How to Perform Quadratic Regression in SPSS: A Step-by-Step Guide

Authored by
stats writer

March 14, 2026

RECOMMENDED CITATION

stats writer (2026). *How to Perform Quadratic Regression in SPSS: A Step-by-Step Guide*. PSYCHOLOGICAL SCALES. Retrieved from https://scales.arabpsychology.com/?p=135808

How can I perform Quadratic Regression using SPSS?

In the expansive field of **statistical modeling**, researchers frequently encounter datasets where the relationship between a **dependent variable** and an **independent variable** does not follow a straight line. While **linear regression** is the standard approach for quantifying proportional changes, it often fails to capture the complexity of real-world phenomena. When the data exhibits a "U-shaped" or inverted "U-shaped" trend, it indicates that the rate of change is not constant, necessitating a more sophisticated approach. This is where **quadratic regression** becomes an essential tool for data analysts and social scientists.

Quadratic regression is a specialized form of **polynomial regression** that models the relationship between variables using a second-degree equation. Unlike a standard linear model, which follows the formula y = mx + b, a quadratic model incorporates a squared term, taking the form $y = ax^2 + bx + c$. This mathematical structure allows the regression line to curve, providing a much more accurate fit for **curvilinear data**. By utilizing this method, researchers can identify optimal points--such as the peak of a performance curve or the minimum of a cost function--that a linear model would simply overlook.

To execute this analysis effectively, many professionals rely on **SPSS** (Statistical Package for the Social Sciences), a comprehensive software suite designed for complex **data analysis**. **SPSS** provides a robust environment for managing **quantitative data**, offering built-in functions to transform variables and run sophisticated **regression models**. This tutorial will guide you through the systematic process of performing a quadratic regression within **SPSS**, ensuring that your findings are both statistically valid and practically meaningful.

The Theoretical Foundation of Quadratic Modeling

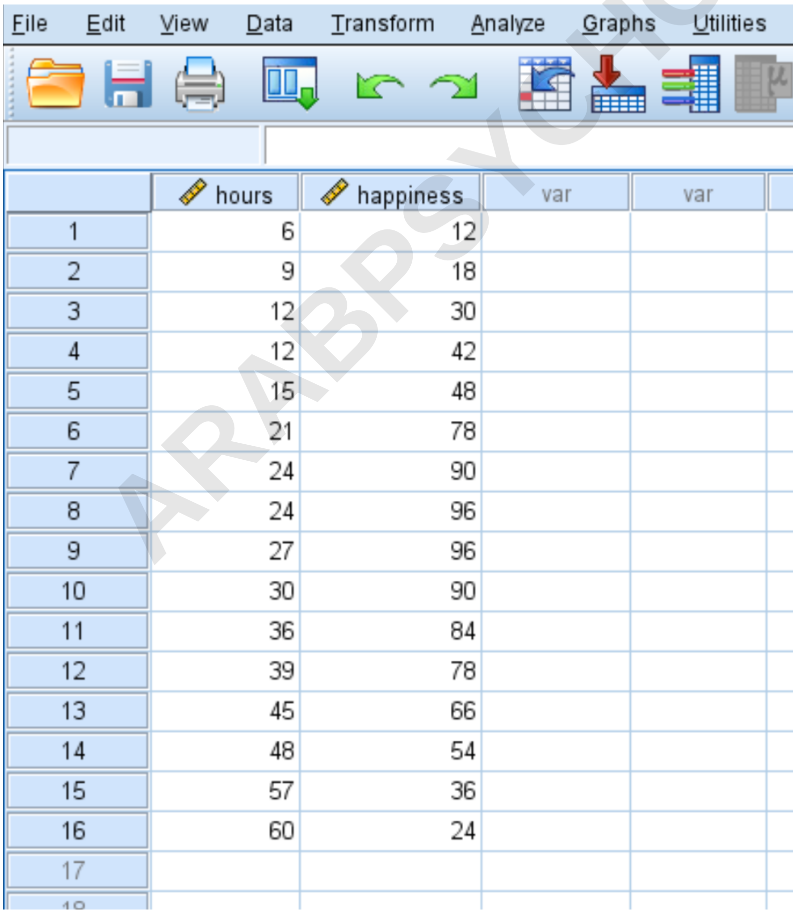
Before diving into the software mechanics, it is crucial to understand when and why a **quadratic regression** is appropriate. In many biological, economic, and psychological studies, variables interact in a way that reaches a point of diminishing returns. For instance, in **organizational psychology**, the relationship between stress and performance is often quadratic; a moderate amount of stress improves focus, but excessive stress leads to a sharp decline in productivity. Modeling such a relationship with a straight line would lead to a poor **R-squared** value and potentially misleading conclusions.

The **quadratic model** essentially treats the squared version of the **independent variable** as a separate predictor. By doing so, the model can account for the "bend" in the data. If the coefficient of the squared term is positive, the curve will be convex (opening upwards); if it is negative, the curve will be concave (opening downwards). This flexibility makes it one of the most common **non-linear models** used in **academic research** and **business analytics**. However, analysts must be cautious of **multicollinearity**, as a variable and its square are often highly correlated, which can sometimes distort the **statistical significance** of individual predictors.

Applying this method in **SPSS** requires a structured workflow: data visualization, variable transformation, model execution, and careful interpretation. In the following example, we will examine a hypothetical study regarding labor and well-being. We aim to determine how the number of hours worked per week influences an individual's self-reported happiness. Because work-life balance is a delicate equilibrium, we suspect that the relationship is not linear but follows a curve where both too little and too much work could potentially decrease happiness levels.

Illustrative Example: Hours Worked vs. Happiness

Consider a scenario where a researcher collects data from 16 participants to evaluate their **subjective well-being**. Each participant reports the average number of hours they work per week and rates their overall happiness on a **Likert scale** or a continuous 0-100 scale. The goal is to determine if there is an "ideal" number of working hours that maximizes happiness. Below is the initial dataset as it appears in the **SPSS** Data View window, showing the two primary variables: **hours** and **happiness**.



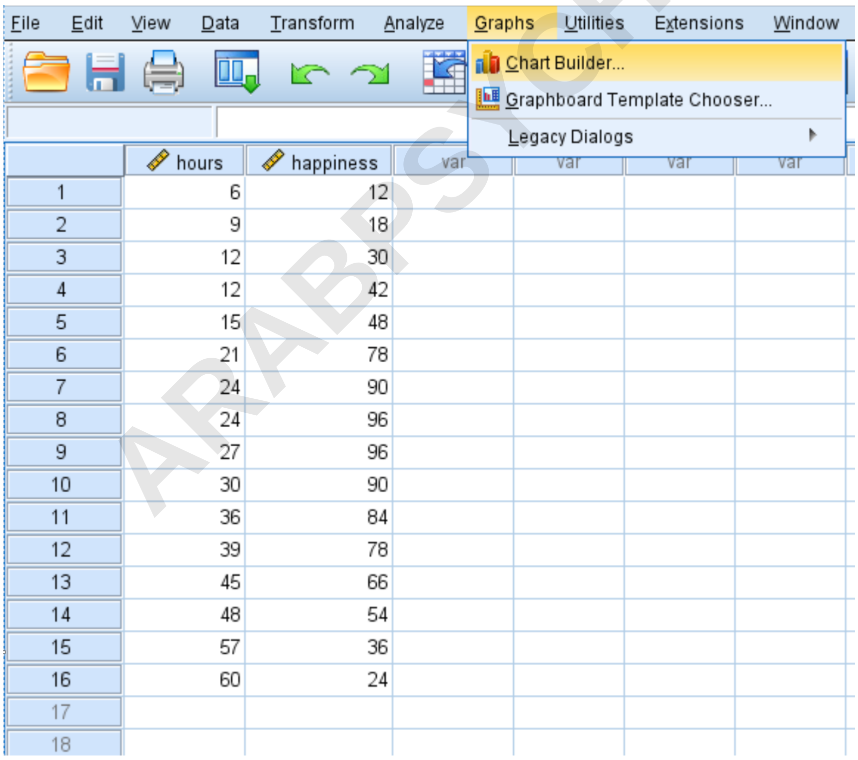
	hours	happiness	var	var
1	6	12		
2	9	18		
3	12	30		
4	12	42		
5	15	48		
6	21	78		
7	24	90		
8	24	96		
9	27	96		
10	30	90		
11	36	84		
12	39	78		
13	45	66		
14	48	54		
15	57	36		
16	60	24		
17				

Upon initial inspection of the raw data, it may be difficult to discern the exact nature of the relationship. Some participants working 20 hours are relatively happy, while those working 40 hours seem to reach a peak, and those working 60 hours show a significant decline. This pattern suggests that a **linear model** would be insufficient. In **statistical software**, the first step should always involve **exploratory data analysis** to confirm these visual intuitions before calculating **regression coefficients**.

The following sections will detail the five essential steps required to perform a **quadratic regression** in **SPSS**. This includes generating a **scatterplot**, computing the squared term, running the **linear regression** procedure with the added polynomial component, and interpreting the complex output tables generated by the software.

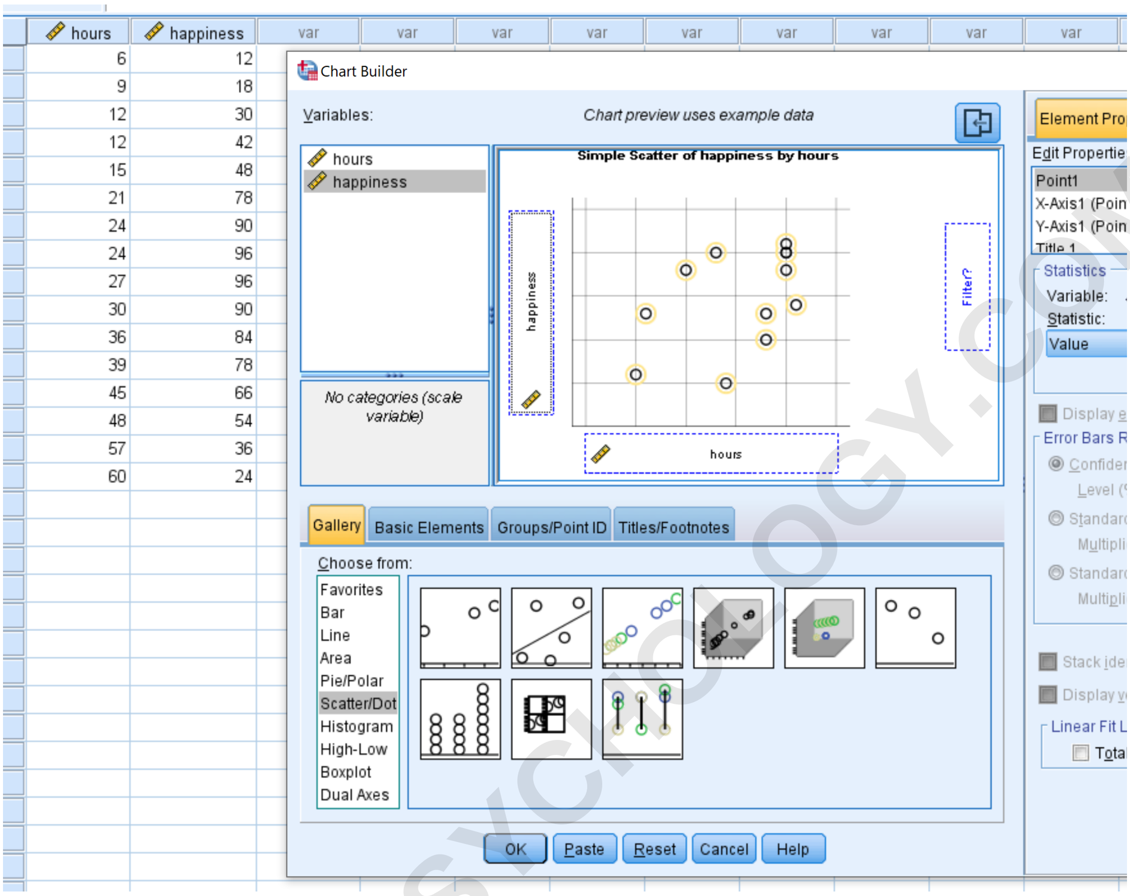
Step 1: Visualizing the Curvilinear Relationship

The most effective way to justify using a quadratic model is through **data visualization**. A **scatterplot** allows you to see the distribution of data points and identify whether a straight line or a curve provides a better visual fit. In **SPSS**, you can access visualization tools by navigating to the **Graphs** menu and selecting the **Chart Builder** option. This interface is highly intuitive, allowing for drag-and-drop customization of your figures.



	hours	happiness
1	6	12
2	9	18
3	12	30
4	12	42
5	15	48
6	21	78
7	24	90
8	24	96
9	27	96
10	30	90
11	36	84
12	39	78
13	45	66
14	48	54
15	57	36
16	60	24
17		
18		

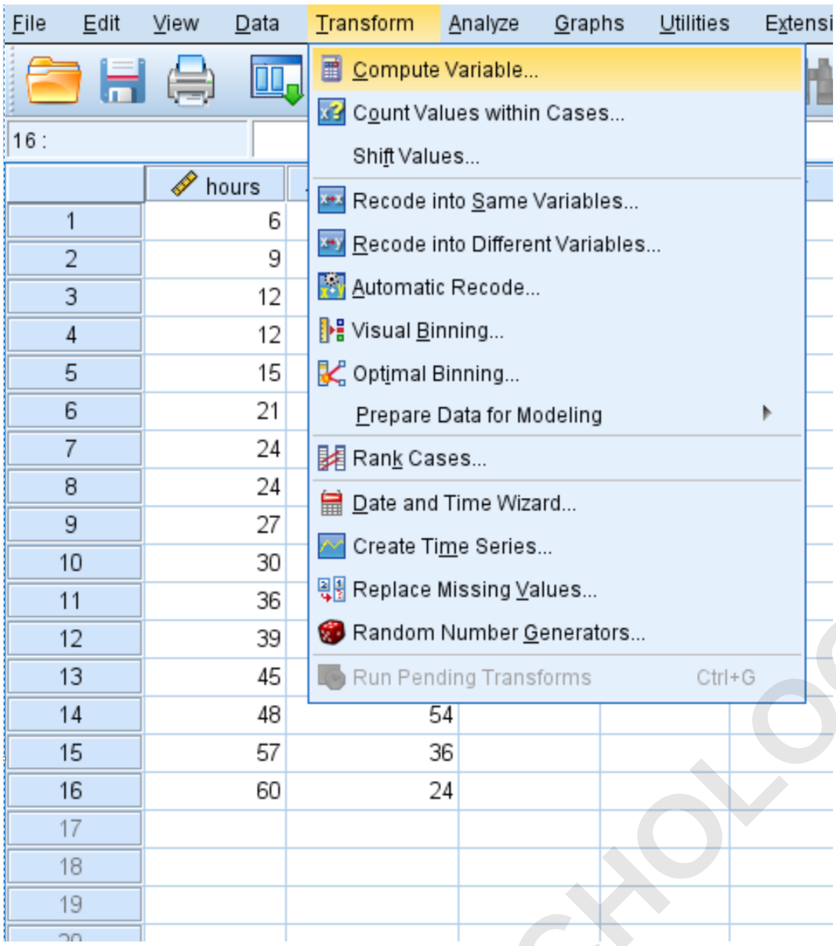
Once the **Chart Builder** dialog box appears, you should select **Scatter/Dot** from the list of available chart types. Drag the **Simple Scatter** icon into the main canvas. To define the axes, place the **independent variable** (hours) on the X-axis and the **dependent variable** (happiness) on the Y-axis. This setup is fundamental for identifying **bivariate relationships**. After clicking **OK**, **SPSS** will generate the graph in the Output Viewer.



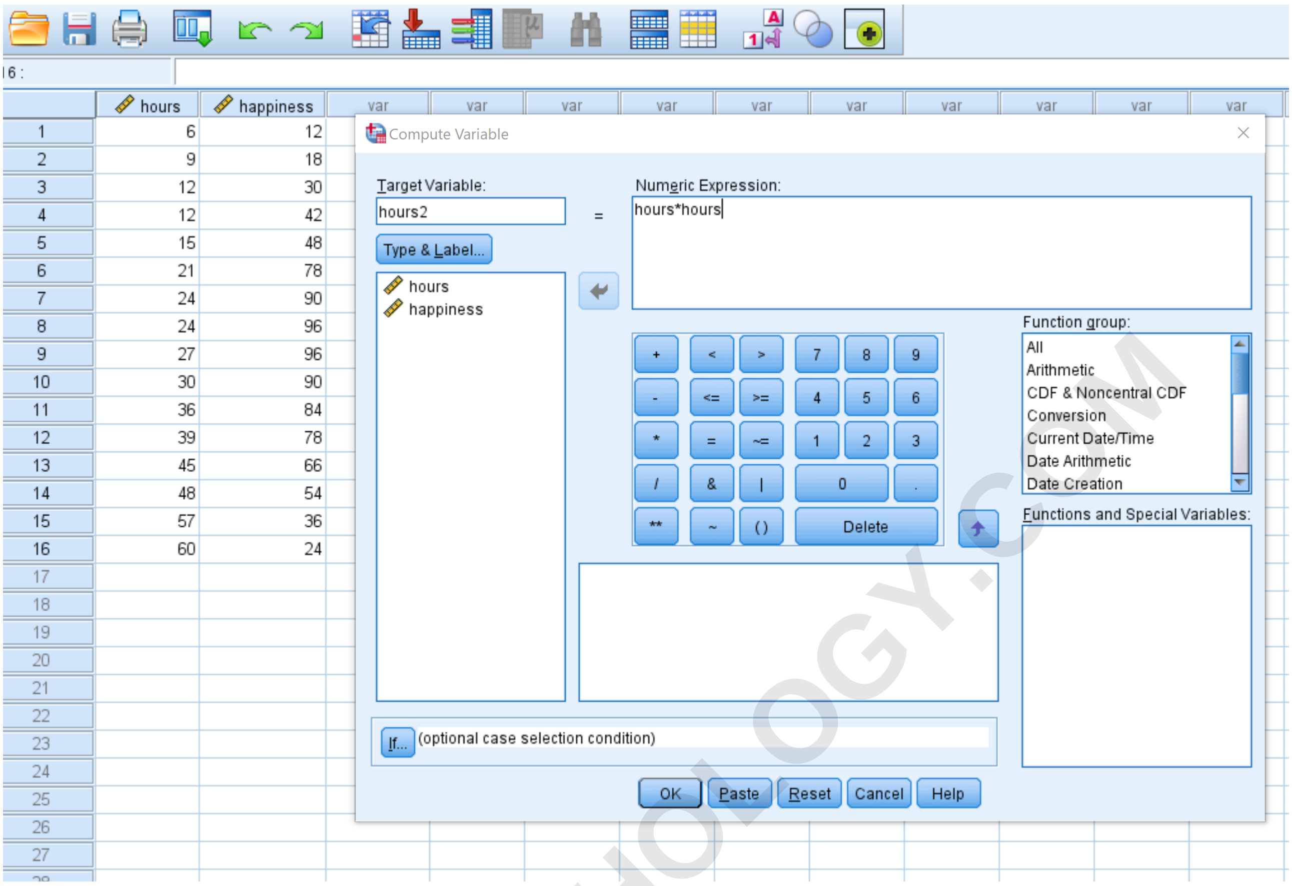
The resulting **scatterplot** is a critical diagnostic tool. If the points appear to rise and then fall (or vice-versa), you have clear evidence of a **quadratic relationship**. As shown in the image below, the data points for our happiness study follow a distinct parabolic path. The happiness level increases as work hours move from 0 toward 35, but begins to drop sharply as hours exceed 45. This visual confirmation ensures that moving forward with a **quadratic regression** is the correct **methodological choice**.

Step 2: Creating the Squared Predictor Variable

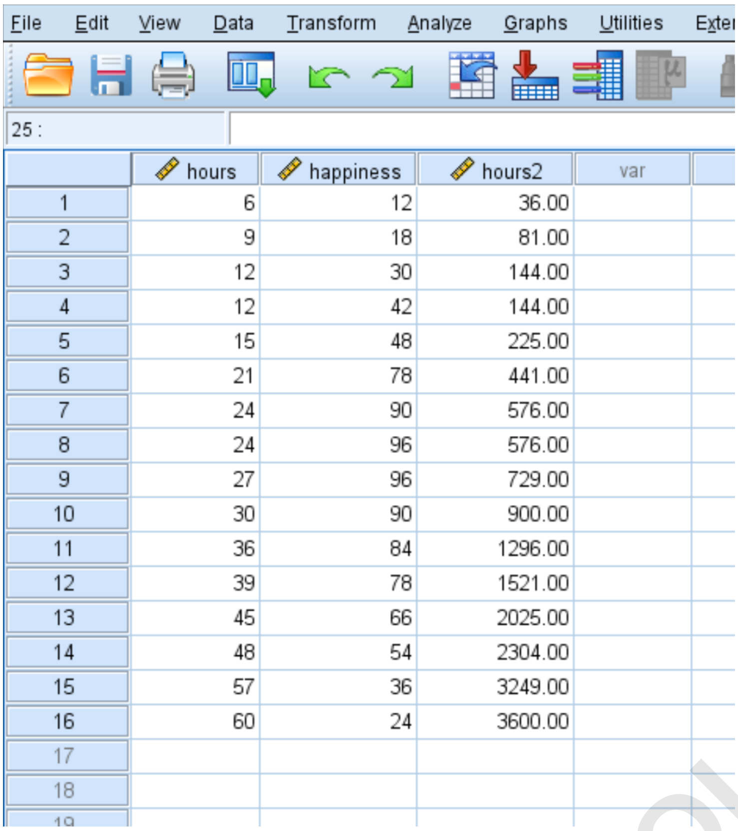
To perform a **quadratic regression** in a standard **linear regression** module, you must first create a new variable that represents the square of your **independent variable**. This process is known as **data transformation**. In **SPSS**, this is achieved through the **Compute Variable** function, which allows you to apply mathematical formulas to existing columns in your dataset.



Navigate to the **Transform** menu and click on **Compute Variable**. In the dialog box, you will need to specify a **Target Variable** name, such as "hours2" or "hours_squared". In the **Numeric Expression** box, you define the calculation by selecting the original "hours" variable and multiplying it by itself (hours * hours). This new variable will serve as the quadratic component in our **regression analysis**, allowing the model to account for the curvature observed in the **scatterplot**.



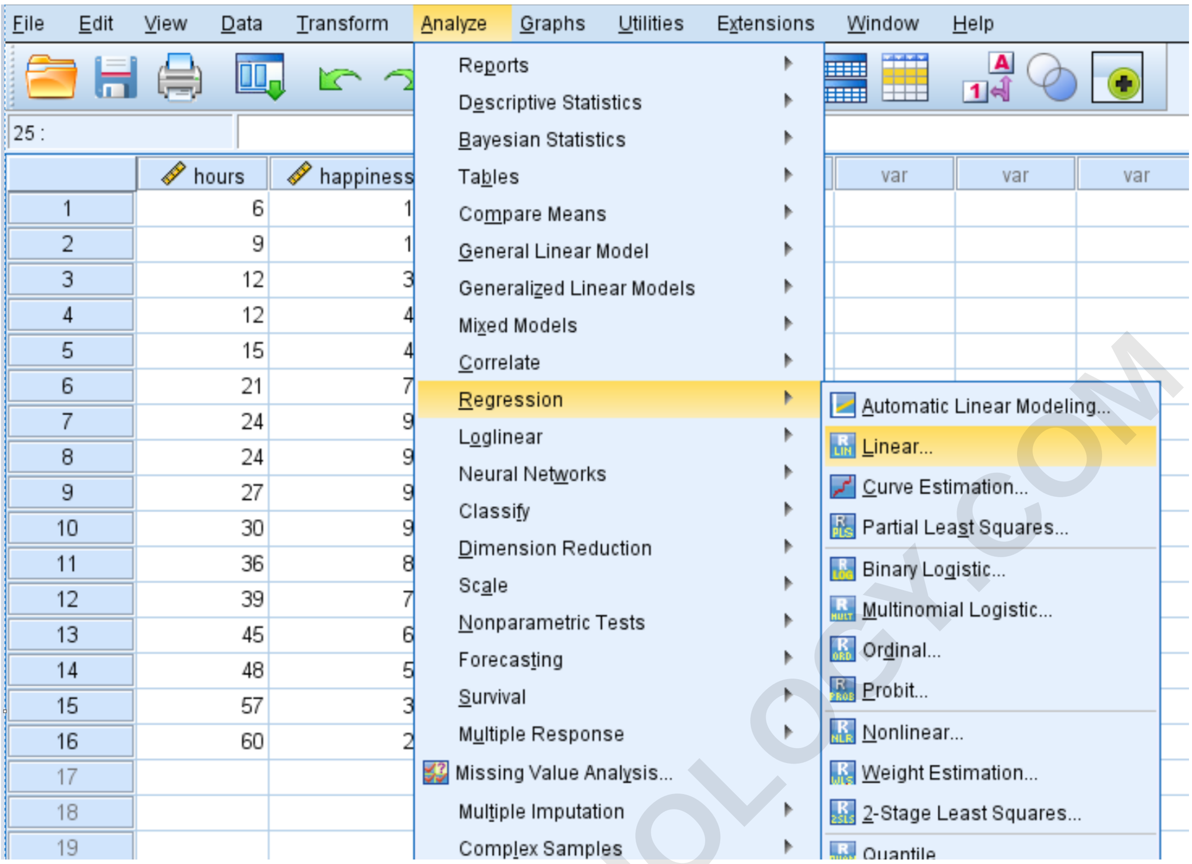
After clicking **OK**, **SPSS** will process the command and a new column will appear in your **Data Editor**. It is essential to verify that the values in this new column are indeed the squares of the original variable to avoid **calculation errors**. This step is a prerequisite for most **statistical software** packages when the user is not using a dedicated "curve fit" module. By having both the linear term (hours) and the quadratic term (hours2) in the dataset, you are ready to build a **multiple regression** model.



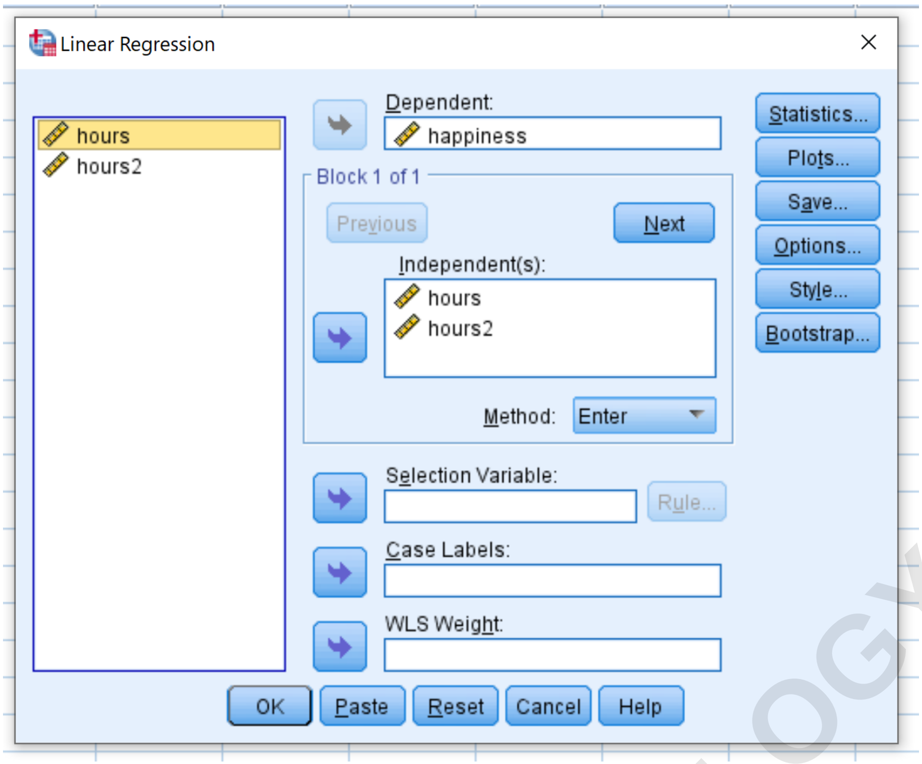
	hours	happiness	hours2	var
1	6	12	36.00	
2	9	18	81.00	
3	12	30	144.00	
4	12	42	144.00	
5	15	48	225.00	
6	21	78	441.00	
7	24	90	576.00	
8	24	96	576.00	
9	27	96	729.00	
10	30	90	900.00	
11	36	84	1296.00	
12	39	78	1521.00	
13	45	66	2025.00	
14	48	54	2304.00	
15	57	36	3249.00	
16	60	24	3600.00	
17				
18				

Step 3: Executing the Regression Analysis

With the variables prepared, you can now proceed to the core **statistical analysis**. Even though we are modeling a curve, we use the **Linear Regression** procedure because the model is "linear in the parameters"--meaning the coefficients themselves are additive. To start, go to the **Analyze** menu, select **Regression**, and then choose **Linear**. This window is the primary hub for specifying **predictive models** in **SPSS**.



In the **Linear Regression** dialog box, you must assign the variables to their respective roles. Drag the "happiness" variable into the **Dependent** box. Next, drag both "hours" and the newly created "hours2" into the **Independent(s)** box. It is vital to include both terms; the linear term handles the general slope, while the squared term handles the **acceleration** or deceleration of that slope. This combination is what creates the **parabolic effect** in the resulting equation.



Before clicking **OK**, you may want to explore the **Statistics** button to request additional diagnostics, such as **collinearity diagnostics** or **Durbin-Watson** tests, to ensure the **assumptions of regression** are met. Once you are satisfied with the settings, execute the command. **SPSS** will then populate the Output Viewer with several tables, including the Model Summary, **ANOVA** table, and the Coefficients table, each providing unique insights into the data.

Step 4: Interpreting the Model Summary and Goodness of Fit

The first table to examine in the **SPSS** output is the **Model Summary**. This table provides an overview of how well the **quadratic model** explains the variation in the **dependent variable**. The most critical value here is the **R-squared** (R^2), which represents the proportion of **variance** in happiness that is predictable from the hours worked. A higher R^2 indicates a model that fits the data points closely.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.954[a]	.909	.895	9.519

a. Predictors: (Constant), hours2, hours

In our example, the **R-squared** value is 0.909, which is exceptionally high. This suggests that 90.9% of the fluctuations in reported happiness can be explained by the combination of working hours and working hours squared. Additionally, the **Standard Error of the Estimate** is 9.519. This metric tells us the average distance that the observed happiness scores deviate from the **regression line**. A smaller standard error indicates more precise **predictions**.

When comparing a **quadratic regression** to a simple linear one, you will often notice a significant increase in the **R-squared** value. This improvement justifies the added complexity of the model. However, researchers should also look at the **Adjusted R-squared**, especially when adding multiple predictors, as it penalizes the model for adding variables that do not contribute significantly to its predictive **power**.

Step 5: Analyzing the ANOVA Table and Statistical Significance

After confirming the goodness of fit, the next step is to determine if the relationship is statistically significant. The **ANOVA** (Analysis of Variance) table tests the **null hypothesis** that the model has no predictive value. It provides an **F-statistic** and a corresponding **p-value**, which in **SPSS** is labeled as "Sig."

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11797.700	2	5898.850	65.095	.000[b]
	Residual	1178.050	13	90.619		
	Total	12975.750	15			

a. Dependent Variable: happiness

b. Predictors: (Constant), hours2, hours

In this specific analysis, the **p-value** is reported as 0.000 (which actually means $p < 0.001$). Since this value is well below the standard **alpha level** of 0.05, we reject the null hypothesis. This indicates that the **regression model** as a whole--including both the linear and quadratic terms--is a statistically significant predictor of happiness. The **F-statistic** of 65.095 further reinforces that the observed relationship is unlikely to have occurred by chance.

The **ANOVA** table is essential because it validates the entire model before you begin looking at individual predictors. If the **p-value** here were non-significant, any individual coefficients found later would be considered unreliable. In **formal research**, reporting the F-ratio and the **degrees of freedom** is standard practice to allow readers to assess the **statistical power** of your study.

Step 6: Deriving the Regression Equation from Coefficients

The final table, **Coefficients**, provides the specific values needed to construct the **mathematical equation** for your model. The **Unstandardized B** column contains the weights for the **intercept** (Constant), the linear term (hours), and the quadratic term (hours2). These coefficients allow us to calculate the predicted happiness level for any given number of working hours.

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-30.253	8.766		-3.451	.004
	hours	7.173	.632	4.145	11.356	.000
	hours2	-.107	.009	-4.127	-11.308	.000

a. Dependent Variable: happiness

Based on the **SPSS** output, our **regression equation** is as follows: **Estimated Happiness = -30.253 + 7.173(hours) - 0.107(hours^2)**. The negative coefficient for the squared term (-0.107) confirms that the curve is concave, meaning happiness increases to a certain point and then declines. We can use this equation for **predictive modeling**. For instance, if an individual works 30 hours, the model predicts a happiness score of 88.65. If they increase their labor to 60 hours, the predicted happiness drops significantly to 14.97.

It is also important to check the "Sig." column for each individual coefficient. In our case, both "hours" and "hours2" have **p-values** below 0.05, meaning both the linear trend and the curvature are statistically significant components of the model. This detailed level of **data interpretation** allows researchers to not only say that a relationship exists but to describe its exact shape and **inflection point**.

Reporting Quadratic Regression Results Formally

The final stage of any **statistical analysis** is documenting the findings in a clear and professional manner. When reporting **quadratic regression** results in a **thesis** or a **peer-reviewed journal**, you must include the **sample size**, the **F-test** results, the **R-squared** value, and the final equation. This ensures **transparency** and allows other researchers to replicate or verify your work.

A formal summary might read: "A quadratic regression analysis was conducted to examine the relationship between weekly work hours and happiness levels among a sample of 16 participants. The results indicated that the **quadratic model** was a significant fit for the data, $F(2, 13) = 65.095$, $p < .001$, accounting for 90.9% of the variance in happiness. Both the linear term ($\beta = 7.173$, $p <$

.001) and the quadratic term ($\beta = -0.107$, $p < .001$) were significant predictors. The **parabolic nature** of the relationship suggests that happiness peaks at a moderate level of work and declines with excessive hours."

By following these structured steps in **SPSS**, you can transform raw data into a sophisticated **statistical model**. Whether you are working in **social sciences**, **market research**, or **public health**, mastering **quadratic regression** enables you to uncover deeper insights into the **non-linear dynamics** that define our world. Remember to always validate your **statistical assumptions** and use **data visualization** to guide your analytical strategy.