_organic2 + A_organic3
A_packaging = ~NA*A_packaging1 + A_packaging2 + A_packaging3
A_crueltyfree = ~NA*A_crueltyfree1 + A_crueltyfree2 + A_crueltyfree3

A_organic1 ~~a*A_packaging1
A_organic1 ~~a*A_crueltyfree1
A_packaging1 ~~a*A_crueltyfree1
A_organic2 ~~b*A_packaging2
A_organic2 ~~b*A_crueltyfree2
A_packaging2 ~~b*A_crueltyfree2
A_organic3 ~~A_packaging3
A_organic3 ~~A_crueltyfree3
A_packaging3 ~~A_crueltyfree3

A_organic ~~ 1*A_organic
A_packaging ~~ 1*A_packaging
A_crueltyfree ~~ 1*A_crueltyfree
A_organic ~~ A_packaging
A_organic ~~ A_crueltyfree
```


Table 4: Population regression coefficients in both SEMs.

Regression coefficient	General SEM		Equal population regression coefficients	
	unstandardized	standardized	unstandardized	standardized
BI_organic~A_organic	0.62 ***	0.68 ***	0.64 ***	0.69 ***
BI_packaging~A_packaging	0.69 ***	0.68 ***	0.64 ***	0.71 ***
BI_crueltyfree~A_crueltyfree	0.66 ***	0.72 ***	0.64 ***	0.68 ***

```

A_packaging ~~ A_crueltyfree

#structural model
BI_organic ~p*A_organic
BI_packaging ~p*A_packaging
BI_crueltyfree ~p*A_crueltyfree
'

fitsem2 <- sem(sem2,sample.cov = cormat, sample.nobs = nrow(cosmetics))
sum_sem2 <- summary(fitsem2)
sum_sem2_std <- standardizedSolution(fitsem2)
anovase1 <- anova(fitsem1,fitsem2)
anovase2 <- anovase1$`Pr(>Chisq)`[2]

```

Since an anova test for the two SEMs has a p-value of 0.291, we cannot reject the null hypothesis that the models are the same, meaning this new, simpler SEM fits as well as the more elaborate model.

- an increase of one unit in attitude_organic increases the behavior intention with 0.69.
- an increase of one unit in attitude_packaging increases the behavior intention with 0.71.
- an increase of one unit in attitude_crueltyfree increases the behavior intention with 0.685.

2 Task 2

2.1 Canonical correlation analysis

```

library(candisc)
zbenefits <- benefits
zbenefits[,2:14] <- scale(zbenefits[,2:14],scale=TRUE,center=TRUE)

cancor.out <- cancor(
  cbind(SL_pensioners, SL_unemployed, SL_old_gvntresp, SL_unemp_gvntresp)
~SB_strain_economy+SB_prevent_poverty+SB_equal_society+
SB_taxes_business+ SB_make_lazy+SB_caring_others+ unemployed_notmotivated+
SB_often_lessthanentitled+ SB_often_notentitled,
data=zbenefits)

#print summary results
summary(cancor.out)

```

```
##
```

```
## Canonical correlation analysis of:
```

```
## 9 X variables: SB_strain_economy, SB_prevent_poverty, SB_equal_society, SB_taxes_business, SB_make_lazy, SB_caring_others, unemployed_notmotivated, SB_often_lessthanentitled, SB_often_notentitled
```

```
## with 4 Y variables: SL_pensioners, SL_unemployed, SL_old_gvntresp, SL_unemp_gvntresp
##
##      CanR   CanRSQ   Eigen percent   cum                                scree
## 1 0.48323 0.233515 0.30466 79.8465 79.85 *****
## 2 0.22817 0.052061 0.05492 14.3939 94.24 *****
## 3 0.13741 0.018883 0.01925 5.0442 99.28 **
## 4 0.05218 0.002723 0.00273 0.7155 100.00
##
## Test of H0: The canonical correlations in the
## current row and all that follow are zero
##
##      CanR LR test stat approx F numDF   denDF   Pr(> F)
## 1 0.48323      0.71092   32.719    36 12357.1 < 2.2e-16 ***
## 2 0.22817      0.92751   10.477    24 9565.8 < 2.2e-16 ***
## 3 0.13741      0.97845    5.163    14 6598.0 8.545e-10 ***
## 4 0.05218      0.99728    1.501     6 3300.0 0.1735
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Raw canonical coefficients
##
## X variables:
##
##           Xcan1      Xcan2      Xcan3      Xcan4
## SB_strain_economy -0.0909717 0.4172121 0.564470 -0.059128
## SB_prevent_poverty 0.0779679 -0.0254661 -0.329579 -0.125299
## SB_equal_society 0.1279718 0.3828047 -0.585296 -0.097459
## SB_taxes_business -0.0850983 0.0972611 -0.067364 -0.947887
## SB_make_lazy -0.3819813 0.0411048 -0.206351 0.231770
## SB_caring_others 0.0069064 0.0060264 0.128499 -0.149934
## unemployed_notmotivated -0.4933957 -0.1393655 -0.333507 0.134556
## SB_often_lessthanentitled 0.2525276 -0.6831611 0.127790 -0.360191
## SB_often_notentitled -0.1393188 -0.4867982 -0.255268 0.146316
##
## Y variables:
##
##           Ycan1      Ycan2      Ycan3      Ycan4
## SL_pensioners 0.220475 0.651836 -0.28265 0.78198
## SL_unemployed -0.526682 0.156985 -0.64871 -0.63976
## SL_old_gvntresp -0.098433 -0.599184 -0.55693 0.72377
## SL_unemp_gvntresp 0.764899 0.057483 -0.33698 -0.71784

#compute redundancies
R2tu<-cancor.out$cancor^2
R2tu<-cancor.out$cancor^2
VAFYbyt<-apply(cancor.out$structure$Y.scores^2,2,sum)/3
redund<-R2tu*VAFYbyt
round(cbind(R2tu,VAFYbyt,redund,total=cumsum(redund)),4)

##           R2tu VAFYbyt redund total
## Ycan1 0.2335 0.3799 0.0887 0.0887
## Ycan2 0.0521 0.4266 0.0222 0.1109
## Ycan3 0.0189 0.3635 0.0069 0.1178
## Ycan4 0.0027 0.1633 0.0004 0.1182
```

```
#print canonical loadings
```

```
round(cancor.out$structure$X.xscores,2)
```

```
##                Xcan1 Xcan2 Xcan3 Xcan4
## SB_strain_economy   -0.54  0.27  0.44 -0.27
## SB_prevent_poverty    0.22  0.10 -0.53 -0.18
## SB_equal_society     0.33  0.33 -0.73 -0.15
## SB_taxes_business   -0.45  0.12  0.01 -0.85
## SB_make_lazy        -0.80 -0.02 -0.02 -0.05
## SB_caring_others     -0.56 -0.06  0.07 -0.21
## unemployed_notmotivated -0.80 -0.19 -0.26 -0.02
## SB_often_lessthanentitled 0.30 -0.73  0.06 -0.36
## SB_often_notentitled  -0.56 -0.47 -0.19  0.00
```

```
round(cancor.out$structure$Y.yscores,2)
```

```
##                Ycan1 Ycan2 Ycan3 Ycan4
## SL_pensioners      0.18  0.81 -0.36  0.42
## SL_unemployed     -0.61  0.31 -0.65 -0.32
## SL_old_gvntresp    0.11 -0.71 -0.60  0.34
## SL_unemp_gvntresp  0.85 -0.11 -0.42 -0.30
```

2.2 Split-half approach

```
train <- benefits[seq(2,3310,by=2),]
valid <- benefits[seq(1,3310,by=2),]
train[,2:14]<-scale(train[,2:14],center=TRUE,scale=TRUE)
valid[,2:14]<-scale(valid[,2:14],center=TRUE,scale=TRUE)
```

```
#conduct CCA on training data
```

```
cancor.train<-cancor(cbind(SL_pensioners, SL_unemployed, SL_old_gvntresp, SL_unemp_gvntresp)
~SB_strain_economy+SB_prevent_poverty+SB_equal_society+
SB_taxes_business+ SB_make_lazy+SB_caring_others+ unemployed_notmotivated+
SB_often_lessthanentitled+ SB_often_notentitled , data=train)
```

```
#conduct CCA on validation data
```

```
cancor.valid<-cancor(cbind(SL_pensioners, SL_unemployed, SL_old_gvntresp, SL_unemp_gvntresp)
~SB_strain_economy+SB_prevent_poverty+SB_equal_society+
SB_taxes_business+ SB_make_lazy+SB_caring_others+ unemployed_notmotivated+
SB_often_lessthanentitled+ SB_often_notentitled , data=valid)
```

```
# canonical variates calibration set
```

```
train.X1<-cancor.train$score$X
```

```
train.Y1<-cancor.train$score$Y
```

```
# compute canonical variates using data of calibration set and coefficients estimated on validation
```

```
train.X2<-as.matrix(train[,6:14])%*%cancor.valid$coef$X
```

```
train.Y2<-as.matrix(train[,2:5])%*%cancor.valid$coef$Y
```

```
round(cor(train.Y1,train.Y2),3)
```

```
##          Ycan1  Ycan2  Ycan3  Ycan4
## Ycan1 -0.985  0.121 -0.148  0.044
## Ycan2 -0.057 -0.989 -0.116 -0.036
## Ycan3  0.146  0.083 -0.973 -0.145
## Ycan4  0.069  0.006 -0.130  0.988
```

```
round(cor(train.X1,train.X2),3)
```

```
##          Xcan1  Xcan2  Xcan3  Xcan4
## Xcan1 -0.985 -0.013 -0.058 -0.100
## Xcan2  0.040 -0.893 -0.219  0.283
## Xcan3  0.031  0.027 -0.557 -0.206
## Xcan4 -0.091  0.100  0.072  0.257
```

```
round(cor(train.X1,train.Y1),3)
```

```
##          Ycan1 Ycan2 Ycan3 Ycan4
## Xcan1  0.482 0.000 0.000 0.000
## Xcan2  0.000 0.244 0.000 0.000
## Xcan3  0.000 0.000 0.145 0.000
## Xcan4  0.000 0.000 0.000 0.046
```

```
round(cor(train.X2,train.Y2),3)
```

```
##          Ycan1  Ycan2 Ycan3  Ycan4
## Xcan1  0.468 -0.067 0.065 -0.026
## Xcan2  0.019  0.215 0.022  0.011
## Xcan3  0.019  0.043 0.089  0.016
## Xcan4  0.040 -0.076 0.027  0.011
```

```
round(cor(train.Y2,train.Y2),3)
```

```
##          Ycan1  Ycan2 Ycan3 Ycan4
## Ycan1  1.000 -0.050 0.001 0.006
## Ycan2 -0.050  1.000 0.014 0.034
## Ycan3  0.001  0.014 1.000 0.010
## Ycan4  0.006  0.034 0.010 1.000
```

```
round(cor(train.X2,train.X2),3)
```

```
##          Xcan1  Xcan2  Xcan3 Xcan4
## Xcan1  1.000 -0.037 -0.047 0.020
## Xcan2 -0.037  1.000  0.024 0.017
## Xcan3 -0.047  0.024  1.000 0.035
## Xcan4  0.020  0.017  0.035 1.000
```

3 Appendix

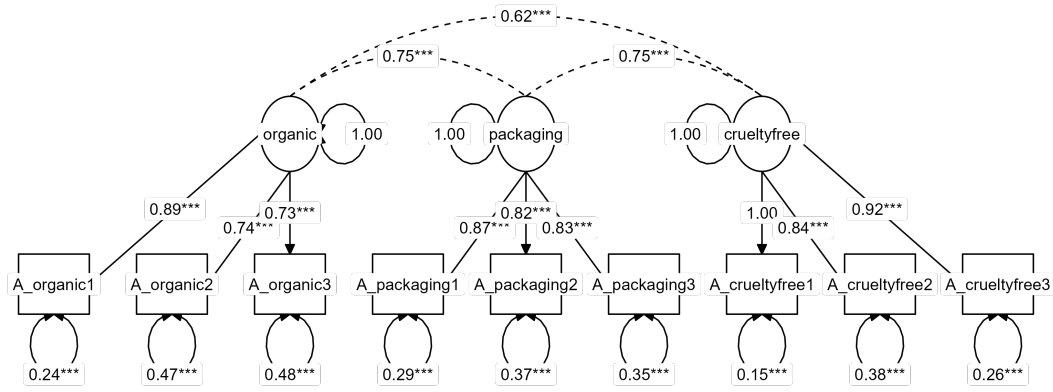


Figure 1: A graphical representation of the simple model for the attitudes.

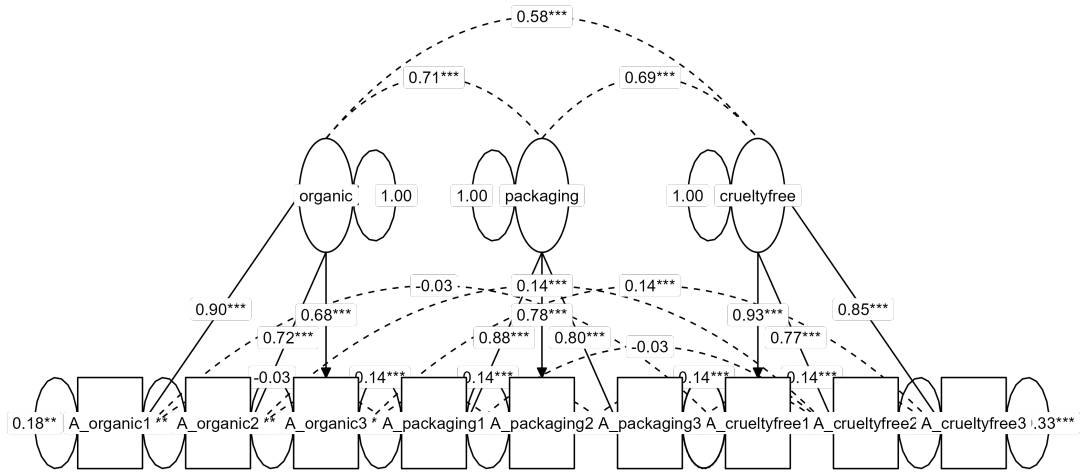


Figure 2: A graphical representation of the model for the attitudes with correlated error terms for all pairs of items that focus on the same aspect.

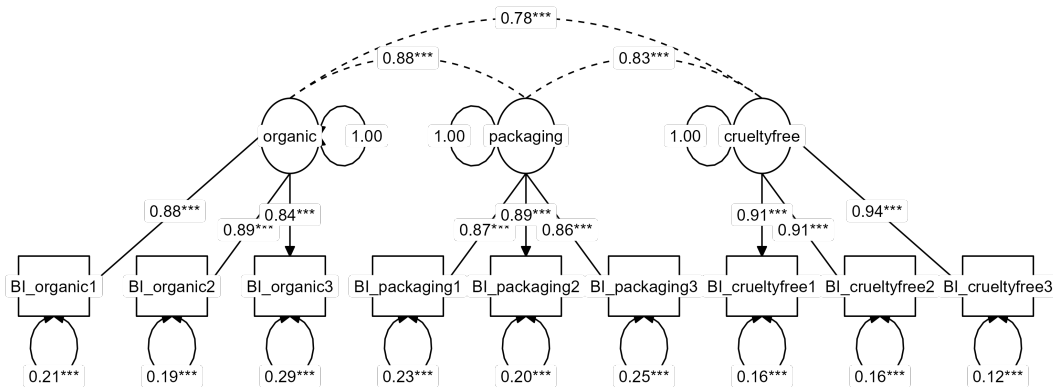


Figure 3: A graphical representation of the simple model for the behavior-intent items.

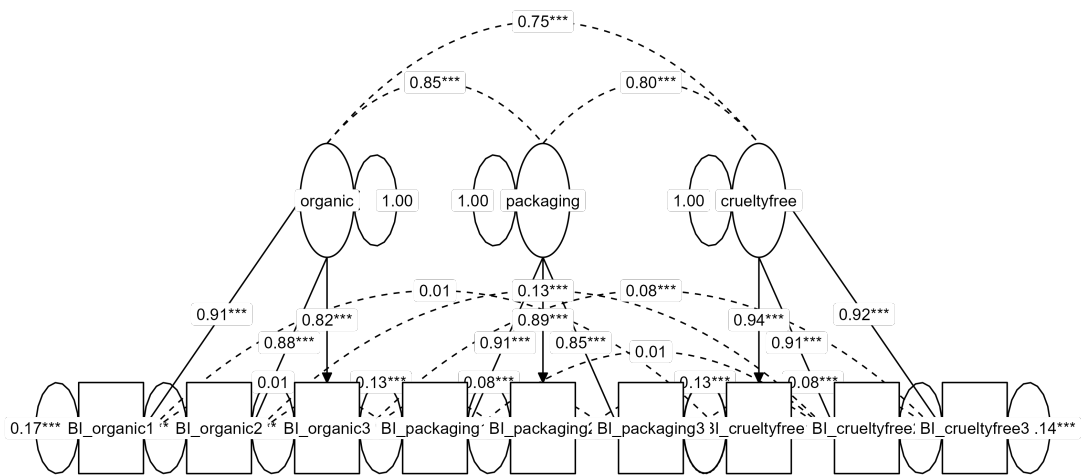


Figure 4: A graphical representation of the model with correlated error terms for the behavior-intent items that focus on the same aspect.