Basic and Advanced Quantitative Data Analysis USING SPSS

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Data Analysis USING SPSS – New Approach

Statistical Analysis (Research Methodology):

- 3.1 Common Method Variance
- 3.2 Exploratory Factor Analysis

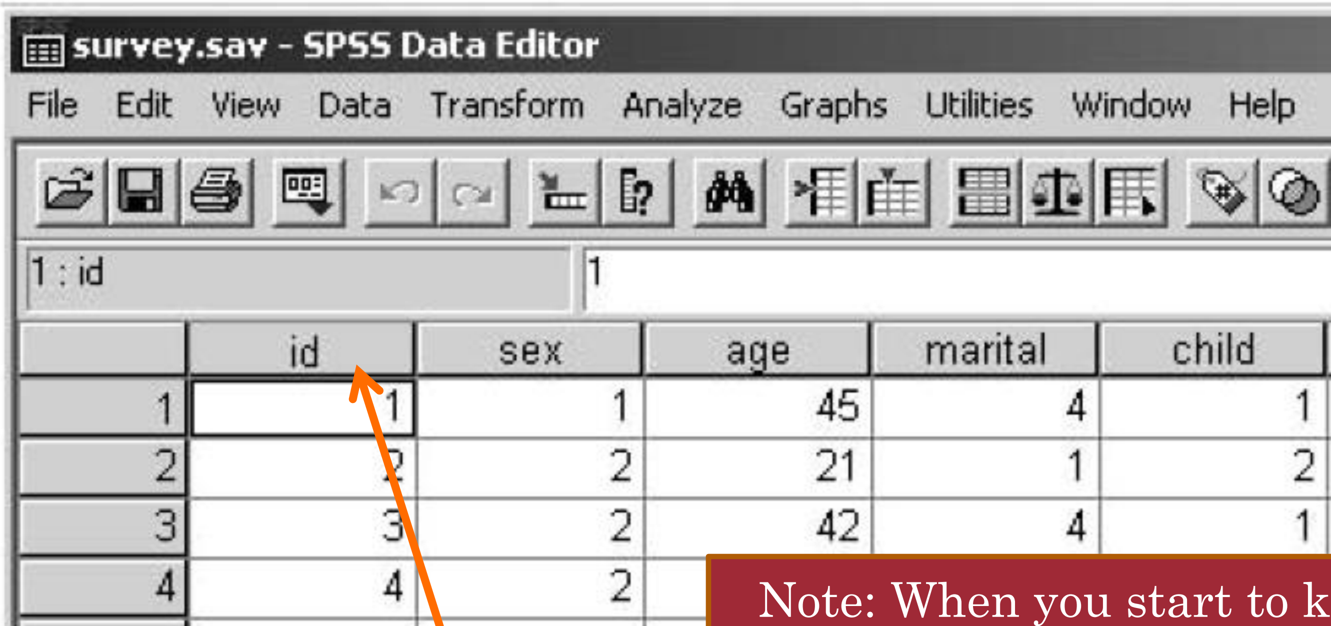
  (Varimax vs Promax Rotation)
- 3.3 Reliability Analysis
- 3.4 Descriptive Statistics
- 3.5 Correlation Analysis
- 3.6 Multiple Regression Analysis

  (the use of t-value) & f2(effect size)
- 3.7 Hierarchical Regression Analysis
- 3.7.1 Mediated Regression Analysis (the end of Baron & Kenny, 1986; Preacher & Hayes (2004) SOBEL test; (2008) Indirect – Multiple Mediation; SYNTAX)
- 3.7.2 Moderated Regression Analysis (the use of Mean Centering)

Chapter 4 Data Analysis

- 4.1 Introduction
- 4.2 Data Collection and Response Rate
- 4.3 Profile of Respondents
- 4.4 Factor Analysis
- 4.5 Reliability Analysis
- 4.6 Modification of Research Conceptual Framework
- 4.7 Hypotheses Statements
- 4.8 Descriptive Analysis
- 4.9 Correlation Analysis
- 4.10 Multiple Regression Analysis
- 4.11 Hierarchical Regression Analysis

BEFORE ENTERING DATA



Create= id label

Note: When you start to key in the survey questionnaires, you need to write an id number for each of the survey questionnaires…easier to detect when there is a missing value or wrongly key in value , most importantly we can use this id to detect outliers

Screening and cleaning data

The data screening process involves a number of steps:

- *Step 1: Checking for errors.* First, you need to check each of your variables for scores that are out of range (i.e. not within the range of possible scores).
- *Step 2: Finding the error in the data file.* Second, you need to find where in the data file this error occurred (i.e. which case is involved).
- *Step 3: Correcting the error in the data file.* Finally, you need to correct the error in the data file itself.

Finding the error in the data file

Procedure for checking categorical variables

1. From the main menu at the top of the screen click on: **Analyze**, then click on **Descriptive Statistics**, then **Frequencies**.
2. Choose the variables that you wish to check (e.g. sex, marital, educ.).
3. Click on the arrow button to move these into the variable box.
4. Click on the **Statistics** button. Tick **Minimum** and **Maximum** in the **Dispersion** section.
5. Click on **Continue** and then on **OK**.

The output generated using this procedure is displayed below (only selected output is displayed).

Statistics

		SEX	Marital status	Highest educ completed
N	Valid	439	439	439
	Missing	0	0	0
Minimum		1	1	1
Maximum		2	8	6

Finding the error in the data file (Pallant, 2005, p.44)

Method 2

1. From the menu at the top of the screen click on: **Analyze**, then click on **Descriptive Statistics**, then **Explore**.
2. In the **Display** section click on **Statistics**.
3. Click on the variables that you are interested in (e.g. sex) and move them into the **Dependent list** by clicking on the arrow button.
4. In the **Label cases** section choose **ID** from your variable list. This will give you the ID number of the case, and will allow you to trace back to the questionnaire/record with the mistake.
5. In the **Statistics** section choose **Outliers**. To save unnecessary output you may also like to remove the tick from Descriptives (just click once). Click on **Continue**.
6. In the **Options** section choose **Exclude cases pairwise**. Click on **Continue** and then **OK**.

The output generated from Explore (Method 2) is shown below.

Extreme Values

			Case Number	ID	Value
SEX	Highest	1	3	9	3
		2	209	39	2
		3	241	115	2
		4	356	365	2
		5	345	344	.[a]
	Lowest	1	145	437	1
		2	132	406	1
		3	124	372	1
		4	81	244	1
		5	126	374	.[b]

a. Only a partial list of cases with the value 2 are shown in the table of upper extremes.

b. Only a partial list of cases with the value 1 are shown in the table of lower extremes.

Note: check here whether got any mistake

PROFILE OF RESPONDENTS

Procedure for obtaining descriptive statistics for categorical variables

1. From the menu at the top of the screen click on: **Analyze**, then click on **Descriptive Statistics**, then **Frequencies**.
2. Choose and highlight the categorical variables you are interested in (e.g. sex). Move these into the **Variables** box.
3. Click on the **Statistics** button. In the **Dispersion** section tick **Minimum** and **Maximum**. Click on **Continue** and then **OK**.

The output generated from this procedure is shown below.

Statistics

SEX

N	Valid	439
	Missing	0
Minimum		1
Maximum		2

SEX

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	MALES	185	42.1	42.1	42.1
	FEMALES	254	57.9	57.9	100.0
	Total	439	100.0	100.0	

Common method bias.

- Common method bias refers to the amount of spurious covariance shared between independent and dependent variables that are measured at the same point in time, such as in a cross-sectional survey, using the same instrument, such as a questionnaire.
- In such cases, the phenomenon under investigation may not be adequately separated from measurement artifacts. Standard statistical tests are available to test for common method bias, such as Harmon's single-factor test (Podsakoff et al. 2003), Lindell and Whitney's (2001) market variable technique, and so forth. This bias can be potentially avoided if the independent and dependent variables are measured at different points in time, using a longitudinal survey design, of if these variables are measured using different methods, such as computerized recording of dependent variable versus questionnaire-based self-rating of independent variables.

What is Common Method Variance?

- Common method variance needs to be examined when data are collected **via self-reported questionnaires** and, in particular, **both the predictor and criterion variables are obtained from the same person** (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

- Podsakoff and Todor (1985) also noted that: "**Invariably, when self-reported measures obtained from the same sample are utilized in research, concern over same-source bias or general method variance arise**" (p. 65).

Methods

- Several researchers (Podsakoff et al. 2003; Podsakoff et al. 2012; Williams, Hartman, & Cavazotte, 2010) have noted that there are two fundamental ways to control for method biases.

- One way is to **statistically control** for the effects of method biases after the data have been gathered; the other is to minimize their effects through the **careful design of the study's procedures**.

Harman's Single Factor

- This is done by entering all the principal constructs into a principal component factor analysis (*Podsakoff & Organ, 1986*).

- Evidence method bias exists when:
  - a single factor emerges from the factor analysis, or
  - one general factor accounts for the majority of the covariance among the measures (*Podsakoff et al., 2003*).

- Does each principal construct explain roughly equal variance (range from 5 – 18%)

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.326	34.420	34.420	10.326	34.420	34.420
2	3.273	10.910	45.331	3.273	10.910	45.331
3	1.615	5.384	50.715	1.615	5.384	50.715
4	1.480	4.932	55.647	1.480	4.932	55.647
5	1.290	4.301	59.948	1.290	4.301	59.948
6	1.166	3.888	63.836	1.166	3.888	63.836
7	.931	3.102	66.938			
8	.863	2.878	69.815			
9	.761	2.538	72.353			
10	.662	2.205	74.558			
11	.644	2.146	76.705			
12	.585	1.950	78.654			
13	.576	1.920	80.574			
14	.551	1.836	82.410			
15	.500	1.666	84.076			
16	.473	1.577	85.654			
17	.454	1.515	87.169			
18	.399	1.331	88.499			
19	.378	1.259	89.759			
20	.368	1.227	90.986			
21	.349	1.165	92.150			
22	.328	1.093	93.243			
23	.319	1.064	94.307			
24	.301	1.004	95.311			
25	.273	.911	96.222			
26	.263	.878	97.100			
27	.250	.832	97.932			
28	.218	.727	98.659			
29	.203	.678	99.336			
30	.199	.664	100.000			

Extraction Method: Principal Component Analysis.

Not more than 50%

Factor analysis

- The purpose of using factor analysis is to summarize patterns of correlations among observed variables, to reduce a large number of observed variables to a smaller numbers of factors, and to provide an operational definition (a regression equation) for an underlying process by using observed variables, or to test a theory about the nature of underlying processes (Tabachnick & Fidell, 2007, p. 608).
- Factor analysis can also be used to reduce a large number of related variables to a more manageable number, prior to using them in other analyses such as multiple regression or multivariate analysis of variance (Pallant, 2005).

Exploratory vs. Confirmatory Factor Analysis

- There are two main approaches to factor analysis that you will see described.
- Exploratory factor analysis is often used in the early stages of research to gather information about (explore) the interrelationships among a set of variables.
- Confirmatory factor analysis is a more complex and sophisticated set of techniques used later in the research process to test (confirm) specific hypotheses or theories concerning the structure underlying a set of variables.

APPROPRIATENESS OF FACTOR ANALYSIS

- In order to ensure the appropriateness of factor analysis, six assumptions need to be met according to the guideline recommended by Hair et al. (2006; 2010).

  1) Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) values must exceed .50. (**.70** Neuman, 2003). (.60, Tabachnick & Fidell, 2008)

  2) The result of the Bartlett's test of sphericity should be at least significant at .05.

  3) Anti-image correlation matrix of items should be at least above .50.

  4) Communalities of the variables must be greater than .50.

  5) The factor loadings of .30 or above for each item are considered practical and statistically significant for sample sizes of 350 or greater.

  6) Factors with eigenvalues greater than 1 are considered significant. (Has been criticized)

  7) Percentage of varianced explained usually 60% or higher.

  8) No cross loaded

- Note: In terms of communalities, Field (2005) and others scholars (MacCallum, Widaman, Zhang, & Hong, 1999) have suggested that those items/variables that have communality values less than 0.5 can be retained when the sample size is over 500. Hair et al. (2006) also noted that a researcher may take into account whether to retain or remove those items/variables which have a low communality. If the low communality item contributes to a well-defined factor, a researcher should consider retaining it.

Cutoff-point factor loading based on sample size

TABLE 2 Guidelines for Identifying Significant Factor Loadings Based on Sample Size

Factor Loading	Sample Size Needed for Significance[a]
.30	350
.35	250
.40	200
.45	150
.50	120
.55	100
.60	85
.65	70
.70	60
.75	50

[a] Significance is based on a .05 significance level (α), a power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficients.

Source: Computations made with SOLO *Power Analysis*, BMDP Statistical Software, Inc., 1993.

KMO MEASURE OF SAMPLING ADEQUACY

- Kaiser-Meyer-Olkin measure of sampling adequacy (KMO) values must exceed .50. (**.70,** Neuman, 2003). (.60, Tabachnick & Fidell, 2008)

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.874
Bartlett's Test of Sphericity	Approx. Chi-Square	3966.539
	df	190
	Sig.	.000

KMO

Bartlett's test of sphericity

The KMO measure of sampling adequacy is a test of the amount of variance within the data could be explained by factors. As a measure of factorability: a KMO value of .5 is poor; .6 is acceptable; a value closer to 1 is better.

Measure of sampling adequacy (MSA)

A third measure to quantify the degree of intercorrelations among the variables and the appropriateness of factor analysis is the **measure of sampling adequacy** (MSA). This index ranges from 0 to 1, reaching 1 when each variable is perfectly predicted without error by the other variables. The measure can be interpreted with the following guidelines: .80 or above, meritorious; .70 or above, middling; .60 or above, mediocre; .50 or above, miserable; and below .50, unacceptable [22, 23]. The MSA increases as (1) the sample size increases, (2) the average

(Hair et al., 2010)

Factor Analysis – Anti image correlation matrix

Anti-image Matrices

		LOYpositiv	LOYfriends	LOYrecom	LOYfirst	LOYrepeat	LOYcontinu
Anti-image Covariance	LOYpositiv	.542	-.198	-.072	-.023	-.059	-.042
	LOYfriends	-.198	.508	-.186	-.042	.023	-.026
	LOYrecom	-.072	-.186	.490	-.075	-.069	-.041
	LOYfirst	-.023	-.042	-.075	.598	-.075	-.113
	LOYrepeat	-.059	.023	-.069	-.075	.401	-.216
	LOYcontinu	-.042	-.026	-.041	-.113	-.216	.383
Anti-image Correlation	LOYpositiv	.876[a]	-.377	-.140	-.041	-.126	-.091
	LOYfriends	-.377	.816[a]	-.373	-.077	.051	-.059
	LOYrecom	-.140	-.373	.876[a]	-.139	-.155	-.095
	LOYfirst	-.041	-.077	-.139	.919[a]	-.154	-.237
	LOYrepeat	-.126	.051	-.155	-.154	.808[a]	-.551
	LOYcontinu	-.091	-.059	-.095	-.237	-.551	.811[a]

a. Measures of Sampling Adequacy (MSA)

Anti-image correlation must above .50

COMMUNALITIES OF THE VARIABLES MUST BE GREATER THAN .50.

The communalities indicate how much variance in each variable is explained by the analysis

The extraction communalities are calculated using the extracted factors only, so these are the useful values> For "LOYcontinu" .68% of the variance is explained by the extracted factors.

If a particular variable has a low communality, then consider dropping it from the analysis.

Note: you need to take note to those variables below 0.5

Communalities

	Initial	Extraction
LOYpositiv	1.000	.573
LOYf riends	1.000	.556
LOYrecom	1.000	.640
LOYf irst	1.000	.539
LOYrepeat	1.000	.649
LOYcontinu	1.000	.677

Extraction Method: Principal Component Analysis.

Communalities

	Initial	Extraction
Q01	1.000	.435
Q02	1.000	.414
Q03	1.000	.530
Q04	1.000	.469
Q05	1.000	.343
Q06	1.000	.654
Q07	1.000	.545
Q08	1.000	.739
Q09	1.000	.484
Q10	1.000	.335
Q11	1.000	.690
Q12	1.000	.513
Q13	1.000	.536
Q14	1.000	.488
Q15	1.000	.378
Q16	1.000	.487
Q17	1.000	.683
Q18	1.000	.597
Q19	1.000	.343
Q20	1.000	.484
Q21	1.000	.550
Q22	1.000	.464
Q23	1.000	.412

Extraction Method: Principal Component

EIGENVALUES AND % TOTAL VARIANCE

Factors with eigenvalues greater than 1 are considered significant.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.250	31.249	31.249	6.250	31.249	31.249
2	3.396	16.979	48.228	3.396	16.979	48.228
3	1.223	6.113	54.341	1.223	6.113	54.341
4	1.158	5.788	60.130	1.158	5.788	60.130
5	.898	4.490	64.619			
6	.785	3.926	68.546			
7	.731	3.655	72.201			
8	.655	3.275	75.476			
9	.650	3.248	78.724			
10	.601	3.004	81.728			
11	.586	2.928	84.656			
12	.499	2.495	87.151			
13	.491	2.456	89.607			
14	[illegible]	[illegible]	[illegible]			
15	[illegible]	[illegible]	[illegible]			
16	[illegible]	[illegible]	[illegible]			
17	[illegible]	[illegible]	[illegible]			
18	[illegible]	[illegible]	[illegible]			
19	.223	1.117	99.126			
20	.175	.874	100.000			

Extraction Method: Principal Component Analysis.

The four extracted components together explained 60.13% of variance.

Note: cumulative% should not below 50%, usually 60% or higher

Eigenvalues and % total variance

Total Variance Explained

Component	Initial Eigenvalues Total	Initial Eigenvalues % of Variance	Initial Eigenvalues Cumulative %	Extraction Sums of Squared Loadings Total	Extraction Sums of Squared Loadings % of Variance	Extraction Sums of Squared Loadings Cumulative %
1	6.250	31.249	31.249	6.250	31.249	31.249
2	3.396	16.979	48.228	3.396	16.979	48.228
3	1.223	6.113	54.341	1.223	6.113	54.341
4	1.158	5.788	60.130	1.158	5.788	60.130
5	.898	4.490	64.619			
6	.785	3.926	68.546			
7	.731	3.655	72.201			
8	.655	3.275	75.476			
9	.650	3.248	78.724			
10	.601	3.004	81.728			
11	.586	2.928	84.656			
12	.499	2.495	87.151			
13	.491	2.456	89.607			
14	.393	1.964	91.571			
15	.375	1.875	93.446			
16	.331	1.653	95.100			
17	.299	1.496	96.595			
18	.283	1.414	98.010			
19	.223	1.117	99.126			
20	.175	.874	100.000			

Extraction Method: Principal Component Analysis.

Factor 1 had an eigenvalue of 6.25 and explained 31.25% of the total variance.
Factor 2 captured 16.98% of the total variance with an eigenvalue of 3.40.

Need to remove item if it cross-loaded on other factor(s) : one by one, after remove it you need to re-run the data reduction process again until you fulfill Hair et al. (2010) guideline

Rotated Component Matrix [a]

	Component			
	1	2	3	4
SOBimpres	.838			
SOBaccept	.831			
SOBimprov	.810			
SOBapprov	.727			.360
EBfeelgood		.837		
EBdelight		.810		
EBpleasure		.654		
EBconfiden	.317	.625		
EBfeelsexy		.538		.355
FBsuitable			.795	
FBreliable			.772	
FBconvnien			.647	
FBsolution			.611	
FBremove			.596	
FBbeauty			.558	
SYBprestig				.786
SYBtaste				.774
SYBdesire				.749
SYBfitsocia	~~.340~~			.728

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 5 iterations.

Cross-loaded

Varimax rotation vs Direct Oblimin, Promax

- There are two main approaches to rotation, resulting in either orthogonal (uncorrelated) or oblique (correlated) factor solutions. According to Tabachnick and Fidell (2007), orthogonal rotation results in solutions that are easier to interpret and to report; however, they do require the researcher to assume (usually incorrectly) that the underlying constructs are independent (not correlated). Oblique approaches allow for the factors to be correlated, but they are more difficult to interpret, describe and report (Tabachnick & Fidell 2007, p. 638). In practice, the two approaches (orthogonal and oblique) often result in very similar solutions, particularly when the pattern of correlations among the items is clear (Tabachnick & Fidell 2007).
- Many researchers conduct both orthogonal and oblique rotations and then report the clearest and easiest to interpret. I always recommend starting with an oblique rotation to check the degree of correlation between your factors.
- Within the two broad categories of rotational approaches there are a number of different techniques provided by SPSS (orthogonal: Varimax, Quartimax, Equamax; oblique: Direct Oblimin, Promax).

Varimax rotation vs Direct Oblimin, Promax

- The most commonly used orthogonal approach is the Varimax method, which attempts to minimise the number of variables that have high loadings on each factor. The most commonly used oblique technique is Direct Oblimin. For a comparison of the characteristics of each of these approaches, see Tabachnick and Fidell (2007, p. 639).

Run Factor Analysis

1. From the menu at the top of the screen click on: **Analyze**, then click on **Data Reduction**, then on **Factor**.
2. Check that all the required variables (or items on the scale) are still listed in the **Variables** box (pn1 to pn20).
3. Click on the **Descriptives** button.
   - To save repeating the same analyses as obtained in the previous SPSS output you should remove the tick in the **Initial Solution** box, the **Coefficients** box and the **KMO and Bartlett's Test** box. To do this just click on the box with the tick and it should disappear.
   - Click on **Continue**.
4. Click on the **Extraction** button.
   - In the **Method** section make sure **Principal Components** is listed.
   - In the **Analyze** section make sure the **Correlation matrix** option is selected.
   - In the **Display** section, remove the tick from the **Screeplot** and the **Unrotated factor solution**.
   - In the **Extract** section select the **Number of Factors** option. In the box type in the number of factors that you wish to extract (in this case 2).
   - Click on **Continue**.
5. Click on the **Options** button.
   - In the Missing Values section click on **Exclude cases pairwise**.
   - In the **Coefficient Display Format** section make sure that there is a tick in **Sorted by size** and **Suppress absolute values less than .3**.
   - Click on **Continue**.
6. Click on the **Rotation** button.
   - In the **Method** section click on **Varimax**.
7. Click on **Continue** and then **OK**.

Rotated component matrix

Rotated Component Matrix [a]

	Component	
	1	2
PN17	.819	
PN12	.764	
PN18	.741	
PN13	.724	
PN1	.697	
PN15	.679	
PN9	.663	
PN7	.617	
PN6	.614	
PN4	.541	
PN19		.787
PN14		.732
PN3		.728
PN8		.728
PN20		.708
PN2		.704
PN11		.647
PN10		.595
PN16		.585
PN5		.493

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

[a] Rotation converged in 3 iterations.

FACTOR LOADING CUT-OFF POINT BASED ON SAMPLE SIZE

TABLE 2 Guidelines for Identifying Significant Factor Loadings Based on Sample Size

Factor Loading	Sample Size Needed for Significance[a]
.30	350
.35	250
.40	200
.45	150
.50	120
.55	100
.60	85
.65	70
.70	60
.75	50

[a] Significance is based on a .05 significance level (α), a power level of 80 percent, and standard errors assumed to be twice those of conventional correlation coefficients.

Source: Computations made with SOLO *Power Analysis*, BMDP Statistical Software, Inc., 1993.

Reliability Test

- Reliability analysis is to test whether a group of items (i.e. items measuring a construct generated from factor analysis) consistently reflected the construct it is measuring (Field, 2005).
- The ability of a measure to produce consistent results when the same entities are measured under different conditions.
- In other words, if we use this scale to measure the same construct multiple times, do we get pretty much the same result every time, assuming the underlying phenomenon is not changing?
- The most common measure of reliability is internal consistency of the scale (Hair et al., 2006). Cronbach's alpha was calculated in order to examine the internal consistency of the scales used in this study.
- Cronbach's alpha coefficient can range from 0.0 to 1.0. A Cronbach's alpha close to 1.0 indicates that the item is considered to have a high internal consistency reliability, above 0.8 is considered good, 0.7 is considered acceptable and less than 0.6 is considered to be poor (Sekaran, 2003).

Run reliability analysis

Procedure for checking the reliability of a scale

Important: Before starting, you should check that all negatively worded items in your scale have been reversed (see Chapter 8). If you don't do this you will find you have very low (and incorrect) Cronbach alpha values.

1. From the menu at the top of the screen click on: **Analyze**, then click on **Scale**, then **Reliability Analysis**.
2. Click on all of the individual items that make up the scale (e.g. lifsat1, lifsat2, lifsat3, lifsat4, lifsat5). Move these into the box marked **Items**.
3. In the **Model** section, make sure **Alpha** is selected.
4. Click on the **Statistics** button. In the **Descriptives for** section, click on **Item**, **Scale**, and **Scale if item deleted**.
5. Click on **Continue** and then **OK**.

Reliability result

Case Processing Summary

		N	%
Cases	Valid	436	99.3
	Excluded[a]	3	.7
	Total	439	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	N of Items
.890	5

Item Statistics

	Mean	Std. Deviation	N
lifsat1	4.37	1.528	436
lifsat2	4.57	1.554	436
lifsat3	4.69	1.519	436
lifsat4	4.75	1.641	436
lifsat5	3.99	1.855	436

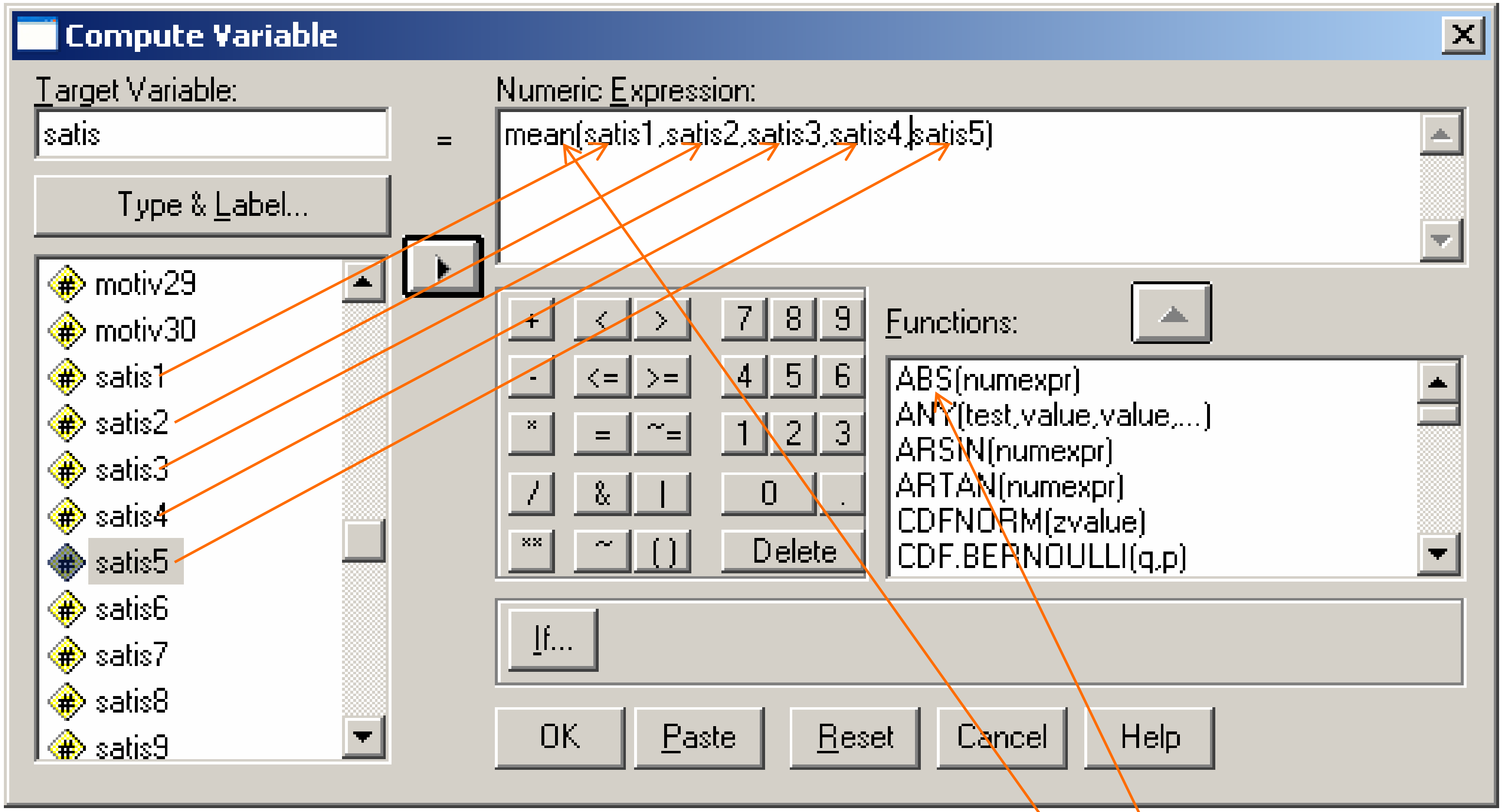
Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
lifsat1	18.00	30.667	.758	.861
lifsat2	17.81	30.496	.752	.862
lifsat3	17.69	29.852	.824	.847
lifsat4	17.63	29.954	.734	.866
lifsat5	18.39	29.704	.627	.896

After checking reliability analysis

- when you are satisfied with reliability analysis of each of the dimensions and/or constructs that was generated from the factor analysis
- You need to compute the mean scores for each of the dimensions and/or construct(s).

1. From the menu at the top of the screen click on: **Transform**, then click on **Compute.**
2. In the **Target variable** box type in the new name you wish to give to the total scale scores



Double-check that all items are correct and in the correct places. Click **OK.**

Click All, then find Mean

Descriptive Analysis

- The **mean and standard deviation** values for all of the study variables/construct.
- Based upon the scale of 1 to 5, the mean scores can be explained as:
- a mean score that is less than 2 is rated as low,
- a mean score between 2 to 4 is rated as average, and
- a mean score of greater 4 is rated as high.

Descriptive Analysis

Procedure for obtaining descriptive statistics for continuous variables

1. From the menu at the top of the screen click on: **Analyze**, then click on **Descriptive Statistics**, then **Descriptives**.
2. Click on all the continuous variables that you wish to obtain descriptive statistics for. Click on the arrow button to move them into the **Variables** box (e.g. age, total perceived stress etc.).
3. Click on the **Options** button. Click on **mean, standard deviation, minimum, maximum, skewness, kurtosis**.
4. Click on **Continue**, and then **OK**.

The output generated from this procedure is shown below.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std.	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
AGE	439	18	82	37.44	13.20	.606	.117	-.203	.233
Total perceived stress	433	12	46	26.73	5.85	.245	.117	.182	.234
Total Optimism	435	7	30	22.12	4.43	-.494	.117	.214	.234
Total Mastery	436	8	28	21.76	3.97	-.613	.117	.285	.233
Total PCOISS	431	20	88	60.60	11.99	-.395	.118	.247	.235
Valid N (listwise)	425								

Correlation analysis

- Pearson correlation is used to examine the strength and the direction of the relationship between all the constructs in the study.
- The Pearson correlation coefficient values can vary from -1.00 to +1.00.
- A correlation value of +1.00 indicates a perfect positive correlation, while a value of -1.00 represents a perfect negative correlation, and a value of 0.00 indicates no linear relationship between the X and Y variables or between two variables (Tabachnick & Fidell, 2007; Pallant, 2007).
- Cohen (1988) interprets the correlation values as: small/weak when the correlation value is r = .10 to .29 or r = -.10 to -.29, medium/moderate when the value is r = .30 to .49 or r = -.30 to -.49, and large/strong when the value is r = .50 to 1.0 or r = -.50 to -1.0 large.

Procedure for calculating Pearson product-moment correlation

1. From the menu at the top of the screen click on: **Analyze**, then click on **Correlate**, then on **Bivariate**.
2. Select your two variables and move them into the box marked **Variables** (e.g. total perceived stress, total PCOISS). You can list a whole range of variables here, not just two. In the resulting matrix, the correlation between all possible pairs of variables will be listed. This can be quite large if you list more than just a few variables.
3. Check that the **Pearson** box and the **2 tail** box have a cross in them. The two-tail test of significance means that you are not making any specific prediction concerning the direction of the relationship between the variables (positive/negative). You can choose a **one-tail** test of significance if you have reasons to support a specific direction.
4. Click on the **Options** button.
   For **Missing Values**, click on the **Exclude cases pairwise** box.
   Under **Options** you can also obtain means, standard deviations if you wish. Click on **Continue**.
5. Click **OK**.

The output generated from this procedure is shown below.

Correlations

		Total PCOISS	Total perceived stress
Total PCOISS	Pearson Correlation	1.000	-.581**
	Sig. (2-tailed)	.	.000
	N	431	426
Total perceived stress	Pearson Correlation	-.581**	1.000
	Sig. (2-tailed)	.000	.
	N	426	433

** Correlation is significant at the 0.01 level (2-tailed).

Correlation analysis cont.

Step 3: Determining the strength of the relationship

The third thing to consider in the output is the size of the value of Pearson correlation (r). This can range from −1.00 to 1.00. This value will indicate the strength of the relationship between your two variables. A correlation of 0 indicates no relationship at all, a correlation of 1.0 indicates a perfect positive correlation, and a value of −1.0 indicates a perfect negative correlation.

How do you interpret values between 0 and 1? Different authors suggest different interpretations; however, Cohen (1988) suggests the following guidelines:

r=.10 to .29 or r=−.10 to −.29	small
r=.30 to .49 or r=−.30 to −.4.9	medium
r=.50 to 1.0 or r=−.50 to −1.0	large

These guidelines apply whether or not there is a negative sign out the front of your r value. Remember, the negative sign refers only to the direction of the relationship, not the strength. The *strength* of correlation of r=.5 and r=−.5 is the same. It is only in a different *direction*.

In the example presented above there is a large correlation between the two variables (r=−.58), suggesting quite a strong relationship between perceived control and stress.

Run correlation analysis

Procedure for calculating Pearson product-moment correlation

1. From the menu at the top of the screen click on: **Analyze**, then click on **Correlate**, then on **Bivariate**.
2. Select your two variables and move them into the box marked **Variables** (e.g. total perceived stress, total PCOISS). You can list a whole range of variables here, not just two. In the resulting matrix, the correlation between all possible pairs of variables will be listed. This can be quite large if you list more than just a few variables.
3. Check that the **Pearson** box and the **2 tail** box have a cross in them. The two-tail test of significance means that you are not making any specific prediction concerning the direction of the relationship between the variables (positive/negative). You can choose a **one-tail** test of significance if you have reasons to support a specific direction.
4. Click on the **Options** button.
   For **Missing Values**, click on the **Exclude cases pairwise** box.
   Under **Options** you can also obtain means, standard deviations if you wish. Click on **Continue**.
5. Click **OK**.

Correlation Results

TABLE X

Pearson Product-Moment Correlations Between Measures of Perceived Control and Wellbeing

Measures	**1**	**2**	**3**	**4**
(1) PCOISS				
(2) MAST	.52 ***			
(3) PA	.46 ***	.43 ***		
(4) NA	−.48 ***	−.46 ***	−.29 ***	
(5) LifeSat	.37 ***	.44 ***	.42 ***	−.32 ***

N=428. PCOISS=Perceived Control of Internal States scale; MAST=Mastery scale; PA=Positive Affect scale; NA=Negative Affect scale; LifeSat=Satisfaction with Life scale.

***p<.001

Table 4.12

Pearson Correlations Matrix of Study Variables (N=583)

	Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Price-Value for money	1																
2	Brand Reputation	.390**	1															
3	Brand Origin	.281**	.521**	1														
4	Advertising Credibility	.383**	.500**	.407**	1													
5	Channel Reputation	.174**	.445**	.465**	.395**	1												
6	After-sales Service	.113**	.377**	.325**	.295**	.349**	1											
7	Sales Personnel	.216**	.426**	.320**	.287**	.438**	.485**	1										
8	Product Ingredients	.246**	.387**	.272**	.350**	.262**	.338**	.366**	1									
9	Functional Benefits	.336**	.574**	.432**	.386**	.436**	.354**	.477**	.427**	1								
10	Social Benefits	.107**	.260**	.287**	.267**	.190**	.213**	.198**	.152**	.298**	1							
11	Symbolic Benefits	.192**	.289**	.305**	.319**	.272**	.217**	.163**	.175**	.333**	.550**	1						
12	Experiential Benefits	.213**	.331**	.261**	.317**	.275**	.217**	.228**	.271**	.428**	.464**	.503**	1					
13	Dominance Personality	-.078	-.031	-.067	.008	-.009	-.006	-.050	-.026	-.096*	.106*	.210**	.150**	1				
14	Social Conformity	.126**	.209**	.136**	.143**	.190**	.025	.062	.077	.235**	.096*	.164**	.236**	.106*	1			
15	Defiance Personality	.049	.021	-.035	.060	.040	.070	.040	.010	.019	.124**	.117**	-.025	.118**	-.047	1		
16	Overall Satisfaction	.321**	.597**	.47**	.383**	.429**	.334**	.423**	.371**	.628**	.365**	.452**	.493**	-.009	.230**	.041	1	
17	Loyalty Intention	.273**	.577**	.389**	.365**	.321**	.371**	.399**	.391**	.542**	.260**	.353**	.426**	.005	.186**	.025	.621**	1

****Correlation is significant at the 0.01 level (2-tailed) *Correlation is significant at the 0.05 level (2-tailed)** (See Appendix H for full results on page 440)

Multi-collinearity

- No correlation coefficient values of the studied variables were above 0.8. Therefore, multicollinearity does not exist in the study (Hair et al., 2006).

Multiple Regression Analysis

- Multiple regression is a statistical technique that permits the researcher to examine the relationship between a single dependent variable and several independent variables (Tabachnick & Fidell, 2007; Hair et al., 2006).
- Before conducting the multiple regression analysis, several main assumptions were considered and examined in order to ensure that the multiple regression analysis was appropriate (Hair et al., 2006).
- The assumptions to be examined are as follow:
- (1) outliers,
- (2) normality linearity and homoscedascitity, and
- (3) mulitiollinearity

Outliers

- Need to check Data whether there are any potential outliers existing in the analysis.
- Pallant (2007) noted that "multiple regression is very sensitive to outliers (i.e. very high or low score)" (p. 165). Outliers can influence the values of the estimated regression coefficients (Field, 2005).
- Thus, outliers should be removed before running the regression analysis (Tabachnick & Fidell, 2007).
- Multivariate outliers can be detected by using statistical methods such as casewise diagnostics, Mahalanobis distance, Cook's distance and COVRATIO (Hair et al., 2006; Tabachnick & Fidell, 2007).

Outliers

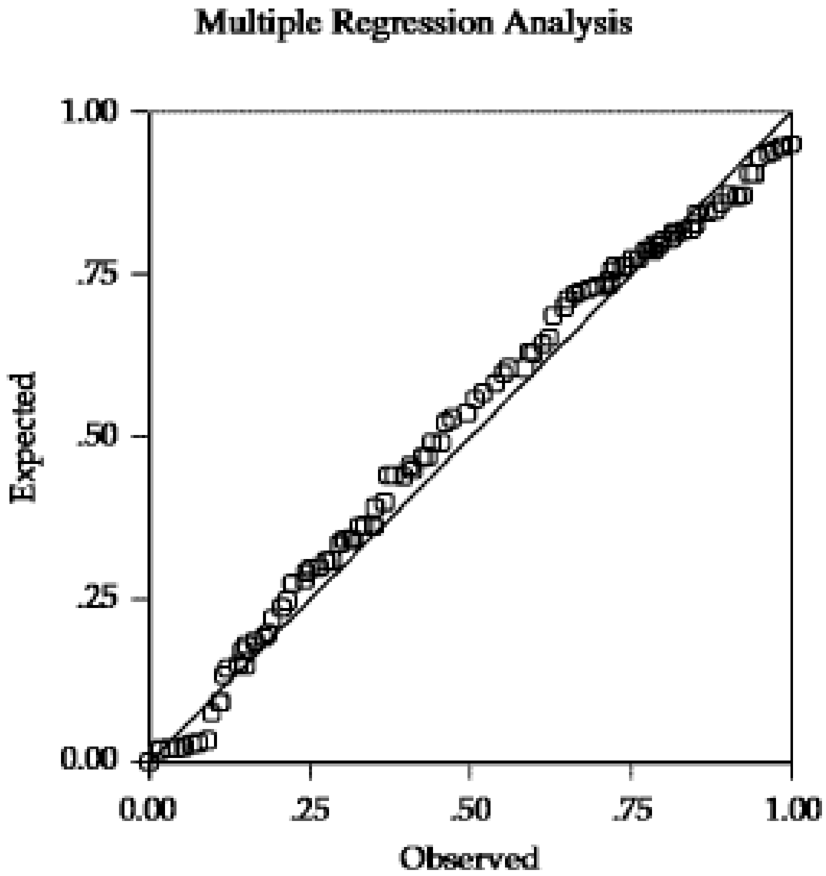


FIGURE 12 Normal Probability Plot: Standardized Residuals

MULITICOLLINEARITY

- Multicollinearity appears "when any single independent variable is highly correlated with a set of other independent variables" (Hair et al., 2006, p. 170).
- Multicollinearity was examined by inspection of the Tolerance and VIF values.
- Hair et al. (2006) suggested a tolerance value greater than .1 and the variation inflation factor (VIF) value smaller than 10; now VIF shouldn't be more than 5 or 3 and the conditional index value smaller than 30, as an indication that there was not a high muliticolinearity.

Multicollinearity

- No correlation coefficient values of the studied variables were above 0.8. Therefore, multicollinearity does not exist in the study (Hair et al., 2006).

Run regression analysis

Procedure for standard multiple regression

1. From the menu at the top of the screen click on: **Analyze**, then click on **Regression**, then on **Linear**.
2. Click on your continuous dependent variable (e.g. total perceived stress: tpstress) and move it into the **Dependent** box.
3. Click on your independent variables (total mastery: tmast; total PCOISS: tpcoiss) and move them into the **Independent** box.
4. For **Method**, make sure **Enter** is selected (this will give you standard multiple regression).
5. Click on the **Statistics** button.
   - Tick the box marked **Estimates**, **Confidence Intervals**, **Model fit**, **Descriptives**, **Part and partial correlations** and **Collinearity diagnostics**.
   - In the **Residuals** section tick the **Casewise diagnostics** and **Outliers outside 3 standard deviations**.
   - Click on **Continue**.

Run regression analysis

6. Click on the **Options** button. In the **Missing Values** section click on **Exclude cases pairwise**.
7. Click on the **Plots** button.
   - Click on *__ZRESID__ and the arrow button to move this into the **Y** box.
   - Click on *__ZPRED__ and the arrow button to move this into the **X** box.
   - In the section headed **Standardized Residual Plots**, tick the **Normal probability plot** option.
   - Click on **Continue**.
8. Click on the **Save** button.
   - In the section labelled **Distances** tick the **Mahalanobis** box (this will identify multivariate outliers for you) and **Cook's**.
   - Click on **Continue**.
9. Click on **OK**.

The output generated from this procedure is shown below.

Table 4.13

Regression Analysis of Brand Image Attributes and Brand Image Benefits with Loyalty Intention

Dependent Variable	Independent Variable		Std. Coefficient Beta (β)
Loyalty intention	Brand Image:		
	Price/Value for money		.010
	Brand reputation		.270**
	Brand origin		.077*
	Advertising credibility		.007
	Channel reputation		-.061
	After-sales service		.071*
	Sales personnel		.076*
	Product ingredients		.134**
	Functional benefits		.153**
	Social benefits		-.010
	Symbolic benefits		.136**
	Experiential benefits		.179**
	R^2	.537	
	Adjust R^2	.527	
	Sig. F	52.30**	

Note: Significant levels: $**p < 0.01$, $*p < 0.05$

Significant level and t-values

Significant Levels	1 Tailed	2 Tailed
1%** ($p < 0.01$)	t-value 2.33	t-value 2.58
5%* ($p < 0.05$)	t-value 1.645	t-value 1.96

ONE-TAILED TEST VS TWO-TAILED TEST

- All statistical tests are based on an area of acceptance and an area of rejection.
- For what is termed a one-tailed test, the rejection area is either the upper or lower tail of the distribution. A one-tailed test is used when the hypothesis is directional, that is, it predicts an outcome at either the higher or lower end of the distribution. But there may be cases when it is not possible to make such a prediction.
- In these circumstances, a two-tailed test is used, for which there are two areas of rejection – both the upper and lower tails.

Effect Size

- One way that you can assess the importance of your finding is to calculate the 'effect size' (also known as 'strength of association'). This is a set of statistics that indicates the relative magnitude of the differences between means, or the amount of the total variance in the dependent variable that is predictable from knowledge of the levels of the independent variable (Tabachnick & Fidell 2013, p. 54).

Calculating Effect Size (f^2)

- Effect size f^2 is not automatically given in PLS, we have to do manual calculation using the formula:

$$\text{Effect size}: f^2 = \frac{R^2_{incl} - R^2_{excl}}{1 - R^2_{incl}}$$

- According to **Cohen (1988)**, f^2 is assessed as:
  - **0.02 small**
  - **0.15 medium**
  - **0.35 large**

Hierarchical Regression Analysis

- Hierarchical regression analysis is used to test the mediating variable and moderating variable.
- **To establish mediation**, a series of regression analyses were performed following the guidelines suggested by Baron and Kenny (1986).
- **To test for moderating effects**, a three step hierarchical regression process was carried out following the procedures suggested by Sharma, Durand and Gur-Arie. (1981).

Assessing R^2

- According to **Chin (1998b)**, *R^2 values for endogenous latent* variables *are assessed as follows:*
  - **0.67 substantial**
  - **0.33 moderate**
  - **0.19 weak**
- Also path coefficients range between 0.20 – 0.30 along with measures that explain 50% or more variance is acceptable (**Chin, 1998b**)

Assessing R^2

- According to **Cohen (1988)**, *R^2 values for endogenous latent* variables *are assessed as follows:*
  - **0.26 substantial**
  - **0.13 moderate**
  - **0.02 weak**
- Also path coefficients range greater than 0.1 is acceptable (**Lohmoller, 1989**)

Moderator vs. Mediator

Moderator variables –

- "In general terms, a moderator is a qualitative (e.g., sex, race, class) or quantitative (e.g., level of reward, personality, locus of control) variable that affects the direction and/or strength of the relation between an independent or predictor variable and a dependent or criterion variable.
- Specifically within a correlational analysis framework, a moderator is a third variable that affects the zero-order correlation between two other variables. ... In the more familiar analysis of variance (ANOVA) terms, a basic moderator effect can be represented as an interaction between a focal independent variable and a factor that specifies the appropriate conditions for its operation." (Baron & Kenney, 1986, *p. 1174)*

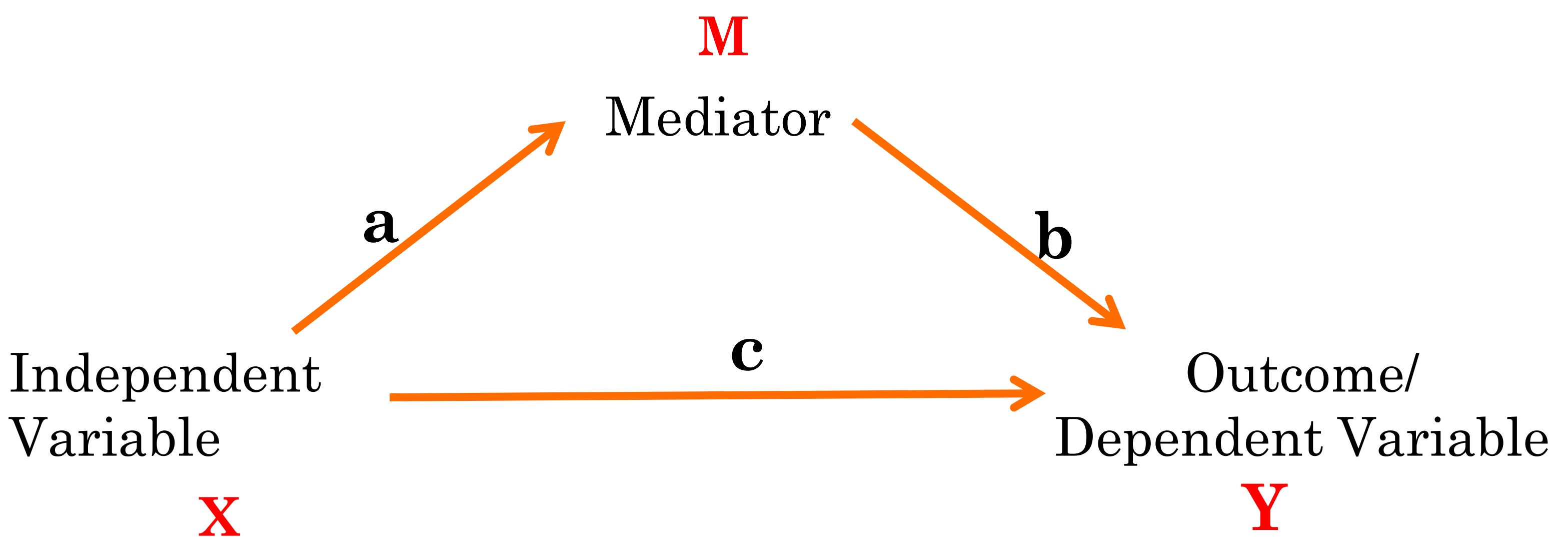
Moderator vs. Mediator cont

Mediator variables –

- "In general, a given variable may be said to function as a mediator to the extent that it accounts for the relation between the predictor and the criterion.
- Mediators explain how external physical events take on internal psychological significance. Whereas moderator variables specify when certain effects will hold, mediators speak to how or why such effects occur." (Baron & Kenny, 1986, *p. 1176).*

Moderator vs. Mediator cont.

- The general test for mediation is to examine the relation between the predictor (independent) and the criterion (dependent) variables, the relation between the predictor and the mediator variables, and the relation between the mediator and criterion variables. All of these correlations should be significant. The relation between predictor and criterion should be reduced (to zero in the case of total mediation) after controlling the relation between the mediator and criterion variables.
- Another way to think about this issue is that a moderator variable is one that influences the strength of a relationship between two other variables, and a mediator variable is one that explains the relationship between the two other variables.


M
Mediator
a
b
c
Independent
Variable
X
Outcome/
Dependent Variable
Y

MEDIATION ANALYSES

- To establish mediation, a series of regression analyses were performed following the guidelines suggested by Baron and Kenny (1986).
- First, the independent variable must have a significant effect on the mediator, when regressing the mediator on the independent variable.
- Secondly, the independent variable must have a significant effect on the dependent variable, when regressing the dependent variable on the independent variable.
- Third, the mediator must have a significant effect on the dependent variable, when regressing the dependent variable on both the independent variable and mediating variable.
- If these conditions all hold in the predicted directions, then the effect of the independent on the dependent variable must be less in the third equation than in the second equation.
- Perfect mediation holds if the independent variable has no effect when the mediator is controlled (Baron & Kenney, 1986, p. 1177).
- However, partial mediation occurs when the independent variable's effect is reduced in magnitude, but is still significant when the mediator is controlled (Baron & Kenney, 1986).

How do I conduct a mediation analysis?

- **A.** Mediation analysis uses the estimates and standard errors from the following regression equations (MacKinnon, 1994):

- $Y = c\,X + e_1$ The independent variable (X) causes the outcome variable (Y)
  $M = a\,X + e_2$ The independent variable (X) causes the mediator variable (M)
  $Y = c'\,X + bM + e_3$. The mediator (M) causes the outcome variable (Y) when controlling for the independent variable (X). This must be true
- If the effect of X on Y is zero when the mediator is included ($c' = 0$), there is evidence for mediation (Judd & Kenny, 1981a, 1981b). This would be *full* mediation.
- If the effect of X on Y is reduced when the mediator is included ($c' < c$), then the direct effect is said to be *partially* mediated

Table 4.16

Mediating Effect of Overall Customer Satisfaction on the Relationship between Brand Image and Loyalty Intention

Dependent Variable	Variables	Std. beta without mediator (model 1)	Std. beta with mediator (model 2)	Result
Loyalty Intention	***Independent Variables:***			
	Brand reputation	.328**	.254**	Partial mediation
	Brand origin	.077*	.043	Full mediation
	Product ingredients	.107**	.094**	Partial mediation
	Functional benefits	.215**	.126**	Partial mediation
	Symbolic benefits	.108**	.058	Full mediation
	Experiential benefits	.177**	.124**	Partial mediation
	Mediator:			
	Overall satisfaction		.304**	
R^2		.542	.583	
Adjust R^2		.537	.578	
R^2 change		.542	.041	
F change		109.84**	54.31**	

Note: Significant levels: *$p < 0.05$, **$p < 0.01$

Q. What articles would you suggest for someone just learning about mediation?

- **A.** Some good background references include:

- Baron, R.M. & Kenny, D.A. (1986). The moderator-mediator distinction in social psychological research: Conceptual, Strategic, and statistical considerations. *Journal of Personality and Social Psychology, 51*, 1173-1182.
- Judd, C. M., & Kenny, D. A. (1981a). *Estimating the effects of social interventions*. New York: Cambridge University Press.
- Judd, C.M. & Kenny, D.A. (1981b). Process Analysis: Estimating mediation in treatment evaluations. *Evaluation Review, 5*, 602-619.
- MacKinnon, D.P. (1994). Analysis of mediating variables in prevention and intervention research. In A. Cazares and L. A. Beatty, *Scientific methods in prevention research*. NIDA Research Monograph 139. DHHS Pub. No. 94-3631. Washington, DC: U.S. Govt. Print. Office, pp. 127-153.
- MacKinnon, D.P. & Dwyer, J.H. (1993). Estimating mediated effects in prevention studies. *Evaluation Review*, 17, 144-158.

Mediator Variable

- A mediator specifies how (or the mechanism by which) a given effect occurs (Baron & Kenny, 1986; James & Brett, 1984).
- Baron and Kenny (1986, pp. 1173, 1178) describe a mediator variable as the following:
- *The generative mechanism through which the focal independent variable is able to influence the dependent variable of interest . . . (and) Mediation . . . is best done in the case of a strong relation between the predictor and criterion variable.*

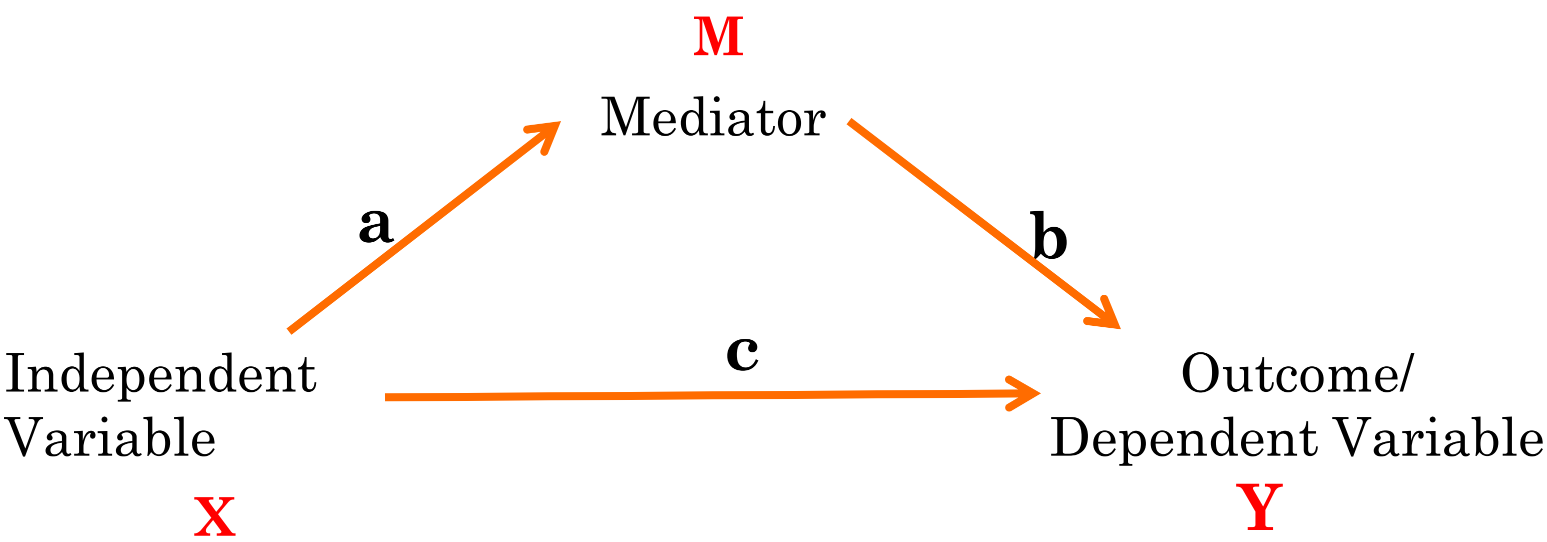
Mediator Variable

- Shadish and Sweeney (1991) stated that “the independent variable causes the mediator which then causes the outcome”. Also critical is the prerequisite that there be a significant association between the independent variable and the dependent variable before testing for a mediated effect.

Mediator Effect

- According to McKinnon et al, (1995), mediation is generally present when:

  1. the IV significantly affects the mediator,
  2. the IV significantly affects the DV in the absence of the mediator,
  3. the mediator has a significant unique effect on the DV, and
  4. the effect of the IV on the DV shrinks upon the addition of the mediator to the model.


M
Mediator
a
b
c
Independent Variable
X
Outcome/ Dependent Variable
Y

Mediator Analysis

- Judd and Kenny (1981), a series of regression models should be estimated. To test for mediation, one should estimate the three following regression equations:

1. regressing the mediator on the independent variable;
2. regressing the dependent variable on the independent variable;
3. regressing the dependent variable on both the independent variable and on the mediator.

Mediator Analysis

1) variations in levels of the independent variable significantly account for variations in the presumed mediator (i.e., Path c),

2) variations in the mediator significantly account for variations in the dependent variable (i.e., Path *b), and*

3) when Paths *a and b are controlled, a previously significant relation between the independent and* dependent variables is no longer significant, with the strongest demonstration of mediation occurring when Path *c is zero.*

Mediator Analysis

- Separate coefficients for each equation should be estimated and tested.
- There is no need for hierarchical or stepwise regression or the computation of any partial or semipartial correlations.

- TEST OF HOMOGENEITY OF REGRESSION (X*M INTERACTION)

	R-sq	F	df1	df2	p
SATISFAC	.0107	2.7899	4.0000	573.0000	.0258

- ***

- INDIRECT EFFECT(S) THROUGH:
- SATISFAC

	Effect	SE(boot)	LLCI	ULCI
FUNCTION	.2344	.0342	.1707	.3013
SYMBOLIC	.0508	.0137	.0288	.0829
SOCIAL	.0111	.0126	-.0127	.0380
EXPERIEN	.0676	.0251	.0279	.1258

	LLCI	ULCI
FUNCTION	.1707	.3013 (Mediation)
SYMBOLIC	.0288	.0829 (Mediation)
SOCIAL	-.0127	.0380 (No mediation)there is 0 in between
EXPERIEN	.0279	.1258(Mediation)

Report for mediator (Multiple IVs, Single Mediator and DV)

TEST OF HOMOGENEITY OF REGRESSION (X*M INTERACTION)

	R-sq	F	df1	df2	p
SATISFAC	.0107	2.7899	4.0000	573.0000	.0258

****
**

INDIRECT EFFECT(S) THROUGH:

SATISFAC

	Effect	SE(boot)	LLCI	ULCI
FUNCTION	.2344	.0342	.1707	.3013
SYMBOLIC	.0508	.0137	.0288	.0829
SOCIAL	.0111	.0126	-.0127	.0380
EXPERIEN	.0676	.0251	.0279	.1258

Based on the results

	LLCI	ULCI	
FUNCTION	.1707	.3013	(Mediation)
SYMBOLIC	.0288	.0829	(Mediation)
SOCIAL	-.0127	.0380	(No mediation)there is 0 in between
EXPERIEN	.0279	.1258	(Mediation)

Moderated analysis

- To test for moderating effects, a three step hierarchical regression process was carried out following the procedures suggested by Sharma, Durand and Gur-Arie. (1981).
- In the first step, the dependent/criterion variable (overall customer satisfaction) is regressed on the independent variable (i.e. the entire dimensions of brand image) was entered, followed by the moderator variable (i.e. entered dominance, defiance, social conformity and dwelling area separately) was entered and finally the interaction terms of the independent variable and moderator variable (independent * moderating variable) was entered.
- Pure moderation would exist if *b(x)* and *b(x*z)* are significant and *b(z)* is non-significant. While, quasi moderation would exist if *b(x)*, *b(z)* and *b(x*z)* are significant (Sharma, 2002).

Moderated analysis

- Step (1) $y = a + b_1x,$
- Step (2) $y = a + b_1x + b_2z,$
- Step (3) $y = a + b_1x + b_2z + b_3(x*z),$

- Where y = dependent variable
- a = intercept term
- b = regression coefficient
- x = independent variable
- z = the moderator variable
- $x*z$ = the interaction of independent variable and moderating variable

Hierarchical Regression Results of the Moderating Effect of Aggressive-Dominance on Relationship between Brand Image and Overall Customer Satisfaction

Dependent Variable	Variables	Std. beta step 1	Std. beta step 2	Std. beta step 3
Overall customer satisfaction	***Independent Variable:***			
	Brand Image Dimensions:			
	Price-Value for money	.043	.042	.062
	Brand reputation	.247**	.251**	.262**
	Brand origin	.097**	.095**	.079*
	Advertising credibility	-.044	-.044	-.111**
	Channel reputation	.028	.028	.058
	After-sales service	.042	.041	.050
	Sales Personnel	.048	.050	.089*
	Product ingredients	.061*	.059*	.041
	Functional benefits	.359**	.354**	.294**
	Social benefits	-.005	-.005	.055
	Symbolic benefits	.127**	.133**	.089*
	Experiential benefits	.169**	.171**	.244**
	Moderating variable:			
	Aggressive-Dominance (Ag-Dom)		-.030	-.060
	Interaction Terms:			
	Ag-Dom X Price-Value for money			-.091
	Ag-Dom X Brand reputation			-.031
	Ag-Dom X Brand origin			.109
	Ag-Dom X Advertising credibility			.620*
	Ag-Dom X Channel reputation			-.299
	Ag-Dom X After-sale service			-.089
	Ag-Dom X Sales personnel			-.139
	Ag-Dom X Product ingredients			.188
	Ag-Dom X Functional benefits			.584
	Ag-Dom X Social benefits			-.620**
	Ag-Dom X Symbolic benefits			.423*
	Ag-Dom X Experiential benefits			-.641*
R^2		.706	.707	.728
Adjusted R^2		.699	.699	.713
R^2 Change		-	.001	.021
F Change		97.32	1.44	2.97
Sig. F Change		.000	.230	.001

***$p < 0.05$, **$p < 0.01$**

Moderator results

Model Summary[d]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.764[a]	.584	.581	.27477	.584	184.381	4	525	.000	
2	.764[b]	.584	.580	.27498	.000	.179	1	524	.672	
3	.774[c]	.599	.592	.27126	.014	4.626	4	520	.001	2.071

a. Predictors: (Constant), Experiental, Function, Social, Symbolic

b. Predictors: (Constant), Experiental, Function, Social, Symbolic, dwellmod

c. Predictors: (Constant), Experiental, Function, Social, Symbolic, dwellmod, dwellXSYMB, dwellXSOCB, dwellXEB, dwellXFB

d. Dependent Variable: Satisfaction

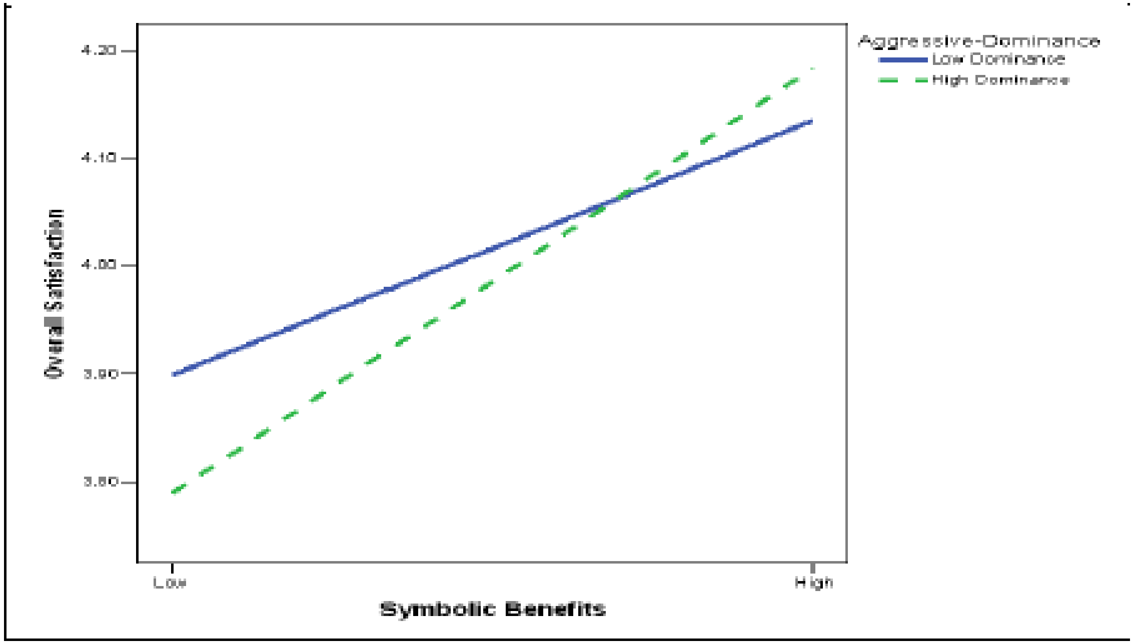


Figure 4.4 Moderating effect of aggression-dominance on the relationship between symbolic benefits and overall customer satisfaction.