

# PLS-SEM: Model Summary and Evaluation

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## 1 Load required and new packages

```
if (!require("pacman")) install.packages("pacman")
```

```
## Loading required package: pacman
```

```
library(pacman)  
pacman::p_load("here", "glue", "crayon", "readxl", "writexl", "dplyr", "tidyr", "rstatix")  
pacman::p_load("seminr")
```

## 2 Set data paths and details

```
main.path = here::here()  
data.path = file.path(main.path, "02 Data")  
output.path = file.path(main.path, "04 Outputs")  
  
file.name = "Data - For Analysis.xlsx"  
sheet.name = "Final"  
output.name = paste0(format(Sys.Date(), "%m%d%y"), "_OUTPUT", ".xlsx")
```

## 3 Load dataset

```
df.raw = readxl::read_excel(file.path(data.path, file.name),  
                             sheet = sheet.name)
```

## 4 Process data

```
df.proc = df.raw %>%  
  dplyr::select(-PR4)
```

## 5 Implement methodology

## 5.1 Define measurement models

```
df.mm = seminr::constructs(  
  seminr::composite("PE", seminr::multi_items("PE", 1:3)),  
  seminr::composite("EE", seminr::multi_items("EE", 1:3)),  
  seminr::composite("SI", seminr::multi_items("SI", 1:2)),  
  seminr::composite("FC", seminr::multi_items("FC", 1:3)),  
  seminr::composite("PI", seminr::multi_items("PI", 1:4)),  
  seminr::composite("PR", seminr::multi_items("PR", 1:3)),  
  seminr::composite("BI", seminr::multi_items("BI", 1:2))  
)
```

## 5.2 Define structural models

```
df.sm = seminr::relationships(  
  seminr::paths(from = c("PE", "EE", "SI", "FC", "PI", "PR"), to = c("BI"))  
)
```

## 5.3 Estimate PLS-SEM model

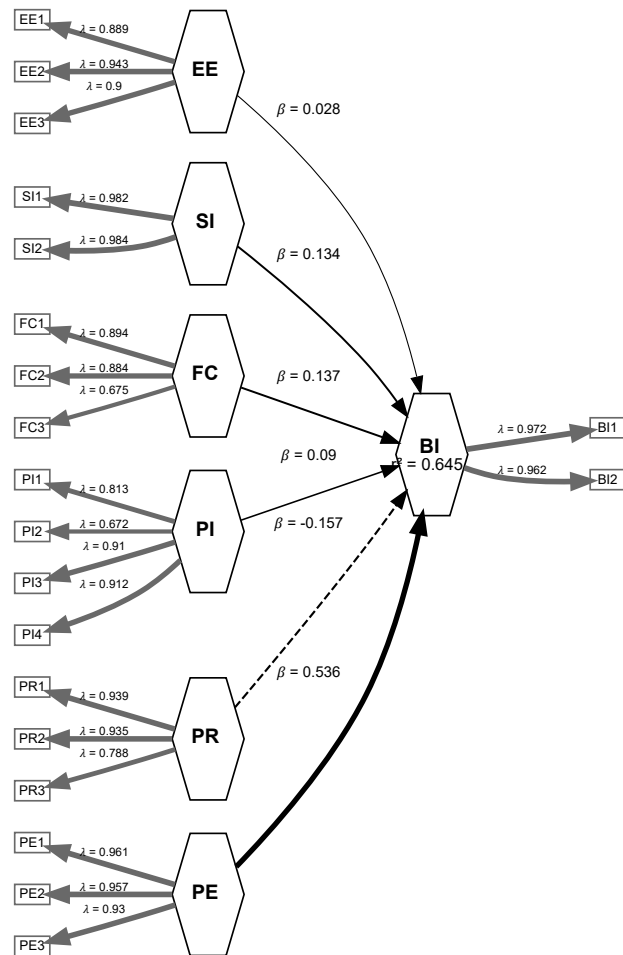
```
pls.model = seminr::estimate_pls(data = df.proc,  
                                measurement_model = df.mm,  
                                structural_model = df.sm,  
                                inner_weights = seminr::path_weighting,  
                                missing = seminr::mean_replacement,  
                                missing_value = -99)
```

```
## Generating the seminr model
```

```
## All 106 observations are valid.
```

## 5.4 Summarize PLS-SEM model

```
graphics::plot(pls.model,  
               edge.display = TRUE,  
               node.color = "lightblue",  
               node.frame.color = "black")
```



```
pls.summary = summary(pls.model)
```

```
items.desc = pls.summary$descriptives$statistics$items
```

```
items.desc.df = cbind("Indicators" = rownames(items.desc), as.data.frame(items.desc)) %>%
```

```
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4))) %>%
```

```
  dplyr::select(-`No.` , -Missing)
```

```
items.desc.df
```

##	Indicators	Mean	Median	Min	Max	Std.Dev.	Kurtosis	Skewness
##	PE1	PE1 4.5472	5	2	5	0.6919	4.1530	-1.3831
##	PE2	PE2 4.5943	5	2	5	0.6441	4.9998	-1.5371
##	PE3	PE3 4.4811	5	3	5	0.7333	2.6038	-1.0266
##	EE1	EE1 4.5283	5	1	5	0.7199	7.3127	-1.7922
##	EE2	EE2 4.4340	5	3	5	0.7435	2.3604	-0.8900
##	EE3	EE3 4.6038	5	3	5	0.6276	3.6038	-1.3255
##	SI1	SI1 4.5377	5	2	5	0.7061	4.9364	-1.5204
##	SI2	SI2 4.5660	5	2	5	0.6764	5.6184	-1.6326
##	FC1	FC1 4.7170	5	3	5	0.4732	3.1806	-1.2316
##	FC2	FC2 4.6038	5	3	5	0.5803	3.3093	-1.1447
##	FC3	FC3 4.6226	5	1	5	0.6684	10.2282	-2.2820
##	PI1	PI1 4.3491	5	1	5	0.8949	5.4468	-1.5431
##	PI2	PI2 3.2075	3	1	5	0.9229	3.1092	0.2358
##	PI3	PI3 4.2736	4	3	5	0.7750	1.8487	-0.5125
##	PI4	PI4 4.1698	4	1	5	0.8888	4.5783	-1.1554
##	PR1	PR1 4.7264	5	1	5	0.6551	13.0600	-2.9213
##	PR2	PR2 4.6604	5	1	5	0.7156	14.1891	-3.0042
##	PR3	PR3 4.1038	4	1	5	0.8273	6.5485	-1.4111
##	BI1	BI1 4.6321	5	2	5	0.6373	5.5806	-1.7241
##	BI2	BI2 4.6415	5	2	5	0.6353	5.7491	-1.7743

```

constructs.desc = pls.summary$descriptives$statistics$constructs
constructs.desc.df = cbind("Constructs" = rownames(constructs.desc), as.data.frame(constructs.desc)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4))) %>%
  dplyr::select(-`No.` , -Missing)
constructs.desc.df

```

##	Constructs	Mean	Median	Min	Max	Std.Dev.	Kurtosis	Skewness
##	PE	PE 0	0.6962	-3.4853	0.6962	1	3.6824	-1.2464
##	EE	EE 0	0.7492	-2.4261	0.7492	1	2.8029	-1.0207
##	SI	SI 0	0.6592	-3.7615	0.6592	1	5.4600	-1.5895
##	FC	FC 0	0.7499	-2.2732	0.7499	1	2.0792	-0.8329
##	PI	PI 0	-0.0169	-2.4060	1.3181	1	2.2964	-0.5413
##	PR	PR 0	0.3491	-5.6041	0.6472	1	13.9079	-2.9583
##	BI	BI 0	0.5906	-4.2827	0.5906	1	5.7314	-1.7004

## 5.5 Perform bootstrapping

```

pls.boot = seminr::bootstrap_model(seminr_model = pls.model,
                                   nboot = 10000,
                                   cores = NULL,
                                   seed = 102899)

```

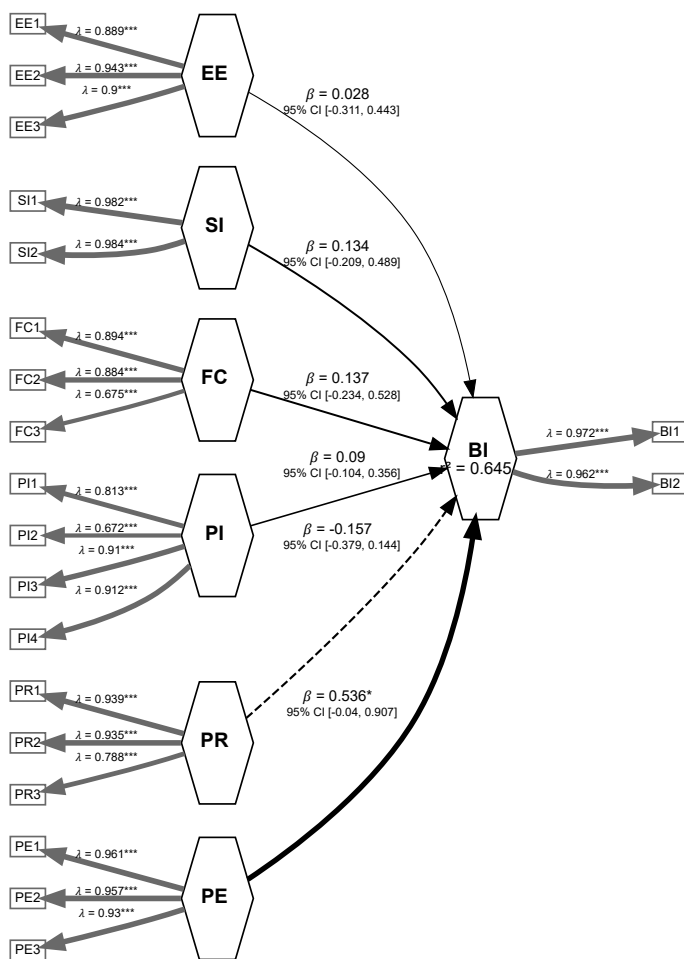
```
## Bootstrapping model using seminr...
```

```
## SEMinR Model successfully bootstrapped
```

```
pls.boot.summary = summary(pls.boot, alpha = 0.05)
pls.boot.summary$bootstrapped_paths
```

##		Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI	97.5% CI
##	PE -> BI	0.536	0.487	0.243	2.210	-0.040	0.907
##	EE -> BI	0.028	0.043	0.190	0.146	-0.311	0.443
##	SI -> BI	0.134	0.143	0.179	0.748	-0.209	0.489
##	FC -> BI	0.137	0.141	0.192	0.714	-0.234	0.528
##	PI -> BI	0.090	0.102	0.117	0.765	-0.104	0.356
##	PR -> BI	-0.157	-0.119	0.133	-1.179	-0.379	0.144

```
graphics::plot(pls.boot,
  edge.display = TRUE,
  node.color = "lightblue",
  node.frame.color = "black")
```



## 5.6 Evaluate measurement models

### 5.6.1 Evaluate indicator reliability

```
mm.ir = pls.summary$loadings
mm.ir.df = cbind("Indicators" = rownames(mm.ir), as.data.frame(mm.ir)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4)))
mm.ir.df
```

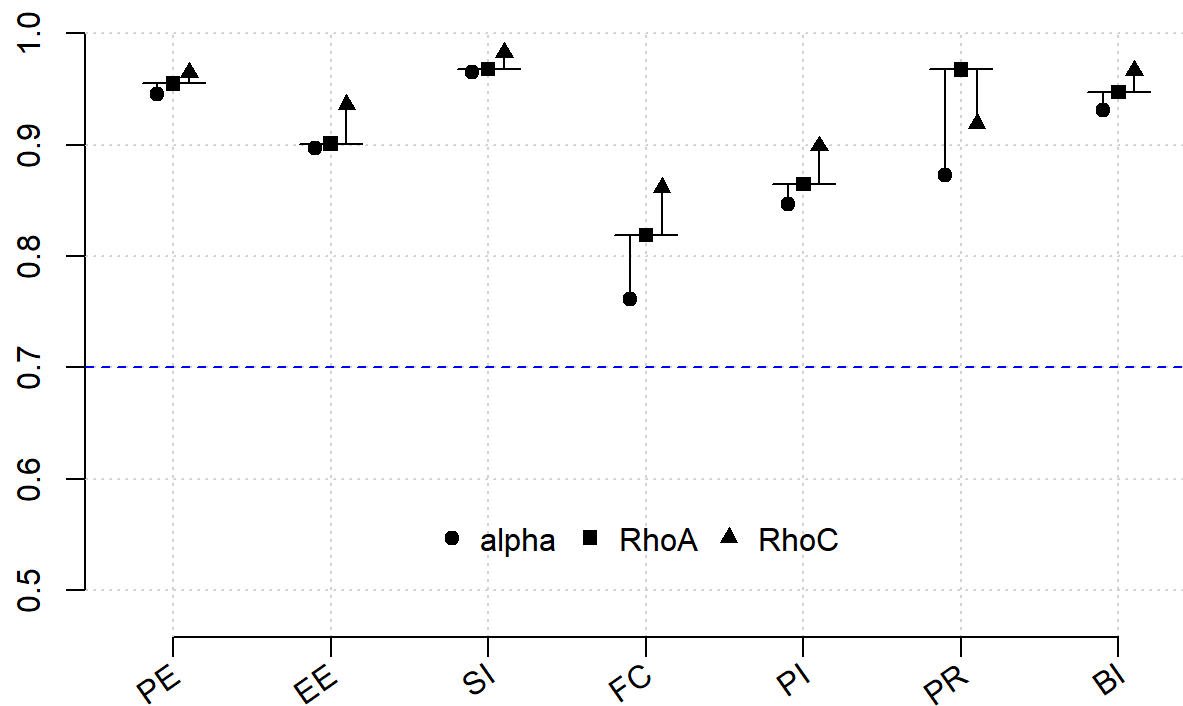
##	Indicators	PE	EE	SI	FC	PI	PR	BI
##	PE1	PE1 0.9608	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
##	PE2	PE2 0.9566	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
##	PE3	PE3 0.9295	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
##	EE1	EE1 0.0000	0.8893	0.0000	0.0000	0.0000	0.0000	0.0000
##	EE2	EE2 0.0000	0.9428	0.0000	0.0000	0.0000	0.0000	0.0000
##	EE3	EE3 0.0000	0.8997	0.0000	0.0000	0.0000	0.0000	0.0000
##	SI1	SI1 0.0000	0.0000	0.9817	0.0000	0.0000	0.0000	0.0000
##	SI2	SI2 0.0000	0.0000	0.9839	0.0000	0.0000	0.0000	0.0000
##	FC1	FC1 0.0000	0.0000	0.0000	0.8941	0.0000	0.0000	0.0000
##	FC2	FC2 0.0000	0.0000	0.0000	0.8835	0.0000	0.0000	0.0000
##	FC3	FC3 0.0000	0.0000	0.0000	0.6749	0.0000	0.0000	0.0000
##	PI1	PI1 0.0000	0.0000	0.0000	0.0000	0.8129	0.0000	0.0000
##	PI2	PI2 0.0000	0.0000	0.0000	0.0000	0.6718	0.0000	0.0000
##	PI3	PI3 0.0000	0.0000	0.0000	0.0000	0.9096	0.0000	0.0000
##	PI4	PI4 0.0000	0.0000	0.0000	0.0000	0.9119	0.0000	0.0000
##	PR1	PR1 0.0000	0.0000	0.0000	0.0000	0.0000	0.9391	0.0000
##	PR2	PR2 0.0000	0.0000	0.0000	0.0000	0.0000	0.9347	0.0000
##	PR3	PR3 0.0000	0.0000	0.0000	0.0000	0.0000	0.7876	0.0000
##	BI1	BI1 0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9721
##	BI2	BI2 0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.9618

### 5.6.2 Evaluate internal consistency

```
mm.ic = pls.summary$reliability
mm.ic.df = cbind("Constructs" = rownames(mm.ic), as.data.frame(mm.ic)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4))) %>%
  dplyr::select(Constructs, alpha, rhoA, rhoC)
mm.ic.df
```

##	Constructs	alpha	rhoA	rhoC
##	PE	PE 0.9451	0.9549	0.9646
##	EE	EE 0.8973	0.9008	0.9360
##	SI	SI 0.9648	0.9677	0.9827
##	FC	FC 0.7617	0.8190	0.8618
##	PI	PI 0.8463	0.8646	0.8989
##	PR	PR 0.8723	0.9675	0.9190
##	BI	BI 0.9309	0.9470	0.9664

```
graphics::plot(pls.summary$reliability)
```



### 5.6.3 Evaluate convergent validity

```
mm.cv = pls.summary$reliability
mm.cv.df = cbind("Constructs" = rownames(mm.cv), as.data.frame(mm.cv)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4))) %>%
  dplyr::select(Constructs, AVE)
mm.cv.df
```

##	Constructs	AVE
##	PE	PE 0.9008
##	EE	EE 0.8298
##	SI	SI 0.9660
##	FC	FC 0.6785
##	PI	PI 0.6928
##	PR	PR 0.7920
##	BI	BI 0.9350

## 5.6.4 Evaluate discriminant validity

```
mm.dv = pls.boot.summary$bootstrapped_HMTT
mm.dv.df = cbind("Constructs" = rownames(mm.dv), as.data.frame(mm.dv)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4)),
               Constructs = gsub(" -> ", "and", Constructs))
mm.dv.df
```



##		Constructs	Original Est.	Bootstrap Mean	Bootstrap SD	T Stat.	2.5% CI
## PE	-> EE	PE and EE	0.8897	0.8898	0.0666	13.3688	0.7460
## PE	-> SI	PE and SI	0.8680	0.8688	0.0401	21.6564	0.7849
## PE	-> FC	PE and FC	0.9165	0.9193	0.0387	23.7128	0.8430
## PE	-> PI	PE and PI	0.8258	0.8252	0.0515	16.0350	0.7147
## PE	-> PR	PE and PR	0.4922	0.5043	0.0952	5.1686	0.3163
## PE	-> BI	PE and BI	0.8180	0.8148	0.0586	13.9505	0.6829
## EE	-> SI	EE and SI	0.7864	0.7854	0.0536	14.6640	0.6724
## EE	-> FC	EE and FC	0.9873	0.9883	0.0563	17.5456	0.8805
## EE	-> PI	EE and PI	0.8497	0.8482	0.0684	12.4300	0.7049
## EE	-> PR	EE and PR	0.2727	0.3014	0.1415	1.9266	0.0725
## EE	-> BI	EE and BI	0.7737	0.7741	0.0644	12.0180	0.6323
## SI	-> FC	SI and FC	0.7606	0.7645	0.0605	12.5761	0.6390
## SI	-> PI	SI and PI	0.6363	0.6360	0.0787	8.0833	0.4734
## SI	-> PR	SI and PR	0.2932	0.3101	0.1124	2.6088	0.1037
## SI	-> BI	SI and BI	0.7335	0.7292	0.0817	8.9816	0.5497
## FC	-> PI	FC and PI	0.9575	0.9555	0.0757	12.6399	0.8073
## FC	-> PR	FC and PR	0.5556	0.5750	0.1229	4.5214	0.3333
## FC	-> BI	FC and BI	0.7838	0.7880	0.0750	10.4469	0.6375
## PI	-> PR	PI and PR	0.5449	0.5472	0.0792	6.8780	0.3832
## PI	-> BI	PI and BI	0.6920	0.6937	0.0710	9.7469	0.5440
## PR	-> BI	PR and BI	0.2284	0.2623	0.1362	1.6772	0.0604
##		97.5% CI					
## PE	-> EE	1.0030					
## PE	-> SI	0.9416					
## PE	-> FC	0.9938					
## PE	-> PI	0.9170					
## PE	-> PR	0.6873					
## PE	-> BI	0.9119					
## EE	-> SI	0.8841					
## EE	-> FC	1.1030					
## EE	-> PI	0.9734					
## EE	-> PR	0.6198					
## EE	-> BI	0.8860					
## SI	-> FC	0.8785					
## SI	-> PI	0.7816					
## SI	-> PR	0.5445					
## SI	-> BI	0.8679					
## FC	-> PI	1.1046					
## FC	-> PR	0.8181					
## FC	-> BI	0.9325					
## PI	-> PR	0.6930					
## PI	-> BI	0.8201					
## PR	-> BI	0.5828					

## 5.6 Evaluate structural model

### 5.6.1 Evaluate collinearity issues

```
sm.co = pls.summary$vif_antecedents
sm.co.df = cbind("Constructs" = names(sm.co[[1]]), as.data.frame(sm.co))
sm.co.df
```

```
##      Constructs      BI
## PE      PE 6.149061
## EE      EE 5.530130
## SI      SI 3.390875
## FC      FC 4.776124
## PI      PI 3.027738
## PR      PR 1.584300
```

### 5.6.2 Evaluate significance and relevance of relationships

```
sm.single.path = pls.boot.summary$bootstrapped_paths
sm.single.path.df = cbind("Paths" = rownames(sm.single.path), as.data.frame(sm.single.path)) %>%
  dplyr::mutate(pvalue = stats::pt(-abs(`T Stat.`), df = nrow(df.proc) - 1) * 2,
               dplyr::across(dplyr::where(is.numeric), ~ round(., 4)),
               Paths = gsub(" -> ", "to", Paths))
sm.single.path.df
```

```
##           Paths Original Est. Bootstrap Mean Bootstrap SD T Stat. 2.5% CI
## PE -> BI PE to BI      0.5363      0.4867      0.2427  2.2099 -0.0398
## EE -> BI EE to BI      0.0277      0.0430      0.1898  0.1461 -0.3110
## SI -> BI SI to BI      0.1337      0.1434      0.1787  0.7484 -0.2091
## FC -> BI FC to BI      0.1371      0.1408      0.1919  0.7145 -0.2336
## PI -> BI PI to BI      0.0897      0.1017      0.1173  0.7646 -0.1041
## PR -> BI PR to BI     -0.1567     -0.1188      0.1329 -1.1791 -0.3786
##           97.5% CI pvalue
## PE -> BI  0.9069 0.0293
## EE -> BI  0.4429 0.8841
## SI -> BI  0.4895 0.4559
## FC -> BI  0.5278 0.4765
## PI -> BI  0.3559 0.4462
## PR -> BI  0.1444 0.2410
```

```
sm.total.path = pls.boot.summary$bootstrapped_total_paths
sm.total.path.df = cbind("Paths" = rownames(sm.total.path), as.data.frame(sm.total.path)) %>%
  dplyr::mutate(pvalue = stats::pt(-abs(`T Stat.`), df = nrow(df.proc) - 1) * 2,
               dplyr::across(dplyr::where(is.numeric), ~ round(., 4)),
               Paths = gsub(" -> ", "to", Paths))
sm.total.path.df
```

```
##           Paths Original Est. Bootstrap Mean Bootstrap SD T Stat. 2.5% CI
## PE  ->  BI PE to BI          0.5363          0.4867          0.2427  2.2099 -0.0398
## EE  ->  BI EE to BI          0.0277          0.0430          0.1898  0.1461 -0.3110
## SI  ->  BI SI to BI          0.1337          0.1434          0.1787  0.7484 -0.2091
## FC  ->  BI FC to BI          0.1371          0.1408          0.1919  0.7145 -0.2336
## PI  ->  BI PI to BI          0.0897          0.1017          0.1173  0.7646 -0.1041
## PR  ->  BI PR to BI         -0.1567         -0.1188          0.1329 -1.1791 -0.3786
##           97.5% CI pvalue
## PE  ->  BI  0.9069 0.0293
## EE  ->  BI  0.4429 0.8841
## SI  ->  BI  0.4895 0.4559
## FC  ->  BI  0.5278 0.4765
## PI  ->  BI  0.3559 0.4462
## PR  ->  BI  0.1444 0.2410
```

## 5.6.3 Evaluate explanatory power

```
sm.rSquare = pls.summary$paths
sm.rSquare.df = cbind("Constructs" = rownames(sm.rSquare), as.data.frame(sm.rSquare)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4)))
sm.rSquare.df
```

```
##           Constructs          BI
## R^2           R^2  0.6446
## AdjR^2       AdjR^2  0.6230
## PE           PE  0.5363
## EE           EE  0.0277
## SI           SI  0.1337
## FC           FC  0.1371
## PI           PI  0.0897
## PR           PR -0.1567
```

```
sm.fSquare = pls.summary$fSquare
sm.fSquare.df = cbind("Constructs" = rownames(sm.fSquare), as.data.frame(sm.fSquare)) %>%
  dplyr::mutate(dplyr::across(dplyr::where(is.numeric), ~ round(., 4)))
sm.fSquare.df
```

```
##           Constructs PE EE SI FC PI PR          BI
## PE           PE  0  0  0  0  0  0 0.1358
## EE           EE  0  0  0  0  0  0 0.0002
## SI           SI  0  0  0  0  0  0 0.0142
## FC           FC  0  0  0  0  0  0 0.0100
## PI           PI  0  0  0  0  0  0 0.0080
## PR           PR  0  0  0  0  0  0 0.0459
## BI           BI  0  0  0  0  0  0 0.0000
```

## 6 Export necessary data

```

export.list = list(items_desc = items.desc.df,
                  constructs_desc = constructs.desc.df,
                  reliability = mm.ir.df,
                  consistency = mm.ic.df,
                  convergence = mm.cv.df,
                  discriminant = mm.dv.df,
                  collinearity = sm.co.df,
                  single_paths = sm.single.path.df,
                  total_paths = sm.total.path.df,
                  r_square = sm.rSquare.df,
                  effect_size = sm.fSquare.df)

if(length(export.list) != 0){
  if (!file.exists(file.path(output.path, output.name))) {
    writexl::write_xlsx(export.list, file.path(output.path, output.name))
    cat(crayon::green("File successfully written. "))
  } else {
    cat(crayon::red(glue::glue("Filename already used: {output.name}")))
    overwrite = readline(prompt = "Overwrite (1 for Yes, 0 for No): ")
    if (overwrite == "1") {
      writexl::write_xlsx(export.list, file.path(output.path, output.name))
      cat(crayon::green("File successfully overwritten"))
    } else {
      cat(crayon::red("File not overwritten"))
    }
  }
}
}

```

```
## File successfully written.
```