SH SPSS TUTORIALS

BASICS SING AVAILUSES T-TEST OF NOVA CHI-SQUARE TEST

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You are here: Strong Values

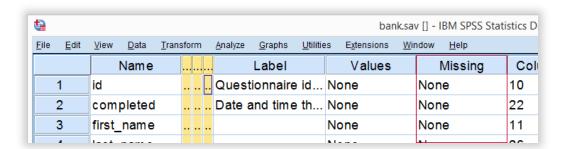


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SPSS Missing User Missing Values

Values Tutorialecting Missing Values per Variable





What are "Missing Values" in SPSS?

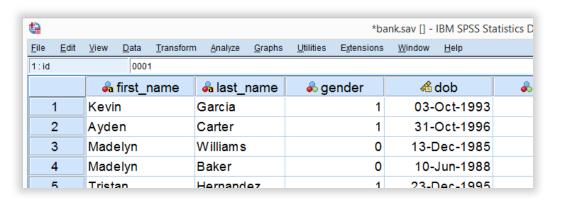
In SPSS, "missing values" may refer to 2 things:

- System missing values are values that are completely absent from the data. They are shown as periods in data view.
- User missing values are values that are invisible while analyzing or editing data. The SPSS user specifies which values -if any- must be excluded.



This tutorial walks you through both. We'll use bank.sav -partly shown below- throughout. You'll get the most out of this tutorial if you try the examples for yourself after downloading and opening this file.



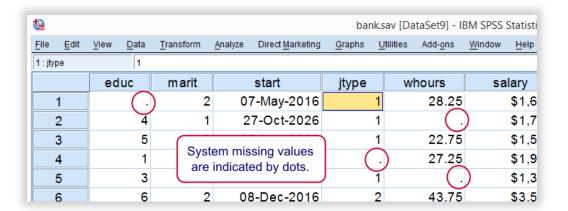


SPSS System Missing Values

System missing values are values that are completely absent from the data.

System missing values are shown as dots in data view as shown below.







System missing values are only found in numeric variables. String variables don't have system missing values. Data may contain system missing values for several **reasons**:





- some respondents weren't asked some questions due to the questionnaire routing;
- a respondent skipped some questions;
- something went wrong while converting or editing the data;
- some values weren't recorded due to equipment failure.

In some cases system missing values make perfect sense. For example, say I ask

"do you own a car?"

and somebody answers "**no**". Well, then my survey software should skip the next question:

"what color is your car?"

In the data, we'll probably see system missing values on color for everyone who does *not* own a car. These missing values make perfect sense.

In other cases, however, it may not be clear why there's system missings in your data. Something may or may not have gone wrong. Therefore, you should try to

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find out why some values are system missing

especially if there's many of them.

So how to detect and handle missing values in your data? We'll get to that after taking a look at the second type of missing values.





SPSS User Missing Values

User missing values are values that are excluded when analyzing or editing data.

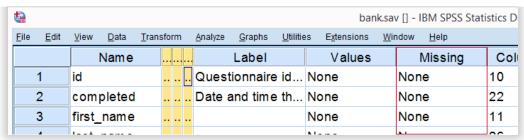
"User" in user missing refers to the SPSS user. Hey, that's you! So it's you who may need to set some values as user missing. So which -if any-values must be excluded? Briefly,

- for categorical variables, answers such as "don't know" or "no answer" are typically excluded from analysis.
- For metric variables, unlikely values -a reaction time of 50ms or a monthly salary of € 9,999,999- are usually set as user missing.

For bank.sav, no user missing values have been set yet, as can be seen in variable view.

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Let's now see if any values should be set as user missing and how to do so.

User Missing Values for Categorical Variables



A quick way for inspecting categorical variables is running frequency distributions and corresponding bar charts. Make sure the output tables show both values and value labels. The easiest way for doing so is running the syntax below.



*Show both values and value labels in succeeding outposet tnumbers both.

*Basic frequency table for q1.

frequencies q1 to q9.



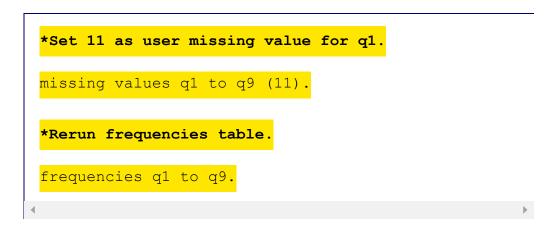
Result

q1 This company takes good care of its employees.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	20	4.3	4.4	4.4
	3	43	9.3	9.6	14.0
	9	35	7.5	7.8	93.6
	10 Totally agree	23	5.0	5.1	98.7
	11 No answer	→ 11 MUS	T BE SET	AS USER MIS	SING VALUE 100.0
	Total	450	97.0	100.0	
Missing	System	14	3.0		
Total		464	100.0	© 2018 www.	spss-tutorials.com

First note that q1 is an ordinal variable: higher values indicate higher levels of agreement. However, this does not go for 11: "No answer" does not indicate more agreement than 10 - "Totally agree". Therefore, only values 1 through 10 make up an ordinal variable and 11 should be excluded.

The syntax below shows the right way to do so.



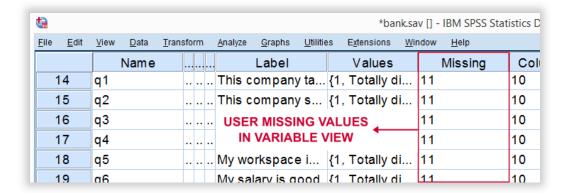
Result

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	2	20	4.3	4.5	4.5
	10 Totally agree	23	5.0	5.2	100.0
	Total	444	95.7	100.0	
Missing	11 No answer	6-	→ 11 = USE	ER MISSING VAL	UE
	System	14 —	→ SYSTEN	I MISSING VALUE	S
	Total	20	4.3		
Total		464	100.0	© 2018 www	

Note that 11 is shown among the missing values now. It occurs 6 times in q1 and there's also 14 system missing values. In variable view, we also



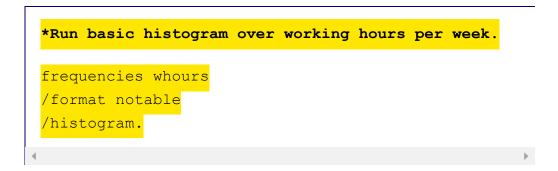
see that 11 is set as a user missing value for q1 through q9.



User Missing values for Metric Variables

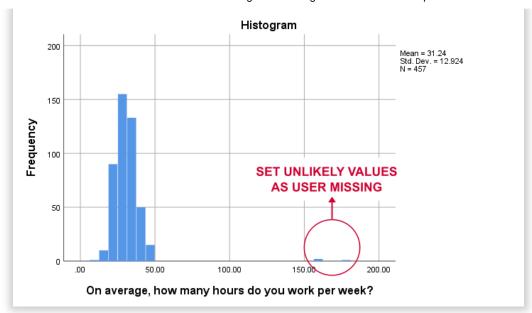


The right way to inspect metric variables is running histograms over them. The syntax below shows the easiest way to do so.

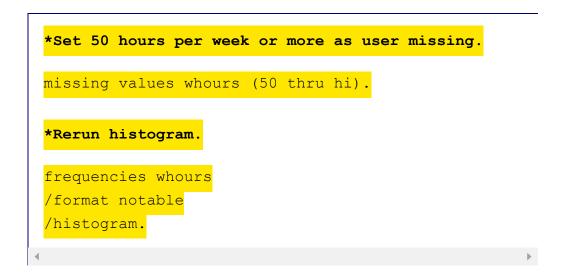


Result





Some respondents report working over 150 hours per week. Perhaps these are their monthly -rather than weekly- hours. In any case, such values are not credible. We'll therefore set all values of 50 hours per week or more as user missing. After doing so, the distribution of the remaining values looks plausible.



Inspecting Missing Values per Variable

A super fast way to inspect (system and user) missing values per variable is running a basic DESCRIPTIVES table. Before doing so, make sure you don't have any WEIGHT or FILTER switched on. You can check this by running

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SHOW WEIGHT FILTER N.

Also note that there's 464 cases in these data. So let's now inspect the descriptive statistics.

```
*Check missing values per variable.

descriptives q1 to q9.

*Note: (464 - N) = number of missing values.
```



Result

	N	Minimum	Maximum	Mean	Std. Deviation
q1 This company takes good care of its employees.	444	2	10	5.99	2.106
q2 This company supports me in my work.	438 –	→ (464 - 43	8 =) 26 MIS	SING V	ALUES ON Q2
q9 The cooperation with my colleagues is good.	440	3	10	6.97	1.799
Valid N (listwise)	309 -	→ 309 CAS	ES COMPL	ETE ON	Q1 TO Q9

The N column shows the number of non missing values per variable. Since we've 464 cases in total, (464 - N) is the number of missing values per variable. If any variables have high percentages of missingness, you may want to exclude them from -especially- multivariate analyses. Importantly, note that **Valid N (listwise) = 309**. These are the cases without any missing values on all variables in this table. Some procedures will use only those 309 cases -known as **listwise exclusion** of missing values in SPSS.

Conclusion: none of our variables -columns of cells in data view- have huge percentages of missingness. Let's now see if any cases -rows of cells in data view- have many missing values.





Inspecting Missing Values per Case

For inspecting if any cases have many missing values, we'll create a new variable. This variable holds the number of missing values over a set of variables that we'd like to analyze together. In the example below, that'll be q1 to q9.

We'll use a short and simple variable name: mis_1 is fine. Just make sure you add a description of what's in it -the number of missing...- as a variable label.

*Create new variable holding number of missing values

count mis_1 = q1 to q9 (missing).

*Set description of mis_1 as variable label.

variable labels mis_1 'Missing values over q1 to q9'.

*Inspect frequency distribution missing values.

frequencies mis_1.

Result



mis_1 Missing values over q1 to q9 Frequency Valid Percent **Cumulative Percent** 309 CASES COMPLETE ON Q1 TO Q9 Valid .00 309 1.00 125 26.9 26.9 93.5 2.00 22 4.7 4.7 98.3 8.00 1 .2 .2 99.6 9.00 .4 100.0 2 .4 Total 464 100.0

In this table, 0 means zero missing values over q1 to q9. This holds for **309** cases. This is the **Valid N** (**listwise**) we saw in the descriptives table earlier on.

Also note that 1 case has 8 missing values out of 9 variables. We may doubt if this respondent filled out the questionnaire seriously. Perhaps we'd better exclude it from the analyses over q1 to q9. The right way to do so is using a FILTER.



SPSS Data Analysis with Missing Values

So how does SPSS analyze data if they contain missing values? Well, in most situations,

SPSS runs each analysis on all cases it can use for it.

Right, now our data contain 464 cases. However, most analyses can't use all 464 because some may drop out due to missing values. Which cases drop out depends on which analysis we run on which variables.

Therefore, an important best practice is to

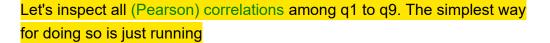


always inspect how many cases are actually used for each analysis you run.

This is not always what you might expect. Let's first take a look at pairwise exclusion of missing values.



Pairwise Exclusion of Missing Values



correlations q1 to q9.

If we do so, we get the table shown below.

					4		_	7		
		q1	q2	q3	q4	q5	q6	q7	q8	q9
q1	Pearson Correlation	1	.566	.129	.168	.086	.110	.117	.073	.153
	Sig. (2-tailed)		.000	.008	.000	.080	.023	.016	.134	.002
	N	444	423	419	433	416	427	425	427	425
q2	Pearson Correlation	.566	1	.227	.138	.085	.076	.128	.069	.180
	Sig. (2-tailed)	.000		.000	.004	.086	.120	.009	.158	.000
	N	423	438	412	425	409	419	420	420	419
a2	Poorson Correlation	120	227	- 1	2/12	115	1/10	1/17	204	144

Note that each correlation is based on a different number of cases. Precisely, each correlation between a pair of variables uses all cases having valid values on these 2 variables. This is known as **pairwise exclusion** of missing values. Note that most correlations are based on some 410 up to 440 cases.



Listwise Exclusion of Missing Values



Let's now rerun the same correlations after adding a line to our minimal syntax:



correlations q1 to q9 /missing listwise.

After running it, we get a smaller correlation matrix as shown below. It no longer includes the number of cases per correlation.

		q1	q2	q3	q4	q5	q6	q7	q8	q9
q1	Pearson Correlation	1	.584	.089	.153	.082	.104	.109	.050	.168
	Sig. (2-tailed)		.000	.116	.007	.149	.067	.055	.378	.003
q2	Pearson Correlation	.584	1	.168	.155	.105	.102	.106	.077	.182
	Sig. (2-tailed)	.003	.001	.002	.000	.006	.004	.024	.045	

Each correlation is based on the same 309 cases, the **listwise N**. These are the cases without missing values on *all* variables in the table: q1 to q9. This is known as **listwise exclusion** of missing values.

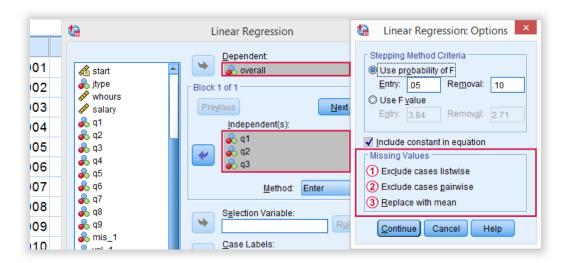
Obviously, listwise exclusion often uses far fewer cases than pairwise exclusion. This is why we often recommend the latter: we want to use as many cases as possible. However, if many missing values are present, pairwise exclusion may cause computational issues. In any case, make sure you



know if your analysis uses
listwise or pairwise exclusion of missing values.

By default, regression and factor analysis use listwise exclusion and in most cases, that's *not* what you want.





Exclude Missing Values Analysis by Analysis

Analyzing if 2 variables are associated is known as bivariate analysis. When doing so, SPSS can only use cases having valid values on both variables. Makes sense, right?

Now, if you run several bivariate analyses in one go, you can exclude cases **analysis by analysis**: each separate analysis uses all cases it can. Different analyses may use different subsets of cases.

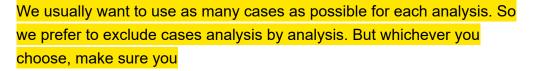
If you don't want that, you can often choose **listwise** exclusion instead: each analysis uses only cases without missing values on *all* variables for *all* analyses. The figure below illustrates this for ANOVA.







- 1 The test for q1 and educ uses all cases having valid values on q1 and educ, regardless of q2 to q4.
- 2 All tests use only cases without missing values on q1 to q4 and educ.



know how many cases are used for each analysis.

So check your output carefully. The Kolmogorov-Smirnov test is especially tricky in this respect: by default, one option excludes cases analysis by analysis and the other uses listwise exclusion.

Editing Data with Missing Values

Editing data with missing values can be tricky. Different commands and functions act differently in this case. Even something as basic as computing means in SPSS can go very wrong if you're unaware of this. The syntax below shows 3 ways we sometimes encounter. With missing values, however, 2 of those yield **incorrect results**.





```
*Right way to compute mean.

compute mean_a = mean(q1 to q9).

*Compute mean - wrong way 1.

compute mean_b = (q1 + q2 + q3 + q4 + q5 + q6 + q7 +

*Compute mean - wrong way 2.

compute mean_c = sum(q1 to q9) / 9.

*Check results.

descriptives mean_a to mean_c.
```

Result

	N	Minimum	Maximum	Mean	Std. Deviation
mean_a	462	CORI	RECT -	→ 5.8961	1.02598
mean_b	309 ◀	— и тос	LOW	5.8972	1.02899
mean_c	462	MEAN TO	oo Low —	▶ 5.6190	1.10704
Valid N (listwise)	309				

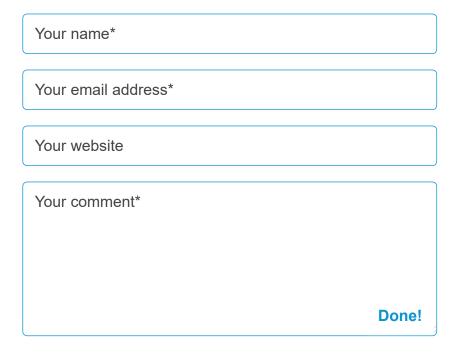
Final Notes



In real world data, missing values are common. They don't usually cause a lot of trouble when analyzing or editing data but in some cases they do. A little extra care often suffices if missingness is limited. Double check your results and know what you're doing.

Thanks for reading.

Let me know what you think!



^{*}Required field. Your comment will show up after approval from a moderator.

This tutorial has 28 comments

By Yang Chia Heng on October 29th, 2019 after so much slides read, i still dont understand how to find the missing data By neema on June 5th, 2019 Good explanation.



By Ruben Geert van den Berg on April 10th, 2019

Good question. I tried it (see below) but it crashes.



You can, however, RECODE syste

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Get In Touch! SPSS Help (Netherlands)

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