Lucija
GOSAK

Leona
CILAR BUDLER

Roger
WATSON

Gregor
ŠTIGLIC

Advanced Quantitative Research Methods in Nursing

University of Maribor Press

University of Maribor

Faculty of Health Sciences

Advanced Quantitative Research Methods in Nursing

Authors
Lucija Gosak
Leona Cilar Budler
Roger Watson
Gregor Štiglic

July 2024

Title	**Advanced Quantitative Research Methods in Nursing**
Authors	Lucija Gosak (University of Maribor, Faculty of Health Sciences) Leona Cilar Budler (University of Maribor, Faculty of Health Sciences) Roger Watson (University of Hull, Faculty of Health Sciences) Gregor Štiglic (University of Maribor, Faculty of Health Sciences)
Review	Graeme D. Smith (Saint Francis University) David R. Thompson (Queens University Belfast)
Language editor	Stojan Primožič (University of Maribor)
Technical editor	Jan Perša (University of Maribor, University Press)
Cover designer	Jan Perša (University of Maribor, University Press)
Graphic material	Sources are own unless otherwise noted. Gosak, Cilar Budler, Watson, Štiglic (authors), 2024
Cover graphics	Diversity-people-heads-group (7803661), author: geralt, pixabay.com, 2024
Published by *Založnik*	**University of Maribor** **University Press** Slomškov trg 15, 2000 Maribor, Slovenija https://press.um.si, zalozba@um.si
Issued by *Izdajatelj*	**University of Maribor** **Faculty of Health Sciences** Žitna ulica 15, 2000 Maribor, Slovenia https://press.um.si, zalozba@um.si
Izdaja	First edition
Publication type	E-book
Available at	http://press.um.si/index.php/ump/catalog/book/899
Izdano	Maribor, Slovenia, July 2024

```
CIP - Kataložni zapis o publikaciji
Univerzitetna knjižnica Maribor

616-083(0.034.2)

    ADVANCED Quantitative Research Methods in Nursing [Elektronski vir] / authors
Lucija Gosak ... [et. al.]. - 1st ed. - E-knjiga. - Maribor : University of
Maribor, University Press, 2024

Način dostopa (URL): https://press.um.si/index.php/ump/catalog/book/899
ISBN 978-961-286-888-8 (Pdf)
doi: 10.18690/um.fzv.2.2024
COBISS.SI-ID 202111491
```

ISBN 978-961-286-888-8 (pdf)

DOI https://doi.org/10.18690/um.fzv.2.2024

Cena *Price* Free copy

For publisher *Odgovorna oseba založnika* Prof. Dr. Zdravko Kačič, Rector of University of Maribor

Attribution *Citiranje* Gosak, L., Cilar Budler, L., Watson, R., Štiglic, G. (2024). *Advanced Quantitative Research Methods in Nursing*. University of Maribor, University of Maribor Press. doi: 10.18690/um.fzv.2.2024

Table of Contents

University of Maribor Press

Symbols and Abbreviations Used

CI	confidence interval
CVI	content validity
H0	null hypothesis
Ha, H1	working hypothesis
I-CVI	item content validity index
M	Mean
Mo	Mode
Me	Median
P	P-value (statistical significance)
RCT	Randomized controlled trial
S-CVI	scale content validity index
S-CVI/Ave	scale-level content validity index based on the average method
S-CVI/AU	scale-level content validity index based on the universal agreement method
SD	Standard deviation

1 Data and Quantitative Research Methods in Nursing

Nurses use and generate a lot of data in their daily work with patients. The main goal of patient care is to provide high-quality and evidence-based nursing care, so nurses are obliged to keep up to date with and apply the latest studies and evidence to their work. It is, therefore, important that nurses have the knowledge and understanding of data and data analysis techniques, as this is the only way to understand the latest evidence. Presented here is a short guide that includes basic information on quantitative research methods and information on statistical tests with which nurses need to be familiar in their work.

The data used in the book is based on data collected using the Self-Care of Diabetes Index (SCODI) questionnaire (Ausili, et al., 2017). The data were collected as part of a pilot study on patients with diabetes in Slovenia. The data are intended for educational and research purposes only.

There are many hands-on examples included to make the materials more engaging. We hope you will find this introduction to quantitative data analysis for nurses useful.

2 Quantitative Study

The following section describes the basic characteristics of quantitative research and breaks down the different types of quantitative research. The final part of the chapter gives a brief overview of how to produce a quantitative research report. The learning objectives of this chapter are to enable the reader to understand the basic concepts of quantitative research, to learn about the different types of quantitative research and to acquire the basic skills to produce a quantitative research report.

In the natural and social sciences, quantitative research is the systematic empirical study of observable phenomena using statistical, mathematical, or computational techniques. **Figure 2.1** shows different aspects of the quantitative study.

The basic characteristics of the quantitative study (in comparison to qualitative) are:

- Data are collected using structured research instruments (surveys, structured interviews, experiments, observations, reviews of records or documents where any variable can be measured);
- it answers the questions: What? When?;
- it is mostly based on numbers;

- usually, a deductive process is used to test the predefined concepts, constructs, and hypotheses;
- the results are based on larger sample sizes that are representative of the population but provide less in-depth information;
- the research study can usually be repeated;
- the researcher has a clearly defined research question which demands objective answers;
- all aspects of the study are carefully designed before data collection;
- data are in the form of numbers, and results are often arranged in numerical tables, graphs, figures, or other non-textual form;
- broader understanding of concepts, predicting future results, or exploring a causal relationship;
- provides the observed effects (interpreted by the researchers);
- the researcher uses tools, such as questionnaires or computer software, to collect numerical data;
- usually, more time is needed in the planning phase and less in the analysis phase;
- the overall goal of a quantitative study is to classify characteristics, count them, and build statistical models to try to explain what we observe (Watson, 2015; Holton & Burnett, 2005; Reaves, 1992).

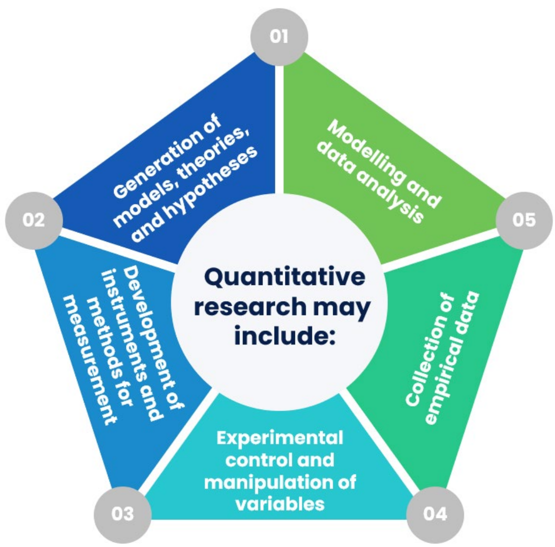


Figure 2.1: Different Aspects of Quantitative Study

The types of quantitative study are shown in **Figure 2.2**.

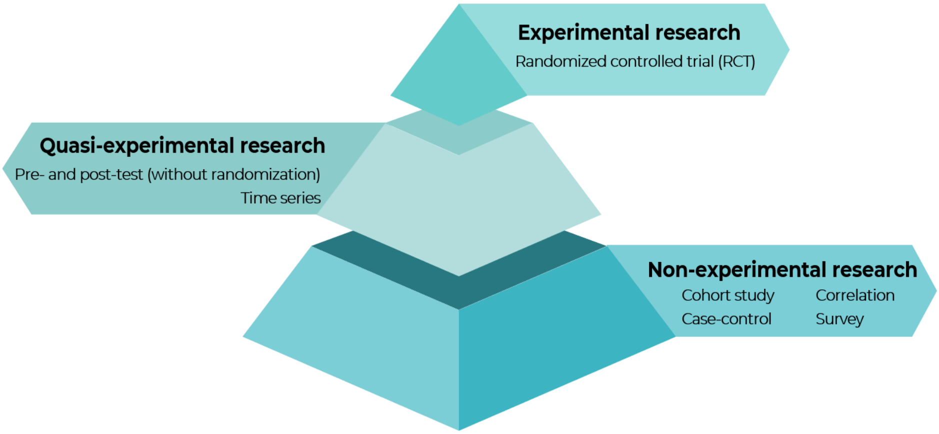


Figure 2.2: Quantitative Study Types

Researchers sometimes classify types of studies differently. Thus, instead of descriptive and correlation studies, they often refer to observational and quasi-experimental and experimental research intervention studies. Observational studies include cross-sectional studies, case studies with controls, cohort studies (retrospective, prospective), case studies, and case series studies. The experimental study is used to determine whether there is a cause-and-effect relationship between variables.

The following are basic definitions of the most common quantitative study types:

– **Randomized controlled trial (RCT):** In randomised controlled trials, participants are divided into an experimental group and one or more control groups. The only difference between the groups is the intervention being studied (**Fig. 2.3**). Studies can be known as single-, double- or triple-blind randomised controlled trials. Single-blind means that the participants do not know which group they are allocated to, double-blind means that the researchers collecting the data do not know which of the participants belongs to a control or intervention group and triple-blind means that the researchers analysing the data do not know which group anyone was in (Stanley, 2007; Spieth, et al., 2016).

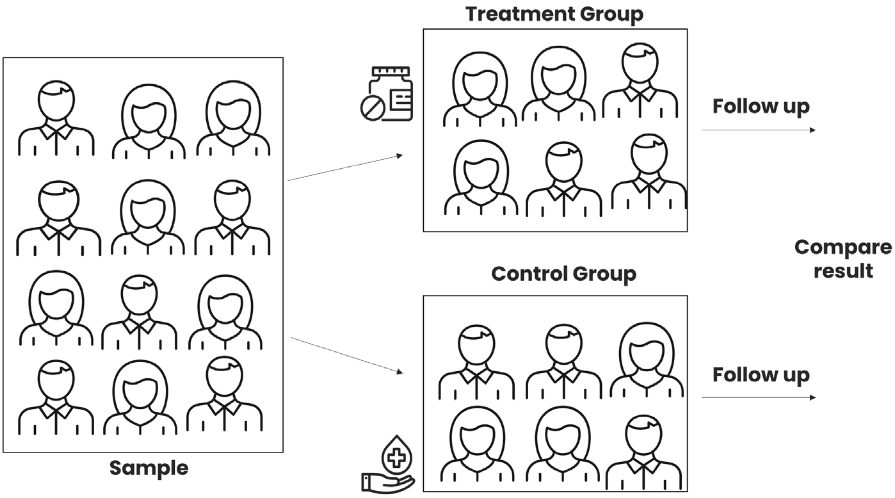


Figure 2.3: Randomized Controlled Trial

Pre- and post-test study (without randomization): This is a type of quasi-experimental study where the outcome of interest is measured twice, with variables measured before and after the intervention (**Fig. 2.4**). Participants are selected in a non-random way (Dugard & Todman, 1995; Marsden & Torgerson, 2012).

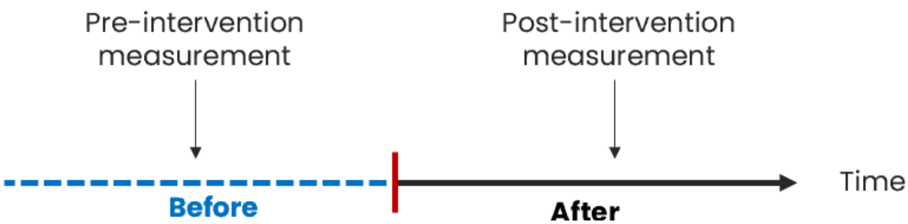


Figure 2.4: Pre- and Post-Test Study

– **Cross-sectional study:** A cross-sectional study is a study that analyses data on variables collected over a given period (**Fig. 2.5**). It also measures the outcome and exposure of the study participants at the same time. Participants are selected based on inclusion and exclusion criteria established for the study.

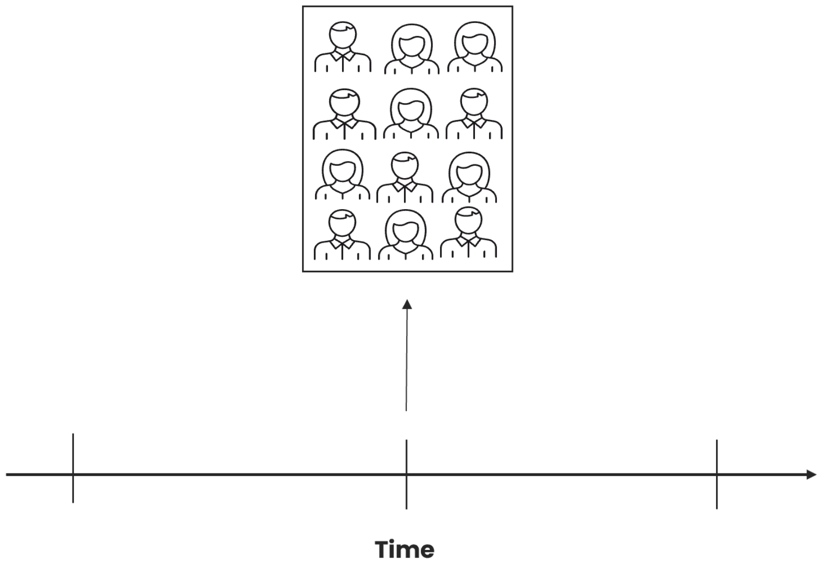


Figure 2.5: Cross-Sectional Study

– **Longitudinal study:** Data are collected over time at different time points (**Fig. 2.6**). The researchers observe and collect data without trying to influence the variables.

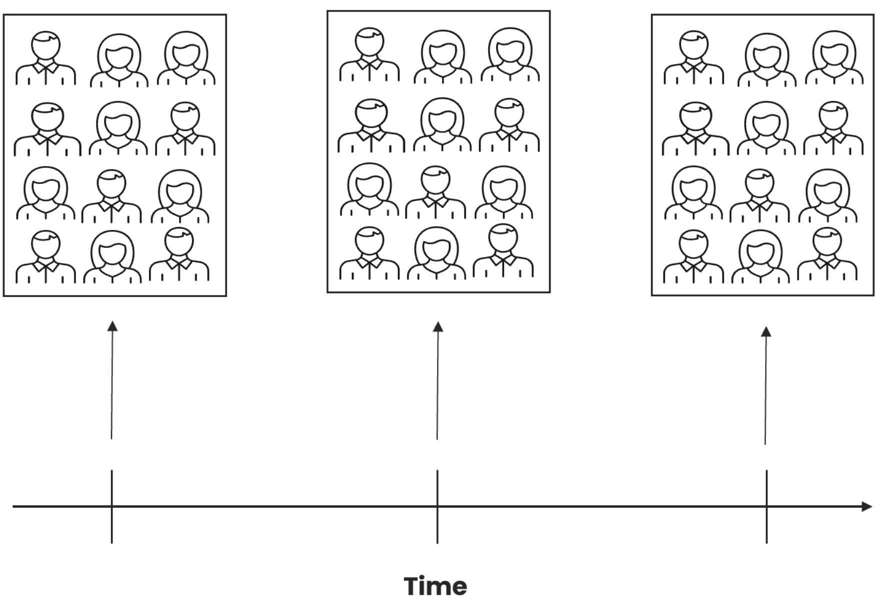


Figure 2.6: Longitudinal Study

- **Cohort study:** In cohort studies, researchers investigate the links between risk factors and outcomes.
- **Retrospective cohort study:** A retrospective cohort study is a longitudinal cohort study that compares cohorts of individuals where one group is exposed to a factor and the other is not. This is to determine the impact of that factor on the phenomenon. They have the advantage that they can be carried out immediately because they look at the situation retrospectively but may have less control over the exposure of the participants to the factor.
- **Prospective cohort study:** This is a longitudinal study that follows groups of similar individuals over time, differing in a trait/factor that may influence a particular condition.

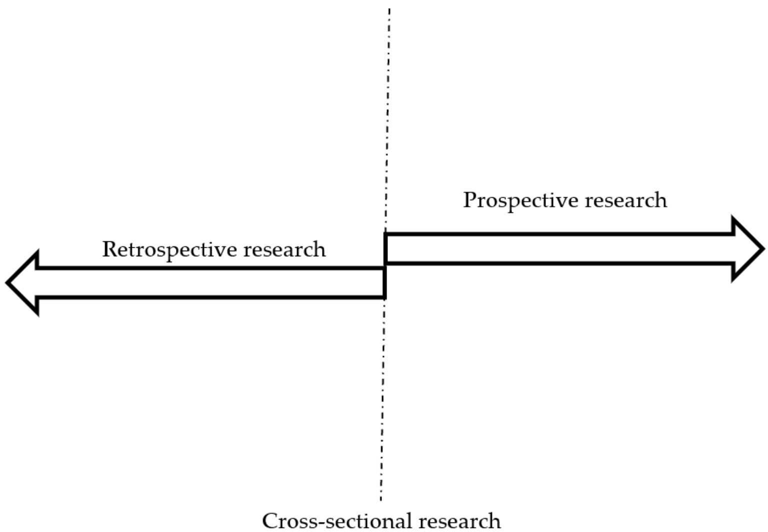


Figure 2.7: Types of Studies According to the Time of Data Collection

- **Case-control study:** Comparison of two groups of people, where one group has the condition in question and the other group does not (**Fig. 2.8**). Here, researchers look at the history of the participants (health, lifestyle) to see which factors are associated with a particular condition.

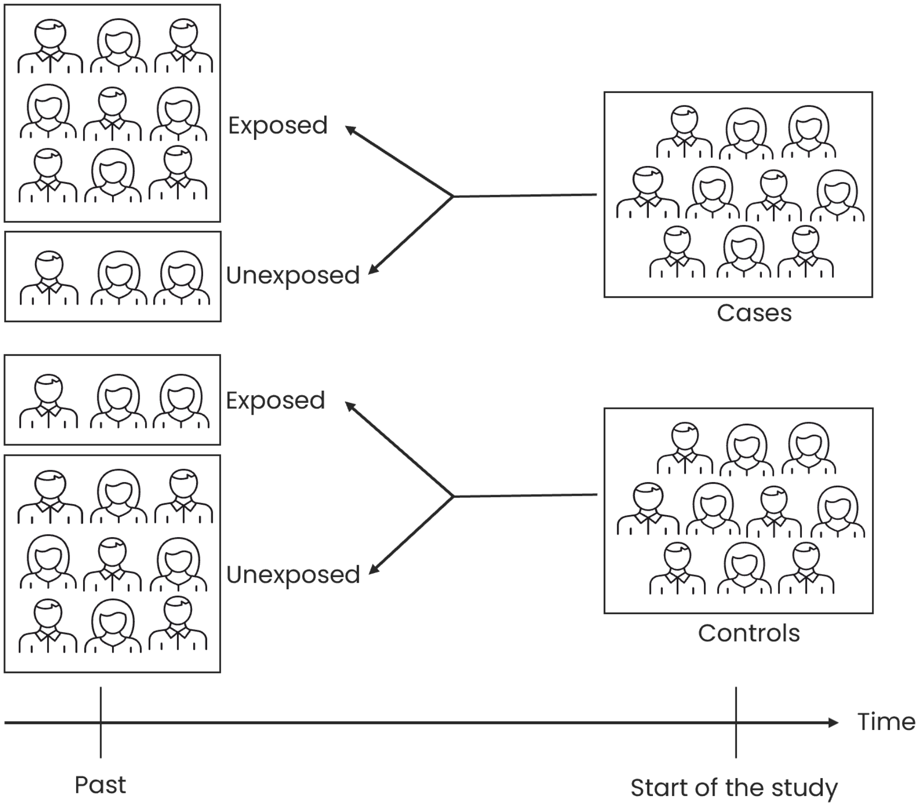


Figure 2.8: Case-Control Study

- **Correlation study:** Correlational study is used to study the relationships between different subjects and variables. A correlational study is non-experimental, meaning that none of the variables are influenced or controlled by the researcher. We distinguish between positive or negative correlation and no correlation. Correlational studies cannot prove cause-and-effect relationships between variables.
- **Survey study:** Descriptive surveys are used to formulate a hypothesis, but only after all the necessary data have been collected. Participants in the survey answer a set of questions asked by the researcher. These surveys are mainly carried out at the beginning of projects or larger research studies to identify the problem and the direction of the study.

Methods, in general, can be divided into data collection methods, data analysis methods, data synthesis methods, and data display methods. These depend on the study plan or type of study.

Quantitative methods emphasize the use of objective measurements and statistical, mathematical, or numerical analysis of data collected through surveys or questionnaires and or the manipulation of existing statistics using computational techniques. The quantitative study focuses on the collection of numerical data and their generalization by groups of people or the explanation of a particular phenomenon.

Before designing a quantitative survey, we need to decide on a study plan/design that will determine how the results are collected, analyzed, and interpreted. In a descriptive study, we follow the following rules: the object of study is usually measured once; the purpose is only to establish links between the variables; the study may include a sample population of hundreds or thousands of subjects to provide a valid estimate of the overall relationship between the variables. The experimental design includes subjects measured before and after a particular treatment. The sample population can be very small and purposefully selected, and it is designed to establish causality between variables. **Figure 2.9** shows the steps in a quantitative study.

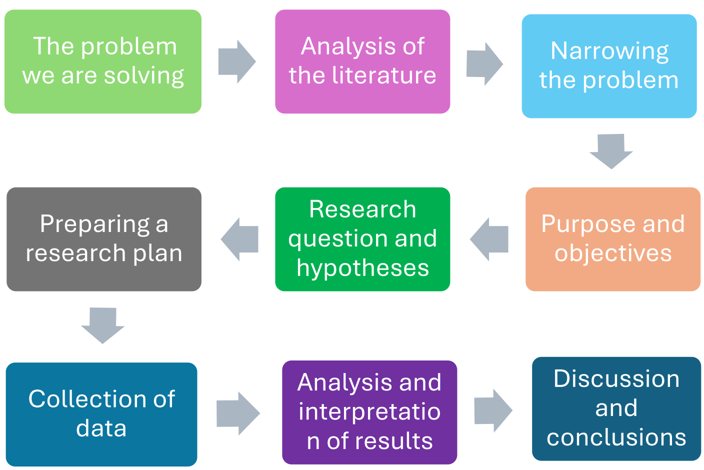


Figure 2.9: Quantitative Study Process
Source: (Kmetec, et al., 2019; Grove, et al., 2015)

The main features of a quantitative study concerning individual sections, when reported in a scientific paper, are described below.

2.1 Introduction

The introduction to a quantitative study is usually written in the present tense and from a third-party perspective. It covers the following data:

- **Identifies the research problem** - as with any academic study, we should clearly and concisely state the research problem.
- **Reviews the literature** - review studies on this topic, synthesize key topics, and, if necessary, list studies that use similar methods of investigation and analysis. Consider where there are key knowledge gaps and how your study helps fill those gaps or clarify existing knowledge.
- **Describes the theoretical framework** - give an outline of the theory or hypothesis on which your study is based. If necessary, identify unknown or complex terms, concepts, or ideas and provide relevant background information to place the research problem in an appropriate context.

2.2 Methodology and Methods

The sketch on the quantitative study methods should describe how each goal of your study will be achieved. Provide sufficient detail to enable the reader to make an informed assessment of the methods used to obtain results related to the research topic. The section on methods should be presented in the past tense:

- **Sample and sampling** - where the data comes from; note where gaps exist or what has been ruled out. Follow the procedures used to select them.
- **Data collection** - describe the tools and methods used to collect information and identify variables; describe the methods used to obtain the data; note if the data already existed or you collected them yourself. If you collected them yourself, describe what instrument you used and why. Note that no data set is complete - describe any limitations in data collection methods.
- **Data analysis** - describe the procedures for data processing and analysis. Where appropriate, describe the specific analysis instruments used to study each

research objective, including the mathematical techniques and the type of computer software (e.g., Jamovi, JASP, Orange, R, etc.) used to process the data.

2.3 Results

The study findings must be reported objectively and in a concise and accurate format. In quantitative studies, it is common to use graphs, tables, and other non-textual elements to help the reader understand the data. Make sure that the non-textual elements do not stand apart from the text but are used to supplement the general description of the results and to clarify the key tense.

– **Statistical analysis** - how did you analyse the data? What were the key findings? The findings should be presented in a logical sequence. Describe but do not explain these trends or negative results; save this for discussion. The results should be presented in the past period.

2.4 Discussion

The discussion should be analytical, logical, and comprehensive. The discussion should combine your findings in conjunction with the findings of the literature review and place them in the context of the theoretical framework on which the study is based. The debate needs to be presented at present:

– **Interpretation of results** - re-emphasize the study problem and compare the findings with the research questions on which the research is based. Did you confirm the announced results, or did you refute them with the data?
– **Description of trends, comparison of groups, or relationships between variables** - describe any trends that have emerged from your analysis and explain any unforeseen and statistically significant findings.
– **Discussion of consequences** - what is the meaning of your results? Highlight key findings based on general results and consider findings that you consider relevant. How do the results help to fill gaps in understanding the research problem?
– **Limitations** - describe any limitations or unavoidable biases in your study and, if necessary, consider why these limitations did not hinder the effective interpretation of the results.

2.5 Conclusion

Completing studies means summarizing the main findings of your research and giving a final comment or guidance:

- **Summary of findings** - do not report statistics; provide a narrative summary of key findings and synthesize answers to your research questions.
- **Recommendations** - if appropriate for the aim of the research, link the key findings to policy recommendations or actions to be taken in practice.
- **Future research** - consider the need for future research related to study limitations or other gaps in the literature that have not been addressed in your study.

Different types of quantitative studies will demand different structures and requirements for reporting the results. Therefore, it is suggested to follow EQUATOR's (https://www.equator-network.org) internationally accepted guidelines for the presentation of different quantitative studies.

3 Sampling and Sample Size

The following section presents the basic features of sampling, including the theoretical background and practical applications. The different types of sampling such as simple random sampling, stratified sampling, systematic sampling and other relevant methods are discussed in detail. It also explains the process of sample size calculation using SPSS software. The learning objectives of this chapter are to enable the reader to understand the basic concepts and importance of sampling in the research process. The reader will become familiar with the different types of sampling and their characteristics. It will also provide practical knowledge of how to perform sample size calculations using SPSS. It also aims to develop the ability to evaluate critically and select the appropriate sampling method according to specific research needs, which is crucial for conducting high quality and reliable research.

The statistical population consists of all the participants in the group about which you want to draw inferences by observation. The statistical sample represents the individual part of the group (subgroup) from which the data will be collected (**Fig. 3.1**). The statistical unit represents one individual member of the population (element of the set).

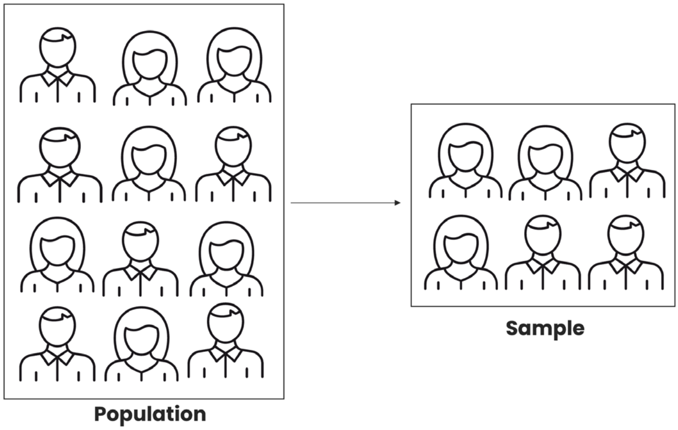


Figure 3.1: Statistical Sample

Sampling methods fall into two broad groups: probability samples, where each element has a known probability of occurring in the class, and non-probability sampling, where the above condition is not met.

- **Simple random sampling:** Individuals are randomly selected from the total population. This gives a sample that is not necessarily representative (**Fig. 3.2**) (Simkus, 2022).

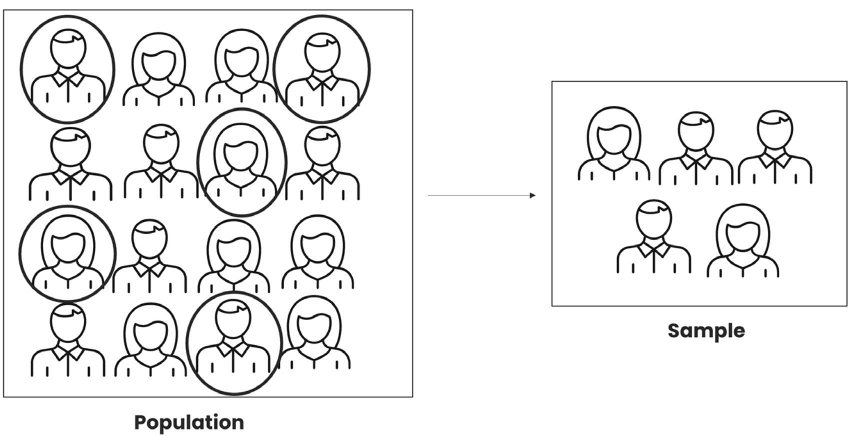


Figure 3.2: Simple Random Sampling

– **Stratified sampling:** The population is divided into classes according to certain characteristics (e.g., sex, age class, etc.). Then, random sampling (proportional or disproportionate) is carried out from each class.

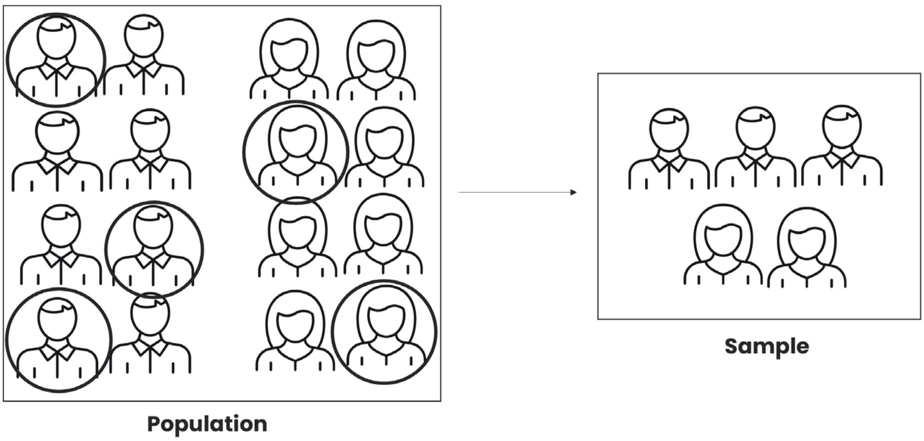


Figure 3.3: Stratified Sampling

– **Systematic sampling:** The first element is selected randomly, followed by every kth element (k = population size/sample size).

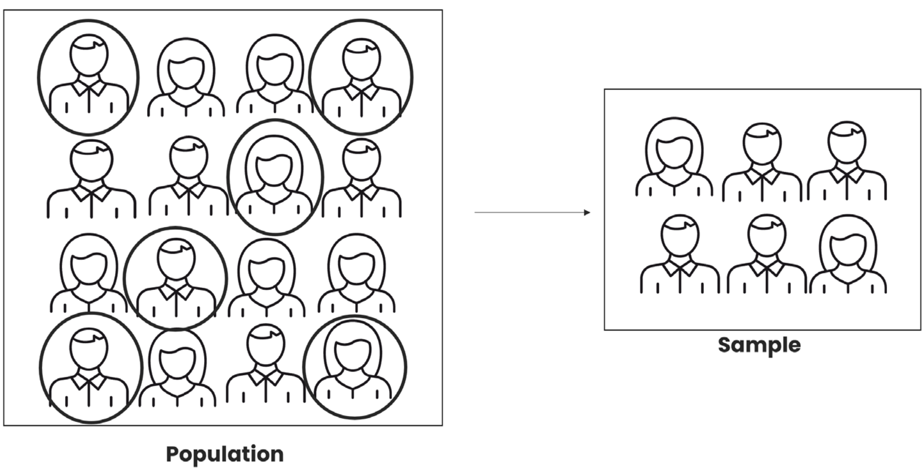


Figure 3.4: Systematic Sampling

– **Cluster sampling:** Use known information on the grouping of elements (sampling by provinces, localities, communities, by schools, classes, etc.).

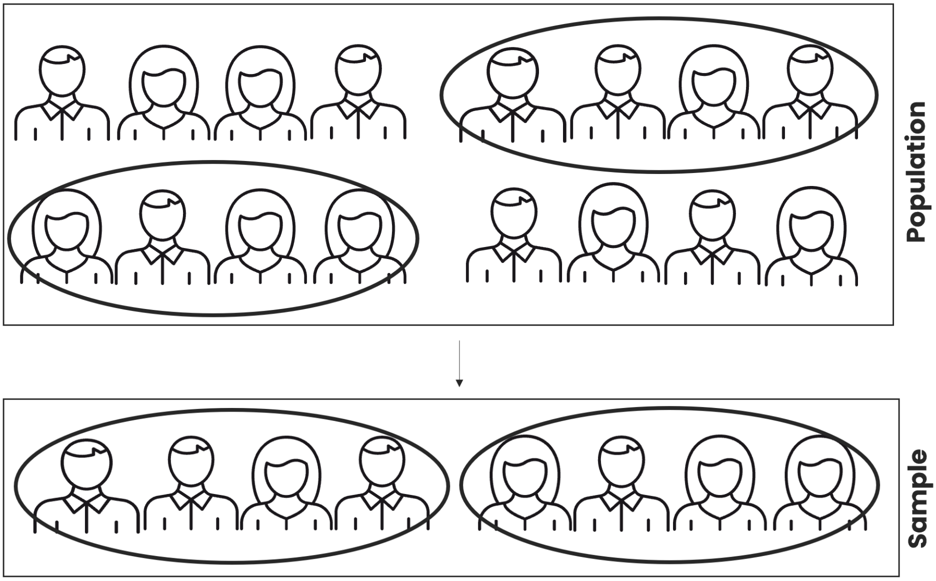


Figure 3.5: Cluster Sampling

– **Snowball sampling:** First, we select a smaller sample of more accessible individuals, who are asked to disseminate the sample or questionnaire through their contacts.

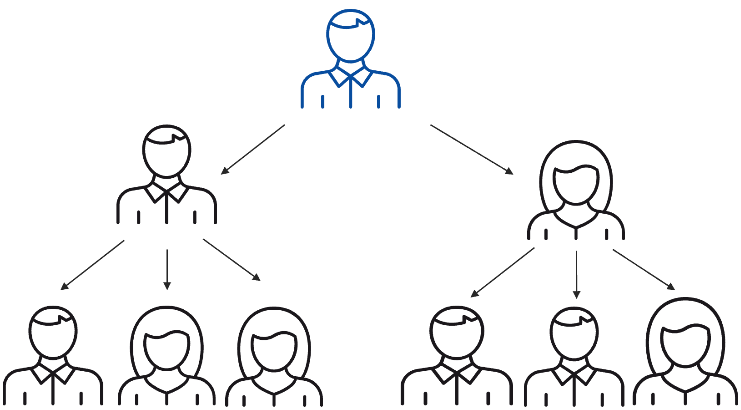


Figure 3.6: Snowball Sample

– **Convenience sampling:** A convenience/occasional sample simply includes individuals who are most accessible to the researcher (Simkus, 2022).

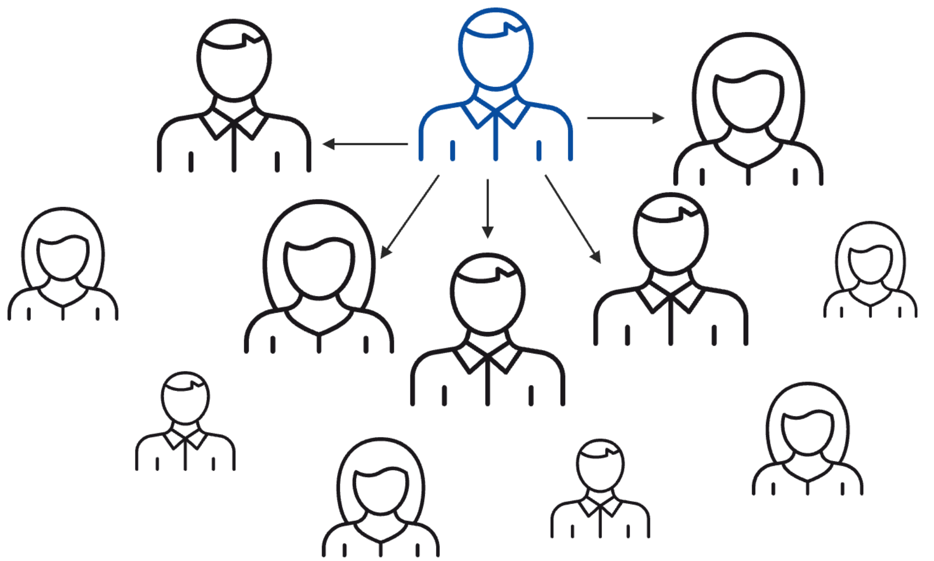


Figure 3.7: Convenience Sampling

– **Purposive sampling:** the researcher uses his/her expertise to select the sample that is most useful for the purposes of the research.

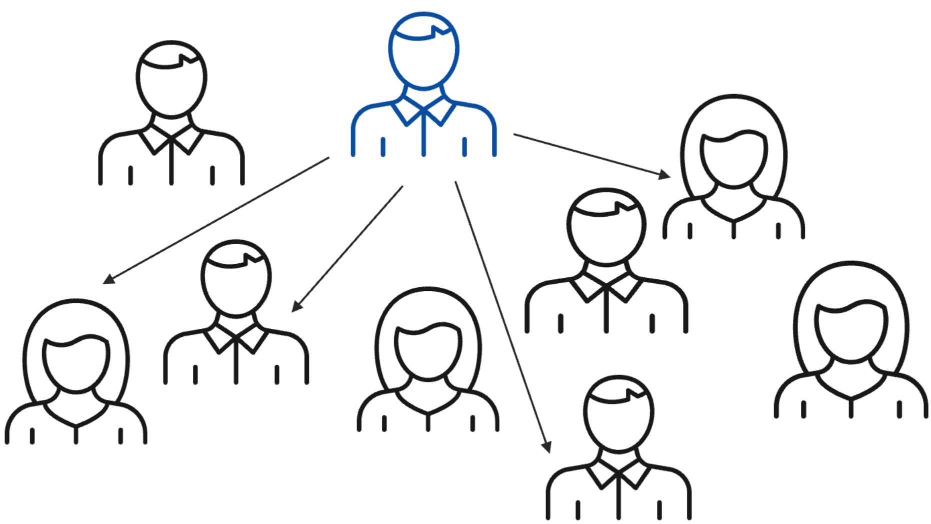


Figure 3.8: Purposive Sampling

3.1 Calculating the Required Sample Size Using SPSS

One of the frequently asked questions during the study planning phase is, "How many participants do I need to test my hypotheses?". The answer to this question is not straightforward. In fact, we could write a whole book on different techniques of so-called power analysis that can be used to estimate the minimal required sample size for a given hypothesis. Calculating the sample size is key to ensuring accurate and reliable results, as it reduces the error rate and increases the precision of the estimates (Andrade, 2020).

As already mentioned in the initial chapters, to test the hypothesis, we need to know some characteristics of our data – especially the type of variables and distribution of collected data for the variables that are involved in the hypothesis testing.

There are many specialized computer programs available that allow us to conduct Power analysis. However, from IBM SPSS version 27, it is also possible to use the Power analysis function directly in the SPSS (*Analyze -> Power Analysis*).

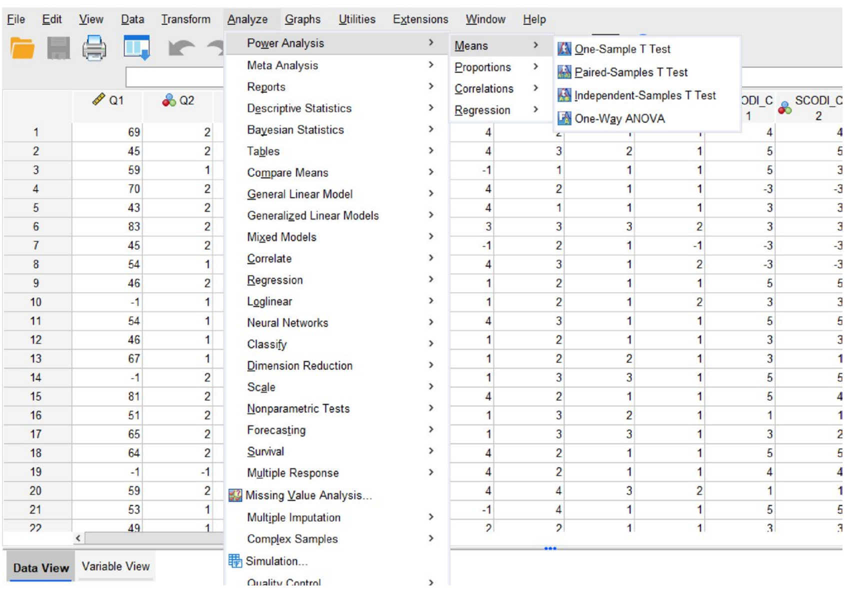


Figure 3.9: Power Analysis in SPSS

As it can be seen from Fig. 89, as of the IBM SPSS 28, the Power Analysis function in SPSS allows estimation of minimal sample size for four different groups of statistical tests:

- Comparison of means (univariate and bivariate t-tests, One-way ANOVA).
- Proportions (univariate and bivariate binomial tests).
- Correlations (Pearson, Spearman, partial).
- Regression (univariate linear).

Here, we provide a step-by-step demonstration of using the SPSS Power Analysis function to estimate the minimal required sample size for an independent t-test scenario.

After the selection of the *Analyze -> Power Analysis -> Means -> Independent-Samples t-Test*, we are asked to enter information for both compared groups (**Fig. 3.10**).

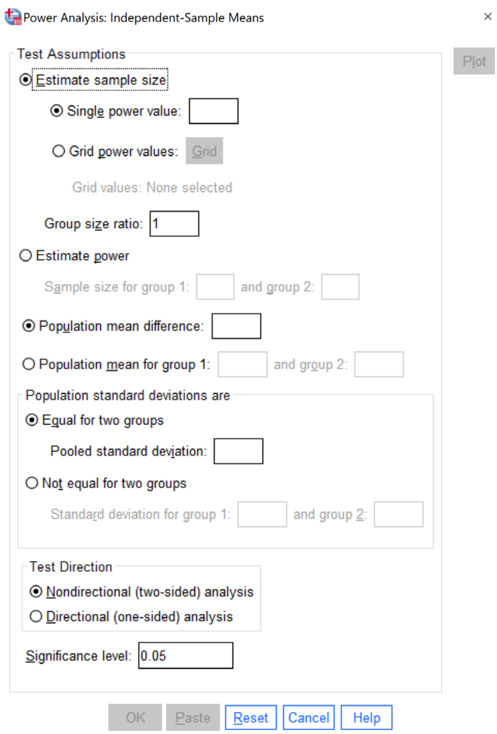


Figure 3.10: Power Analysis for Independent-Samples t-Test

In this step, we will have to provide the "Single power value", which is usually set at 0.90 or 0.95. **Figure 3.11** shows an example of the minimal sample size estimation for a scenario where we performed a pilot study on a small sample of students, measuring student satisfaction (measured on a scale from 1 to 5) of the undergraduate (group A, n=25) and postgraduate (group B, n=23) students. We obtained the following results:

- Average satisfaction level in group A was 4.5, and 4.8 in group B;
- Standard deviations of 0.9 (group A) and 0.8 (group B) were calculated;
- In the hypothesis we were interested only whether there are any differences in average satisfaction between undergraduate and post-graduate students (Nondirectional, two-sided analysis).

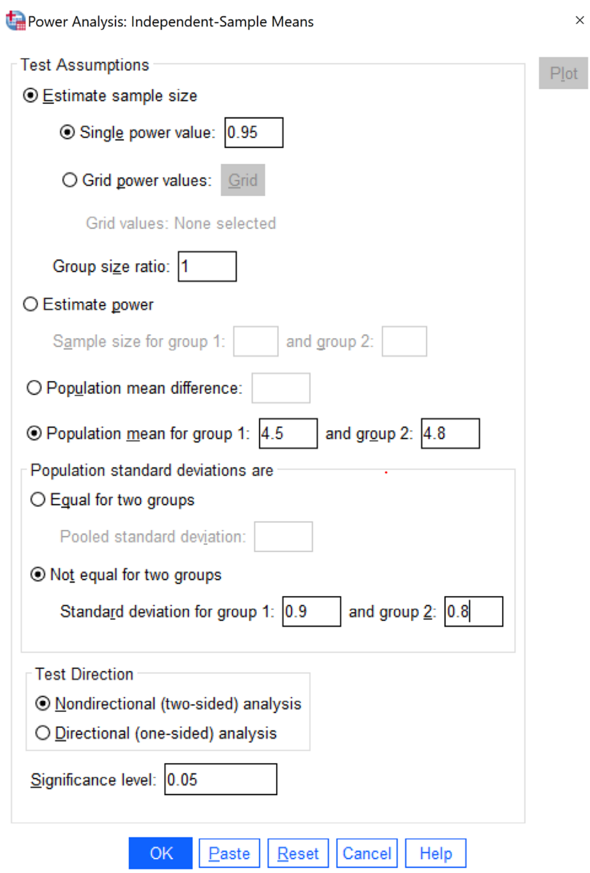


Figure 3.11: Power Analysis Data Entry Example

Power Analysis - Independent Sample Means

Power Analysis Table

	N1	N2	Actual Power[b]	Test Assumptions				
				Power	Std. Dev1	Std. Dev2	Mean Difference	Sig.
Test for Mean Difference[a]	211	211	.951	.95	.9	.8	.300	.05

a. Two-sided test.

b. Based on noncentral t-distribution.

Figure 3.12: Results from the Power Analysis for an Independent Samples t-Test

4 Review of Statistical Basics

The next section introduces basic statistical concepts, such as hypotheses and variables, and provides basic information about basic descriptive statistics in SPSS software. The chapter also introduces the different statistical tests that are performed in SPSS. The learning objectives of this chapter are to enable the reader to understand basic statistical concepts and their importance in the research process. The reader will become familiar with formulating and testing hypotheses and will learn about the different types of variables and their influence on research results. They will also acquire basic skills in descriptive statistics in SPSS, including mean, median and standard deviation. Finally, the reader will learn how to perform and interpret various statistical tests in SPSS, such as t-tests, ANOVA, correlation tests and others. This chapter will provide the reader with a comprehensive understanding of key statistical concepts and methods.

Statistics is a fundamental tool in nursing, enabling nurses to analyse data systematically, which is key to improving the quality of patient care and making informed decisions. Understanding statistical concepts is essential for critically evaluating research studies that help to identify the most effective therapeutic approaches, establish associations between different risk factors and treatment outcomes, and optimise the management of healthcare resources.

Understanding statistics also enables nurses to evaluate critically and apply research findings in their daily practice. This enables them to make more informed, evidence-based decisions that improve patient care and enhance the professionalism of their work:

- **Statistical population** - These are all the objects (or "entities") that we observe; mathematically, the universal set.
- **Statistical unit** - Individual member of the population; the element of the crowd.
- **Statistical sample** - Part of the population; a subset.
- **Statistical variable** - Property of individual members of the population.
- **Statistical parameter** - Measured quantity describing a statistical population.

Hypothesis

- A hypothesis (plural hypotheses) is a proposed explanation for a phenomenon.
- An assumption that can be empirically verified.
- Consists of variables (descriptions, unit properties).
- Working, null, alternative, non-directional, directional.

We talk about a hypothesis when the problem is specific and well-defined and, therefore, can be formulated into a claim, which is then accepted or rejected by certain statistical tests. A hypothesis is an assumed statement of the relationship between two or more variables.

The null hypothesis (H_0) states that there is no statistically significant difference or relationship among variables. The working hypothesis (H_a, H_1) states exactly the opposite.

Using the p-value, we determine the degree of confidence with which we can reject the null hypothesis:

- **Simple:** shows a relationship between one dependent and one independent variable.
- **Complex:** shows the relationship between two or more dependent variables and two or more independent variables.

- **Directional:** the hypothesis assumes a relationship between two variables and is based on existing theory (E.g. Women are more confident in taking self-care for their diabetes).
- **Non-directional:** is used when no theory is involved. It is a statement that a relationship exists between two variables without predicting the exact nature (direction) of the relationship (E.g. There is a difference in diabetes self-care confidence between women and men).
- **Null:** provides the statement which is contrary to the hypothesis. It is a negative statement, with no relationship between independent and dependent variables (E.g. The average diabetes self-care confidence score is 60).
- **Associative and causal:** Associative hypothesis occurs when there is a change in one variable, resulting in a change in the other variable. Causal hypotheses propose a cause-and-effect interaction between two or more variables.

Variables

- To test hypotheses, we need to collect enough data for the variables involved in a hypothesis. A variable that causes a condition to develop is known as an independent variable because its values are independent of other variables. A variable that is influenced by an independent variable is called a dependent variable because its value depends on the cause (**Fig. 4.1**).

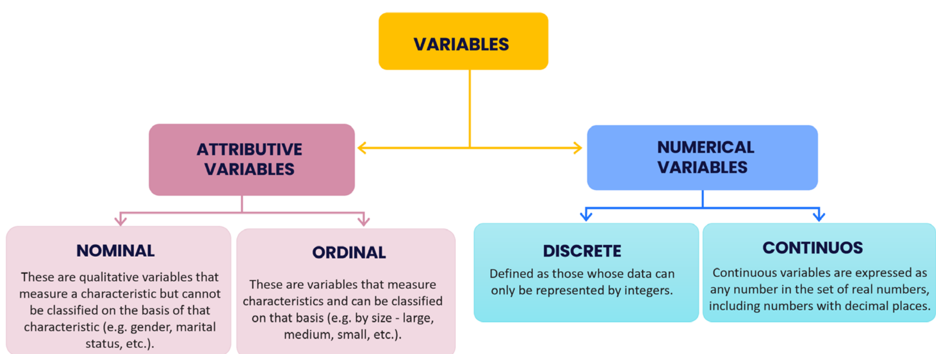


Figure 4.1: Type of Statistical Variables
Source: (Liguori & Moreira, 2018)

4.1 Start the IBM SPSS Software Package

To run SPSS, double-click on the icon .

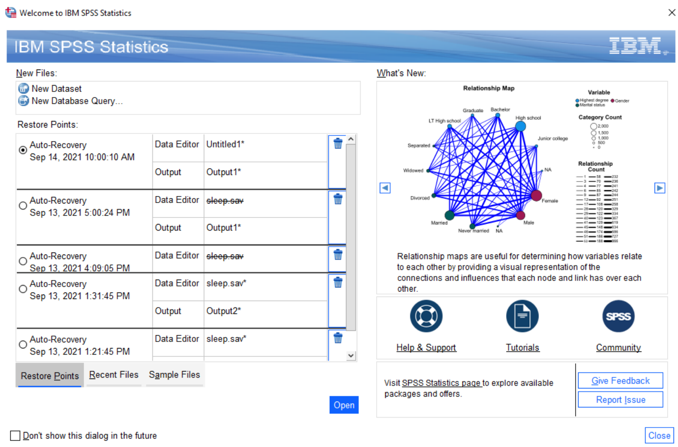


Figure 4.2: Start the SPSS Package

For SPSS analysis, we can use:

– data prepared for analysis in SPSS format (.sav file);
– data downloaded from other programs (e.g. Excel);
– data entered manually in the Data Editor window.

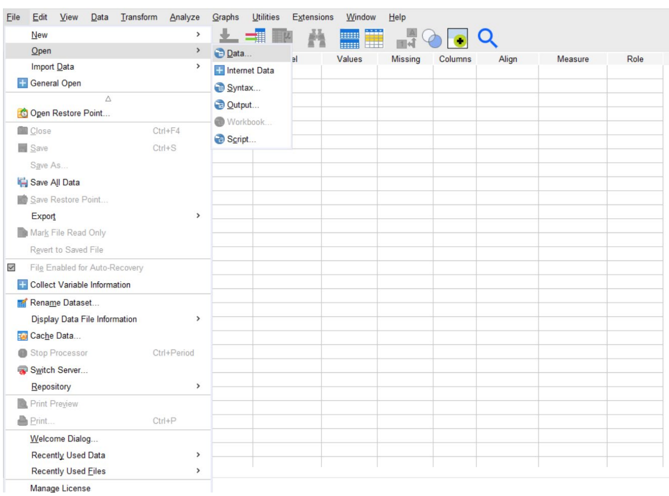


Figure 4.3: Importing Data Into SPSS

The Data View shows the dataset (**Fig. 4.4**). The columns represent variables, and the rows represent individual cases. Variable View shows information about the variables.

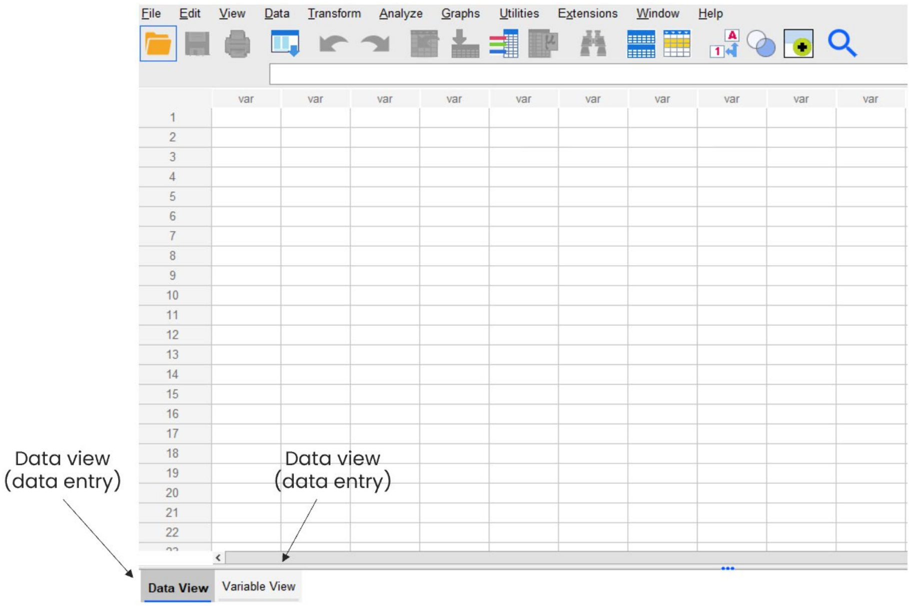


Figure 4.4: Data View Window in SPSS

Variable View includes the following information:

- name of variable;
- type of variable (e.g. string, numeric, etc.);
- number of signs (Width);
- number of decimal places (Decimals);
- variable brief description (Label);
- description of the variable value for coded categorical variables (Values);
- missing values (Missing);
- width of column (Columns);
- alignment of the variable values in Data View – can be left, right or center justified (Align);
- type according to measurement (Measure; e.g., nominal, ordinal, or scale);
- role (e.g., input, target, both, etc.).

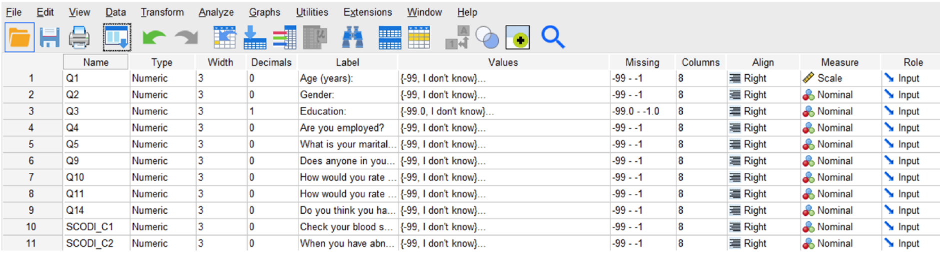


Figure 4.5: Variable View

4.2 Creating New Variables

a) Compute Variable

In the following section, we were interested in how are confident patients with diabetes in carrying out self-care activities and maintaining their health. Patients were asked to answer eleven questions using a Likert scale from 1 to 4. The formula for calculating the total score is given below:

Self-care Confidences = (SUM(SCODI_D1+ SCODI_D2+ SCODI_D3+ SCODI_D4+ SCODI_D5+ SCODI_D6+ SCODI_D7+ SCODI_D8+ SCODI_D9+ SCODI_D10+ SCODI_D11)-11)*(100/44)

To calculate a new variable from the given variables, we can use the Compute Variable function (**Fig. 4.6**).

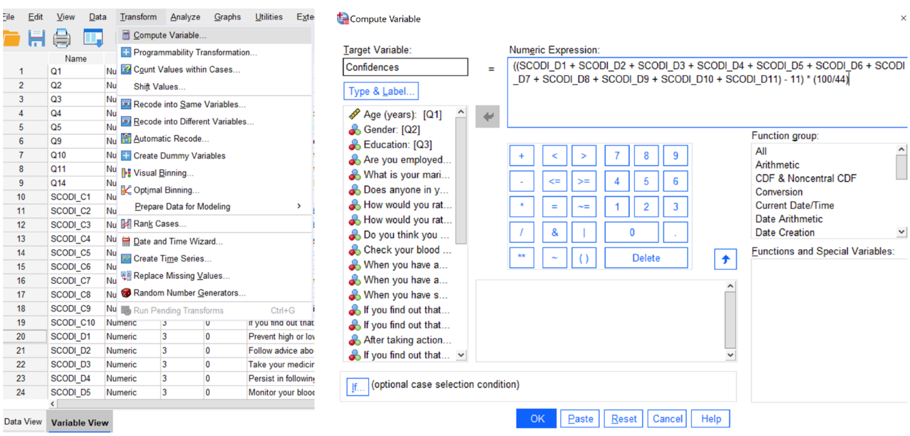


Figure 4.6: Compute New Variable

b) Record into Same or into Different Variables

If we want to map the existing values of a variable into new values, but do not want to create a new variable, we can use the Recode into Same Variables function. If we want to convert existing variables into new ones, we can use the Recode into Different Variables function (**Fig. 4.7**). In case we also have missing values, we need to add the conversion of the missing values back into the missing values.

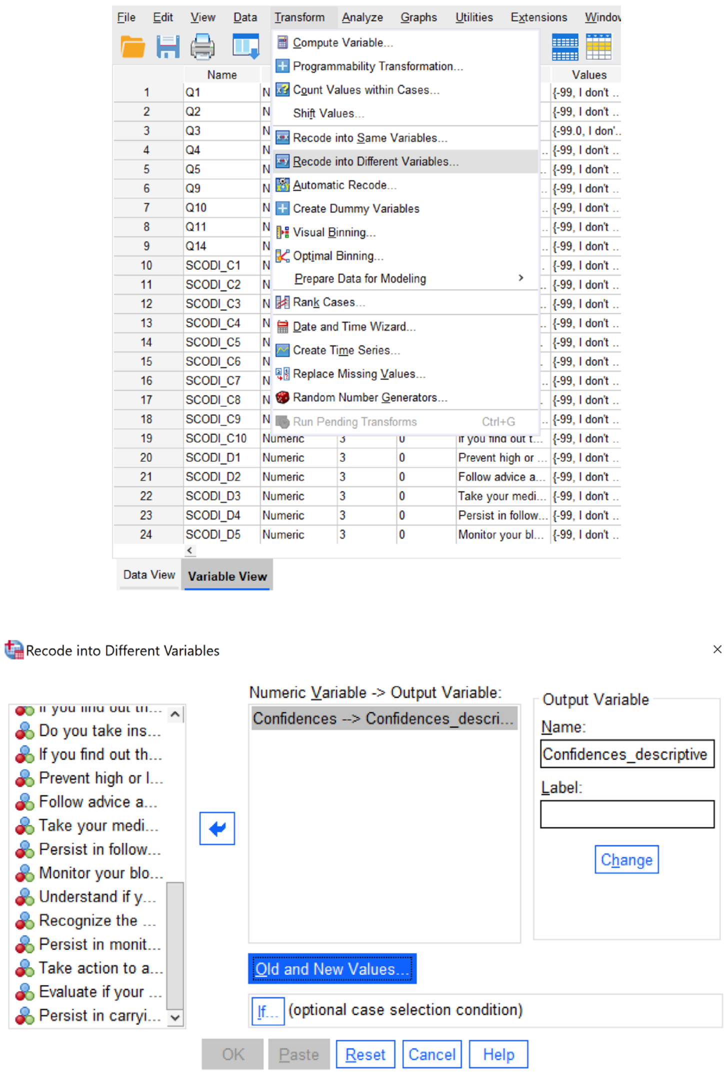


Figure 4.7: Recode Into a New Variable

We divided the values on a scale from 0 to 100 into four parts. 0 to 25 was low self-confidence, 25 to 50 was insufficient self-confidence, 50 to 75 was adequate self-confidence and 75 to 100 was good self-confidence.

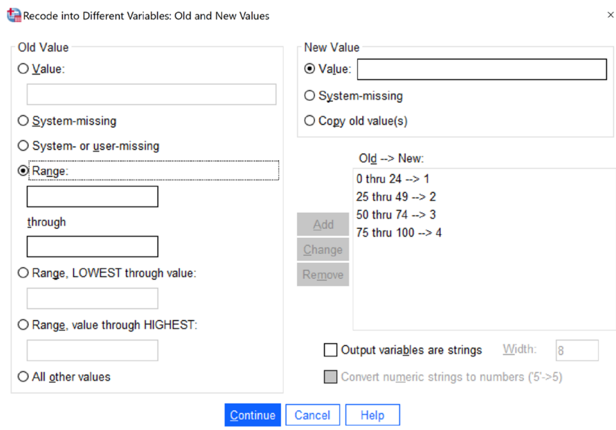


Figure 4.8: Define New Variables

4.3 Steps for Conducting Descriptive Statistics in SPSS

a) Frequencies

We click the following: *Analyze -> Descriptive Statistics -> Frequencies.*

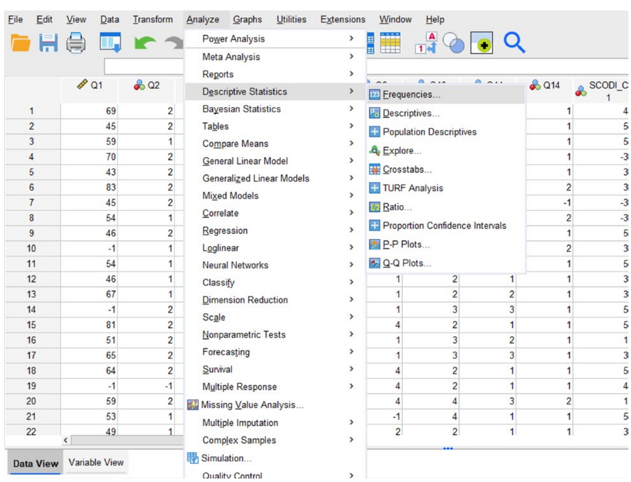


Figure 4.9: First Step in Choosing Frequencies Function

If you also want to display the variables as an illustration, click *Charts*, select the type of chart (Bar, Pie, Histogram) and specify whether you want to show frequencies or percentages.

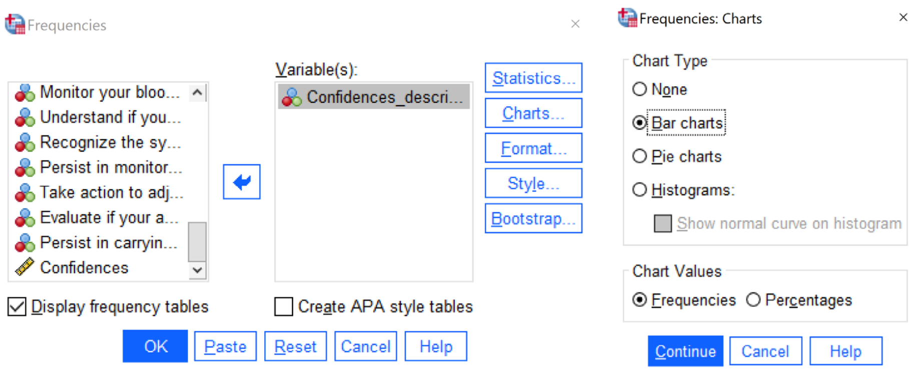


Figure 4.10: Choosing Variables When Conducting Frequencies Function

Results are presented in two tables:

Frequencies

Statistics

Confidence_descriptve

N	Valid	101
	Missing	40

Confidence_descriptve

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Low self-confidences	1	.7	1.0	1.0
	Insufficient self-confidences	3	2.1	3.0	4.0
	Adequate self-confidences	34	24.1	33.7	37.6
	Good self-cnfidence	63	44.7	62.4	100.0
	Total	101	71.6	100.0	
Missing	System	40	28.4		
Total		141	100.0		

Figure 4.11: Results When Conducting Frequencies Function

The results are shown using frequencies and percentages. The valid percentage and cumulative percentage are also shown. The valid percentage is the percentage of cases that have non-missing values for each category. The cumulative percentage is the calculation of the valid percentages for each category or for previous categories.

The results can be reported as follows: One participant (1.0%) had low self-confidence, three participants (3.0%) had insufficient self-confidence, 34 participants (33.7%) had adequate self-confidence, and 63 participants (62.4%) had high self-confidence.

The results can also be plotted using graphs.

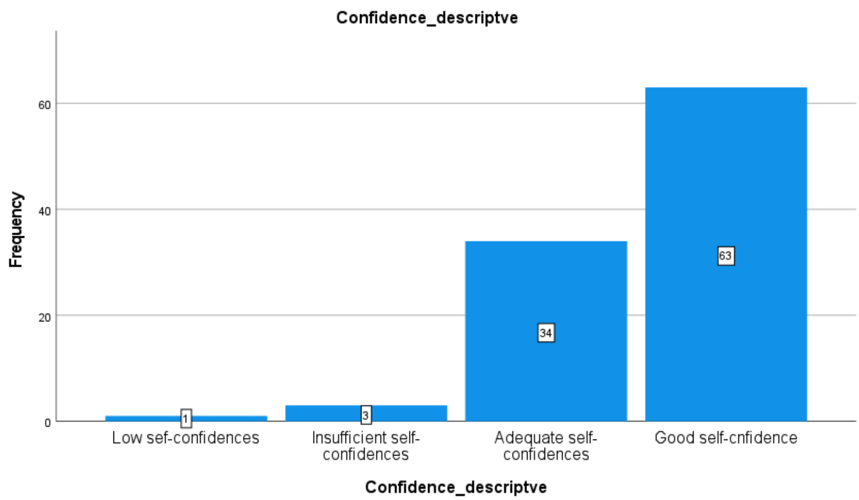


Figure 4.12: Results in Graphs When Conducting Frequencies Function

b) Descriptives

We click on *Analyze -> Descriptive Statistics -> Descriptives.*

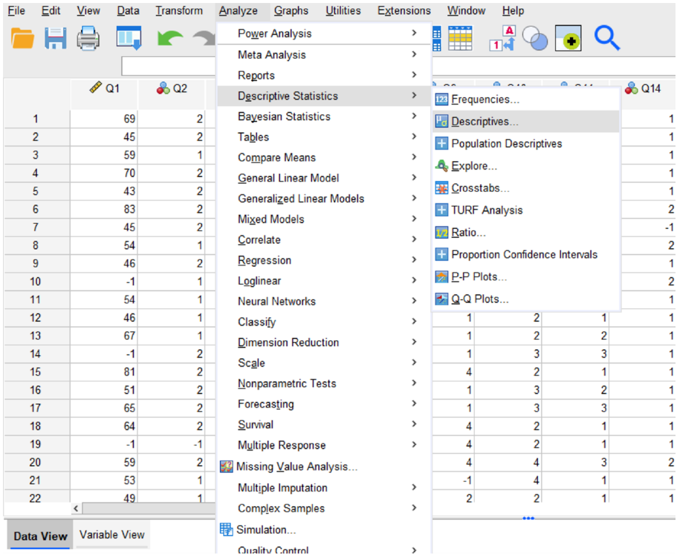


Figure 4.13: First Step in Choosing Descriptives Function

Then click on Statistics, and we can choose different statistical parameters, such as Mean, Minimum, Maximum, Standard deviation, etc.

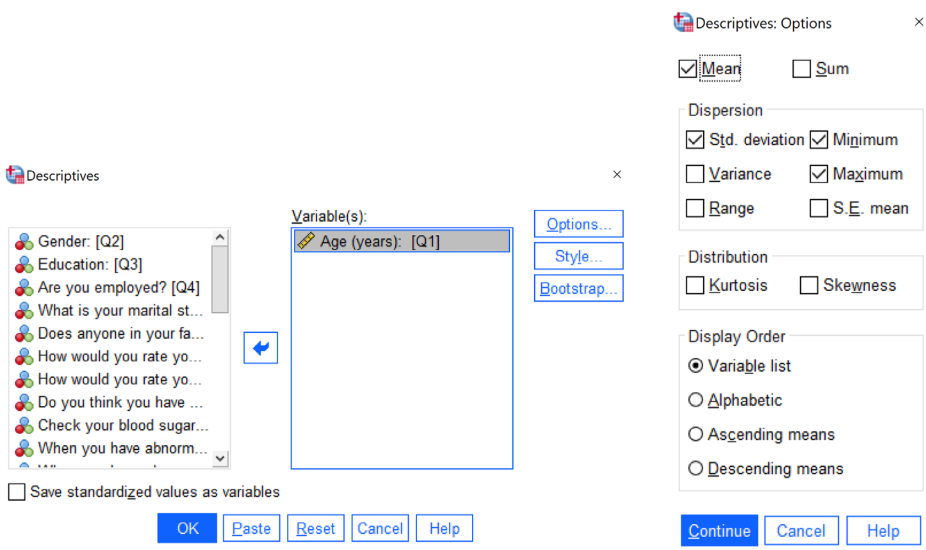


Figure 4.14: Choosing Variables When Conducting Descriptives Function

The results can be reported as follows: The average age of participants is 63.08 years (SD=12.96), with a minimum age of 24 years and a maximum age of 87 years (**Fig. 4.15**).

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age (years):	132	24	87	63.08	12.961
Valid N (listwise)	132				

Figure 4.15: Results When Conducting Descriptives Function

c) Explore

When choosing the function *Explore*, we can also choose different plots (e.g., Histogram, Stem and leaf, etc.) to present our data.

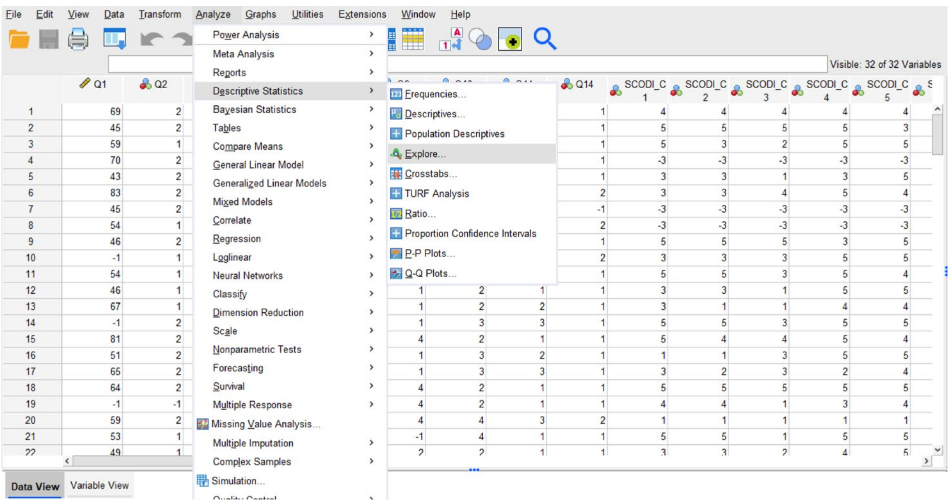


Figure 4.16: First Step in Choosing Explore Function

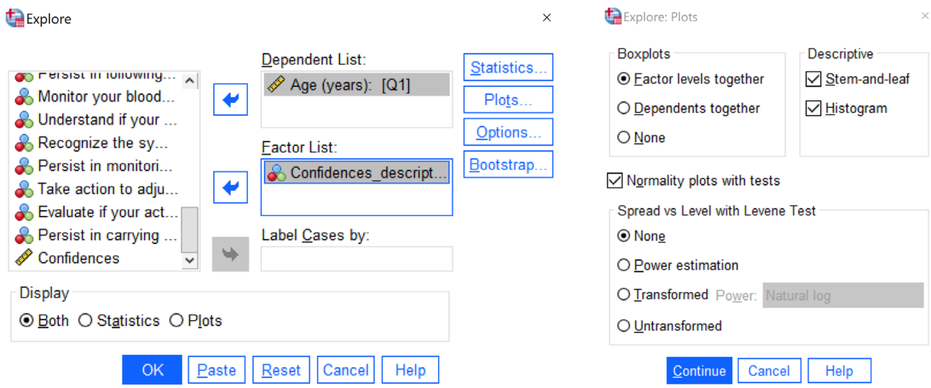


Figure 4.17: Choosing Variables When Conducting Explore Function

Results are presented in three tables:

Case Processing Summary

		Cases					
		Valid		Missing		Total	
	Confidence_descriptve	N	Percent	N	Percent	N	Percent
Age (years):	Low self-confidences	1	100.0%	0	0.0%	1	100.0%
	Insufficient self-confidences	3	100.0%	0	0.0%	3	100.0%
	Adequate self-confidences	31	91.2%	3	8.8%	34	100.0%
	Good self-cnfidence	60	95.2%	3	4.8%	63	100.0%

Figure 4.18: Summary Result When Conducting Explore Function

Skewness is a measure of symmetry. Kurtosis is a measure of the distribution. When the mean, median and mode coincide, it is called a symmetric distribution, i.e. skewness = 0, kurtosis = 0. Skewness and Kurtosis parameters must lie between 1 and -1 for the distribution to be approximately normal. This is a less reliable method for small to medium-sized samples (i.e. n < 300) because it cannot adjust the standard error. In this case, we apply a z-test using skewness and kurtosis (Mishra, et al., 2019).

Descriptives[a]

	Confidence_descriptve			Statistic	Std. Error
Age (years):	Insufficient self-confidences	Mean		73.67	2.728
		95% Confidence Interval for Mean	Lower Bound	61.93	
			Upper Bound	85.41	
		5% Trimmed Mean		.	
		Median		72.00	
		Variance		22.333	
		Std. Deviation		4.726	
		Minimum		70	
		Maximum		79	
		Range		9	
		Interquartile Range		.	
		Skewness		1.390	1.225
		Kurtosis		.	.
	Adequate self-confidences	Mean		64.35	2.075
		95% Confidence Interval for Mean	Lower Bound	60.12	
			Upper Bound	68.59	
		5% Trimmed Mean		64.64	
		Median		67.00	
		Variance		133.437	
		Std. Deviation		11.551	
		Minimum		41	
		Maximum		83	
		Range		42	
		Interquartile Range		14	
		Skewness		-.623	.421
		Kurtosis		-.503	.821

Figure 4.19: Descriptives Results With the Explore Function

For small samples (less than 50 units), the Shapiro-Wilk test is recommended, although it can be used for larger samples, whereas the Kolmogorov-Smirnov test can only be used for larger samples (more than 50 units). If the p-value is higher than 0.05, we can confirm the normal distribution (Mishra, et al., 2019).

The results can be interpreted as follows: The Shapiro-Wilk test shows that the age distribution is normally distributed in all three groups (**Fig. 4.20**).

Tests of Normality[a]

	Confidence_descriptve	Kolmogorov-Smirnov[b]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Age (years):	Insufficient self-confidences	.304	3	.	.907	3	.407
	Adequate self-confidences	.135	31	.158	.934	31	.056
	Good self-cnfidence	.075	60	.200*	.983	60	.589

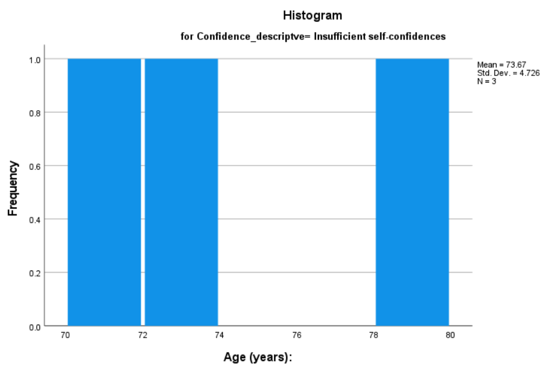
*. This is a lower bound of the true significance.

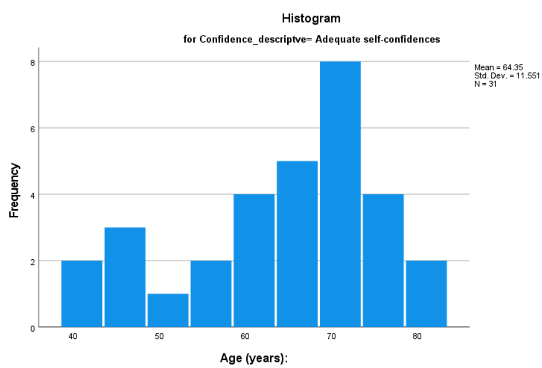
a. Age (years): is constant when Confidence_descriptve = Low self-confidences. It has been omitted.

b. Lilliefors Significance Correction

Figure 4.20: Tests of Normality When Conducting Explore Function

The data distribution can also be viewed by looking at the histogram. The histogram is an estimate of the probability distribution of the continuous variable. If we have a bell-shaped and symmetrical graph about the mean, we can assume that the data are normally distributed (Barton & Peat, 2014; Mishra, et al., 2019). In **Figure 4.21**, we see the abnormal age distribution in people with insufficient and sufficient self-confidence.





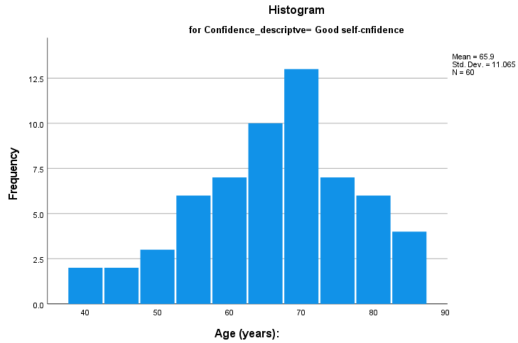
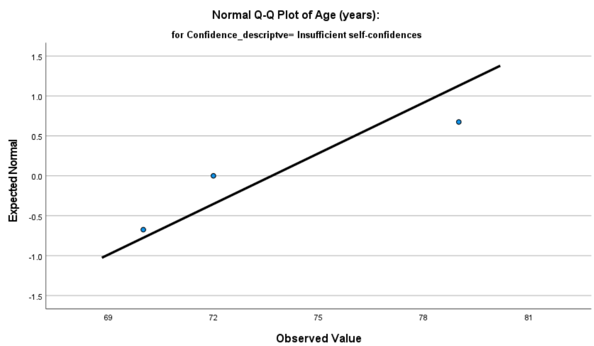
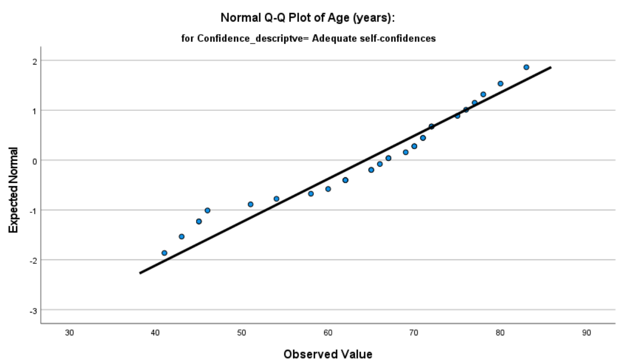


Figure 4.21: Histogram

The Q-Q normal plot (**Fig. 4.22**) shows the relationship between two sets of quantiles (observed and expected). For normally distributed data, the observed data are approximately equal to the expected data.





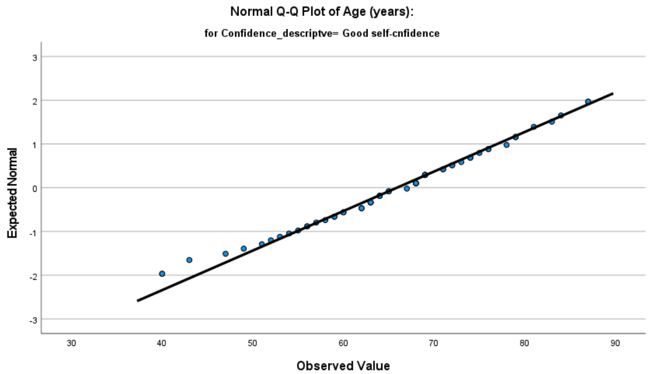


Figure 4.22: Q-Q Normal Plot

We can also assess the normality of the data distribution using a box plot (**Fig. 4.23**). It shows the median as a horizontal line inside the box and the IQR (the range between the first and third quartiles) as the length of the box.

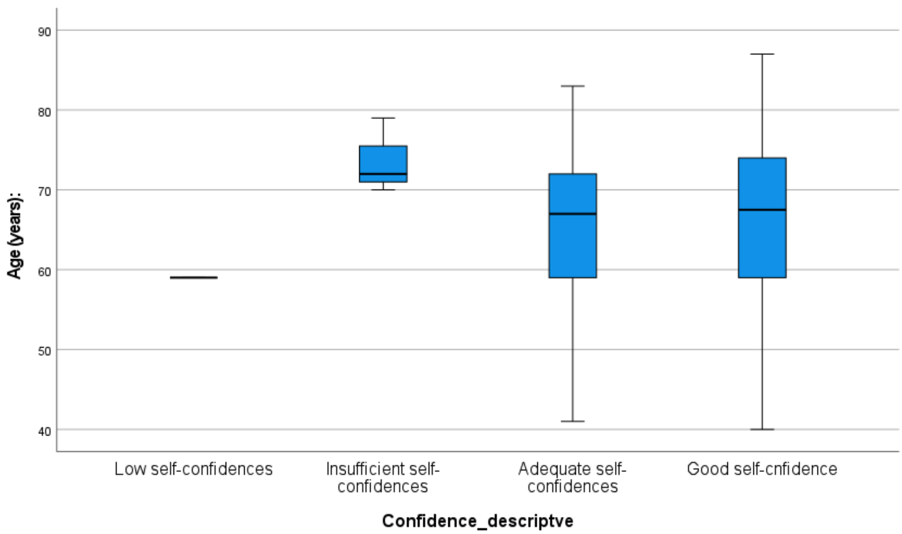


Figure 4.23: Box Plot

d) Crosstabs

Crosstabs can used to describe the relationship between two categorical variables. We click the following: *Analyze -> Descriptive Statistics -> Crosstabs.*

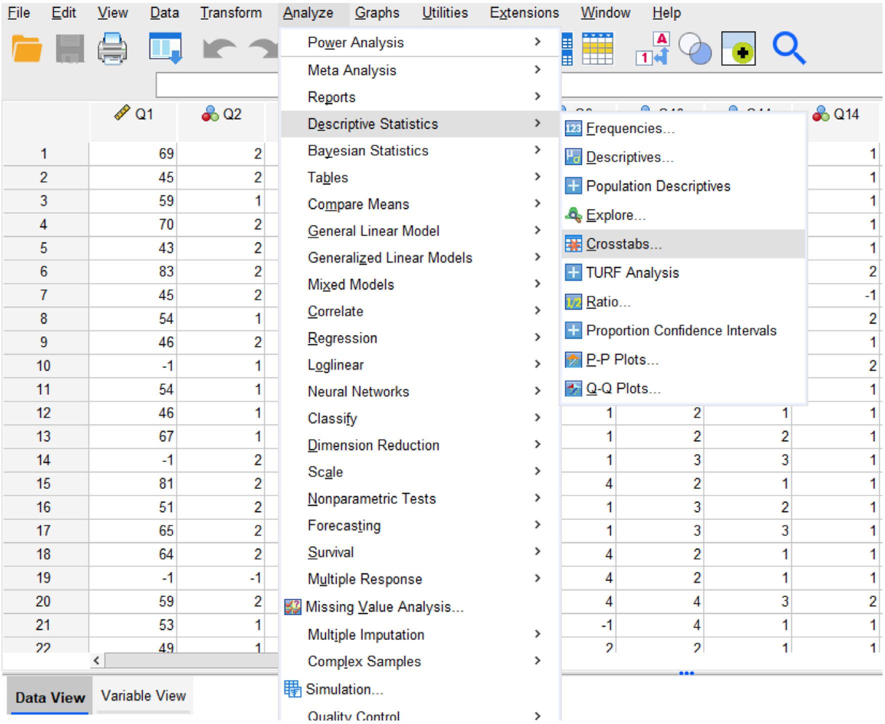


Figure 4.24: Crosstabs

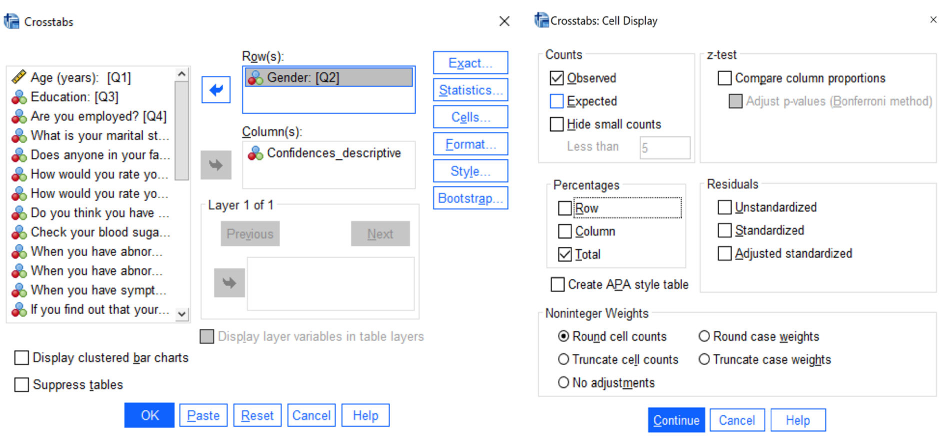


Figure 4.25: Choosing Variables When Conducting Crosstabs

The results can be seen in **Figure 4.26**:

In this table, the columns represent the values of the first variable, and the rows represent the values of the second variable. Cross-tabulations allow us to show the proportion of cases in subgroups.

Gender: * Confidence_descriptve Crosstabulation

			Confidence_descriptve				
			Low self-confidences	Insufficient self-confidences	Adequate self-confidences	Good self-cnfidence	Total
Gender:	Men	Count	0	2	17	25	44
		% of Total	0.0%	2.0%	17.0%	25.0%	44.0%
	Women	Count	1	1	17	37	56
		% of Total	1.0%	1.0%	17.0%	37.0%	56.0%
Total		Count	1	3	34	62	100
		% of Total	1.0%	3.0%	34.0%	62.0%	100.0%

Figure 4.26: Results When Conducting Crosstabs

e) Compare Means

Compare means allows a comparison between numerical variables. We click the following: *Analyze -> Compare Means -> Means.*

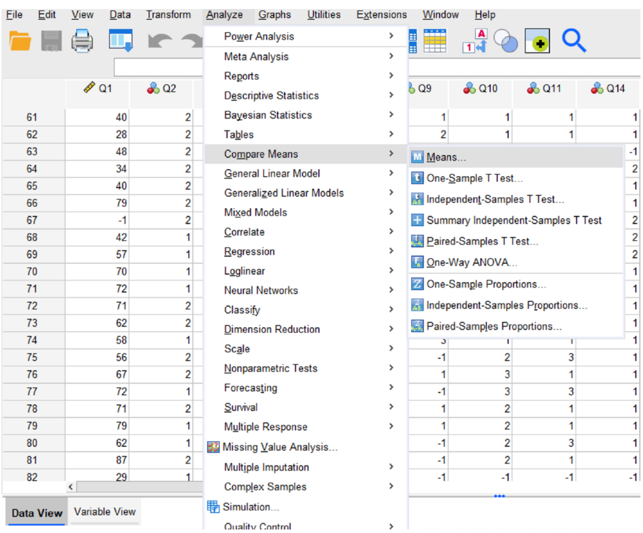


Figure 4.27: Compare Means

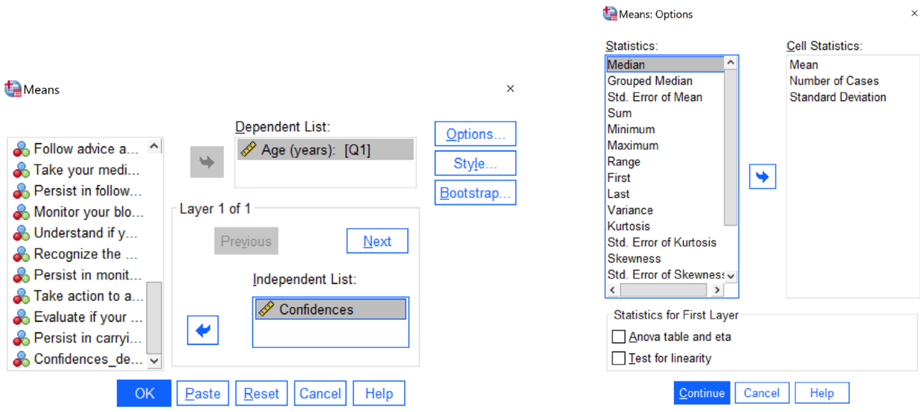


Figure 4.28: Choosing Variables When Conducting Comparison Means

The results are shown in the following table:

Report

Variables Age (years):

confidencesscore	Mean	N	Std. Deviation
22.73	59.00	1	.
31.82	72.00	1	.
36.36	79.00	1	.
47.73	70.00	1	.
50.00	67.00	2	7.071
52.27	60.50	2	27.577
54.55	59.00	3	13.528
56.82	76.00	1	.
59.09	45.00	1	.
61.36	66.25	4	5.737
63.64	71.50	2	.707
65.91	68.00	2	2.828
68.18	66.50	4	11.328
70.45	66.20	5	14.025
72.73	60.20	5	12.677
75.00	65.57	7	11.844
77.27	71.50	8	9.366
79.55	70.29	7	10.515
81.82	74.00	1	.
84.09	54.50	4	9.983
86.36	64.57	7	13.227
88.64	70.00	3	15.133
90.91	66.00	5	9.849
93.18	60.67	6	11.361
95.45	68.25	4	4.500

Figure 4.29: Result when Conducting Compare Means

f) Custom Tables

This is a frequency table that allows comparisons between variables. We click the following: *Analyze -> Tables -> Custome Tables.*

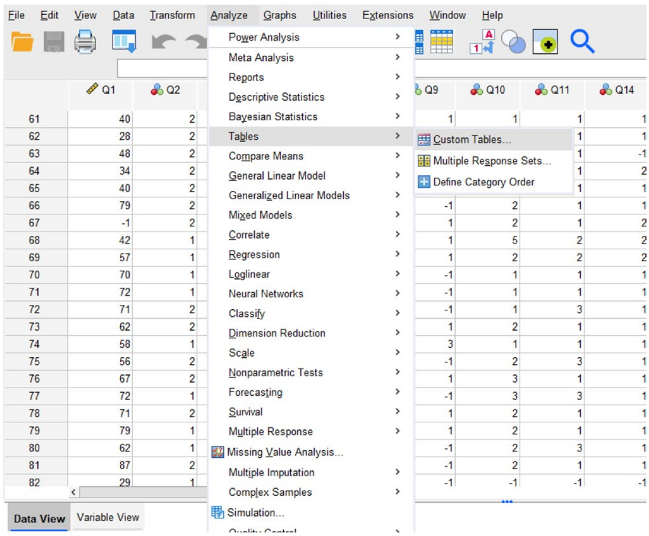


Figure 4.30: Custom Tables

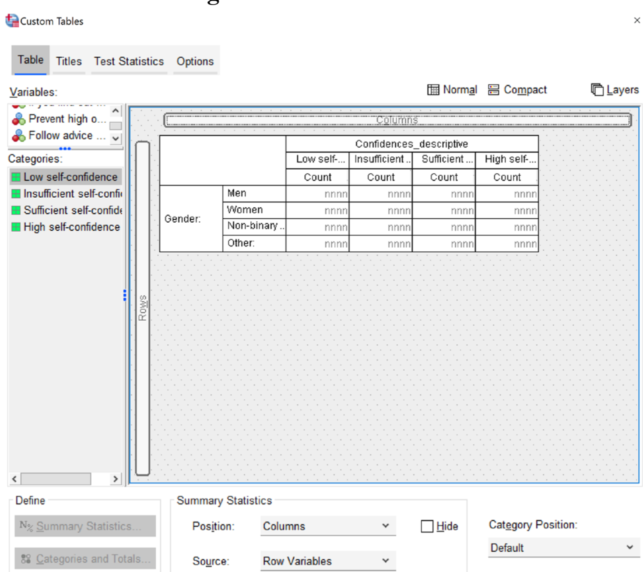


Figure 4.31: Choosing Variables When Conducting Custom Tables

The results are shown in **Figure 4.32**. In the figure, we can see the gender distribution of diabetes self-care and self-confidence levels.

Custom Tables

		Confidence_descriptve			
		Low self-confidences	Insufficient self-confidences	Adequate self-confidences	Good self-cnfidence
		Count	Count	Count	Count
Gender:	Men	0	2	17	25
	Women	1	1	17	37
	Non-binary gender	0	0	0	0
	Other:	0	0	0	0

Figure 4.32: Results When Conducting Custom Tables

g) Chart Builder

If you want to display the variables in a graph, click the following: *Graphs -> Chart Builder*.

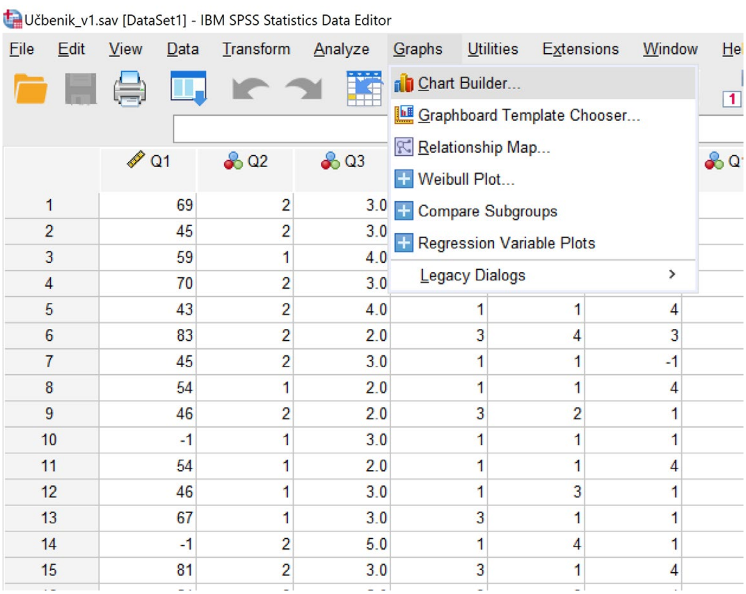


Figure 4.33: Chart Builder

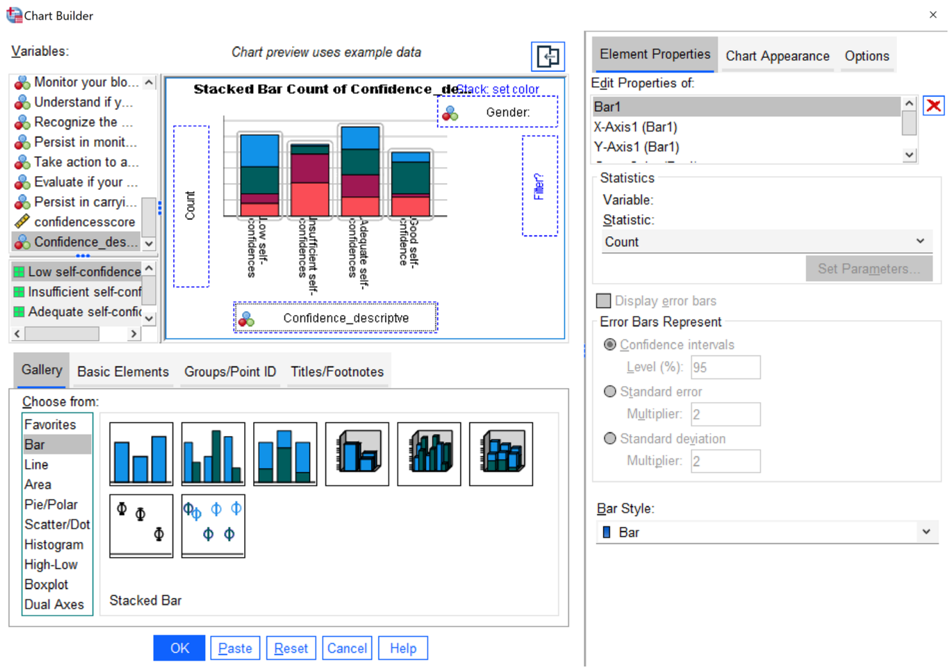


Figure 4.34: Choosing a Variable for the Chart

Figure 4.35 shows graphically the gender ordering of the level of self-confidence of patients with diabetes mellitus.

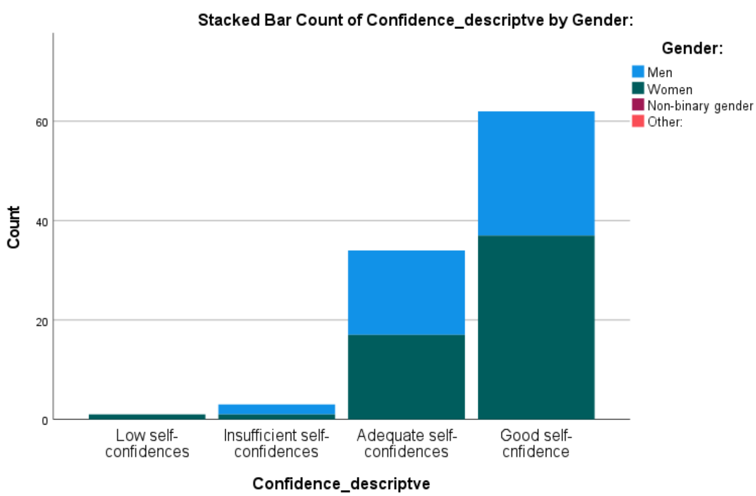


Figure 4.35: Gender Distribution of Self-Confidence Levels in the Chart

4.4 Statistical Inference

Statistical inference is the process of concluding populations or scientific truths from data. There are many modes of performing inference, including statistical modelling, data-oriented strategies, and explicit use of designs and randomization in analyses.

Statistical tests can also be chosen according to the variables involved in the hypothesis and their distribution (**Fig. 4.36**). It should be noted that the following table represents a simplified visualization of statistical tests that can be used to test the hypothesis given the constraints of normal or non-normal distribution.

	Distribution	
Variables	**Normal (Gaussian)**	**Not normal**
2 descriptive	Hi-square test (Crosstabs; Chi-square)	
1 descriptive and 1 numeric	Independent samples t-test (Compare Means; Independent samples t-test)	Mann-Whitney U Test (Nonparametric Tests; Legacy Dialogs; 2 Independents Samples)
2 numerical (correlation)	Correlation (Correlate – Biv. – Pearson coefficient)	Correlation (Correlate – Biv. Spearman's coefficient)
2 numeric (average)	t-test dependent samples (Compare Means; Paired samples t-test)	Wilcoxonov test (Nonparametric Tests; Legacy Dialogs; 2 Related Samples)

Figure 4.36: Choosing a Statistical Test Based on the Distribution

4.5 Performing Independent Samples t-Test in SPSS

If we have one numeric variable and one descriptive variable with two classes and the distribution is normal, we can use the Independent samples t-test. It is used to check whether the mean difference between two groups is statistically significant (Mishra, et al., 2019). To perform the Student t-test we should click the following: *Analyze -> Compare Means -> Independent-Samples t-test* (**Fig. 4.37**).

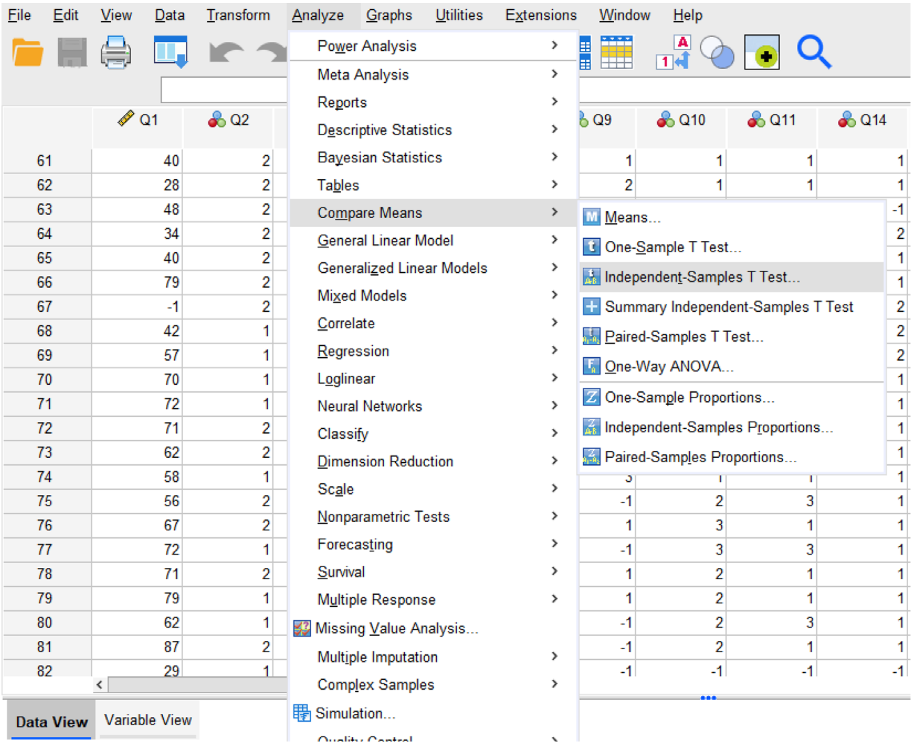


Figure 4.37: First Step in Choosing Independent Samples t-Test

The numerical variable should be placed in the Test variable box, the ordinal variable should be placed in the Grouping variable box. We should also define groups, as presented:

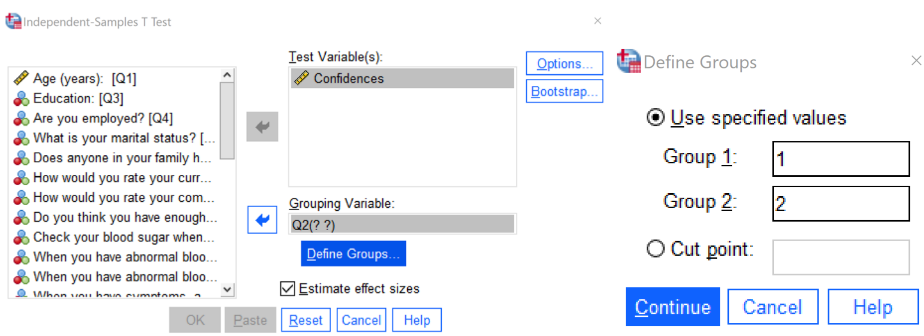


Figure 4.38: Choosing Variables When Conducting a t-Test

Results are presented in three tables:

Group Statistics

	Gender:	N	Mean	Std. Deviation	Std. Error Mean
confidencesscore	Men	51	77.8075	16.93808	2.37180
	Women	64	81.1080	16.47805	2.05976

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
confidencesscore	Equal variances assumed	.251	.618	-1.054	113	.147	.294	-3.30047	3.13150	-9.50453	2.9036
	Equal variances not assumed			-1.051	106.005	.148	.296	-3.30047	3.14135	-9.52849	2.9275

Independent Samples Effect Sizes

		Standardizer[a]	Point Estimate	95% Confidence Interval	
				Lower	Upper
confidencesscore	Cohen's d	16.68317	-.198	-.566	.171
	Hedges' correction	16.79493	-.197	-.562	.170
	Glass's delta	16.47805	-.200	-.569	.170

a. The denominator used in estimating the effect sizes.
Cohen's d uses the pooled standard deviation.
Hedges' correction uses the pooled standard deviation, plus a correction factor.
Glass's delta uses the sample standard deviation of the control group.

Figure 4.39: Results When Conducting a t-Test

First, we check for homogeneity of variance. To test for homogeneity of variances, we will use the results of Levene's test. If the p-value of Levene's test is greater than 0.05, it means that there are no differences in variances between the two groups and we print the results from the top row. A p-value for the Levene's test of less than 0.05 represents a significant difference between variances. We take the result from the row below.

Here is an example of how the results are reported: Based on Levene's test for homogeneity of variances, we found that the assumption of homogeneity of variances for self-confidence score was appropriate for male and female participants (p=0.618). The difference in mean self-confidence score between males and females is not statistically significant (M=-3.300; 95% CI [-9.505; 2.904]; p = 0.294).

4.6 Performing the Kruskal Wallis Test in SPSS

If you have one numeric variable and one descriptive variable with more than two classes, and the distribution is not normal, choose the Kruskal Wallis test. To perform the Kruskal Wallis test we should click the following: *Analyze -> Nonparametric Test -> Legacy Dialogs -> K Independent Samples.*

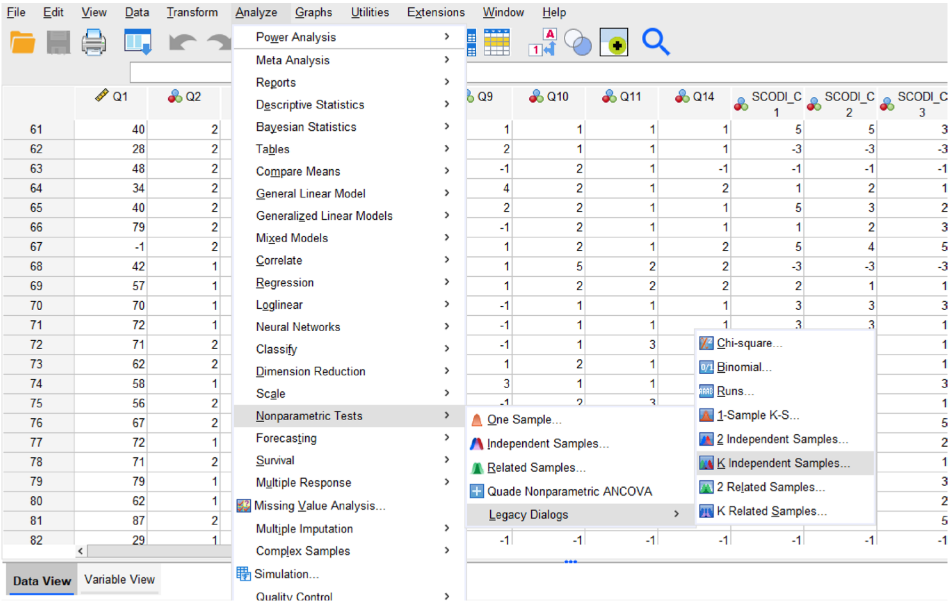


Figure 4.40: First Step in Choosing Kruskal Wallis Test

The numerical variable should be placed in the Test variable box, the ordinal variable should be placed in the Grouping variable box. We should also define groups, based on how many classes are included:

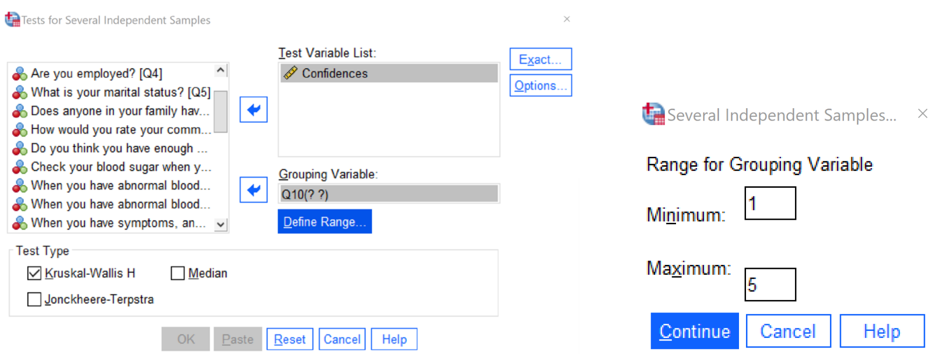


Figure 4.41: Choosing Variables When Conducting Krusal Wallis Test

Results are presented in two tables:

Kruskal-Wallis Test

Ranks

	How would you rate your current health?	N	Mean Rank
Confidences	Very good	12	78.75
	Good	67	64.10
	Sufficient	30	36.92
	Bad	4	46.75
	Very bad	1	21.00
	Total	114	

Test Statistics[a,b]

	Confidences
Kruskal-Wallis H	20.999
df	4
Asymp. Sig.	<.001

a. Kruskal Wallis Test

b. Grouping Variable: How would you rate your current health?

Figure 4.42: Results When Conducting Krusal Wallis Test

The results can be reported as follows: Based on the Kruskal Wallis Test, we found that an assessment of the participant's current state of health statistically affects the self-confidence score ($\chi 2 = 20.999$; $p < 0.001$).

4.7 Performing the ANOVA Test in SPSS

If you have one numeric variable and one descriptive variable with more than two classes, and the distribution is normal, choose the ANOVA test. To perform the ANOVA test, we should click the following: *Analyze -> Compare Means -> One-Way ANOVA*. We can also run a post-hoc test to see which variables are statistically significantly different.

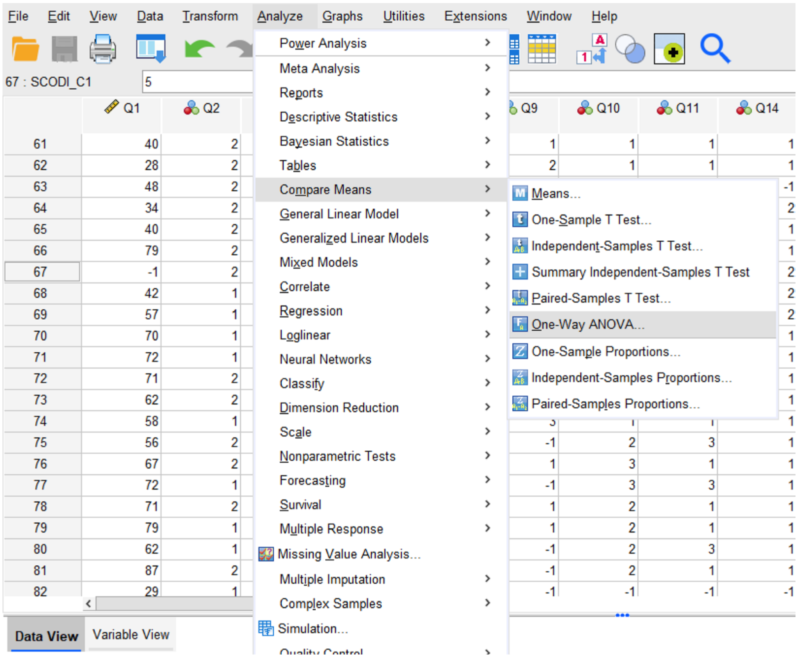


Figure 4.43: First Step in Choosing ANOVA Test

Then, we should choose one numerical and one descriptive variable.

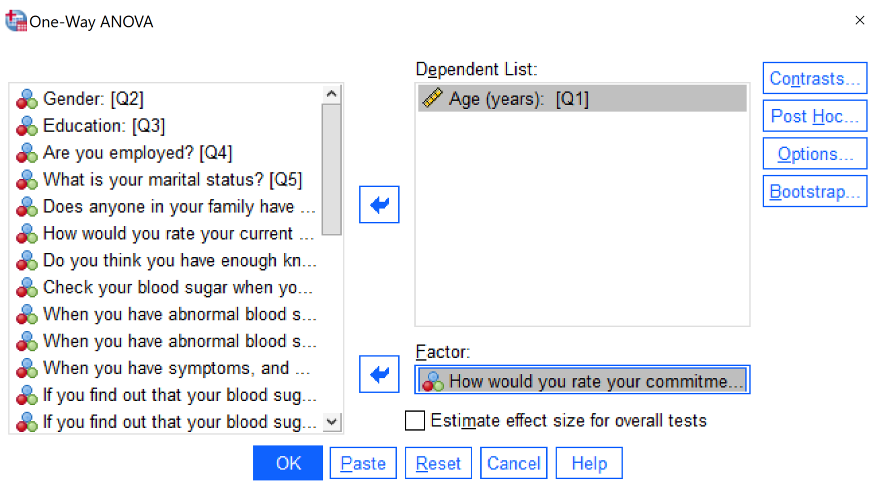


Figure 4.44: Choosing Variables When Conducting ANOVA Test

Oneway

ANOVA

Age (years):

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	677.959	2	338.980	2.124	.124
Within Groups	20109.544	126	159.600		
Total	20787.504	128			

Figure 4.45: Results When Conducting ANOVA Test

The results can be reported as follows: Based on ANOVA, we found that the test is not statistically significant (F(2, 126)=338.980; p=0,124).

4.8 Performing the Correlation Test in SPSS

Correlations are used when we are measuring a linear relationship between two numerical variables. In the case of a normal distribution, we use the Pearson correlation coefficient, and in the case of an unequal distribution, we use the Spearman correlation coefficient.

To perform the correlation test we should click the following: *Analyze -> Correlate -> Bivariate*:

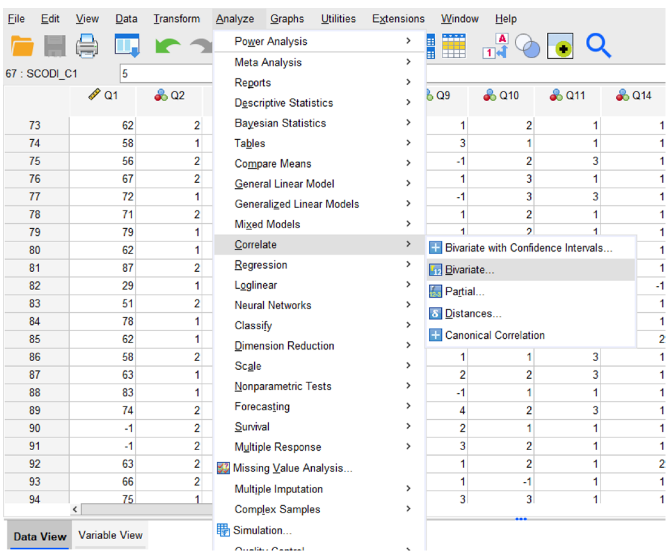


Figure 4.46: First Step in Choosing Correlation Test

Then, we should choose two numerical variables and correlation coefficient:

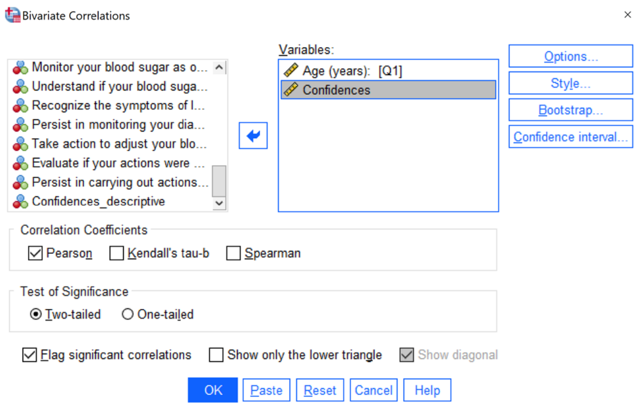


Figure 4.47: Choosing Variables When Conducting Correlation Test

Results are presented in the table (**Fig. 4.48**):

Correlations

Correlations

		Age (years):	Confidences
Age (years):	Pearson Correlation	1	-.076
	Sig. (2-tailed)		.430
	N	132	109
Confidences	Pearson Correlation	-.076	1
	Sig. (2-tailed)	.430	
	N	109	116

Figure 4.48: Results When Conducting Correlation Test

Figure 58 explains the correlation values:

Value	Explanation
-1	Perfect linear relationship (negative)
-0.70	Very strong correlation (negative)
-0.40	Medium or moderate correlation (negative)
-0.10	Very high or very strong downward correlation (negative)
0.00	No coherence
+0.10	Low or weak connectedness (positive)
+0.40	Medium or moderate (positive)
+0.70	Very strong correlation (positive)
+1	Full or functional connectivity (positive)

Figure 4.49: Explanation of Correlation Value

The results can be reported as follows: The Pearson's correlation test did not show a correlation between age and self-care confidence score. Age and self-care confidence scores are not statistically significantly correlated (rs=-0.076; p=0.430).

4.9 Performing the Chi-Square Test in SPSS

To compare two independent descriptive variables, we can use the Chi-square test and Fisher's exact test. The Chi-square test is applied assuming a large sample size, while the Fisher exact test is applied to small samples. The Fisher exact test is generally used for small samples, but can also be used for larger samples (Kim, 2017).

To perform the Chi-square test in the SPSS, we should click the following: *Analyze -> Descriptive Statistics -> Crosstabs*

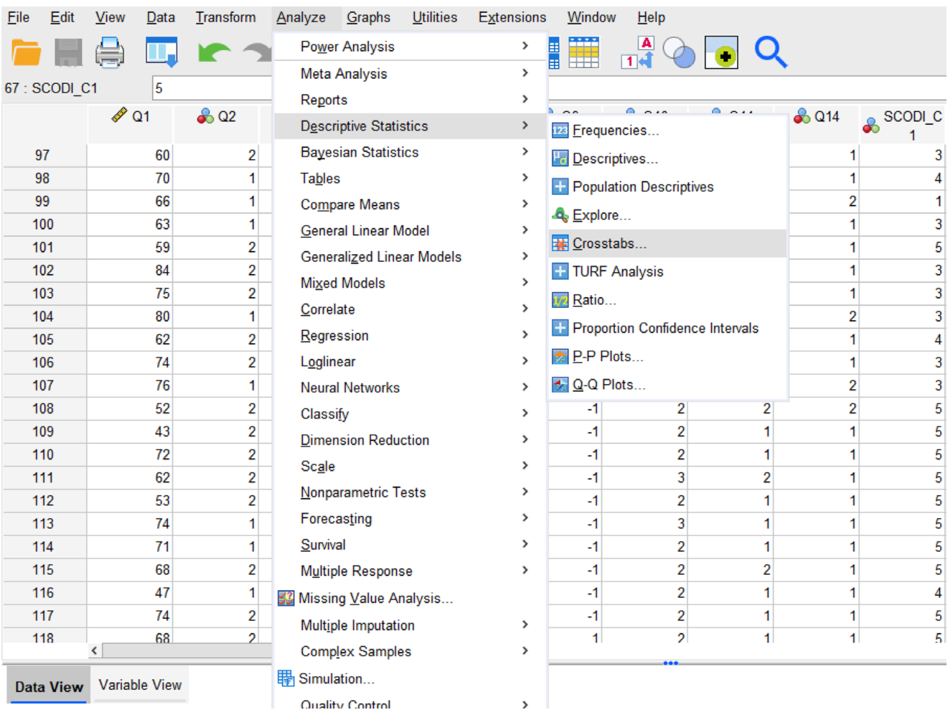


Figure 4.50: First Step in Choosing Chi-Square Test

Both variables are ordinal, one should be placed in the Row and the other in the Column. Then we should click on Statistics to choose the Chi-square test:

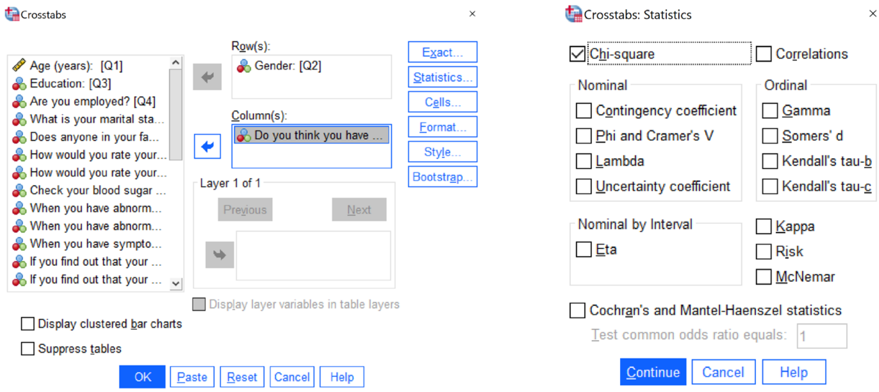


Figure 4.51: Choosing Variables When Conducting Chi-Square Test

Results are presented in tables:

Gender: * Do you think you have enough knowledge about diabetes self-care and management? Crosstabulation

			Do you think you have enough knowledge about diabetes self-care and management?		
			Yes, I think I have sufficient knowledge	No, I don't think I have enough knowledge	Total
Gender:	Men	Count	44	14	58
		% of Total	32.6%	10.4%	43.0%
	Women	Count	64	13	77
		% of Total	47.4%	9.6%	57.0%
Total		Count	108	27	135
		% of Total	80.0%	20.0%	100.0%

Chi-Square Tests

	Value	df	Asymptotic Significance (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	1.088[a]	1	.297		
Continuity Correction[b]	.682	1	.409		
Likelihood Ratio	1.079	1	.299		
Fisher's Exact Test				.385	.204
Linear-by-Linear Association	1.080	1	.299		
N of Valid Cases	135				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 11.60.

b. Computed only for a 2x2 table

Figure 4.52: Results When Conducting Chi-Square Test

The results can be reported as follows: Based on a Chi-square test, there is no static association between gender and diabetes knowledge (p=0.297).

4.10 Performing the Mann-Whitney U Test in SPSS

If you have one numeric variable and one descriptive variable with two classes and the distribution is not normal, use the Mann-Whiteney U test. To perform the Mann-Whiteney U test, we should click the following: *Analyze -> Nonparametric Tests -> Legacy Dialogs -> 2 Independent Samples*.

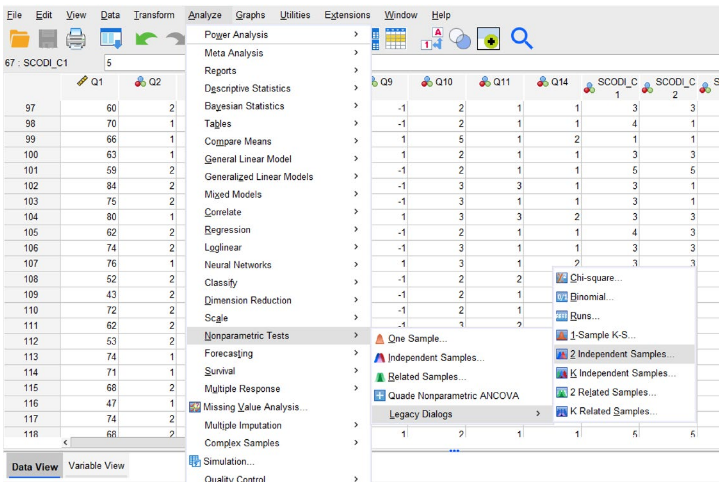


Figure 4.53: First Step in Choosing Mann-Whiteney U Test

The numerical variable should be placed in the Test variable box, the ordinal variable should be placed in the Grouping variable box. We should also define groups as presented:

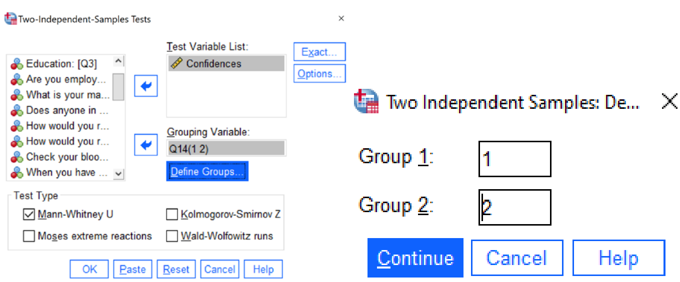


Figure 4.54: Choosing Variables When Conducting Mann-Whiteney U Test

Results are presented in tables:

NPar Tests

Mann-Whitney Test

Ranks

	Do you think you have enough knowledge about diabetes self-care and management?	N	Mean Rank	Sum of Ranks
Confidences	Yes, I think I have sufficient knowledge	92	63.70	5860.50
	No, I don't think I have enough knowledge	22	31.57	694.50
	Total	114		

Test Statistics[a]

	Confidences
Mann-Whitney U	441.500
Wilcoxon W	694.500
Z	-4.105
Asymp. Sig. (2-tailed)	<.001

a. Grouping Variable: Do you think you have enough knowledge about diabetes self-care and management?

Figure 4.55: Results When Conducting Mann-Whiteney U Test

The results can be reported as follows: The Mann-Whitney U test showed that there is a statistical effect of knowledge about diabetes self-care and management on confidences score ($U=441.500$; $p<0.001$).

5 Regression

This chapter introduces the characteristics of regression, with detailed discussions of linear regression, logistic regression and multiple regression. In addition to the theoretical background for each type of regression, practical guidance is provided on how to perform these regression analyses using SPSS software. The learning objectives of this chapter are to enable the reader to understand the basic concepts of the different types of regression, including their application and interpretation of results. The practical part of the chapter will teach the reader how to use SPSS to perform linear, logistic and multiple regression. This includes preparing the data, setting up the analyses and interpreting the output. In this way, the chapter will provide the reader with a comprehensive understanding of the different regression techniques and how they can be applied in practice.

Regression is a method by which we want to test the relationship between two numerical variables. We have univariate, bivariate, and multivariate regression analysis at our disposal. Regression is also distinguished according to the type of dependent variable: regression-numerical (normally distributed) and logistic regression (the dependent variable has a binomial distribution). Regression can also be linear or nonlinear (square, cubic, exponential, ...).

5.1 Linear Regression

Simple (simple, bivariate) linear regression tests the dependence of random variables. The regression function represents the regression line. The variable being predicted is called the dependent variable. The variable used to predict the other variable is called the independent variable. This relationship or model can be written in the form of an equation:

$$Y = \alpha + \beta \cdot X + \varepsilon$$

Where Y is the (dependent) variable or outcome studied, X is the (independent) explanatory variable or predictor, and ε is a random variable (error) whose role is:

a) measurement (rounding) error;
b) another random deviation from the linear relation $Y = \alpha + \beta X$.

We can assume E (ε) = 0. On average, then, a linear relation holds. However, we can also assume that $\varepsilon \sim N(0, \sigma)$ for some unknown deviation σ.

A sample of size n is n pairs of measurements (Xi, Yi). They are obtained by n replications of a random experiment.

The parameters of the model α and β are estimated so that the line $Yb = \alpha + \beta X$ fits the data as closely as possible.

The regression line (y ') can be written as y' = a + bx. We can draw several regression lines between the points that will fit these points. It is necessary to determine the criteria that will determine which line best fits the given points.

The parameter a determines where the regression line intersects the ordinate, a = Y (0), so Y has the value of a when X has the value 0, b determines the slope of the line (positive or negative connection and connection strength). b is called the regression coefficient. It tells how much the value of Y changes if X changes by one unit. If b = 0, then Y does not depend on X (the variable Y is a constant for which the value of the variable X has the same value, i.e. Y '= a).

Most commonly, we use the least-squares method, which requires that the sum of the squares of the deviations from the regression line be minimal.

Performing regression analysis also includes certain steps: verification of certain assumptions, verification of the reasonableness of the model, and interpretation of regression coefficients.

Assumptions for performing linear regression are:

- Variables must be measured at a continuous level.
- The variables must be independently observable of each other.
- The residuals (errors) of the best-fitting regression line have a normal distribution.
- The ratio between X and Y is linear; a linear relationship between the two variables is expected). To check whether a linear relationship exists can create a scatterplot that may look like one of the following:

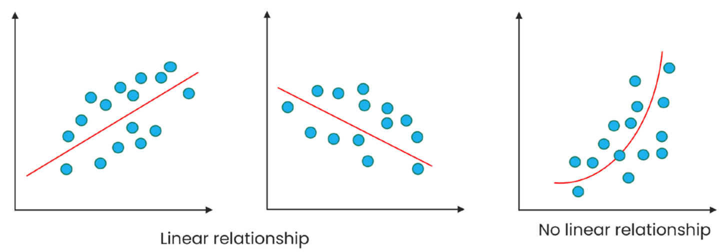


Figure 5.1: Linear Regression

- Y values are normally distributed around the regression line, and there are no significant outliers:

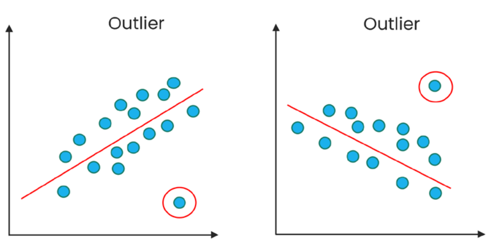


Figure 5.2: Outlier Regression

– The scattering of Y is constant around the regression line, and data show homoscedasticity:

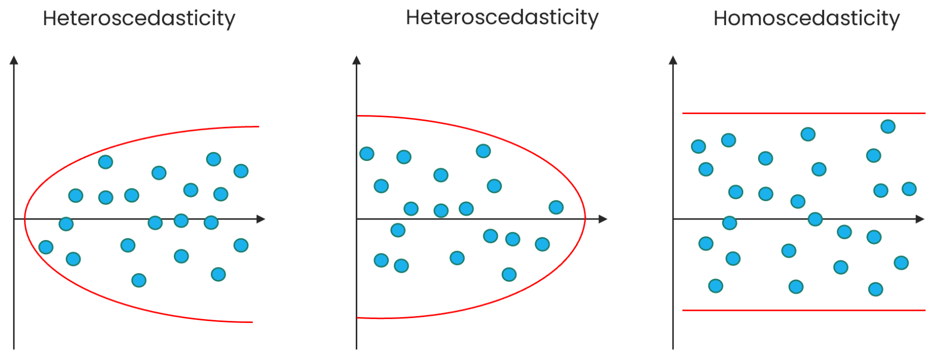


Figure 5.3: Heteroscedasticity Regression

– observations are independent.

Before performing the analysis, the listed assumptions must be verified.

Graphic display

– Spread diagrams are used to show the relationship of two numerical variables. From the scattering graph, we can understand the pairs drawn as points in the coordinate system.
– Responsible surfaces.

We estimate the regression constant (a) and the regression coefficient (b) when interpreting the model.

To judge how good the regression model (regression function) is, we check:

– Determination coefficient (share of explained variance) – a quality indicator of the description of the dependence between the variables with a regression line.
– Standard estimation error - an indicator of the quality of predicting the value of a dependent variable using a regression line.

5.2 Steps to Conduct the Linear Regression in SPSS

To perform the linear regression, we should click the following: *Analyze -> Regression -> Linear.*

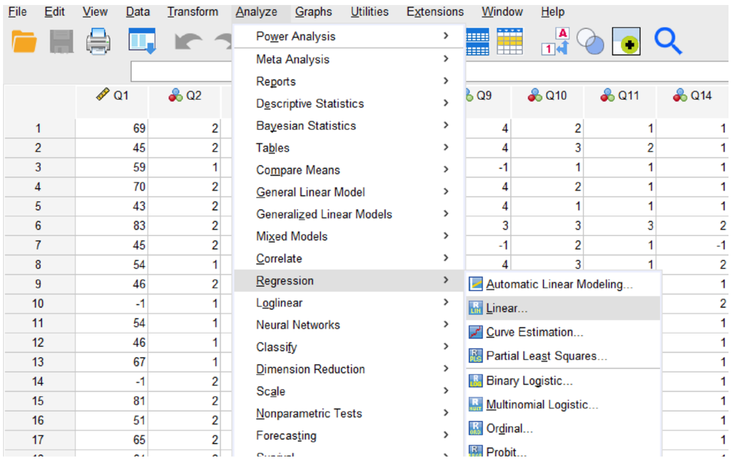


Figure 5.4: First Step When Choosing Linear Regression

Transfer the independent variable (e.g., confidences score), into the Independent(s) box and the dependent variable (e.g., age), into the Dependent box.

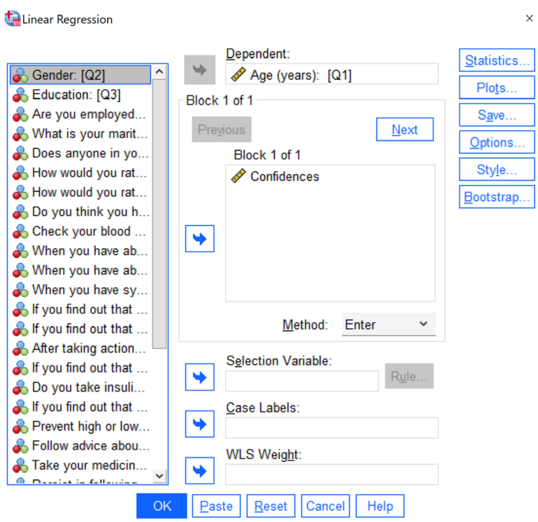


Figure 5.5: Choosing Variables When Conducting Linear Regression

To check the above stated assumptions, the researcher can use the Statistics and Plots features and then select the appropriate options within these two dialogue boxes.

Click on the OK button and generate the results.

The first table is the Model Summary table:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.076[a]	.006	-.003	11.256

a. Predictors: (Constant), Confidences

Figure 5.6: Results (Model Summary) of Linear Regression

This table provides the R and R^2 values. The R value represents the simple correlation and is 0.076 (the "R" Column), indicating the variables are unrelated. If R is close to -1 it means that there is a negative correlation between the variables, if R is close to 0 it means that the variables are uncorrelated, if R is close to 1 it means that the variables have a positive linear relationship between the two variables.

The R^2 value (the "R Square" column) indicates how much of the total variation is in the dependent variable. In this case, 0.6% can be explained as very low.

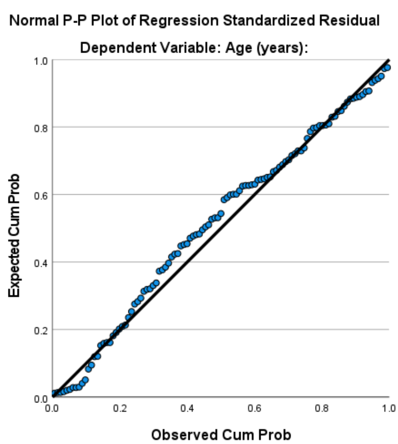


Figure 5.7: Results of Normal P-P Plot of Regression

The next table is the ANOVA table, which reports how well the regression equation fits the data:

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	79.352	1	79.352	.626	.430[b]
	Residual	13556.336	107	126.695		
	Total	13635.688	108			

a. Dependent Variable: Age (years):

b. Predictors: (Constant), Confidences

Figure 5.8: Results (ANOVA) of Linear Regression

This table indicates that the regression model predicts the dependent variable significantly well. How do we know this? Look at the "Regression" row and go to the "Sig." column. This value indicates the statistical significance of the regression model that was run. Here, p = 0.430, indicates that, overall, the regression model does not statistically significantly predict the outcome variable (i.e., it is not a good fit for the data).

The Coefficients table provides us with the necessary information to predict total confidence score from age, as well as determine whether income contributes statistically significantly to the model (by looking at the "Sig." column):

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	69.277	5.295		13.084	<.001
	confidencesscore	-.052	.065	-.076	-.791	.430

a. Dependent Variable: Age (years):

Figure 5.9: Results (Coefficients) of Linear Regression

5.3 Logistic Regression

The logistic regression predicts the probability that a variable falls into one of two dichotomous dependent variable categories based on one or more independent variables.

In the logistic regression, the following assumptions must be met:

- The dependent variable must be measured on a dichotomous scale.
- One or more independent variables, which may be continuous, ordinal or nominal, must be included.
- There must be an independent observation.
- There must be a linear relationship between all independent variables and a logit transformation of the dependent variables (Stoltzfus, 2011; Sperandei, 2014).

5.4 Steps to Conduct the Logistic Regression in SPSS

To perform the logistic regression, we use the following function: *Analyze -> Regression -> Binary Logistic.*

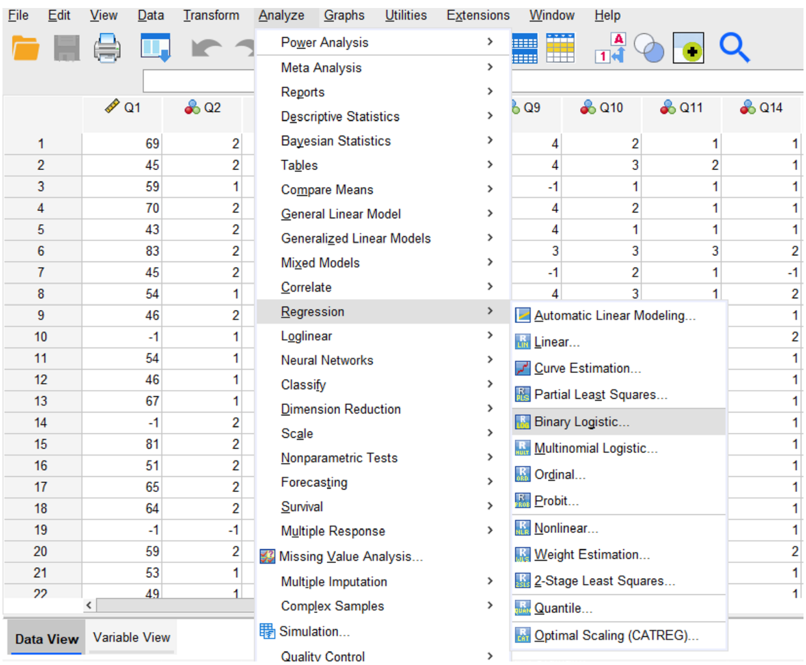


Figure 5.10: First Step When Choosing Logistic Regression

In our case, we have a dependent variable, "Enough knowledge about diabetes self-care and management", with two categories, "yes, I think I have sufficient knowledge" and "no, I don't think I have enough knowledge', and five independent variables, gender, employment status, assessment of current health status, family history of diabetes, level of self-confidences. We use the "Enter" method that is commonly used for standard regression analysis (**Fig. 5.11**). You can choose from the following methods: Enter, Forward: Conditional, Forward: LR, Forward: Wald, Backward: Conditional, Backward: LR, Backward: Wald. The differences between the methods are in how they add or remove variables from the model. The enter method includes all predictor variables simultaneously without selection. In forward methods, the algorithm starts with an empty model and gradually adds predictors one by one until no more significant improvement is observed. Backward methods start with a full model including all possible predictors and gradually remove predictors one by one until no significant improvement is observed.

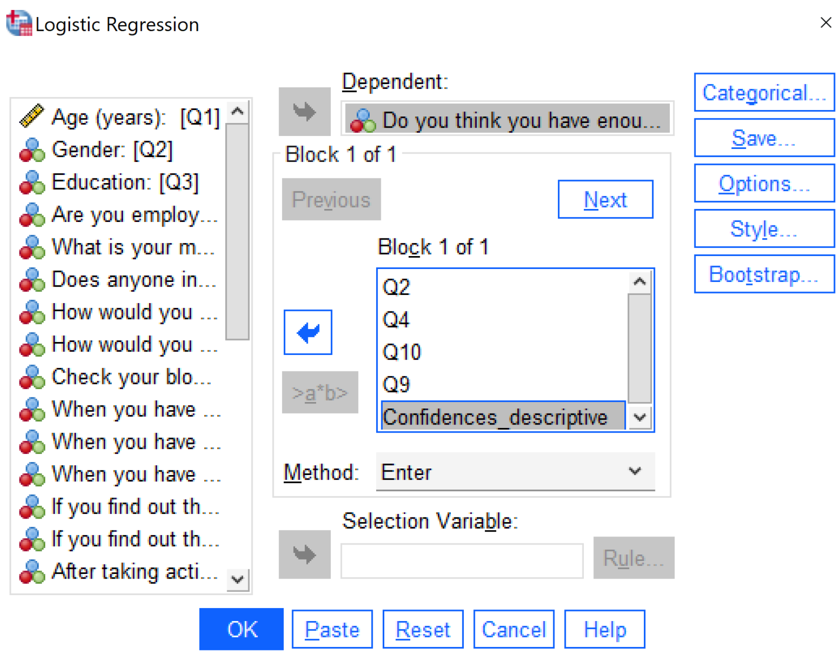


Figure 5.11: Choosing Variables When Conducting Logistic Regression

Next table contains the Cox & Snell R Squared and Nagelkerke R Squared values, which are both methods for calculating a variation (**Fig. 5.12**). The variance of the dependent variable in our model ranges from 22.1% to 32.4%.

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	14.483	5	.013
	Block	14.483	5	.013
	Model	14.483	5	.013

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	51.824[a]	.221	.324

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Figure 5.12: Results (Model Summary) of Logistic Regression

The logistic regression estimates the probability that an event will happen, so in our case, whether a person will have enough knowledge about diabetes self-care and management.

Table index states, "The cut value is 0.500". This means that if the probability of a case being classified as "yes" is greater than 0.500, then that case is classified as "yes". Otherwise, the case is classified as "no" (as mentioned earlier).

In our case, the model classified the 39 people who thought they had sufficient knowledge about diabetes self-care and management into the appropriate group. It classified four people into the group with insufficient knowledge. When classifying persons with enough knowledge about diabetes self-care and management, the accuracy was 90.7%. 10 people who did not have enough knowledge were inappropriately classified as having enough knowledge. Five people were appropriately classified as not having enough knowledge. The model accuracy value was 33.3%. The overall model correctness was 75.9%.

Classification Table[a]

			Predicted: Do you think you have enough knowledge about diabetes self-care and management?		
Observed			Yes, I think I have sufficient knowledge	No, I don't think I have enough knowledge	Percentage Correct
Step 1	Do you think you have enough knowledge about diabetes self-care and management?	Yes, I think I have sufficient knowledge	39	4	90.7
		No, I don't think I have enough knowledge	10	5	33.3
	Overall Percentage				75.9

a. The cut value is .500

Figure 5.13: Results (Classification Table) of Logistic Regression

Figure 5.14 shows the contribution of each independent variable to the model and its statistical significance.
The Wald test (column " Wald ") is used to determine the statistical significance for each of the independent variables. In our case, none of the variables are statistically significant.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Gender:	.677	.737	.846	1	.358	1.969
	Are you employed?	.063	.404	.025	1	.875	1.065
	Does anyone in your family have a diagnosis of diabetes?	-.126	.261	.233	1	.629	.881
	How would you rate your current health?	.621	.527	1.392	1	.238	1.861
	Confidence_descriptve	-1.551	.713	4.733	1	.030	.212
	Constant	1.881	3.317	.322	1	.571	6.561

a. Variable(s) entered on step 1: Gender:, Are you employed?, Does anyone in your family have a diagnosis of diabetes?, How would you rate your current health?, Confidence_descriptve.

Figure 5.14: Results (Variables in the Equation) of Logistic Regression

5.5 Multiple Regression

We speak of a multiple regression when a random variable depends on more than one explanatory variable. The variable we want to predict is called the dependent variable; the variables we are using to predict the value of the dependent variable are called the independent variables.

The multiple regression also allows you to determine the overall fit (variance explained) of the model and the relative contribution of each of the predictors to the total variance explained.

Assumptions for performing multiple regression are:

- The dependent variable should be measured on a continuous scale (i.e., it is either an interval or ratio variable).
- Two or more independent variables must be included, which can be either continuous (i.e., an interval or ratio variable) or categorical (i.e., an ordinal or nominal variable).
- There should be independence of observations (i.e., independence of residuals), which we can easily check using the Durbin-Watson statistic.
- There needs to be a linear relationship between:
    - (a) the dependent variable and each of your independent variables,
    - (b) the dependent variable and the independent variables collectively.
- Data needs to show homoscedasticity, which is where the variances along the line of best fit remain similar as you move along the line.
- Data must not show multicollinearity, which occurs when you have two or more independent variables that are highly correlated with each other.
- There should be no significant outliers, high leverage points, or highly influential points.
- We need to check that the residuals (errors) are approximately normally distributed (we explain these terms in our enhanced multiple regression guide).

5.6 Steps to Conduct the Multiple Regression in SPSS

Click *Analyze* -> *Regression* -> *Linear*:

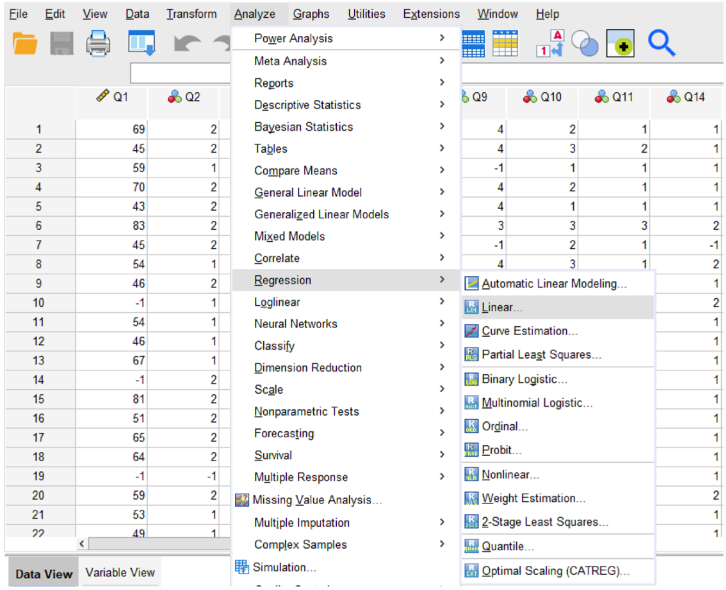


Figure 5.15: First Step When Choosing Multiple Regression

Transfer the dependent variable (i.e., Confidences score) into the Dependent: box and the independent variables (i.e., age, gender, education, family history of diagnosed disease, marital status, assessment of current health status, sufficient knowledge of diabetes self-care and management) into the Independent(s): box:

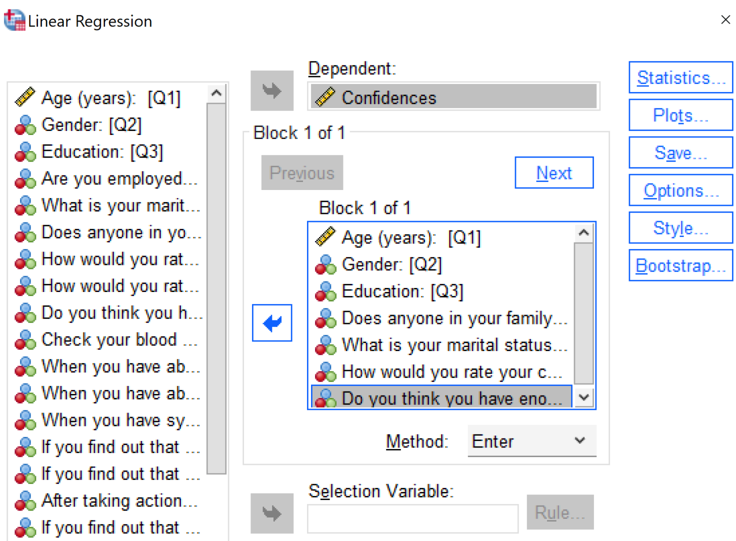


Figure 5.16: Choosing Variables When Performing Multiple Regression

Click on the  button:

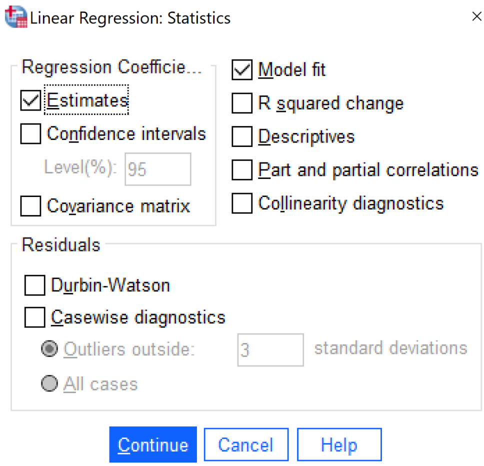


Figure 5.17: Statistics Options When Performing Multiple Regression (1)

In addition to the options that are selected by default, select Confidence intervals in the –Regression Coefficients– area, leaving the Level (%): option at "95":

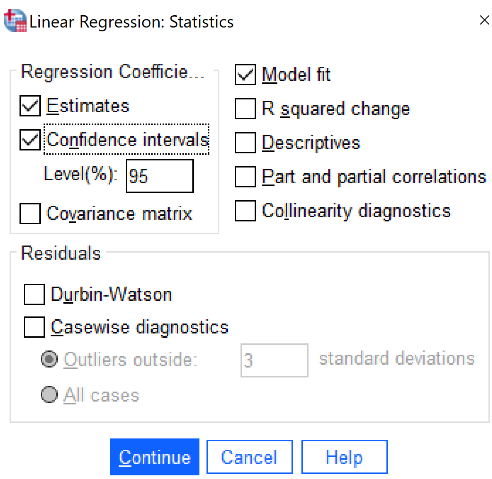


Figure 5.18: Statistics Options When Performing Multiple Regression (2)

Click on the button. You will be returned to the Linear Regression dialogue box. Click on the button. This will generate the output.

The first table is the Model Summary table. This table provides the R, R2, adjusted R2, and the standard error of the estimate, which can be used to determine how well a regression model fits the data:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.725[a]	.525	.463	13.58999

a. Predictors: (Constant), Do you think you have enough knowledge about diabetes self-care and management?, What is your marital status?, Education:, Does anyone in your family have a diagnosis of diabetes?, Gender:, Age (years): , How would you rate your current health?

Figure 5.19: Results (Model Summary) of Multiple Regression

The "R" column represents the value of R, the multiple correlation coefficient. R can be considered to be one measure of the quality of the prediction of the dependent variable, in this case, the confidence score. A value of 0.725, in this example, indicates a middle level of prediction. The "R Square" column represents the R2 value (also called the coefficient of determination), which is the proportion of variance in the dependent variable that can be explained by the independent variables (technically, it is the proportion of variation accounted for by the regression model above and beyond the mean model). You can see from our value of 0.525 that our independent variables explain 52.5% of the variability of our dependent variable, the confidence score.

The F-ratio in the ANOVA table (**Fig. 5.20**) tests whether the overall regression model is a good fit for the data. The table shows that the independent variables statistically significantly predict the dependent variable, $F\ (7, 53) = 8.381$, $p<0.001$.

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8954.810	7	1279.259	8.381	<.001[b]
	Residual	8089.628	53	152.634		
	Total	17044.438	60			

a. Dependent Variable: confidencesscore

b. Predictors: (Constant), Do you think you have enough knowledge about diabetes self-care and management?, What is your marital status?, Education:, Does anyone in your family have a diagnosis of diabetes?, Gender:, Age (years): , How would you rate your current health?

Figure 5.20: Results (ANOVA) of Multiple Regression

The general form of the equation to predict blood sugar from age, gender, education, family history of the diagnosed disease, marital status, assessment of current health status, and sufficient knowledge of diabetes self-care and management is:

– predicted confidences score = 111.437 + (0.067 x age) + (3.614 x gender) + (0.155 x education) + (0.124 x family history of diabetes) + (1.166 x marital status) - (7.878 x assessment of health status) - (20.753 x knowledge)

This is obtained from the Coefficients table (**Fig. 5.21**):

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	111.437	14.396		7.741	<.001
	Age (years):	.067	.160	.045	.419	.677
	Gender:	3.614	3.416	.108	1.058	.295
	Education:	.155	1.164	.014	.133	.894
	Does anyone in your family have a diagnosis of diabetes?	.124	1.242	.010	.100	.921
	What is your marital status?	1.166	1.620	.074	.720	.475
	How would you rate your current health?	-7.878	2.452	-.353	-3.213	.002
	Do you think you have enough knowledge about diabetes self-care and management?	-20.753	4.612	-.494	-4.500	<.001

a. Dependent Variable: confidencesscore

Figure 5.21: Results (Coefficients) of Multiple Regression

Unstandardized coefficients indicate how much the dependent variable varies with an independent variable when all other independent variables are held constant. Consider the effect of age in this example. The unstandardized coefficient, B1, for age, is equal to 0.067 (see Coefficients table). This means that for each one-year increase in age, there is a decrease in confidence score of 0.067.

You can test for the statistical significance of each of the independent variables. This tests whether the unstandardized (or standardized) coefficients are equal to 0 (zero) in the population. If $p<0.05$, you can conclude that the coefficients are statistically significantly different to 0 (zero). The t-value and corresponding p-value are in the "t" and "Sig." columns.

6 Questionnaire Validation

The chapter covers the steps of back translating a questionnaire, developing the questionnaire and validating the questionnaire. It also presents ways of assessing the reliability and validity of a questionnaire. The learning objectives of this chapter are to enable the reader to understand the whole process of questionnaire development, including back-translation techniques to ensure the linguistic and cultural appropriateness of the questionnaire. The reader will be introduced to the key steps in questionnaire design, such as determining the content, structure and format of the questions. In addition, the chapter will introduce the reader to validation methods, which include checking that the questionnaire measures what it is intended to measure. An important part of the chapter will also present ways of assessing the reliability and validity of the questionnaire.

6.1 Questionnaire Translation

Back-translation is necessary for the use of the questionnaire in the local environment. The original questionnaire should be translated into the target language by at least two independent translators. It is recommended that both translators are native speakers of the target language. This step is followed by a back-translation. The translated questionnaire should be translated back into the source language by a second independent translator. The re-translated questionnaire in the original language is checked against the original questionnaire to identify any discrepancies. This step is crucial to ensure an accurate translation of the questionnaire (Tyupa, 2011; Behr, 2017).

6.2 Questionnaire Development

Steps in the process of questionnaire development (Tsang, et al., 2017):

- Identify the dimensionality of the construct.
- Determine the format in which the questionnaire will be administered.
- Determine the item format.
- Item development.
- Determine the intended length of the questionnaire.
- Review and revise the initial pool of items.
- Preliminary pilot testing.

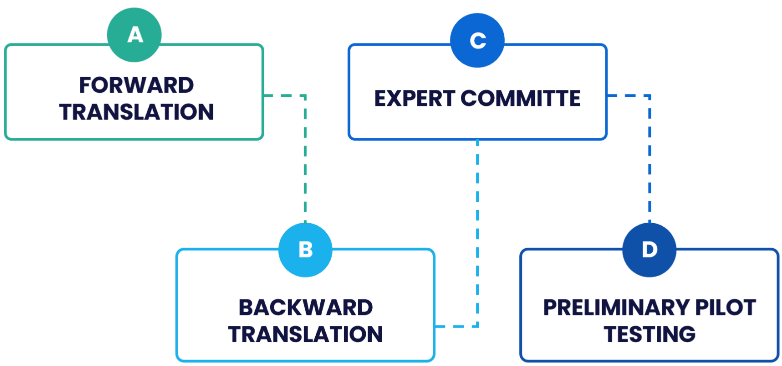


Figure 6.1: Questionnaire Translation Steps

6.3 Reliability vs. Validity

Reliability is the extent to which the outcomes are consistent when the experiment is repeated more than once (Watson, 2015).

Internal consistency reflects the extent to which the questionnaire items are intercorrelated or whether they are consistent in measuring the same construct. Internal consistency is commonly estimated using the coefficient alpha - known as Cronbach's alpha.

Cronbach's alpha ranges from 0 to 1 (when some items are negatively correlated with other items in the questionnaire, it is possible to have negative values of Cronbach's alpha).

6.4 Test-Retest Reliability

Test-retest reliability refers to the extent to which individuals' responses to the questionnaire items remain relatively consistent across repeated administration of the same questionnaire or alternate questionnaire forms. The correlation between the two questionnaires' responses can be referred to as the coefficient of stability. A larger stability coefficient indicates stronger test-retest reliability, reflecting that measurement error of the questionnaire is less likely to be attributable to changes in the individuals' responses over time (Yen & Lo, 2002).

6.5 Inter-Rater Reliability

For questionnaires in which multiple raters complete the same instrument for each examinee (e.g., a checklist of behaviour/symptoms), the extent to which raters are consistent in their observations across the same group of examinees can be evaluated. This consistency is referred to as inter-rater reliability or inter-rater agreement. Validity is the extent to which the instruments that are used in the experiment measure exactly what you want them to measure. The validity of a questionnaire is determined by analysing whether the questionnaire measures what it is intended to measure (Hallgren, 2012).

6.6 Content Validity

Content validity refers to the extent to which the items in a questionnaire are representative of the entire theoretical construct the questionnaire is designed to assess. The experts judge whether the questionnaire items are adequately measuring the construct intended to assess and whether the items are sufficient to measure the domain of interest. Several approaches to quantify the judgment of content validity across experts are also available, such as the content validity ratio and content validation form.

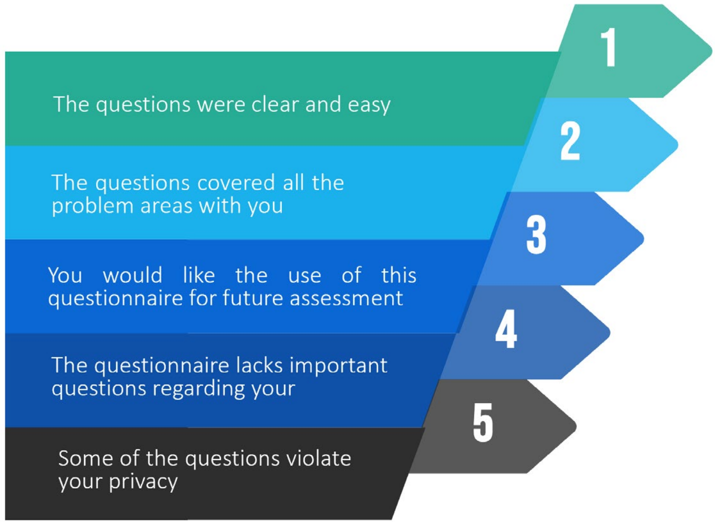


Figure 6.2: Example Items to Assess Content Validity

Figure 6.3 shows the division of CVI (content validity) into CVI for a single index and CVI for the whole scale (Polit, et al., 2007).

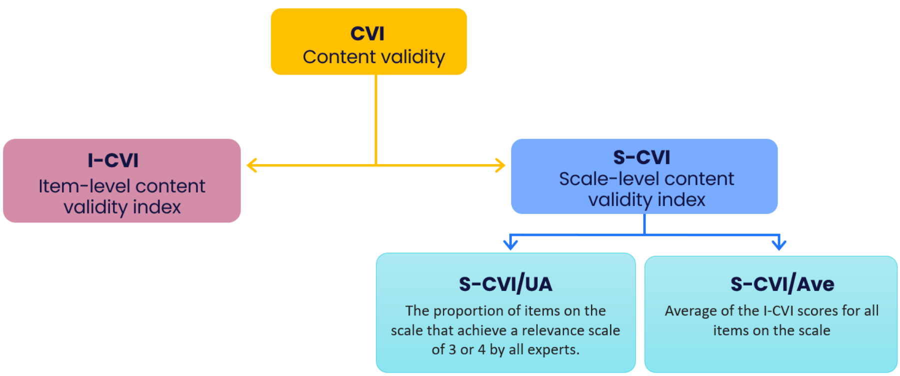


Figure 6.3: Content Validity Index

For the content checks, we prepare a content assessment form (**Fig. 6.4**) for the team of experts who will carry out the review. It is recommended to use the evaluation form (**Fig. 6.5**).

The selection of experts for the review is based on the individual's knowledge and expertise on the topic. Researchers recommend that the number of content reviewers should be at least six and no more than ten (Yusoff, 2019).

Dear Experts,

We will assess participants' self-care using the validated Self-Care of Diabetes Inventory (SCODI) (Ausili, et al., 2017).

We kindly ask you to rate each statement for content relevance on a 4-point scale:

- 1 - content/statement not relevant/not understandable/not relevant;
- 2 - content / claim is poorly understood / very deficient / incomplete / partially relevant;
- 3 - content / claim is partially understandable / partially relevant;
- 4 - the content / claim is fully understandable / fully relevant.

Please complete the table by placing an X under the selected rating and entering any comments, advice, opinions on the content and translation in the "Comments" column.

Figure 6.4: Example of Guidance for Assessing the Relevance of Questions for Content Validation by Experts

SCODI C

Listed below are some of the behaviours a person with diabetes can do to help improve blood sugar levels when they are too high or too low. Participants are asked to identify how often they do (or would do) these actions when symptoms occur or when blood sugar is out of range (rated on a Likert scale from 1 to 5, where 1 represents never and 5 represents always; question 29 asks for a yes or no answer)?

		1	2	3	4	Comments
1.	Check your blood sugar when you feel symptoms (such as thirst, frequent urination, weakness, perspiration, anxiety)?	☐	☐	☐	☐	
2.	When you have abnormal blood sugar levels, do you take notes about the events that could have caused it and actions you took?	☐	☐	☐	☐	
3.	When you have abnormal blood sugar levels, do you ask a family member or friend for advice?	☐	☐	☐	☐	
4.	When you have symptoms, and you discover that your blood sugar is low, do you eat or drink something with sugar to solve the problem?	☐	☐	☐	☐	
5.	If you find out that your blood sugar is high, do you adjust your diet to fix it?	☐	☐	☐	☐	
6.	If you find out that your blood sugar is high, do you adjust your physical activity to fix it?	☐	☐	☐	☐	
7.	After taking actions to adjust an abnormal blood sugar level, do you re-check your blood sugar to assess if the actions you took were effective?	☐	☐	☐	☐	
8.	If you find out that your blood sugar is very low or very high, do you call your health care provider for advice?	☐	☐	☐	☐	
9.	Do you take insulin?	☐	☐	☐	☐	
10.	If you find out that your blood sugar is too high or too low, do you adjust your insulin dosage in the way your health care provider suggested?	☐	☐	☐	☐	

Figure 6.5: Example of a Form for Assessing the Relevance of Content by Experts

The results are then used to calculate I-CVI (item content validity index), S-CVI/Ave (scale-level content validity index based on the average method) and S-CVI/AU (scale-level content validity index based on the universal agreement method).

We scored 1 if the experts rated the items 3 (partially relevant) or 4 (fully relevant) and 0 if the experts rated them 1 (not relevant) or 2 (partially relevant).

Experts agree: represents the sum of all experts who agreed, i.e., gave a rating of 3 or 4. In our example, 5 experts agreed on Q1 (1+1+1+1+1+1+0=5)

I-CVI: Percentage of content experts who rated the relevance of the element as 3 or 4. In our case, I-CVI for Q21 is calculated as 5 divided by 6 experts and is 0.83.

Formula: I-CVI = (number of items rated 3 or 4)/(number of experts)

General agreement (UA): We score 1 for those questions where all experts agree. In our case, such questions were Q4, Q5, Q7 and Q9.

S-CVI/Ave: The average of the I-CVI scores for all items on the scale, or the average of the proportion of importance scored by all experts. The relevance score is the average of the relevance scores given by each expert.

Formula: S-CVI/Ave = (sum of I-CVI scores)/(number of items);
S-CVI/Ave = (sum of relative importance ratings)/(number of experts)

S-CVI/UA: the proportion of items in the scale that achieve a relevance score of 3 or 4 across all experts. The universal agreement (UA) score is given as 1 if the item achieved 100% expert agreement. Otherwise, the UA score is given as 0.

Formula: S-CVI/UA = (sum of UA scores)/(number of items) (Yusoff, 2019).

No.	Question(s)	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6		N	Expert in Agreements	I-CVI	UA
1.	Check your blood sugar when you feel symptoms (such as thirst, frequent urination, weakness, perspiration, anxiety)?	1	1	1	1	1	0					
2.	When you have abnormal blood sugar levels, do you take notes about the events that could have caused it and actions you took?	1	1	1	1	1	0					
3.	When you have abnormal blood sugar levels, do you ask a family member or friend for advice?	1	1	1	1	1	1					
4.	When you have symptoms, and you discover that your blood sugar is low, do you eat or drink something with sugar to solve the problem?	1	1	1	1	1	0					
5.	If you find out that your blood sugar is high, do you adjust your diet to fix it?	1	1	1	1	1	0					
6.	If you find out that your blood sugar is high, do you adjust your physical activity to fix it?	1	1	1	1	1	1					
7.	After taking actions to adjust an abnormal blood sugar level, do you re-check your blood sugar to assess if the actions you took were effective?	1	1	1	1	1	0					
8.	If you find out that your blood sugar is very low or very high, do you call your health care provider for advice?	1	1	1	1	1	1					
9.	Do you take insulin?	1	1	1	1	1	0					
10.	If you find out that your blood sugar is too high or too low, do you adjust your insulin dosage in the way your health care provider suggested?	1	1	1	1	1	0					
										S-CVI/Ave		
	Proportion relevance									S-CVI/UA		
				S-CVI/Ave (based on proportion relevance)								

Figure 6.6: Calculation of I-CVI and S-CVI

6.7 Construct Validity

Construct validity is the most important concept in evaluating a questionnaire that is designed to measure a construct that is not directly observable (e.g., pain, quality of recovery). If a questionnaire lacks construct validity, it will be difficult to interpret results from the questionnaire, and inferences cannot be drawn from questionnaire responses to a behaviour domain. The construct validity of a questionnaire can be evaluated by estimating its association with other variables (or measures of a construct) with which it should be correlated positively, negatively, or not at all (Smith, 2005; Bhandari, 2022).

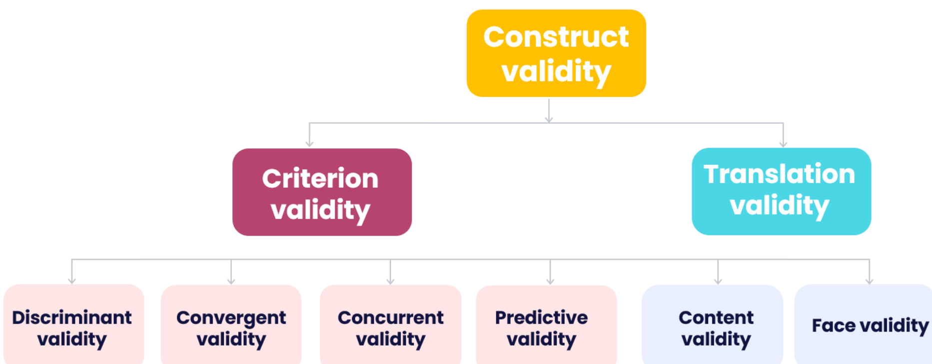


Figure 6.7: Construct Validity Process

Source: (Warren, et al., 2018)

University of Maribor Press

7 Reliability Analysis

The chapter introduces reliability analysis, including intraclass correlation coefficient (ICC) and Cronbach's alpha, and the practical implementation of these analyses in SPSS software. The learning objectives of this chapter are to enable the reader to understand the key concepts and methods for assessing the reliability of survey questionnaires. The reader will learn how to use ICC to measure inter-rater reliability and Cronbach's alpha to assess the internal consistency of a questionnaire. The chapter also provides practical guidance on how to perform these analyses in SPSS.

The following sections consider, in turn: inter-rater reliability, test-retest reliability, and intra-rater reliability. These methods are all based on correlation between sets of measurement, and the test of choice for each is selected from one of a range of forms on intraclass correlations (ICCs) (Koo & Li, 2016). These have replaced other measures of reliability based on correlation, such as Pearson's r and the Kappa statistic, which were previously used. The reason that ICCs are preferred is that, as opposed to these other tests of correlation is that ICCs measure both the correlation between two sets of measurement (raters or ratings) and measure the degree of agreement between the two sets of measurement.

There are 10 different forms of ICC, but in the following, we will consider only the three that are most common and required to test these forms of reliability rigorously. ICCs are described in terms of 'model', 'type' and 'definition'. These depend, respectively, on whether we are: 1. dealing with the same raters between ratings or a random sample of raters; 2. are we using the mean value of several raters or values from single raters; and 3. are we interested in consistency between raters or absolute agreement. For an excellent and detailed consideration of ICCs, consult Koo and Li (2016). As a rule of thumb, we are normally concerned with single-rater measurements. Where different raters are involved in rating the same phenomenon (inter-rater reliability), it is sufficient to look at consistency between measurements, but where the same raters are involved (test-retest reliability and intra-rater reliability), then we need to look at absolute agreement between ratings.

ICCs are normally expressed with 95% confidence intervals, and values, which lie between 0 – 1, are conventionally interpreted as follows:

Value	**Explanation**
< 0.05	Poor
0.05-0.75	Moderate
0.75-0.90	Good
>0.90	Excellent

Figure 7.1: Cronbach Alpha Value and Reliability Level

7.1 Intraclass Correlations

Click *Analyze* > *Scale* > *Reliability analysis*, as shown in **Figure 7.2**:

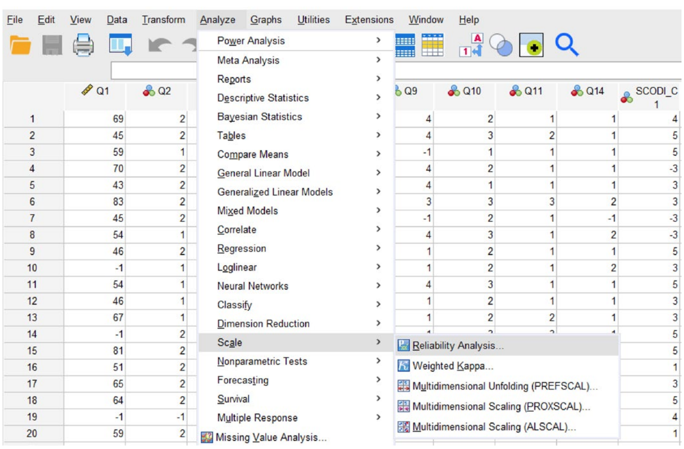


Figure 7.2: First Step When Conducting Reliability Level

Transfer the selected variables. Leave the model Alpha, as this is the command to run Cronbach's Alpha. Select the options highlighted in **Figure 7.3**.

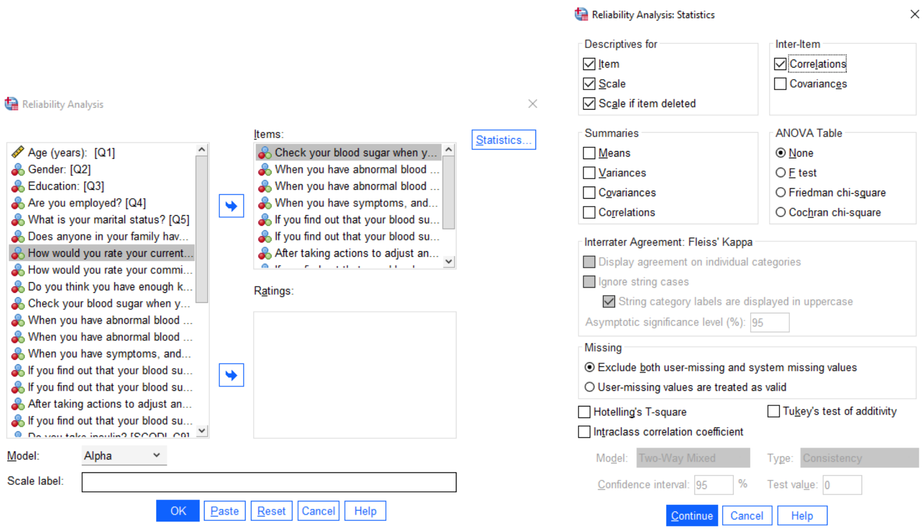


Figure 7.3: Choosing Variables When Performing Reliability Analysis

The first table of results presents the reliability, which is shown by the actual value for Cronbach's alpha. For our questionnaire, the Cronbach alpha is 0.780, which represents good reliability.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.780	.694	10

Figure 7.4: Reliability Statistic Analysis (Cronbach's Alpha)

The most important column in the table is "Cronbach's Alpha if Item Deleted". This column represents the value of Cronbach's alpha if this item were to be deleted (**Fig. 7.5**).

Item-Total Statistics					
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
Check your blood sugar when you feel symptoms (such as thirst, frequent urination, weakness, perspiration, anxiety)?	31.12	32.760	.575	.617	.747
When you have abnormal blood sugar levels, do you take notes about the events that could have caused it and actions you took?	31.73	30.101	.634	.616	.734
When you have abnormal blood sugar levels, do you ask a family member or friend for advice?	32.59	33.999	.281	.272	.790
When you have symptoms, and you discover that your blood sugar is low, do you eat or drink something with sugar to solve the problem?	30.93	31.020	.619	.616	.738
If you find out that your blood sugar is high, do you adjust your diet to fix it?	31.17	31.295	.686	.696	.732
If you find out that your blood sugar is high, do you adjust your physical activity to fix it?	31.59	32.799	.543	.634	.750
After taking actions to adjust an abnormal blood sugar level, do you re-check your blood sugar to assess if the actions you took were effective?	30.88	30.110	.844	.814	.713
If you find out that your blood sugar is very low or very high, do you call your health care provider for advice?	33.44	39.702	-.051	.348	.826
Do you take insulin?	34.34	42.730	-.697	.774	.810
If you find out that your blood sugar is too high or too low, do you adjust your insulin dosage in the way your health care provider suggested?	30.95	30.698	.617	.818	.738

Figure 7.5: Item-Total Statistics ("Cronbach's Alpha if Item Deleted")

7.2 Inter-Rater Reliability

For questionnaires in which multiple raters complete the same instrument for each examinee (e.g., a checklist of behaviour/symptoms), the extent to which raters are consistent in their observations across the same group of examinees can be evaluated. This consistency is referred to as inter-rater reliability or inter-rater agreement. Normally, we are concerned with being able to extrapolate our results to the general population from a randomly selected group of raters, and the appropriate form of ICC to test this is a Two-way random effects model with consistency based on single raters. If we were only specifically interested in the particular group of raters participating in our study, we would use a mixed-effects model.

Click *Analyze* > *Scale* > *Reliability analysis*, as shown in **Figure 7.6**:

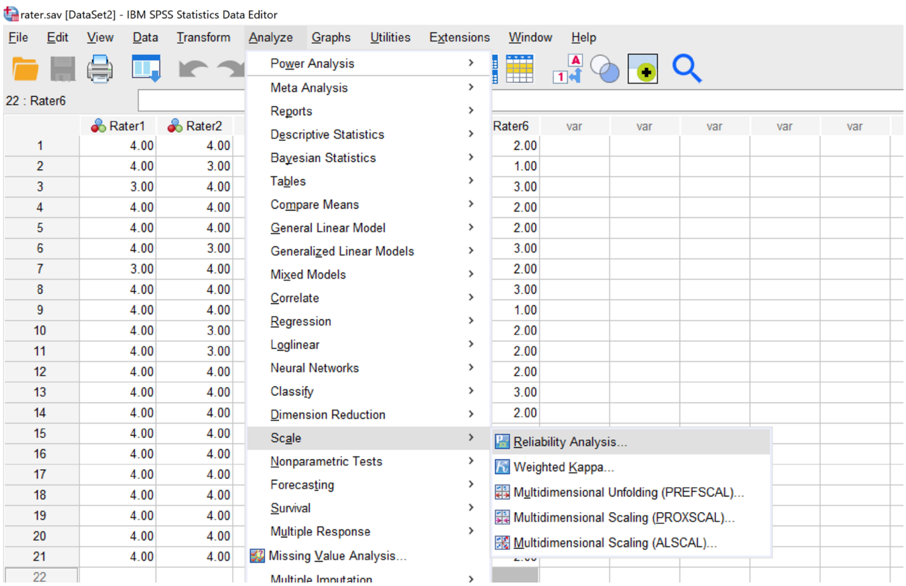


Figure 7.6: First Step When Conducting Reliability Level

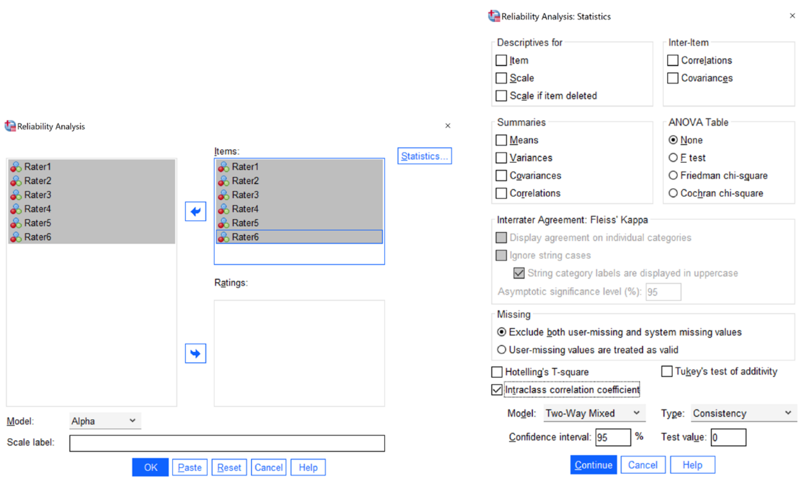


Figure 7.7: Reliability Analysis: Statistics

Figure 7.8 shows the results of the reliability analysis.

Reliability Statistics

Cronbach's Alpha[a]	N of Items
-.184	6

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	-.027[a]	-.100	.122	.844	20	100	.655
Average Measures	-.184[c]	-1.189	.454	.844	20	100	.655

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type C intraclass correlation coefficients using a consistency definition. The between-measure variance is excluded from the denominator variance.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Figure 7.8: Results of the Reliability Analysis

7.3 Test-Retest Reliability

Test-retest reliability refers to how individuals' responses to the questionnaire items remain relatively consistent across repeated administration of the same questionnaire or alternate questionnaire forms. The appropriate form of ICC to use here is a Two-way mixed effects model with absolute agreement based on single raters.

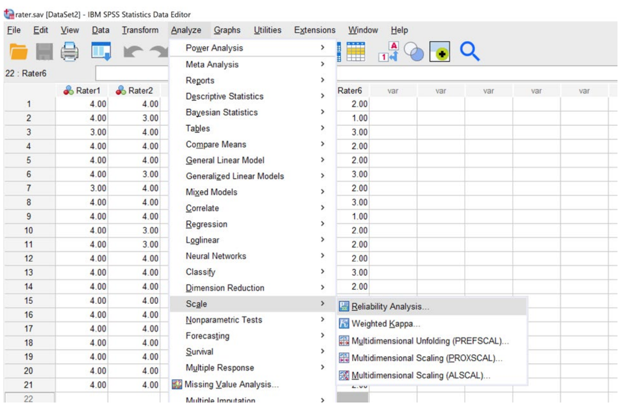


Figure 7.9: First Step When Conducting the Test-Retest Reliability

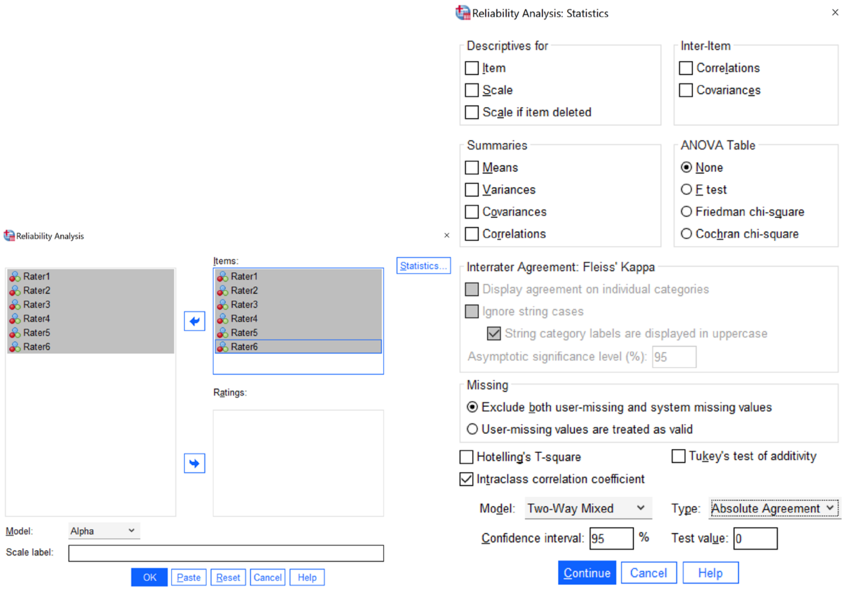


Figure 7.10: Test-Retest Reliability

Figure 7.11 shows the results of the test-retest reliability analysis.

Reliability Statistics

Cronbach's Alpha[a]	N of Items
-.184	6

a. The value is negative due to a negative average covariance among items. This violates reliability model assumptions. You may want to check item codings.

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	-.009[a]	-.035	.050	.844	20	100	.655
Average Measures	-.060[c]	-.255	.240	.844	20	100	.655

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Figure 7.11: Result of the Test-Retest Reliability

7.4 Intra-Rater Reliability

Intra-rate reliability refers to the extent to which individuals rate the same phenomenon and remain relatively consistent across repeated ratings. As with test-retest reliability, the appropriate form of ICC to use here is a Two-way mixed effects model with absolute agreement based on single raters.

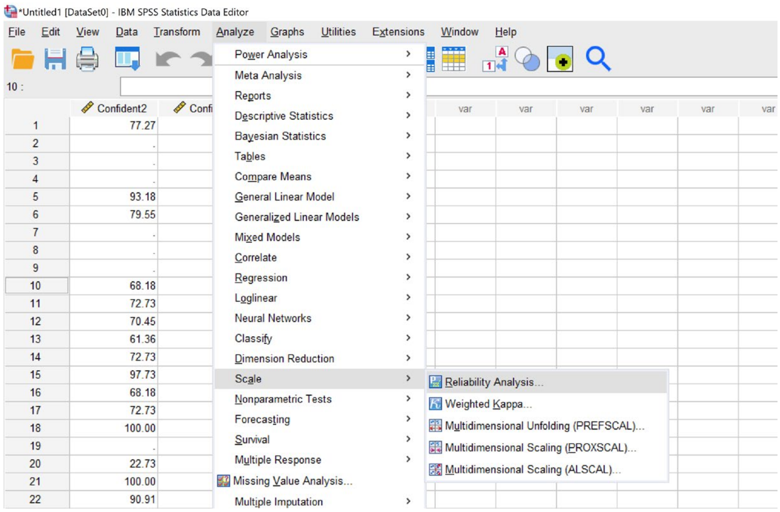


Figure 7.12: First Step When Conducting the Intra-Rater Reliability

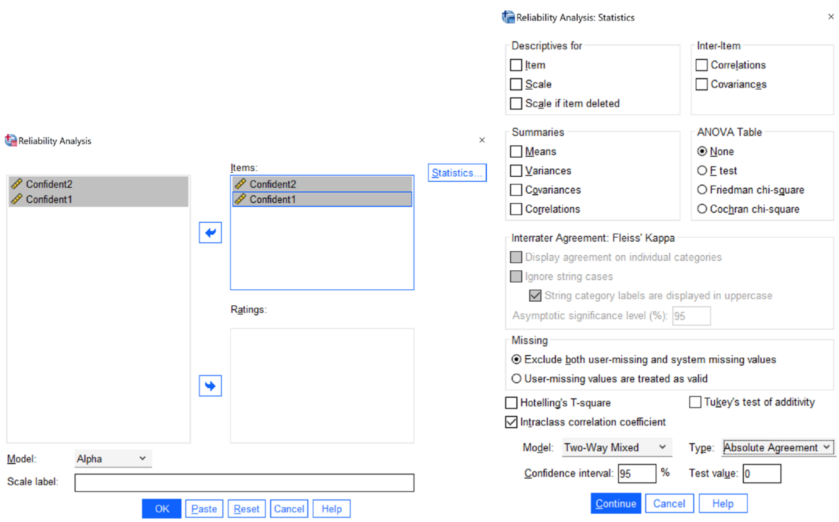


Figure 7.13: Intra-Rater Reliability

Case Processing Summary

		N	%
Cases	Valid	116	82.3
	Excluded[a]	25	17.7
	Total	141	100.0

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

Reliability Statistics

Cronbach's Alpha	N of Items
1.000	2

Intraclass Correlation Coefficient

	Intraclass Correlation[b]	95% Confidence Interval		F Test with True Value 0			
		Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.957[a]	.021	.991	.	115	.	.
Average Measures	.978[c]	.042	.996	.	115	.	.

Two-way mixed effects model where people effects are random and measures effects are fixed.

a. The estimator is the same, whether the interaction effect is present or not.

b. Type A intraclass correlation coefficients using an absolute agreement definition.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Figure 7.14: Result of the Intra-Rater Reliability

8 Factor Analysis

This chapter introduces factor analysis, including a detailed explanation of the basic concepts, the steps to perform principal component analysis (PCA) in SPSS software, and the interpretation of the results. The learning objectives of this chapter are to enable the reader to understand the concepts and methods associated with factor analysis, particularly PCA. The reader will learn about the purpose and usefulness of factor analysis in exploring data and will gain practical skills in performing PCA in SPSS and interpreting the results.

Factor analysis aims to reduce the dimensionality of the original space and to give an interpretation of the new space, which includes a reduced number of new dimensions that are supposed to be the basis for the old ones (Rietvel & van Hout, 1993, p. 254). It is used in areas such as medicine and nursing, economics, behavioural and social sciences, and geography (Yong & Pearce, 2013). Different methods of factor analysis are presented in **Figure 8.1**.

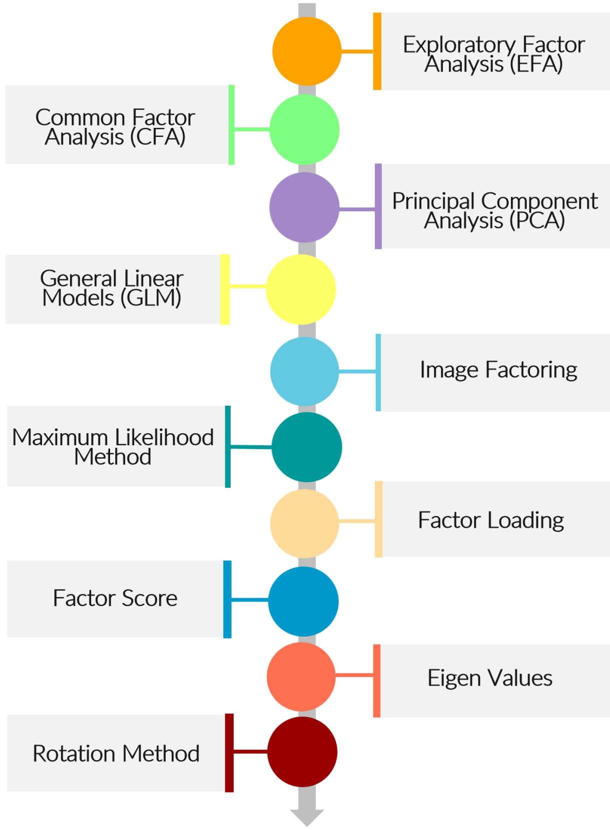


Figure 8.1: Types of Factor Analyses

There are a few methods to verify the adequacy of factor analysis (Nakazawa, 2011):

- criteria for the adequacy of the sample size,
- Kaiser-Meyer-Olkin (KMO) sampling adequacy criteria, which test whether a large number of factors exist in a data set,
- Bartlett's sphericity test, which tests the hypothesis that the correlations between the variables are greater than would be accidentally expected.

Commonly used analysis is Principal Components Analysis (PCA). It is a multivariate data reduction technique that aims to find a new set of variables that is equal in number to the original set of variables, with these synthetic variables not related (Rossiter, 2017). PCA is used to extract maximum variance from the data set with each component to reduce a large number of variables into a smaller number of their weighted sums (components). PCA is conceptually different from factor analysis but is often used synonymously in practice.

PCA can be used for different purposes:

- If we have a large number of variables (questions/statements in a questionnaire) and we believe that some of the variables measure the same phenomenon/construct; if we find a high correlation between the variables, we can include only those variables that best represent the construct, and remove the rest.
- This method can be used when we want to create a new questionnaire/measurement scale, but we are not sure that all the variables (questions/statements) we have included in our tool measure the same construct. This way, we can make sure that the variables we have included are sufficiently representative or that we need to remove them.
- In the case where we want to include as few variables (questions/statements) as possible in an existing questionnaire/measurement scale to shorten it.

To carry out a PCA, the following assumptions must be met:

- Our data must include several variables that must be measured continuously (ordinal variables are often used).
- There must be a linear relationship between all variables.
- A sufficiently large sample size is needed to ensure the reliability of the results obtained. As a general rule, a minimum of 150 cases is recommended, or 5 to 10 cases per variable.
- The data must be suitable for data reduction, meaning there must be an adequate correlation between the variables for them to be reduced.
- There must be no significant outliers in the variables.

8.1 Steps to Conduct PCA in SPSS

We eliminate n components and decide on a number. Criteria (by relevance):

1. substantive meaningfulness,

2. scree plot,
3. Desired eigenvalue> 1.

If more than one component is eliminated, as a rule, we rotate - repeat the analysis with the appropriate number of eliminated components.
Orthogonal rotations (e.g., Varimax): uncorrelated components, fewer inappropriate solutions.
Oblique-angle rotations (e.g., direct oblimin): a simpler interpretation. If the correlations between the components are low (e.g., <0.1), we prefer to use Varimax.

We interpret the rotated components in terms of content ("what variables with high absolute saturations" have in common).

We calculate component achievements if desired:

- **Descriptives:** Univariate descriptives, correlations, reproduced correlations, etc.
- **Important:** At least some correlations should be at least medium-high.
- **Extraction:** The process of extracting components.
- **Method:** Principal components.
- **Extract:** The number of components extracted (in the non-rotated solution anyway - you can start n).
- **Display:** Scree-plot (number of "large" components).
- **Analyse:** If variables with a higher variance are to have a greater effect on the results, we analyse the covariance matrix (usually for item analysis), otherwise correlatively (usually for test analysis).
- **Rotation:** Rotation selection.
- **Loading plot:** Draws a pattern and not correlations (structure) when rotating it at an angle.
- **Scores:** Save as variables: calculating people's achievements.
- **Display factor score coefficient matrix:** displays weights for calculating components.

In the following text, the process of conducting PCA in SPSS is presented in figures. To perform the PCA we should click the following: Click *Analyze -> Dimension Reduction -> Factor.*

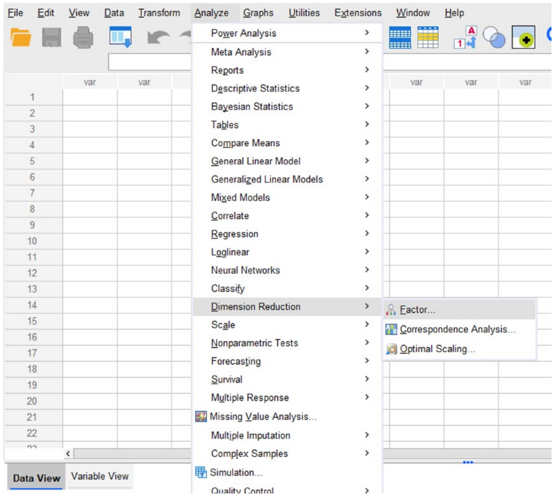


Figure 8.2: First Step when Choosing PCA

Select the variables and specify the appropriate settings, as shown in **Figure 8.3**.

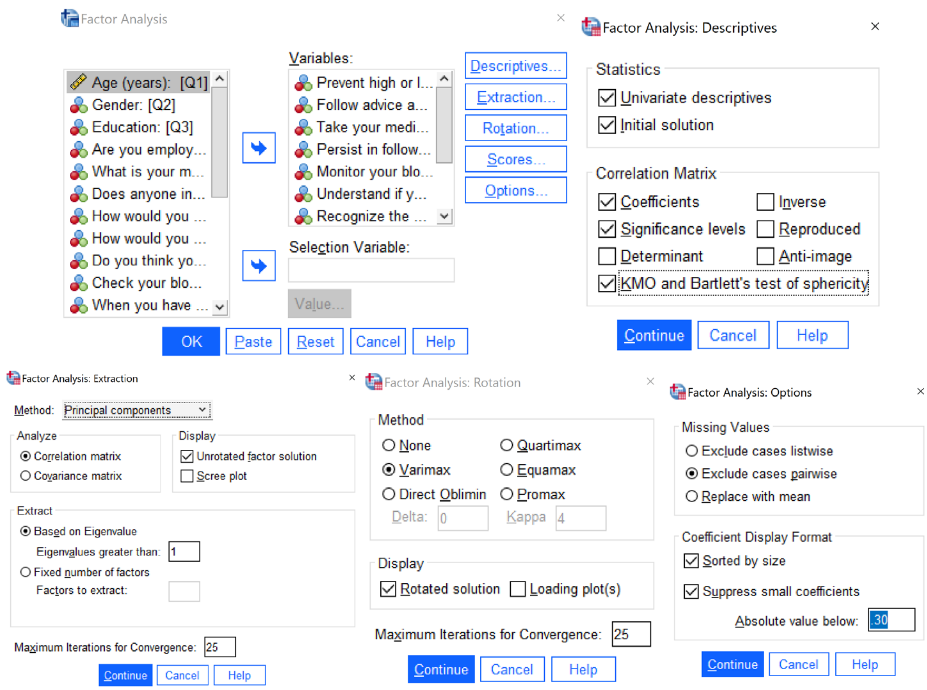


Figure 8.3: Choosing the Right FA Method

This table shows two tests that indicate the suitability of the data for FA implementation. Kaiser-Meyer-Olkin is a statistic that shows the proportion of variance in variables that can be caused by underlying factors. High values (close to 1.0) generally indicate that FA is beneficial. If the value is less than 0.50, FA results are unlikely to be useful. Bartlett's test of sphericity tests the hypothesis that variables are unrelated and, therefore, unsuitable for FA. Small values (less than 0.05) of significance level indicate that FA is beneficial.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.890
Bartlett's Test of Sphericity	Approx. Chi-Square	855.620
	df	55
	Sig.	<.001

Figure 8.4: KMO and Bartlett's Test

Eigenvalue presents the quality of the result; a higher result means higher quality.

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.337	57.612	57.612	6.337	57.612	57.612	4.102	37.295	37.295
2	1.033	9.386	66.999	1.033	9.386	66.999	3.267	29.704	66.999
3	.811	7.373	74.372						
4	.626	5.688	80.060						
5	.545	4.951	85.010						
6	.401	3.643	88.654						
7	.361	3.285	91.939						
8	.295	2.682	94.621						
9	.272	2.471	97.092						
10	.175	1.595	98.686						
11	.144	1.314	100.000						

Extraction Method: Principal Component Analysis.

Figure 8.5: Table of Components and Eigenvalues

Correlation Matrix

		Prevent high or low blood sugar levels and its symptoms.	Follow advice about nutrition and physical activity.	Take your medicines in the appropriate way (including insulin if prescribed).	Persist in following the treatment plan even when it's difficult.	Monitor your blood sugar as often as your health care provider asked you to.	Understand if your blood sugar levels are good or not.	Recognize the symptoms of low blood sugar.	Persist in monitoring your diabetes even when it's difficult.	Take action to adjust your blood sugar and relieve your symptoms.	Evaluate if your actions were effective to change your blood sugar and relieve your symptoms.	Persist in carrying out actions to improve your blood sugar even when it's difficult.
Correlation	Prevent high or low blood sugar levels and its symptoms.	1.000	.648	.416	.507	.321	.455	.423	.481	.558	.684	.559
	Follow advice about nutrition and physical activity.	.648	1.000	.402	.534	.383	.345	.428	.503	.563	.640	.605
	Take your medicines in the appropriate way (including insulin if prescribed).	.416	.402	1.000	.592	.362	.428	.347	.479	.434	.439	.384
	Persist in following the treatment plan even when it's difficult.	.507	.534	.592	1.000	.381	.391	.452	.640	.527	.633	.626
	Monitor your blood sugar as often as your health care provider asked you to.	.321	.383	.362	.381	1.000	.641	.413	.571	.569	.480	.473
	Understand if your blood sugar levels are good or not.	.455	.345	.428	.391	.641	1.000	.525	.601	.585	.460	.470
	Recognize the symptoms of low blood sugar.	.423	.428	.347	.452	.413	.525	1.000	.614	.708	.592	.499
	Persist in monitoring your diabetes even when it's difficult.	.481	.503	.479	.640	.571	.601	.614	1.000	.730	.620	.635
	Take action to adjust your blood sugar and relieve your symptoms.	.558	.563	.434	.527	.569	.585	.708	.730	1.000	.736	.736
	Evaluate if your actions were effective to change your blood sugar and relieve your symptoms.	.684	.640	.439	.633	.480	.460	.592	.620	.736	1.000	.794
	Persist in carrying out actions to improve your blood sugar even when it's difficult.	.559	.605	.384	.626	.473	.470	.499	.635	.736	.794	1.000
Sig. (1-tailed)	Prevent high or low blood sugar levels and its symptoms.		<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001	<.001
	Follow advice about nutrition and physical activity.	.000		.000	.000	.000	.000	.000	.000	.000	.000	.000
	Take your medicines in the appropriate way (including insulin if prescribed).	.000	.000		.000	.000	.000	.000	.000	.000	.000	.000
	Persist in following the treatment plan even when it's difficult.	.000	.000	.000		.000	.000	.000	.000	.000	.000	.000
	Monitor your blood sugar as often as your health care provider asked you to.	.000	.000	.000	.000		.000	.000	.000	.000	.000	.000
	Understand if your blood sugar levels are good or not.	.000	.000	.000	.000	.000		.000	.000	.000	.000	.000
	Recognize the symptoms of low blood sugar.	.000	.000	.000	.000	.000	.000		.000	.000	.000	.000
	Persist in monitoring your diabetes even when it's difficult.	.000	.000	.000	.000	.000	.000	.000		.000	.000	.000
	Take action to adjust your blood sugar and relieve your symptoms.	.000	.000	.000	.000	.000	.000	.000	.000		.000	.000
	Evaluate if your actions were effective to change your blood sugar and relieve your symptoms.	.000	.000	.000	.000	.000	.000	.000	.000	.000		.000
	Persist in carrying out actions to improve your blood sugar even when it's difficult.	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	

Figure 8.6: Item Correlations

Utilities can range from 0 to 1. Higher values mean that a larger proportion of the variance of a particular variable can be explained by other variables. These are more reliable (**Fig. 8.7**).

Communalities

	Initial	Extraction
Prevent high or low blood sugar levels and its symptoms.	1.000	.661
Follow advice about nutrition and physical activity.	1.000	.686
Take your medicines in the appropriate way (including insulin if prescribed).	1.000	.386
Persist in following the treatment plan even when it's difficult.	1.000	.628
Monitor your blood sugar as often as your health care provider asked you to.	1.000	.700
Understand if your blood sugar levels are good or not.	1.000	.744
Recognize the symptoms of low blood sugar.	1.000	.567
Persist in monitoring your diabetes even when it's difficult.	1.000	.726
Take action to adjust your blood sugar and relieve your symptoms.	1.000	.767
Evaluate if your actions were effective to change your blood sugar and relieve your symptoms.	1.000	.792
Persist in carrying out actions to improve your blood sugar even when it's difficult.	1.000	.712

Extraction Method: Principal Component Analysis.

Figure 8.7: The Utility Matrix

The rotated component matrix tells us which variables are most strongly associated with each component.

Rotated Component Matrix[a]

	Component 1	Component 2
Follow advice about nutrition and physical activity.	.810	
Evaluate if your actions were effective to change your blood sugar and relieve your symptoms.	.802	.387
Prevent high or low blood sugar levels and its symptoms.	.789	
Persist in carrying out actions to improve your blood sugar even when it' s difficult.	.738	.409
Persist in following the treatment plan even when it's difficult.	.731	.307
Take your medicines in the appropriate way (including insulin if prescribed).	.508	.359
Understand if your blood sugar levels are good or not.		.837
Monitor your blood sugar as often as your health care provider asked you to.		.818
Persist in monitoring your diabetes even when it's difficult.	.508	.684
Take action to adjust your blood sugar and relieve your symptoms.	.583	.654
Recognize the symptoms of low blood sugar.	.416	.628

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

a. Rotation converged in 3 iterations.

Figure 8.8: Component and Rotated Component Matrix

References

Andrade, C., 2020. Sample size and its importance in research. *Indian journal of psychological medicine*, 42(1), pp.102-103.

Ausili, D., Barbaranelli, C., Rossi, E., Rebora, P., Fabrizi, D., Coghi, C., Luciani, M., Vellone, E., Di Mauro, S. and Riegel, B., 2017. Development and psychometric testing of a theory-based tool to measure self-care in diabetes patients: the Self-Care of Diabetes Inventory. *BMC Endocrine Disorders*, *17*(1), pp.1-12.

Barton, B. and Peat, J., 2014. Medical statistics: A guide to SPSS, data analysis and critical appraisal. John Wiley & Sons.

Behr, D., 2017. Assessing the use of back translation: The shortcomings of back translation as a quality testing method. *International Journal of Social Research Methodology*, 20(6), pp.573-584.

Bhandari, P., 2022. Construct Validity | Definition, Types, & Examples. (Online) Available at: https://www.scribbr.com/methodology/construct-validity/ [Accessed 13 March 2019].

Dugard, P. and Todman, J., 1995. Analysis of pre-test-post-test control group designs in educational research. *Educational Psychology*, 15(2), pp.181-198.

Gelman, A. and Jennifer H., 2007. Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge: Cambridge University Press.

Goertzen, M.J., 2017. Introduction to quantitative research and data. *Library Technology Reports*, 53(4), pp.12-18.

Hallgren, K.A., 2012. Computing inter-rater reliability for observational data: an overview and tutorial. *Tutorials in quantitative methods for psychology*, 8(1), p.23.

Hastie et al., 2009. The Elements of Statistical Learning: Data mining, inference, and prediction, Springer.

Holton, E.F. and Burnett, M.F., 2005. The basics of quantitative research. Research in organizations: Foundations and methods of inquiry, pp.29-44.

Hoy, W.K. and Adams, C.M., 2015. Quantitative research in education: A primer. Sage Publications.

James et al., 2013. An Introduction to Statistical Learning: With applications in R, Springer.

Kim, H.Y., 2017. Statistical notes for clinical researchers: Chi-squared test and Fisher's exact test. *Restorative dentistry & endodontics*, 42(2), pp.152-155.

Koo, T.K. and Li, M.Y., 2016. A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine*, 15(2), pp.155-163.

Liguori, G.R. and Moreira, L.F.P., 2018. Operating with Data-Statistics for the cardiovascular surgeon: Part I. Fundamentals of Biostatistics. *Brazilian journal of cardiovascular surgery*, 33, pp.III-VIII.

Marsden, E. and Torgerson, C.J., 2012. Single group, pre-and post-test research designs: Some methodological concerns. Oxford Review of Education, 38(5), pp.583-616.

Mishra, P., Pandey, C.M., Singh, U., Gupta, A., Sahu, C. and Keshri, A., 2019. Descriptive statistics and normality tests for statistical data. *Annals of cardiac anaesthesia*, 22(1), p.67.

Mishra, P., Singh, U., Pandey, C.M., Mishra, P. and Pandey, G., 2019. Application of student's t-test, analysis of variance, and covariance. *Annals of cardiac anaesthesia*, 22(4), p.407.

Nakazawa, M., 2011. R practice: Factor analysis. (Pdf) Available at: http://minato.sip21c.org/swtips/factor-in-R.pdf [Accessed 13 March 2019].

Polit, D.F., Beck, T. and Owen, S.V., 2007. Focus on research methods is the CVI an acceptable indicator of content validity. *Research in Nursing & Health*, 30(4), pp.459-67.

Reaves, C.C., 1992. Quantitative research for the behavioral sciences. John Wiley & Sons.

Rietvel, T. & van Hout, R., 1993. Statistical Techniques for the Study of Language and Language Behaviour. Berlin: Mouton de Gruyter.

Rossiter, D. G., 2017. Tutorial: An example of statistical data analysis using the R environment for statistical computing. (Pdf) Available at: http://www.css.cornell.edu/faculty/dgr2/teach/R/R_corregr.pdf [Accessed 15 March 2019].

Simkus, J., 2022, Simple Random Sampling: Definition, Steps and Examples. Simply Psychology. (Online) Available at: www.simplypsychology.org/simple-random-sampling.html [Accessed 13 March 2019].

Simkus, J., 2022, Jan 30. Convenience Sampling: Definition, Method and Examples. Simply Psychology. (Online) Available at: www.simplypsychology.org/convenience-samplinghtml [Accessed 13 March 2019].

Smith, G.T., 2005. On construct validity: issues of method and measurement. *Psychological assessment*, 17(4), p.396.

Sperandei, S., 2014. Understanding logistic regression analysis. *Biochemia medica*, 24(1), pp.12-18.

Spieth, P.M., Kubasch, A.S., Penzlin, A.I., Illigens, B.M.W., Barlinn, K. and Siepmann, T., 2016. Randomized controlled trials–a matter of design. *Neuropsychiatric disease and treatment*, 12, p.1341.

Stanley, K., 2007. Design of randomized controlled trials. *Circulation*, 115(9), pp.1164-1169.

Stoltzfus, J.C., 2011. Logistic regression: a brief primer. *Academic emergency medicine*, 18(10), pp.1099-1104.

Tyupa, S., 2011. A theoretical framework for back-translation as a quality assessment tool. *New Voices in Translation Studies*, 7(1), pp.35-46.

Yen, M. and Lo, L.H., 2002. Examining test-retest reliability: an intra-class correlation approach. *Nursing research*, 51(1), pp.59-62.

Yong, A. G. & Pearce, S., 2013. A Beginner's Guide to Factor Analysis: Focusing on Exploratory Factor Analysis. *Tutorials in Quantitative Methods for Psychology*, 9(2), pp. 79-94.

Yusoff, M.S.B., 2019. ABC of content validation and content validity index calculation. *Resource*, 11(2), pp.49-54.

Watson, R., 2015. Quantitative research. *Nursing Standard*, 29(31), p.44.

Warren, M., Lininger, M.R., Chimera, N.J. and Smith, C.A., 2018. Utility of FMS to understand injury incidence in sports: current perspectives. *Open access journal of sports medicine*, 9, p.171.

ADVANCED QUANTITATIVE RESEARCH METHODS IN NURSING

DOI
https://doi.org/10.18690/um.fzv.2.2024

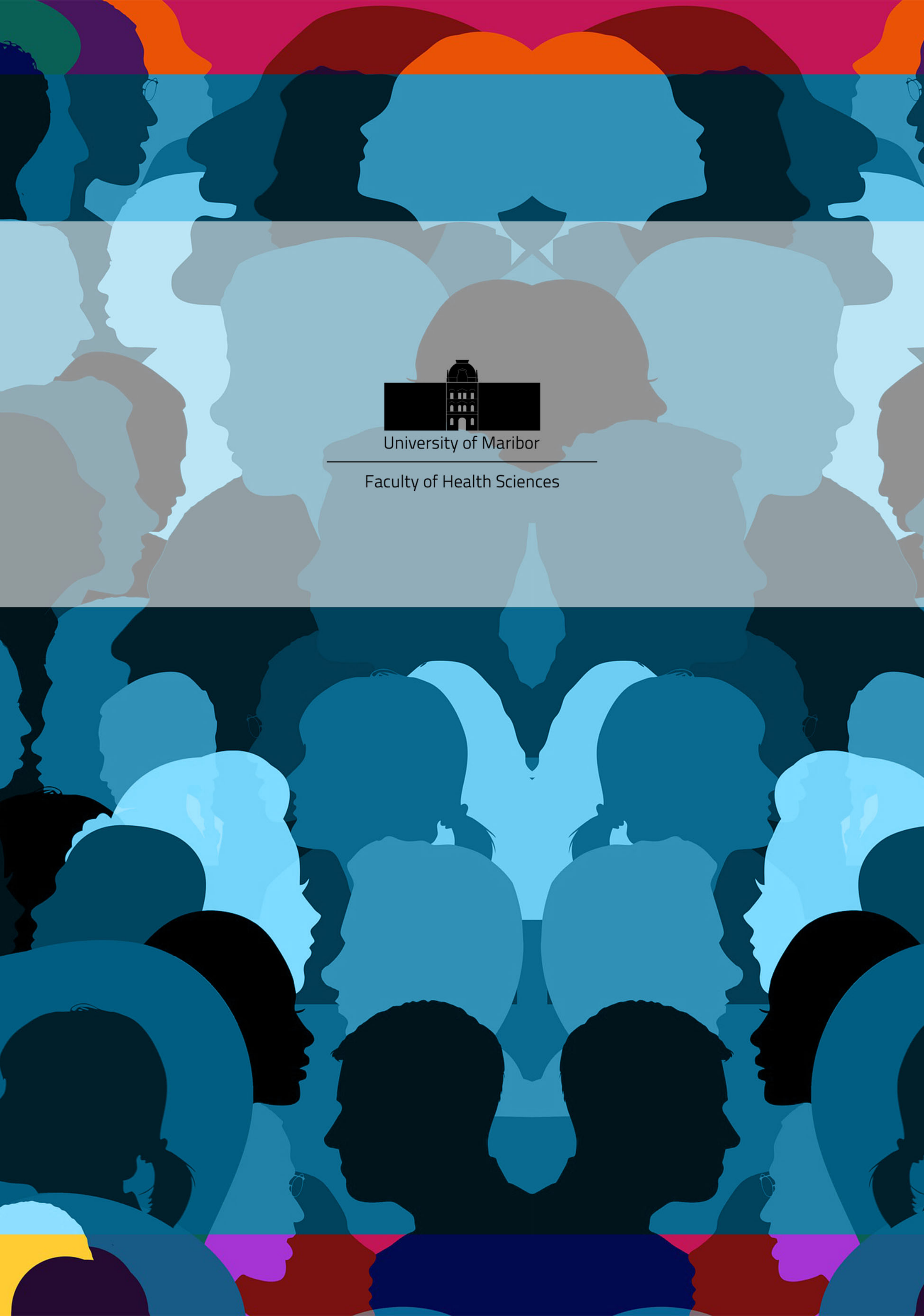
ISBN
978-961-286-888-8

LUCIJA GOSAK ET AL.
University of Maribor, Faculty of Health Sciences, Maribor, Slovenia
lucija.gosak2@um.si

The publication "Analysis of quantitative research data in nursing research: A guide to SPSS" provides nursing students and nurses with the knowledge and skills to interpret the different statistical methods in their field, which can improve users' skills in collecting, analysing and interpreting results from clinical practice, thus contributing to improving the quality of health care. It provides detailed instructions on how to use IBM SPSS and perform statistical analyses that nurses need to be familiar with as they use and generate data in their daily work with patients. The main aim of patient care is to provide high quality, evidence-based care, so nurses have a duty to keep up to date with the latest research and evidence and apply it to their work. The knowledge gained in this book can also help nurses to better understand and interpret previously published results, and thus critically assess the validity and reliability of the results they will use in clinical practice.

Keywords:
quantitative analysis,
statistics,
IBM SPSS,
reliability,
validity,
data analysis

University of Maribor Press



University of Maribor

Faculty of Health Sciences