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Do Simple Slopes Follow-Up Tests Lead Us Astray? Advancements in the Visualization and Reporting of Interactions

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Abstract

Statistical interactions between two continuous variables in linear regression are common in psychological science. As a follow-up analysis of how the moderator impacts the predictor-outcome relationship, researchers often use the pick-a-point simple slopes method. The simple slopes method requires researchers to make two decisions: (a) which moderator values should be used for plotting and testing simple slopes, and (b) which predictor should be considered the moderator. These decisions are meant to be driven by theory, but in practice researchers may use arbitrary conventions or theoretical reasons may not exist. Even when done thoughtfully, simple slopes analysis omits important information about the interaction. Consequently, it is problematic that the simple slopes approach is the primary basis for interpreting interactions. A more nuanced alternative is to utilize the Johnson-Neyman technique in conjunction with a regression plane depicting the interaction effect in three-dimensional space. This approach does not involve picking points but rather shows the slopes at all possible values of the predictor variables and gives both predictors equal weight instead of selecting a de facto moderator. Because this approach is complex and user-friendly implementation tools are lacking, we present a tutorial explaining the Johnson-Neyman technique and how to visualize interactions in 3-D space along with a new open-source tool that completes these procedures. We discuss how this approach facilitates interpretation and communication as well as its implications for replication efforts, transparency, and clinical applications.

Translational Abstract

Understanding how multiple factors combine to predict an outcome is an important issue in psychological research. In typical linear regression, variables are combined linearly, or additively, to optimally predict an outcome. This means that the strength and direction of the relationship between one predictor with the outcome is constant regardless of the values of the other predictors. An interaction is a special case where combining two (or more variables) *multiplicatively* does a better job of predicting the outcome than combining them linearly. That is, in an interaction involving two predictors, the strength and direction of the effects of each predictor on the outcome are different at different levels of the other predictor. Interactions are typically understood using a two-dimensional visualization approach called the simple slopes method, but this approach has limitations. It only allows researchers to pick a few levels of only one of the two predictors for examining relationships with the outcome, when in fact the interaction effect is summarizing the relationships between both predictors and the outcome across the entire range of the predictors. These limitations can lead researchers to misinterpret their results. We propose an alternative

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The data are available at https://github.com/mfinsaas/jnthreedimint/blob/master/simulateddata.final.csv.

The experiment materials are available at https://github.com/mfinsaas/jnthreedimint.

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approach that addresses these issues by presenting the interaction effect in 3-D space along with results from the Johnson-Neyman technique. Along with a tutorial for this approach, we present an open-source easy-to-use tool for conducting these procedures. We discuss how this approach facilitates interpretation and communication as well as its implications for replication efforts, transparency, and clinical applications.

Keywords: regression, interactions, moderation, Johnson-Neyman technique, replication

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Interactions occur when the relationship between a predictor and an outcome variable differs depending on the status of an additional predictor (termed the moderator). Interactions between two continuous variables are common throughout psychological science research and theory. For instance, in clinical psychology, the diathesis stress model posits that stress moderates the association between preexisting vulnerabilities and psychological disorders, such that stress precipitates psychopathology in individuals with a diathesis (left panel of Figure 1; e.g., Monroe & Simons, 1991). Similarly, problem-solving skills and emotional reactivity interact to predict suicidal behavior (Dour, Cha, & Nock, 2011). However, researchers do not simply posit that an interaction will be present, but rather test hypotheses about *how* the moderator impacts the relationship between the primary predictor and outcome variable (e.g., only those with both poor problem solving and volatile emotional reactivity engage in suicidal behaviors). An immensely helpful approach that has become the convention for exploring such questions is simple slopes analysis, which is often reported along with a plot (Aiken & West, 1991; Darlington, 1990; Friedrich, 1982). Aiken and West's (1991) book, which popularized this approach, has been cited more than 40,000 times, highlighting its widespread use. Many empirical and theoretical interpretations are based on the pattern of significance and accompanying visual depiction of simple slopes plots (Figure 1; Belsky & Pluess, 2009; Roisman et al., 2012).

Simple slopes analysis makes it easy to interpret the complex interaction by depicting its form as two or three linear slopes, which in turn facilitates succinct and straightforward communication between scientists. However, this ease of interpretation and communication comes at the cost of omitting vital information about the true nature of the interaction. Moreover, while interactions and simple slopes testing may appear straightforward, decisions made while conducting these analyses can drastically influence results and interpretation, which may have consequences for whether a article is submitted or accepted for publication. These

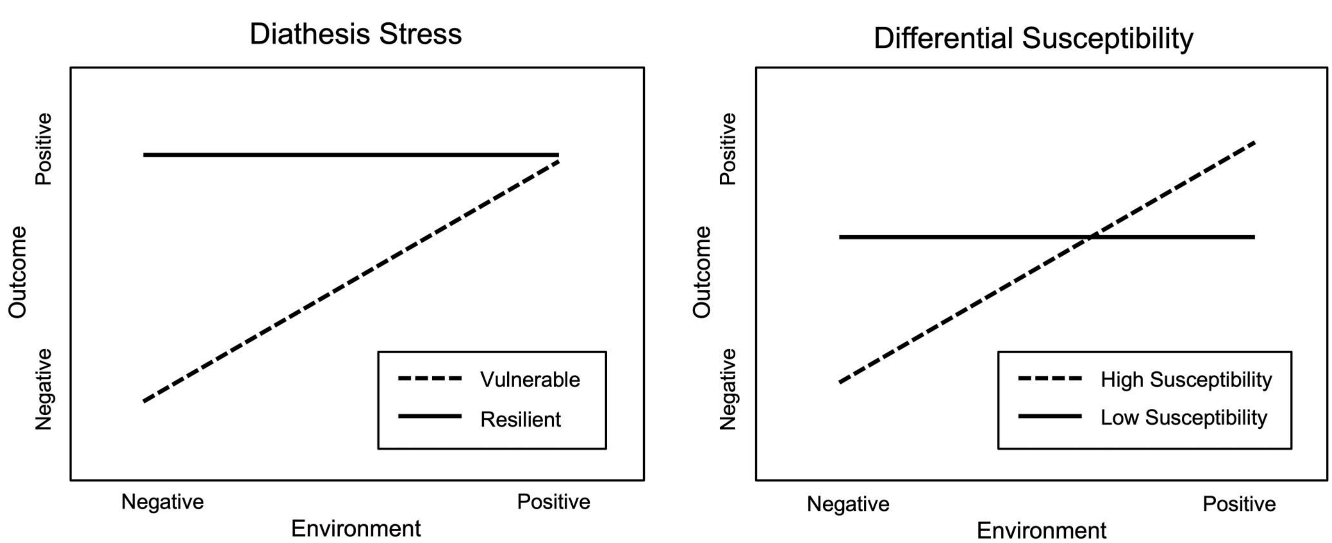

Figure 1. Visual depictions of diathesis stress and differential susceptibility models of risk for psychopathology. In clinical psychology, the diathesis stress model posits that stress moderates the association between preexisting vulnerabilities and psychological disorders, such that stress precipitates psychopathology in individuals with a diathesis. In this model, vulnerable individuals do as well as resilient individuals in positive environments. In contrast, the differential susceptibility model posits that highly susceptible individuals are more affected by negative or positive environments for worse and for better, compared to individuals low on susceptibility who have similar outcomes regardless of environmental influences. Adjudicating between these two models often depends to some degree on visualizing the effects using simple slopes plots, but these plots are determined by (1) which moderator values are used for simple slopes plotting and (2) which variable is construed as the moderator.

concerns are well documented and there is considerable interest in updating tools and best practices for reporting continuous by continuous interactions (Bauer & Curran, 2005; Cohen, Cohen, West, & Aiken, 2003; Hayes, 2013; Hayes & Montoya, 2017; Hayes & Rockwood, 2017; McCabe, Kim, & King, 2018; Miller, Stromeyer, & Schwieterman, 2013; Preacher, Curran, & Bauer, 2006).

The Johnson and Neyman (1936) technique is an alternative method for probing significant interaction terms, but visual depictions of this technique are still in their infancy. In this article, we provide an overview of the Johnson-Neyman technique and a graphical solution. Specifically, we propose plotting the form of the interaction as a regression plane in three-dimensional (3-D) space and shading the plane based on the Johnson-Neyman regions of significance. This approach more accurately represents the form of the interaction by showing the regression surface at all possible values of the predictor variables instead of simple slopes at selected points and by giving both predictors equal weight instead of selecting a de facto moderator. The 3-D plot also highlights the multiplicative form of interactions, while adding information from the Johnson-Neyman analysis facilitates interpretation and communication.

There is growing recognition in the field that we must shift away from reductive analyses toward more complex, nuanced explanations of our findings (e.g., in interpreting the statistical significance of results; Amrhein, Greenland, & McShane, 2019) and we argue that 3-D regression plots in combination with the results from the Johnson-Neyman technique achieves this for representing continuous by continuous interactions.

Therefore, the goals of this article are to: (a) increase awareness of common issues that occur when conducting the simple slopes method; (b) distill the progress made by statisticians on best practices for reporting interactions in a way that is easily accessible to both students and seasoned researchers; (c) present a tutorial for combining 3-D interaction plots with the Johnson-Neyman technique as an alternative visualization approach that addresses problems in conducting follow-up tests of continuous by continuous interactions; and (d) provide a user-friendly open-source tool for implementing this type of visualization. Our examples will draw primarily on clinical science, but the need to update reporting of continuous by continuous interactions is relevant across psychological science.

The Regression Formula and Follow-Up With Simple Slopes

The multiple regression formula with two interacting predictors is as follows:

$$Y = b_0 + b_1(X) + b_2(Z) + b_3(X)(Z) + e$$

In order to understand this equation, we first define each term. Y is the outcome variable and X and Z are the continuous predictors. b_1 and b_2 refer to the coefficients representing the magnitude or slope of the relationship between X and Z, respectively, with the outcome Y. b_3 refers to the coefficient representing the magnitude of the interaction effect. Lastly, b_0 refers to the intercept, or a constant that indicates the value of Y when both the X and Z variables are zero. The e refers to an error term which denotes the difference between observed and predicted scores for individual cases. Because the interaction term (b_3) alone does not clearly convey information about the effect, researchers often rely on the simple slopes approach for interpretation (e.g., Aiken & West, 1991; Bauer & Curran, 2005; Cohen et al., 2003; Friedrich, 1982; Hayes, 2013; McCabe et al., 2018; Preacher et al., 2006). In this approach, the slope of the relationship between the predictor (X) and outcome (Y) is plotted at specific conditional values of the moderator (Z; examples of equations in Table 1). Researchers will typically graph two or three simple slopes and report whether the magnitude of the slopes significantly differ from zero.

Two Critical Decisions and Potential Problems for Researchers Using Simple Slopes

Researcher must make two critical decisions in simple slopes analysis: (a) which moderator values should be used for plotting the simple slopes, and (b) which predictor should be considered the moderator. We now describe how these two decisions can drastically impact results and interpretation of the interaction.

Critical Decision #1: What Values to Select for the Moderator?

The first decision is selecting values for the moderator. In statistical references (Bauer & Curran, 2005; Hayes, 2013), researchers are advised to identify meaningful conditional moderator values. However, most researchers solve simple slopes at the mean and 1 *SD*

Table 1
Solving a Simple Slope at a Value of 1 for the Moderator

Steps	Generic process for solving simples slopes when the moderator (Z) =1	An example regression equation solved when the moderator (Z) is = 1
General equation	$Y = b_0 + b_1(X) + b_2(Z) + b_3(X)(Z)$	$Y = 3 + 1.5(X) + 2(Z) + 2(X)(Z)$
1. Plug in moderator value	$Y = b_0 + b_1(X) + b_2(1) + b_3(X)(1)$	$Y = 3 + 1.5(X) + 2(1) + 2(X)(1)$
2. Simplify with algebra	$Y = b_0 + b_1(X) + b_2 + b_3(X)$	$Y = 3 + 1.5(X) + 2 + 2(X)$
3. Rearrange terms	$Y = b_0 + b_2 + [b_1 + b_3(X)]$	$Y = 3 + 2 + 1.5(X) + 2(X)$
4. Simplify with algebra	$Y = b_{0+2} + b_{1+3}(X)$	$Y = 5 + 3.5(X)$

Note. For this example, the simple slope is solved at a value of 1 for the moderator (Z). The first step is to fill in a value of 1 for all instances of the moderator (Z) in the standard regression. In the next steps, the coefficients are rearranged and summed using simple algebra. Because the b_0 and b_2 coefficients are constants, they can be added together. Similarly, b_1 and b_3 are both constants that are multiplied with the X variable allowing for them to also be summed.

above and below the mean. While this is the convention in the literature, it may in fact impede interpretation and replication efforts.

For starters, slopes at 1 *SD* below the mean and 1 *SD* above the mean are typically referred to as "low" and "high." These labels can be misleading, as the corresponding values may not in fact represent meaningfully "low" and "high" values. This is especially true when dealing with naturally skewed predictors (e.g., psychological symptoms). Figure 2 shows two examples of this problem. Imagine a scenario where a simple slope is significant at 1 *SD* above the mean on a depression symptom measure. The left panel of Figure 2 shows a hypothetical distribution of depression data, which shows that 1 *SD above* the mean falls in a subclinical range. A researcher who uses the typical conventions for simple slopes may summarize their effect as occurring at "high" levels of depression symptoms, when in fact 1 *SD* above the mean in their sample reflects a modest level of depression symptoms. The effect in this example can be more accurately described as significant at subclinical, rather than "high," levels of depression. When skew is even more exaggerated, 1 *SD* above or below the mean may not even include any observed data from a sample (Bauer & Curran, 2005); we depict this phenomenon in the right panel of Figure 2.

An additional problem with using labels like "low" and "high" occurs when considering replication. Imagine a situation in which an interaction effect is present only at "high" values in an impoverished sample but at "low" values in an affluent sample. Is this a replication? It is difficult to determine without knowing the absolute levels of the moderator and how those levels compare across the two samples. That is, the "high" value in the impoverished sample may be equal to the "low" value in the affluent sample in an absolute sense, but this is obscured by the use of low/high labels. While this issue is related to a broader problem concerning differences in the observed range of scores across samples, it is compounded by the practice of selecting moderator values based on conventions from the literature and using group-like labels of high, medium, and low to describe those values. In the worst-case scenario, researchers who follow this convention may be susceptible to misinterpreting their results. For instance, a researcher who finds that the simple slopes at conventional moderator values are not significant may conclude that a hypothesized effect is not supported. However, the effect may have been present at 1.1 or 1.2 *SD* above the mean, which would render their conclusion from the conventional simple slopes analysis incorrect.

In sum, Critical Decision #1—which moderator values to select for plotting simple slopes—is problematic because researchers often rely on the conventional conditional values of −1 *SD*, the mean, and +1 *SD* and discuss them as representing "low," "medium," and "high" values, which can be misleading labels and obscure how results appear to generalize from one sample to another. Moreover, regardless of the specific conditional values selected or the language used to discuss results, simple slopes plots set at specific conditional values can only represent a segment of the interaction effect, and whether the slopes are significant at these few arbitrary moderator values can unduly influence researchers' conclusions.

Critical Decision #2: Which Predictor Is the Moderator?

The second critical decision is choosing the variable that should be viewed as the moderator, which can have unintended consequences for how interactions are interpreted (Berry, Golder, &

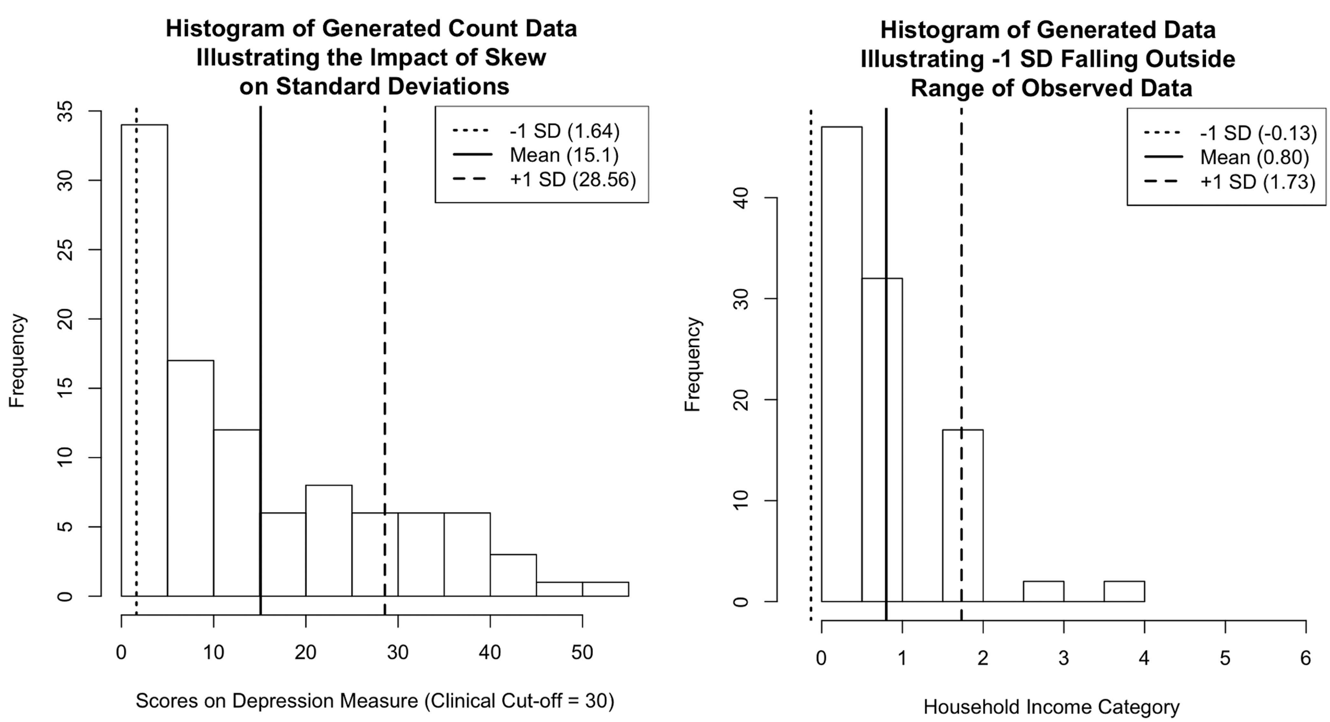

Figure 2. Histograms of generated count data illustrating the impact of skew on standard deviations. *SD* = standard deviation.

Milton, 2012). Bauer and Curran (2005) note that determining which predictor is the moderator should be based on theory because there are no mathematical differences between the X and the Z variables. In some cases, this can be challenging. Take for example the classic observation that an interaction characterized by neuroticism and extraversion is associated with depression (Gershuny & Sher, 1998); in this case, either variable could be the moderator.

However, even when there is a theoretical basis for moderator selection, we argue that focusing on the effects of both variables simultaneously facilitates more accurate interpretations of the interaction term. Misinterpretation can occur when the statistical term "moderate," which refers to combining one variable with another in a nonlinear way to predict an outcome, is used in conceptual discussions of results in ways that imply causality. For example, in the statement, "Genetic risk moderates the impact of life stress on anxiety," the word "moderates" is problematic because genetic risk cannot "physically act" on life stress (Thomas & Sharp, 2019). Another manner in which causality is implied is when researchers discuss the impact of "change" in levels of the moderator. This can give the impression that the moderator is changing within individuals, which in reality can only be tested experimentally. Instead, because the interaction term is at the between-persons level, change in this context refers to different moderator levels across people in the sample. This does not mean that theory may not suppose that one factor acts on another, or that researchers should not design studies to test causality, only that representing and discussing the moderating effects of one variable may lead to misinterpretation of statistical interactions as implying causality.

Moreover, even if researchers are careful to avoid causal inferences, the model is agnostic to which variable is affecting the other, so plotting one variable as the moderator is only partially true; the moderator variable may also have different relationships with the outcome depending on levels of the predictor. Using the example above, a significant interaction may mean that life stress and anxiety are positively related at higher as opposed to lower levels of genetic risk, which may fit with a theoretical notion. However, depending on the form of the interaction, it could be equally valid that at higher as opposed to lower levels of life stress genetic risk and anxiety are positively related.

Designating only one variable as the moderator also determines which simple slopes will be solved and can influence the number of simple slopes that are statistically significant. Figure 3 shows this phenomenon with an example of a single interaction term predicting depression with one plot depicting neuroticism as the moderator and the other depicting life stress as the moderator. That the plots can appear different depending on moderator selection is an especially important consideration for areas of research that hypothesize a particular pattern of the simple slopes as in diathesis-stress and differential susceptibility models (Figure 1; Belsky & Pluess, 2009; Monroe & Simons, 1991). Research areas that emphasize the shape of interactions often focus on where simple slope lines cross one another (the crossover point; Cohen et al., 2003; McCabe et al., 2018; Roisman et al., 2012). When using simple slopes of the relationship between outcome (Y) on predictor (X), the crossover point is tested by taking regression weights into the following formula:

$$X_{cross} = -b_2/b_3$$

This equation highlights that the crossover point is influenced by which variable is considered the moderator (the variable linked to coefficient b_2). Indeed, Cohen, Cohen, West, and Aiken (2003) note that a second crossover point can always be calculated for any interaction through a second equation:

$$Z_{cross} = -b_1/b_3$$

In other words, if one switches perspectives and uses the primary predictor's regression coefficient as the numerator, effectively treating it as a moderator, it produces a different crossover point. The left and right plots in Figure 3 show how the crossover point moves. While a researcher examining crossover points will likely have reasons for looking at one crossover point over the other, if the other exists within the range of data, representing both may be truer to the interaction form. We note that the crossover point is a single point estimate, which is simply the moderator value that corresponds to when the slope of the relationship between the other predictor and the outcome equals 0, and that researchers should consequently be cautious about weighting this specific value too heavily.[1]

In sum, we have shown how researchers must make two critical decisions when reporting simple slopes for interactions—which moderator values to use for plotting and which predictor should function as the moderator—and how these decisions influence results and their interpretation. These decisions are sometimes made arbitrarily, and even when made based on substantive reasoning, lead to a reductive representation of the interaction and cause more than cosmetic problems related to figures. Thus, the field's reliance on simple slopes analysis and visualization for understanding interactions is a problem.

We offer a solution to this problem that combines the Johnson-Neyman technique with 3-D regression planes. The Johnson-Neyman technique (Bauer & Curran, 2005; Johnson & Neyman, 1936) eliminates the need to pick values of the moderator (Critical Decision #1), and visualizing the interaction using a 3-D regression plane eliminates the need to select one variable as the moderator (Critical Decision #2). Plotting interactions in 3-D is a technique that has been used occasionally for many decades (e.g., Cohen et al., 2003; Saunders, 1956). We are the first to propose combining 3-D plots with results from the Johnson-Neyman technique.

To illustrate our visualization technique, we continue to use a straightforward example of the diathesis stress model (Figure 3), where the interactive effect of the personality trait neuroticism and stressful life events is associated with depressive symptoms. This example was derived using an artificially created dataset, and simple slopes and marginal effects plots were created using the *interactions* package (Long, 2019). Table 2 contains descriptive statistics and the regression equation, simple slopes, and Johnson-Neyman results.

[1] Several methods for calculating a confidence interval around this value have been proposed (e.g., Lee, Lei, & Brody, 2015; Widaman et al., 2012). A common aim for examining the crossover point seems to be for distinguishing between ordinal and disordinal interactions, in which case, a sample size of at least 500 appears necessary.

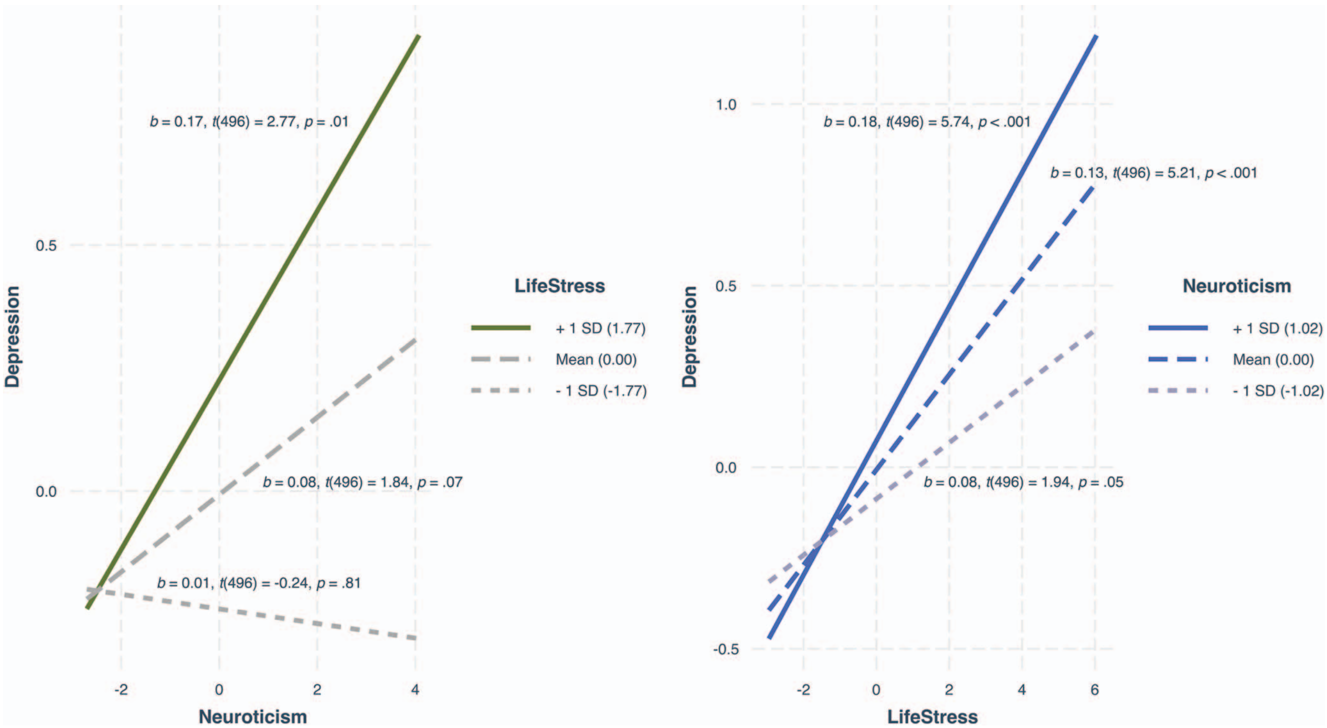

Figure 3. Conventional simple slopes plots of the interaction between life stress and neuroticism predicting depression with both predictors acting as the moderator. The plot on the left depicts simple slopes when life stress is acting as the moderator; the slope of the green line (or solid line) is significantly different from zero whereas the gray (or dashed) lines are not. The crossover point is located where the three lines intersect where neuroticism equals −2.49. The plot on the right depicts simples slopes when neuroticism is acting as the moderator; the slopes of the two blue lines (or solid and long-dashed lines) are significantly different from zero and the crossover point is located where life stress equals −1.49. *SD* = standard deviation. See the online article for the color version of this figure.

Solving Critical Decision #1: The Johnson-Neyman Technique

Formally, the Johnson and Neyman (1936) technique[2] finds the exact two points along the moderator (Z) where the relationship between the primary predictor variable (X) and the outcome (Y) transitions from zero to significantly different from zero, or the other way around (from nonzero to zero). These moderator values are of interest because they can then be used to infer the significance of the simple slopes for the entire range of moderator values; that is, they demarcate the region of significance, or the moderator values that correspond to slope coefficients that are significant at $p < .05$. In the same way that researchers must be cautious when interpreting predictions from linear regression models outside of the range of observed data, we recommend only interpreting Johnson-Neyman bounds that fall within this range and defining the other bound by the minimum or maximum of the data as needed. Several Johnson-Neyman regions of significance patterns are possible and are depicted in Figure 4. While the Johnson-Neyman test always finds two values of the moderator, in some cases, only one region of significance may be observed within the range of scores for the sample (i.e., one of the JN values is above the maximum or below the minimum values of observed data). When both of the moderator values are within the range of observed scores, the interaction can be said to comprise two regions of significance. The clear advantage of the Johnson-Neyman technique is that researchers do not need to pick a small number of moderator values to solve for simple slopes; instead, they have complete information about how the predictor-outcome slopes vary across the full range of the moderator. The researcher no longer asks *whether* a selected slope will be significant, but instead *which* moderator values correspond to significant simple slopes (Spiller, Fitzsimons, Lynch, & McClelland, 2013).

Results from Johnson-Neyman analyses can be depicted graphically in what is termed a marginal-effects or regions of significance plot, as shown in Figure 5 (Bauer & Curran, 2005; Hayes, 2013; McCabe et al., 2018; Miller et al., 2013). Note that the moderator is on the X-axis and the conditional effect of the predictor on the outcome is on the Y-axis. This is in contrast to simple slopes plots, which depict the primary predictor on the X-axis and the outcome variable on the Y-axis. Said another way,

[2] Historically, the Johnson-Neyman technique was developed in the context of analysis of covariance (ANCOVA), in which an interaction is formed between one dichotomous (or group variable) and one continuous variable. It was later expanded by Bauer and Curran (2005) so that it can be used with interactions between two continuous variables (see also Hayes, 2013; Hayes & Rockwood, 2017).

Table 2
Summary of Neuroticism by Life Stress Interaction Predicting Depression

Variable	*M*	*SD*		Range
Neuroticism	0.00	1.02		−2.70 to 4.08
Life stress	0.00	1.77		−2.95 to 6.05
Depression	0.00	1.01		−2.85 to 3.56
Regression results	Estimate	*SE*	*t*	*p*
Intercept	−0.01	0.04	−0.16	.87
Neuroticism	0.08	0.04	1.84	.07
Life stress	0.13	0.03	5.21	<.001
Neuroticism × Life Stress	0.05	0.03	2.05	.04
Simple slopes and Johnson-Neyman equations				
Neuroticism as the moderator				
−1 *SD**				Depression = −0.09 + (0.08)(Life stress)
*M**				Depression = −0.01 + (0.17)(Life stress)
1 *SD*				Depression = .07 + (0.18)(Life stress)
Johnson-Neyman value (−1.01)*				Depression = −0.09 + (0.08)(Life stress)
Life stress as the moderator				
−1 *SD*				Depression = −0.24 − (0.01)(Neuroticism)
M				Depression = −0.01 + (0.08)(Neuroticism)
1 *SD**				Depression = .22 + (0.17)(Neuroticism)
Johnson-Neyman value (0.11)*				Depression = .004 + (0.09)(Neuroticism)

* Slope coefficient is significant at $p < .05$.

in marginal effects plots, the Y-axis is showing the strength of the relationship between Y and X as opposed to predicted values of Y. The line thus represents a series of slope estimates across the range of the moderating variable. It also includes a confidence band to convey the degree of accuracy of the slope estimates (Bauer & Curran, 2005; Hayes, 2013). The points at which the confidence band crosses zero demarcates the regions of significance. Unfortunately, a recent article found that marginal effects plots are rarely used (McCabe et al., 2018). There are also ways in which visualizing the Johnson-Neyman technique can go awry; some articles feature figures where the Johnson-Neyman values are superimposed as vertical lines on top of a simple slopes plot, which is often problematic when examining continuous by continuous interactions (see Appendix A for details).

To further illustrate how simple slopes analysis and the Johnson-Neyman technique are related, Figure 6 presents a plot that depicts slopes at conventional values and at the bounds of the Johnson-Neyman region of significance. Figure 6 also includes a table with selected slope coefficients across the range of the moderator. It can be seen that the slope coefficient is significant

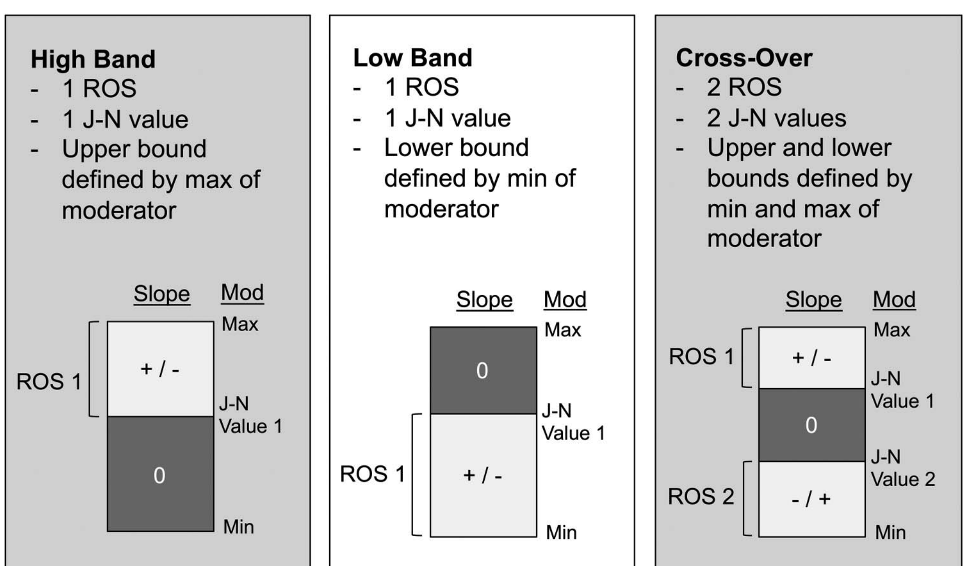

Figure 4. Johnson-Neyman patterns. J-N = Johnson-Neyman; ROS = region of significance; Min = minimum; Max = maximum.

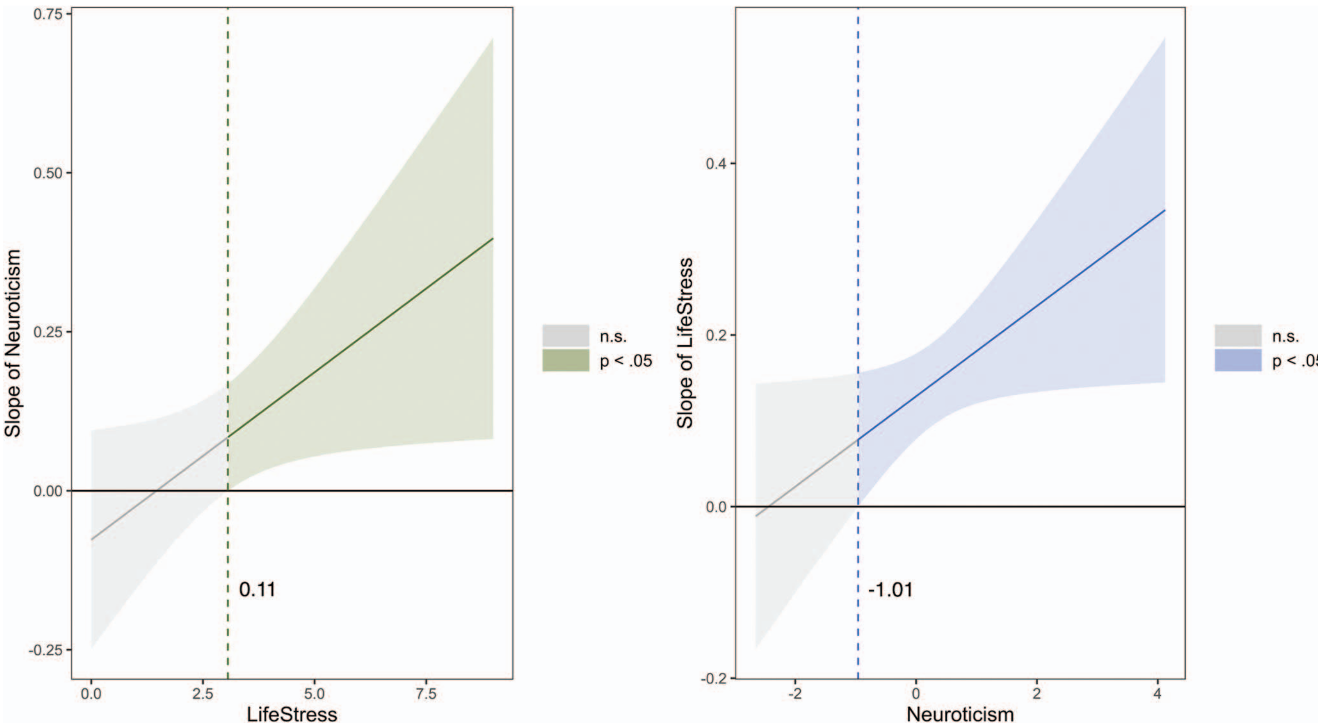

Figure 5. Johnson-Neyman marginal effects or regions of significance plots of the interaction between life stress and neuroticism predicting depression with each predictor acting as the moderator. The left plot depicts the region of significance when life stress is acting as the moderator, and the right when neuroticism is acting as the moderator. The lines represent slope coefficients across values of the moderators. The darker shaded regions represent the region of significance, or range of moderator values when the slope between the predictor and outcome is significantly different from zero. The shaded regions on either side of the line represent the 95% confidence interval around the slope terms. The vertical dashed lines are the Johnson-Neman values, or the points on the moderator at which the confidence intervals no longer cross zero, indicating the slopes here are significantly non-zero. See the online article for the color version of this figure.

when the moderator is slightly above its mean, but not at the mean itself; if a researcher were to use conventional simple slopes plotting, he or she may conclude that effects are significant at only "high" levels of stress, whereas the Johnson-Neyman analysis shows that slopes reach statistical significance very close to the average for this sample. This example also demonstrates how much information is lost about slopes across the full range of the moderator in simple slopes analysis.

Knowing the values and significance of the slope estimates at all levels of the moderator is particularly important in light of the recent commentary in *Nature*, signed by more than 800 psychologists, which warns against discussing "significant" and "nonsignificant" results as categorically different (Amrhein et al., 2019). Unfortunately, the results of simple slopes tests are particularly prone to being interpreted in this way, because they break down a continuous variable into a dichotomous or categorical form. Researchers employing simple slopes testing also rarely focus on the slope estimates themselves and instead heavily interpret whether the effect is significant or not at low, average, and high levels.

However, it is also important to note that the Johnson-Neyman test is not entirely free from the pitfalls of significance testing because the bounds of the regions of significance are based on when p is $<.05$. The specific moderator values at these bounds are also prone to being overvalued in the same way that the significance of simple slopes are overvalued, when in fact, they are just the values that happen to correspond to significant slopes. Moreover, like all confidence intervals, the confidence bands from the Johnson-Neyman analysis reflect reliability in the estimates, which means that the bounds are dependent on sample size (Dawson, 2014). Larger samples produce more reliable slope estimates and smaller confidence bands, which in turn influences the point at which the confidence bands cross zero, or where the region of significance begins or ends. Finally, the Johnson-Neyman is a form of simultaneous inference testing, meaning that multiple significance tests are performed at once, which can increase Type I error rates (Bauer & Curran, 2005; Esarey & Sumner, 2018; conventional simple slopes testing also requires multiple tests but error rates are rarely adjusted in this context). To mitigate these issues, researchers should avoid weighting the exact Johnson-Neyman bound values too heavily. Instead, we recommend focusing on the magnitude of the slope estimates, which are not affected by sample size, especially when comparing across studies. Additionally, researchers may consider implementing a correction to the Johnson-Neyman to control the false discovery rate, although they should be aware these procedures are continually developing and not without their own limitations (Esarey & Sumner, 2018).

J-N Region of Significance

	Mod Value *Life Stress*	Slope *Depression ~ Neuroticism*	*p*
	-2.95	-0.08	.38
	-2.50	-0.05	.49
	-2.05	-0.03	.67
SS: -1 SD	**-1.77**	**-0.01**	**.81**
	-1.60	-0.01	.92
	-1.15	0.02	.73
	-0.70	0.04	.37
	-0.25	0.07	.13
SS: Mean	**0.00**	**0.08**	**.07**
J-N: LB	**0.11**	**0.08**	**.05**
	0.20	0.09	.04
	0.65	0.11	.01
	1.10	0.14	.01
	1.55	0.16	.01
SS: + 1 SD	**1.77**	**0.17**	**.01**
	2.00	0.18	.01
	2.45	0.21	.01
	2.90	0.23	.01
	3.35	0.26	.01
	3.80	0.28	.01
	4.25	0.30	.01
	4.70	0.33	.01
	5.15	0.35	.01
	5.60	0.37	.01
J-N: UB	**6.05**	**0.40**	**.01**

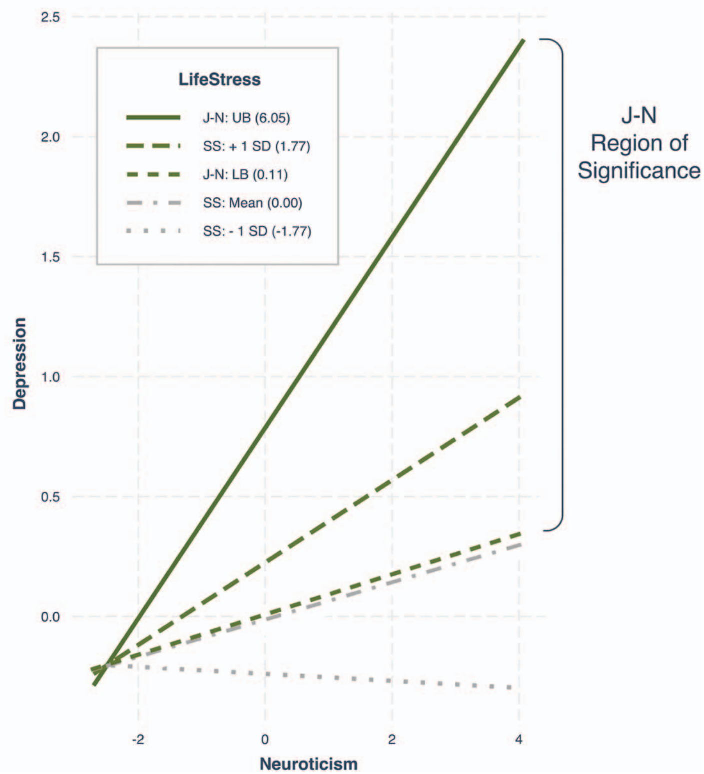

Figure 6. Relating results from conventional simple slopes analysis and the Johnson-Neyman technique when life stress is acting as the moderator of the relationship between neuroticism and depression. J-N = Johnson-Neyman; LB = lower bound of region of significance; UB = upper bound of region of significance; SS = simple slope; *SD* = standard deviation. See the online article for the color version of this figure.

If researchers are aware of the above limitations, the Johnson-Neyman still provides substantive interpretive value compared to simple slopes, despite its tie to significance testing (Dawson, 2014; Spiller et al., 2013). Indeed, in most cases and especially when specific moderator values are not hypothesized to be of interest, researchers are increasingly encouraged to use the Johnson-Neyman approach over simple slopes (Spiller et al., 2013). Its main advantage is that it improves researchers' ability to interpret the interaction by providing a more complete impression of how the conditional effect of the moderator influences the strength of the relationship between the outcome variable and primary predictor. It is also notable that confidence bands can be computed for the entire range of the moderator in the Johnson-Neyman approach, including but even beyond the region of significance. With this information, along with the slope estimate itself, researchers are able to interpret the meaning of the effect at the point estimate, as well as at the low and high ends of the confidence band, in line with recent recommendations for discussing results (Amrhein et al., 2019). Simple slopes analyses would only permit interpretation in this manner at a few values of the moderator. In these ways, the Johnson-Neyman facilitates tests of more specific interaction hypotheses, as advocated by Widaman et al. (2012), which are superior for confirming or disconfirming theoretical predictions.

Solving Critical Decision #2: 3-D Regression Plane

One solution for determining which variable to select as the moderator is to place both variables on equal footing. Earlier we defined an interaction as situations where the relationship between one predictor and an outcome variable differs depending on the status of an additional predictor termed the moderator. An equally valid description of an interaction in linear regression is that two predictors combine multiplicatively to affect a third outcome variable, which is a deviation from the typical linear combination (Cohen et al., 2003). The difference between these descriptions is not simply semantic as the second definition emphasizes that interacting variables are on equal footing (as opposed to construing one as the primary predictor), which avoids arbitrarily selecting one as the moderator. It also emphasizes that the combination of these variables is a nonlinear multiplicative effect. While regression equations are often discussed colloquially as forming a "regression line," this does not apply to regressions that contain interactions. Instead, interactions form a curved plane in 3-D space (see Cohen et al., 2003). Unfortunately, the curved plane that characterizes interactions is lost when graphing simple slopes in two dimensions. 3-D regression planes, in contrast, can be used to depict the joint prediction of an outcome by two predictors (see Appendix B for details).

To begin to illustrate how continuous by continuous interactions always form a curved plane in 3-D space, we first show an example that does *not* include a significant interaction term in two-dimensional (2-D) and 3-D space (see Figure 7). The equation for this model is Depression = 0 + 0.08(Neuroticism) + 0.14(Life Stress). The left regression line shows that a one-unit increase in neuroticism is associated with a 0.08 increase in depression, and the right that a one-unit change in life stress is associated with a 0.14 unit increase. The 3-D plane shows that a joint one-unit change in neuroticism and in life stress is associated with a 0.22 increase in depression (0.08 from neuroticism plus 0.14 from life stress). Because there is no interaction term, the predictors are combined linearly or additively and the plane is flat in 3-D space. In other words, the magnitude of the increase in depression given some increase in one predictor is not dependent on the level of the other predictor.

In contrast to the flat regression plane in 3-D space from a model without an interaction term, Figure 8 depicts a plane from a model that *does* include an interaction term. The curved nature of the plane reveals how change in depression is nonlinear, or multiplicative, and depends on the levels of both predictors. In other words, depression symptoms increase more rapidly at higher values of both neuroticism and life stress. For example, when neuroticism increases from 3 to 4 and stress simultaneously increases from 5 to 6, the increase in depression symptoms is 0.68, whereas the same one unit increase in neuroticism and stress from 0 to 1 corresponds to a 0.26 increase.

A 3-D plot is also useful for examining raw data and determining where cases actually fall along the regression plane. The reason 3-D plots are useful for this purpose is because each participant included in the regression model has three data points: one value for the outcome variable, Y, and one value for each of the predictors, X and Z. Researchers who examine these plots can quickly see whether the majority of the cases fall in particular corners of the 3-D plane or whether other areas on the plane are sparsely represented within the sample. The 3-D plot may also help to visualize multivariate outliers, as cases with extreme scores on X, Z, and Y are easy to identify. Additionally, the distribution of data

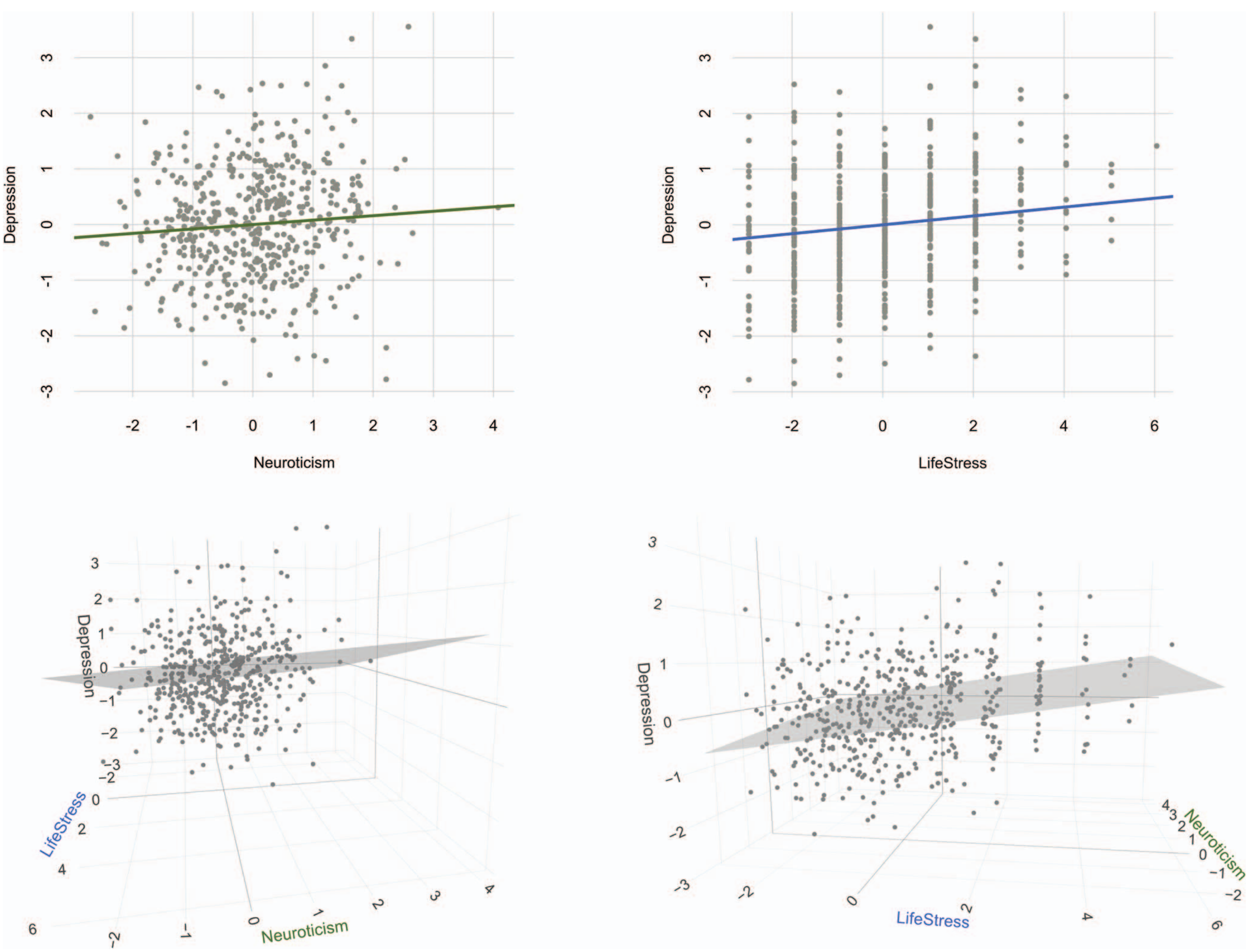

Figure 7. 2-D regression lines and 3-D regression plane for model without an interaction term. The live rotatable version of the 3-D plot can be accessed at http://rpubs.com/sbu_mfinsaas/Figure7/. See the online article for the color version of this figure.

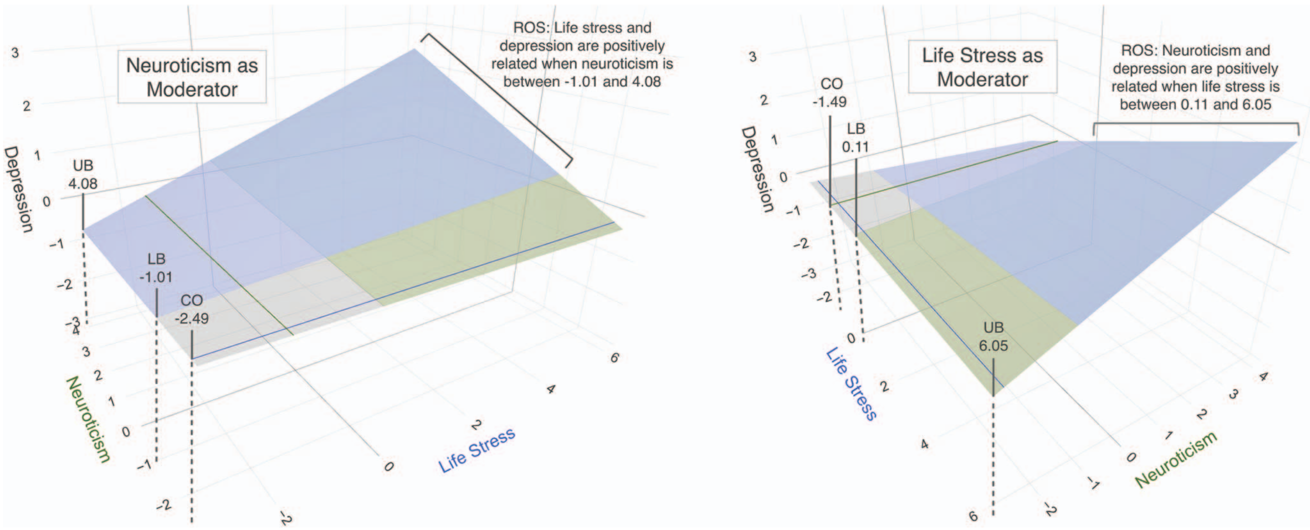

Figure 8. 3-D regression plane for model with significant interaction term in two rotations with Johnson-Neyman overlay. The rotation on the left depicts life stress as the primary predictor and neuroticism as the moderator. The green line denotes the crossover point (life stress = −1.49). We encourage readers to access the live rotatable version of this plot at http://rpubs.com/sbu_mfinsaas/Figure8. ROS = region of significance; UB = upper bound; LB = lower bound; CO = crossover point. See the online article for the color version of this figure.

on the X and Z plane is particularly of interest as these data correspond to the strength of the correlation between the predictor variables. The commonly used 2-D simple slope plot cannot adequately capture raw data as they do not include an axis for the moderator. In other words, 2-D plots cannot easily convey how the X and Z values cluster together.

In sum, using a 3-D plot allows researchers to avoid arbitrarily selecting one variable as the moderator since rotating the plot allows each predictor to be construed as a moderator. Moreover, a 3-D plot best illustrates the inherently multiplicative nature of interactions by showing how the changes that occur in the outcome variable are nonlinear.

A Tool Combining the 3-D Plane With Johnson-Neyman Results

We have made the case that the Johnson-Neyman technique and 3-D plots can address both of the critical decisions that can cause biases in presenting interactions. We now present a new visualization technique that combines these two approaches by shading the region(s) of significance defined by the Johnson-Neyman technique on a 3-D regression plane. Adding information about the interaction from the Johnson-Neyman analysis facilitates interpretation and communication about the 3-D form which can otherwise be somewhat difficult. We first describe the various features of a web-based utility for implementing this approach. Subsequently, we describe an example of figures and results generated from the website. In Appendix C, we provide detailed step-by-step directions for using the website to plot the simulated data used throughout this article.

The web-based tool we developed for visualizing interactions in this way can be accessed at http://3Dinteractions.com/. The tool was created using R (R Core Team, 2016) in the Shiny framework (Chang, Cheng, Allaire, Xie, & McPherson, 2017), and the 3-D plotting was done using the *plotly* package (Sievert et al., 2017). The Johnson-Neyman analysis was conducted using the *interactions* package (Long, 2019). To use the tool, researchers must first upload a data file by clicking the browse button. This data file must have unique variable names at the top of the file, should not contain missing data indicators (but blanks are okay; the program handles missing data using listwise deletion based on variables in the model), and can be a comma-separated (.csv), or SPSS (.sav) file. All variables in the model must be numeric. When the file has been properly uploaded, the dropdown menus for the predictors and outcome will automatically populate with the variable names in the file. The user then specifies the variables that act as the predictors in the interaction term and the outcome by clicking the dropdowns and locating the variables in the list. Alternatively, the user can delete "–" and type in the variable names. The radio buttons "Center," "Standardize," and "Raw" allow the user to transform these variables. The user can also input covariates, which are always centered at their means.

Researchers also have the option to input parameter estimates and asymptotic covariances obtained from another statistical software program, which is a good option for researchers who use structural equation modeling software to handle missing data or to examine interactions of latent variables or utilize robust standard errors.

When the "Run/Update" button is clicked, the 3-D plot of the interaction regression plane will be rendered. Any output from the Johnson-Neyman analysis and crossover points for each of the predictors acting as moderators will appear on the right side of the screen. When a region of significance falls within the observed data, the Johnson-Neyman output will include the values on the moderator that mark the bounds of the region of significance, the range of slope estimates for the predictor-outcome relationship and the percentage of cases within this region, and the observed range of the moderator variable. This output is written using the names of the variables in order to aid the user in understanding the figure.

At this point, the user will see additional checkboxes appear next to the plot. For all models using the raw data upload option, the checkboxes for the regression plane, scatterplot, and 95% confidence interval around the predicted values will appear. The user can add or take away these features on the plot by clicking the checkboxes. The 95% confidence intervals are produced using the *stats* package (R Core Team, 2016) and will appear as semi-opaque planes floating above and below the regression plane.

Which other checkboxes appear below these depend on whether the interaction term is significant and whether there are regions of significance or crossover points for either predictor that fall within the observed range of data. If the interaction is significant, and a region of significance falls within the range of data, the option to shade the region of significance on the regression plane will appear. Selecting the "Solid ROS" button will shade the region of significance on the plot in one color; selecting the "Gradient ROS" button will shade the region using a gradient that reflects the width of the 95% confidence band around the slope estimate; and selecting the "Gradient All" option will shade the entire regression plane according to the confidence bands. Finally, if a crossover point falls within the range of data, an additional checkbox ("Crossover") will appear; checking this box will add the crossover point to the figure.

In addition to the primary output, the program outputs marginal effects plots and a table containing the slope estimates and their corresponding 95% confidence bands and *p*-values at all values of the moderator, found under the "Johnson-Neyman" navigational tab. A researcher who is interested in the bounds of the Johnson-Neyman region of significance regardless of whether they fall within the range of observed data can also find these values next to the marginal effects plots. Finally, the user can view descriptive statistics and raw data under the respective tabs.

Example of a 3-D Plot and Johnson-Neyman Results

Figure 8 depicts a 3-D regression plane for the interaction between neuroticism and life stress predicting depression with both regions of significance shaded on the plane and both crossover points depicted as simple slopes. The reader can access the live version of the plot at http://rpubs.com/sbu_mfinsaas/Figure8, which can be rotated by clicking the mouse on the plot and dragging in any direction. Researchers can use different rotations of these plots to understand and show how each variable can be treated as the moderator, while at the same time highlighting the fact that the interaction term reflects the relationship with the predictor across changes in both variables. Specifically, the variable on the X-axis in a given rotation can be thought of as the focal predictor and the variable providing the depth to the plot on the Z-axis can be thought of as the moderator.

In Figure 8, the left plot depicts neuroticism as the moderator. The shaded blue region denotes the region of significance; between the lower bound value of -1.01 and upper bound value of 4.08 on neuroticism (the maximum value in the dataset), the relationship between life stress (the primary predictor in this rotation) and depression is significantly positive at $p < .05$. The blue line at -2.49 on neuroticism indicates the crossover point, or the point on neuroticism where the slopes between life stress and depression shift from positive to negative. The right plot depicts the same interaction with life stress acting as the moderator. Note that in this rotation, when moving "toward" the viewer along the depth of the moderator, values go from low to high. The shaded green region denotes the region of significance, which falls between the lower bound value of 0.11 and upper bound value of 6.05 on life stress (maximum of life stress in the dataset). Between these values, the relationship between neuroticism and depression is significantly positive. The crossover point, depicted as a green line, falls where life stress equals -1.49. In conclusion, stress and neuroticism interact synergistically to predict depression; the relationship between stress and depression becomes increasingly positive at higher levels of neuroticism, as does the relationship between neuroticism and depression at higher levels of stress.

Figure 9 relates the 3-D Johnson-Neyman interaction plane plot to a conventional simple slopes plot. It illustrates how simple slopes appear in 3-D space and how they depict only a narrow slice of the regression plane.

Because the 3-D plots can be difficult to digest at first, we encourage readers to follow the steps in Appendix C for producing and interpreting the plot with the simulated data, used throughout this article and available at https://github.com/mfinsaas/jnthreedimint, and also to upload their own data and visualize an interaction with which they are already familiar following these same steps.

To increase the user-friendliness of the program, we also outline three suitable approaches for sharing and saving the figures here. The most straightforward but somewhat limited approach is to use a built-in screen grab function to take still snapshots of the figure in various rotations (i.e., PrtScn on Windows; Shift + Command + 4 on Macs). The next most straightforward approach is to use built-in or add-on video capture functions to record the screen while manually rotating the plot; we recommend clicking and dragging above the plot, outside of the portion of the screen that is being recorded, so that the mouse pointer is not in the recording. Images or recordings created using these methods can then be saved to a hard drive or stored online (e.g., using Dropbox, Google Drive). Storing the figures online also allows the user to link to them in journal submissions. The final approach results in a "live" rotatable version of the plot with a permanent link, which is currently only available when raw data are uploaded. It involves four steps: (a) downloading R (https://www.r-project.org/) and RStudio (https://www.rstudio.com/), which are both free programs; (b) running the function code linked to under the "Code for Live Plots" tab on the Shiny app in the RStudio console; (c) running the input code, also linked to in the "Code for Live Plots" tab, in the RStudio console, with the arguments set according to user preference; and (d) clicking the blue "Publish" icon in the RStudio viewer and following the steps to publish to the free service RPubs (http://rpubs.com/). This approach is viable because RStudio supports online publication directly from its viewer window, whereas this action is not supported directly from Shiny apps.

As a brief technical overview, the tool produces the plot by dividing the predictors into 100 equally spaced cells and adding the Johnson-Neyman bounds to these vectors (if they fall within the range of observed data). These vectors are then entered into the

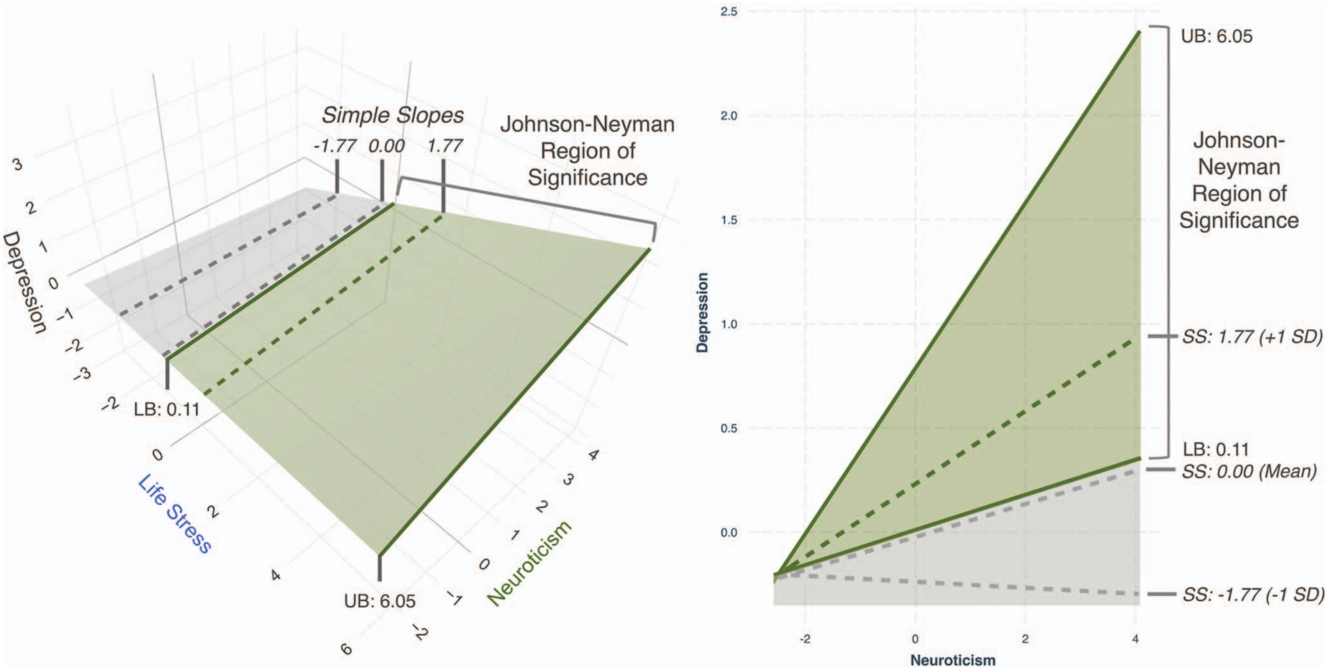

Figure 9. Relating 3-D interaction plot with Johnson-Neyman region of significance overlay to conventional simple slopes plot. On both plots, solid lines are the simple slopes at the bounds of the Johnson-Neyman region of significance, which is shaded in green and denotes the values on life stress for which the relationship between neuroticism and depression is significantly positive. Dashed lines are simple slopes at −1 *SD*, the mean, and +1 *SD* on life stress. The +1 *SD* (1.77) simple slope falls within the region of significance. The other region of significance based on neuroticism acting as the moderator is not depicted here. SS = simple slope; *SD* = standard deviation; UB = upper bound; LB = lower bound. See the online article for the color version of this figure.

regression model to produce a matrix of predicted values, with any covariates set to their means. This matrix of predicted values makes up the regression plane. The bounds of the regions of significance are used to identify the areas on the plane to shade. The axes of the plot are determined by the range of the observed data, which, as noted above, can also be overlaid on the plane as a 3-D scatterplot. The full source code for the web-based tool can be found at https://github.com/mfinsaas/jnthreedimint/blob/master/Shiny/app.R.

Benefits of the Johnson-Neyman and 3-D Approach

Our tool has several benefits for replication and transparency in reporting interactions and facilitates more accurate interpretation of interaction effects. Specifically, in simple slopes plots a researcher is restricted by the need to select a moderator that can only be depicted at a handful of values whereas the 3-D approach encourages researchers to provide the full range of data for both predictors, which facilitates transparency and comparisons across samples. Additionally, our web tool allows researchers to easily examine data for multivariate outliers so that spurious interactions are less likely to be reported in the first place. The 3-D approach can be thought of as a visual complement to the movement toward transparent data practices, especially as the web application facilitates researchers' ability to provide visual depictions of their actual data in 3-D space when submitting their work for publication.

Combining the Johnson-Neyman technique with a 3-D plot is efficient and accurate as it shows both variables acting as the moderator and as primary predictors in a single plot along with the Johnson-Neyman values and predicted values for the outcome variable. This is an improvement upon marginal effects plots or solely providing tables with a list of slope coefficients produced by the Johnson-Neyman approach, both of which are less intuitive, fail to include predicted values of the outcome variable, and require one variable to act as the moderator.

Moreover, this approach has conceptual benefits as the 3-D visual highlights the multiplicative, nonlinear nature of interactions between continuous variables. This draws attention to types of change in the outcome, alongside conditional effects. Other areas of research are already focused on change in this way, such as research on pharmaceutical drug interactions (e.g., Prichard & Shipman, Jr., 1990). In the case of interactions among drugs, acknowledging the curvature of the regression plane helps to emphasize that increasing dosages of both medications can accelerate the chances of adverse complications.

We believe the field of psychological science is similarly interested in change in the outcome as both predictors jointly change as opposed to focusing on how one predictor affects the outcome at fixed conditional values. However, traditional approaches to reporting interactions have limited our ability to conceptualize results in this way. In nonexperimental research, where we cannot hold one variable constant, it is more realistic to think about changes in outcomes as both interacting predictors increase and decrease without constraining either variable to be constant.

Barriers, Limitations, and Cautions to Avoid Misuse

Despite the significant limitations of current practices, researchers may hesitate to alter long established habits for reporting interactions in part because 3-D plots, like most unfamiliar statistical approaches, can be challenging to understand at first. In addition to providing the step-by-step guide in Appendix C, we also provide educational materials on the site that describe the multiplicative nature of interactions in more detail. In addition, in Appendix D, we include a "Conceptual Building Blocks" handout, which may be particularly useful as a teaching material. This handout describes the progressive and cumulative concepts students must understand in order to grasp the 3-D plot. While the handout is not a substitute for in-depth training on each concept, it may be useful as a guide and assessment tool for statistics professors and individual researchers.

Other barriers to use include the fact that 3-D plots are most easily viewed when they can be rotated, but this is not generally possible in most publication formats. However, as scientists increasingly consume articles online it may be possible to embed animated or dynamic figures that can be manipulated directly by readers. It is already possible to link to the figures, as has been done for this article, in the same way that researchers link to other online supplementary materials.

Like all methods, this technique also has the potential to be misused. There are several particular pitfalls researchers should be careful to avoid. First, the Johnson-Neyman regions of significance are not effect sizes. Researchers interested in the interaction effect size may instead reasonably use change in R^2; this value indexes the amount of variance explained by the interaction beyond the conditional effects of all other predictors. However, researchers are typically not interested only in the overall size of the nonlinear effect but rather where and for which variable the moderating effect is largest (thus the need for follow-up tests), and may consider conditional effects to be another type of effect size. In addition, the Johnson-Neyman test only indicates when effects are nonzero, but, as with all significance tests, the researcher must determine whether these effects are meaningful. As noted earlier, the regions of significance are also dependent on the reliability of the estimates and on sample size (i.e., larger sample sizes from the same population will produce larger regions of significance), so researchers should not focus on the bound values in interpretation. Instead, we strongly suggest that researchers interpret the overall pattern of the Johnson-Neyman region(s) of significance. That is, researchers should highlight the regions for both predictors and describe the pattern (see Figure 4). Specific Johnson-Neyman values may be more useful for questions of replication when a large number of studies have tested the same interaction. The regions of significance (and other portions of the interaction surface) may also include areas which are not representative of the actual data. Researchers should use both the percentage of cases that fall within the region and visual examination of raw data in the scatterplot to assess whether they are representative and worth interpreting. Finally, the crossover points are simply point estimates on the moderator corresponding to a slope of zero between the primary predictor and outcome. The particular moderator value is likely to shift depending on the sample.

Simple slopes analysis and marginal effects plots from the Johnson-Neyman technique may also have advantages over 3-D plots in some situations. When one predictor is naturally dichotomous or categorical, simple slopes plots may be preferable because the values of the moderator are already determined (eliminating the need to make Critical Decision #1). This does not, however, eliminate the need to make Critical Decision #2; while the dichotomous or categorical variable is typically depicted as the moderator by default, it is still statistically identical to the other predictor, so either could be construed as the moderator. Indeed, the significance of the interaction term depends on deviation from linearity for both variables, and researchers may encounter situations wherein the slopes at the binary moderator values are quite similar, in which case they may need to consider whether the moderation effect is stronger for the continuous moderator. There may be other situations where simple slopes or marginal effects plots are more suitable than a 3-D plot. We encourage researchers to choose the type of visualization that most closely and truly represents the true form of the interaction given the nature of their data and present the 3-D plot with Johnson-Neyman output as a useful option for continuous by continuous interactions.

Summary

Conventional approaches for reporting and visualizing interactions require researchers to make decisions that can have a major impact on the interpretation of the results. In particular, selecting moderator values to plot the interaction and the variable to treat as a moderator is often done arbitrarily. In the worst-case scenarios, these decisions may lead researchers to misinterpret their results. Even if researchers make careful, theory-driven decisions when conducting simple slopes analyses, simple slopes plots can only convey information about a restricted range of values and do not adequately capture the multiplicative nature of continuous by continuous interactions. Our recommendation is to consider each variable as a moderator of the effect of the other and use the Johnson-Neyman technique along with 3-D plots to standardize the process for presenting interactions. We presented an easy-to-use web-based application that accomplishes these goals. Importantly, this approach is consistent with a movement toward increasing transparency and promoting replicability in psychological science.

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Appendix A

Cautions in Graphing the Johnson-Neyman Technique

In the main text of the article, we note that some statisticians recommend that the Johnson-Neyman technique be depicted using a "marginal effects plot," but this plot is rarely used (McCabe et al., 2018). Instead, researchers may attempt to superimpose the Johnson-Neyman technique onto conventional two-dimensional (2-D) simple slopes plot with the goal of determining where lines significantly differ. The goal of this appendix is to illustrate why this practice is almost always incorrect in the context of continuous by continuous regressions. We provide several graphs and equations to illustrate this problem.

It is worth discussing the origins for superimposing the Johnson-Neyman value onto 2-D regression plots. It is important to recall that the Johnson and Neyman (1936) technique was originally developed for interactions between one dichotomous and one continuous variable known as analysis of covariance (ANCOVA). For example, there could be an interaction between sex (treated as dichotomous) and neuroticism (treated as continuous) to predict depression. In ANCOVA, the Johnson-Neyman technique is used to determine the value of the continuous predictor (treated as the moderator Z) at which the effect between the dichotomous predictor (X) is significantly associated with the outcome (Y). The conventional plot for ANCOVA is normally produced by creating lines to plot based on the dichotomous group variable even though the variable on the *x*-axis is treated as the moderator as shown in Figure A1.

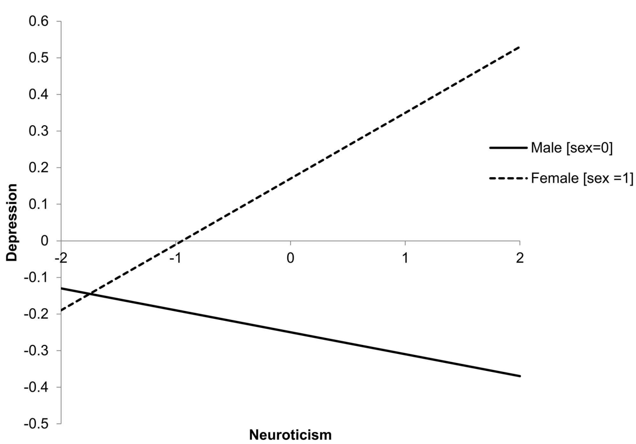

Figure A1. ANCOVA simple slopes plot depicting how sex and neuroticism interact to predict depression. See Table A1 for model coefficients.

As with all interaction plots, it is important to note where each variable is located on this plot. The outcome variable depression is on the Y-axis, neuroticism is on the X-axis, and sex is used to determine the slopes so it is the variable on the figure legend or caption. For the purposes of doing a Johnson-Neyman analysis, neuroticism is being treated as the moderator Z variable, even though it is placed on the X-axis (Roisman et al., 2012). This may appear to be contradictory at first, but recall that in ANCOVA, the Johnson-Neyman technique is used to find the point along the continuous "moderator" variable; it would not make sense to treat sex as the moderator because it is dichotomous and can only have values of 0 and 1 in the dataset (a Johnson-Neyman value for the dichotomous variable would be somewhere in between 0 and 1, but that value cannot possibly occur for any participants). Essentially what is being done in this scenario is calculated a specific simple slope as if neuroticism is the moderator and the value at which to solve the slope is determined by the Johnson-Neyman test.

In this example, the Johnson-Neyman analysis indicates that the relationship between depression (Y) and sex (primary predictor X) is significant when the value for neuroticism equals -0.84 and all values above this point. Researchers have typically visualized this by placing a dotted line and shaded region along the *x*-axis based on the Johnson-Neyman value. In this case, a dotted line is placed at -0.84 for neuroticism along the *x*-axis and the region to the right of that line is shaded in gray as shown in Figure A2.

Researchers then conclude that the two lines differ significantly at the dotted line and at any point between the two lines that falls in the shaded region of significance. But how are they able to do this? It is important to recall that the Johnson-Neyman value corresponds to the value of the moderator that can be plugged into the regression equation to produce a significant simple slope. In this case plugging in the Johnson-Neyman value of -0.84 for neuroticism produces the following simple slope.

Equation 1.

$$\begin{aligned}\text{Depression} &= -0.25 + (-0.06)(\text{neuroticism}) + (0.42)(\text{sex}) \\ &\quad + (0.24)(\text{neuroticism})(\text{sex})\end{aligned}$$

$$\begin{aligned}\text{Depression} &= -0.25 + (-0.06)(-0.84) + (0.42)(\text{sex}) \\ &\quad + (0.24)(-0.84)(\text{sex})\end{aligned}$$

$$\text{Depression} = -0.25 + (0.05) + (0.42)(\text{sex}) + (-0.20)(\text{sex})$$

$$\text{Depression} = -0.20 + (0.22)(\text{sex})$$

(*Appendices continue*)

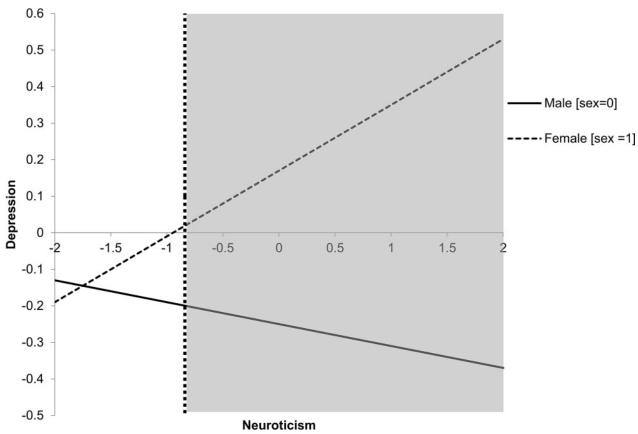

Figure A2. ANCOVA simples slopes plot with properly shaded region of significance.

This simple slope characterizing the relationship between depression and sex has some unique properties because it was solved for the dichotomous variable sex, which can only have 0 or 1 as observed values in the data set. If we further solve this equation at 0 and 1 values for sex, we can determine the predicted values of depression for males and females when neuroticism is at −0.84. More importantly, the difference between the predicted values for males and females at this point along neuroticism corresponds to the "gap" between the lines on Figure A1 (See Table A1 for model coefficients). In this case solving for predicted values of depression for males (sex coded as 0) when neuroticism is held at −0.84.

Equation 2.

$$\text{Depression} = -0.20 + (0.22)(\text{sex})$$
$$\text{Depression} = -0.20 + (0.22)(0)$$
$$\text{Depression} = -0.20$$

Solving for predicted values of depression for females (sex coded as 1) when neuroticism is held at −0.84.

Equation 3.

$$\text{Depression} = -0.20 + (0.22)(\text{sex})$$
$$\text{Depression} = -0.20 + (0.22)(1)$$
$$\text{Depression} = 0.02$$

Table A1
Coefficients from ANCOVA Model Including a Continuous by Dichotomous Interaction Term Predicting Depression

Predictor	*b*	*SE*	*t*	*p*
Intercept	−0.25	0.07	−3.72	<.001
Sex	0.42	0.09	4.80	<.001
Neuroticism	−0.06	0.07	−0.82	.41
Sex × Neuroticism	0.24	0.09	2.68	.008

Note. $R^2 = .07$. $F(3, 496) = 11.65$, $p < .001$.

Taking the difference of these two predicted values of depression reflects that the gap between the groups and their respective lines on the plot is 0.22. Because the Johnson-Neyman value of −0.84 on neuroticism produces a slope for sex that is significant at $p = .05$, a researcher can conclude that the gap between the lines or a difference of 0.22 on depression is significantly different than zero. In other words, the two groups, females and males significantly differ from one another when neuroticism is at a value of −0.84. This can be depicted graphically as shown in Figure A3.

In this scenario adding in a vertical line at the neuroticism value of −0.84 and a shaded region to the right of that value indicates that all of the areas to the right of the dotted line correspond to significant gaps between the lines that significantly differ at least at a level of $p = .05$. In essence, this is saying that there is gender group difference in depression when neuroticism is −0.84 or higher. Note that the value of 0.22 that represents the gap between the lines is the same value as the slope coefficient we solved for originally. This should not be surprising because slope coefficients by definition indicate change for a one-unit increase and the difference between males and females is coded as one unit. Therefore, the Johnson-Neyman test can be used to describe a significant difference between two lines because the Johnson-Neyman value produces a significant slope coefficient that equals the gap between the lines *only when they are separated by one unit of the primary predictor variable* (in this case sex). To put this in terms of a generic *t*-test, one can imagine that if we were to possess a sufficiently large sample of men and women who had exactly the value of −0.84 on neuroticism the mean difference between men and women would be the same as the .22 difference we observed as the gap between the lines. In the case of ANCOVA a plot that is shaded as in Figure A2 is entirely acceptable (for additional demonstrations of appropriate use of this technique see Hayes, 2013 or Preacher et al., 2006).

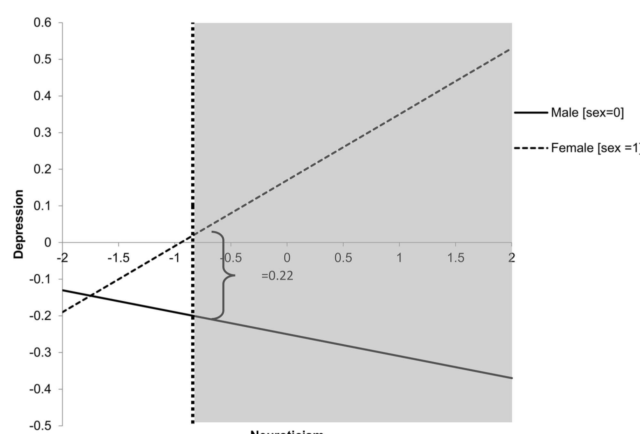

Figure A3. ANCOVA simple slopes plot with gap between lines determined by the Johnson-Neyman slope when neuroticism is treated as the moderator.

(*Appendices continue*)

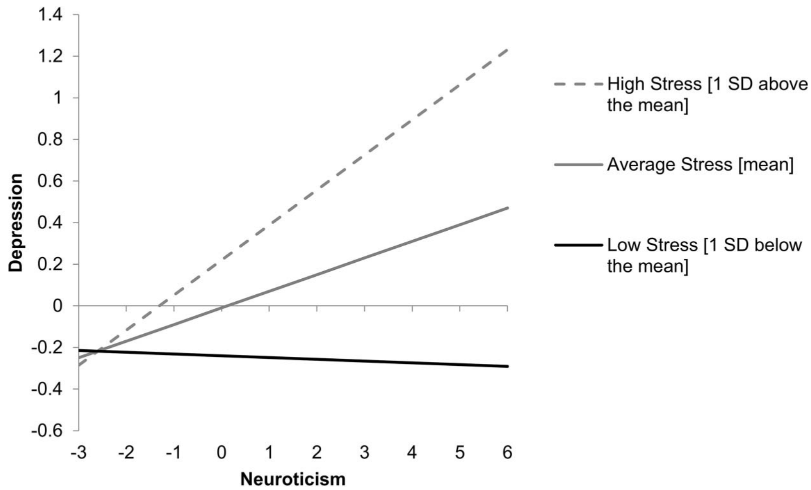

Figure A4. Continuous (neuroticism) by continuous (life stress) variable simple slopes plots. See Table A2 for model regression coefficients.

However, when conducting a continuous by continuous interactions, using the Johnson-Neyman technique to identify differences between lines is almost always performed incorrectly. It is important to recall what a significant slope actually means when conducting this type of analysis based on selected values (e.g., the mean) or on values determined by the Johnson-Neyman technique. Slope coefficients refer to significant change for a one-unit increase in the predictor variable. In the case of dichotomized variables, the one-unit increase is meaningful, as a shift from 0 to 1 represents a change in group membership and the shift in group membership is equal to the same value as the statistically significant slope coefficient as we illustrated in the case of ANCOVA. The problem for continuous by continuous interactions begins in part because natural groups do not exist in the data and researchers incorrectly attempt to use the Johnson-Neyman technique to compare lines at 1 *SD* above and below the mean as if they are "low" and "high" groups. Importantly, 1 *SD* above and below the mean are almost never separated by a single unit and as a result the slope coefficient solved by the Johnson-Neyman test does not equal the gap between the lines.

Let's consider what happens in most plots of continuous by continuous interactions. For the purposes of this demonstration we return to the example of neuroticism and life stress interactions with depression that are used in the main body of the article (Figure A4 and Table A2).

In this scenario researchers may want to know at what point the "low" and "high" stress lines differ from one another and incorrectly attempt to use the Johnson-Neyman approach in the same way as the case of ANCOVA. Specifically, by treating neuroticism as the moderator the goal is to identify the point along the *x*-axis at which the stress lines differ significantly. Again, even though neuroticism is on the *x*-axis it must be treated as the Z variable in order to make this calculation. In the life stress and neuroticism interaction example, the Johnson-Neyman analysis indicates that the relationship between depression (Y) and life stress (primary predictor X) is significant when the value for neuroticism equals −1.01 and all values above this point. Putting a dotted line on the *x*-axis at a neuroticism value of −1.01 is shown in Figure A5.

Table A2
Coefficients from Regression Model Including a Continuous by Continuous Interaction Term Predicting Depression

Predictor	*b*	*SE*	*t*	*p*
Intercept	−0.01	0.04	−0.16	.87
Sex	0.08	0.04	1.84	.07
Neuroticism	0.13	0.03	5.21	<.001
Sex × Neuroticism	0.05	0.03	2.05	.04

Note. $R^2 = 0.08$.

(*Appendices continue*)

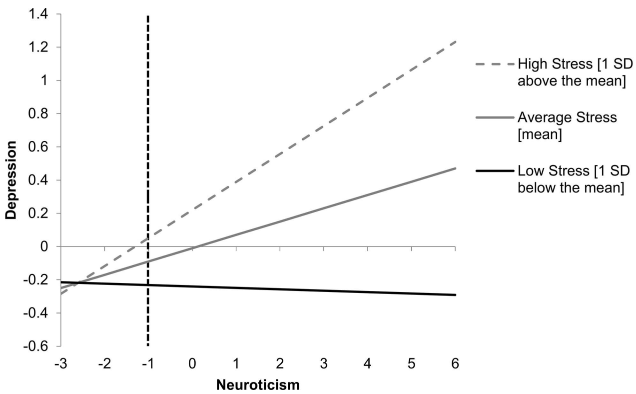

Figure A5. Neuroticism by life stress simple slopes plot with a dotted line demarcating the Johnson-Neyman value for neuroticism.

We demonstrated above that the Johnson-Neyman value can be used to plug into the regression equation to solve for a slope coefficient that is by definition significant at $p = .05$. More importantly, we showed that the slope that is produced based on the Johnson-Neyman value corresponds to the gap between lines that are separated by one unit. Solving the regression for a Johnson-Neyman value of -1.01:

Equation 4.

$$\begin{aligned}\text{Depression} &= -0.01 + 0.08(\text{neuroticism}) + 0.13(\text{stress}) \\ &\quad + 0.05(\text{neuroticism})(\text{stress}) \\ \text{Depression} &= -0.01 + 0.08(-1.01) + 0.13(\text{stress}) \\ &\quad + 0.05(-1.01)(\text{stress}) \\ \text{Depression} &= -0.01 + (-0.0808) + 0.13(\text{stress}) - 0.0505(\text{stress}) \\ \text{Depression} &= -0.09 + 0.08(\text{stress})\end{aligned}$$

In this case, the slope coefficient of 0.08 corresponds to a significant increase in depression symptoms for every one-unit increase in stress. When this is related to differences between plotted lines it means that when neuroticism is at a value of -1.01, stress-based lines that are separated by one unit differ by 0.08 on depression. In this case, a "high" stress value is 1 *SD* above the mean or 1.77 on the life stress scale and a "low" stress value that is 1 *SD* below the mean is -1.77. Clearly, these lines differ by more than one unit on life stress scale. To further illustrate how this relates to the Johnson-Neyman value for neuroticism, we can solve the simple slopes at 1 *SD* above and below the mean and compare the difference in depression scores between those lines when neuroticism is held at -1.01.

Solving for predicted values of depression when stress is "low" at 1 *SD* above the mean when neuroticism is held at -1.01.

Equation 5.

$$\begin{aligned}\text{Depression} &= -0.09 + 0.08(\text{stress}) \\ \text{Depression} &= -0.09 + 0.08(-1.77) \\ \text{Depression} &= -0.23\end{aligned}$$

Solving for predicted values of depression when stress is "high" at 1 *SD* above the mean when neuroticism is held at -1.01.

Equation 6.

$$\begin{aligned}\text{Depression} &= -0.09 + 0.08(\text{stress}) \\ \text{Depression} &= -0.09 + 0.08(1.77) \\ \text{Depression} &= 0.05\end{aligned}$$

The difference in depression scores between "low" and "high" stress lines is 0.28—this is clearly much larger than the slope coefficient value of 0.08 generated when solving the regression at -1.01 for neuroticism (the value identified by the Johnson-Neyman technique). This should not be surprising because the low and high lines differ by more than one unit of stress and the Johnson-Neyman value is used to produce a slope coefficient that is interpretable in one-unit increments. The slope coefficient for stress when neuroticism is at -1.01 can only be used to describe a significant difference at $p = .05$ given a one unit change in life stress. However, the "high" and "low" lines differed by almost 3.5 units on the life stress measure. Furthermore, both the "high" and "low" stress line differs by more than one unit compared with the mean. As a result, it inaccurate to call a -1.01 value for neuroticism the point at which any of the lines begin to differ from one another in Figure A5. The implications are that the dotted line on Figure A5 has absolutely no relevance for all three slopes depicted in the figure.

The takeaway message is that Johnson-Neyman technique can only be used to compare lines that are separated by one unit. This is because the Johnson-Neyman technique identifies a value of the moderator (the variable on the *x*-axis in these examples) that produces a slope coefficient characterizing the relationship between the outcome (the *y*-axis variable) and primary predictor (the variable on the figure legend). The slope coefficient generated by the Johnson-Neyman test is by definition significant at $p = .05$. As a result, the slope coefficients that is produced when the Johnson-Neyman value is used to solve the regression model can then be interpreted as reflecting that a one-unit change in primary predictor leads to a significantly different value on the outcome variable. The Johnson-Neyman test could be used to compare simple slopes only if they are set such that they differ by one unit from one another on the moderator. However, because continuous by continuous interaction plots almost never contain lines that differ by one unit it is almost always wrong to use the Johnson-Neyman technique to describe statistically significant differences between lines. In the case of continuous by continuous interactions this is an important consideration as it is not almost never possible to use the Johnson-Neyman technique to compare the line at +1 *SD* above the mean to -1 *SD* below the mean. The implication of this is that the Johnson-Neyman technique cannot be used to compare these "low" and "high" slopes.

(*Appendices continue*)

Appendix B

Mathematical Demonstration of the Multiplicative Nature of Interactions

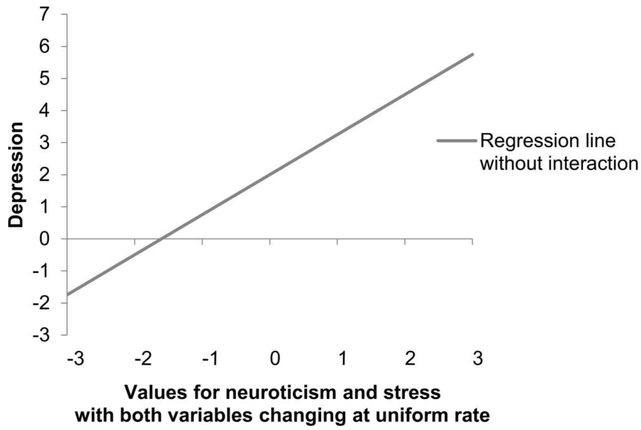

Figure B1. Regression with two continuous predictors but no interaction term.

In the main body of the text we regularly discuss how the inclusion of continuous by continuous interactions always leads to a nonlinear, multiplicative function. It is useful to examine the multiple regression equation to see why this is the case. Let's first consider a regressions with two predictors, but no interaction term producing:

Equation 1

$$Y = b_0 + b_1(X) + b_2(Z) + e$$

When looking at Equation 7 it is easy to see that the predictor variables are always being multiplied by constant values and then summed together. If X and Z are both increased simultaneously by 1, the outcome variable will increase at a constant rate. To illustrate this, we use a hypothetical example where neuroticism and life stress predict depression forming the equation: Y = 2 + 0.5(neuroticism) + 0.75(stress). Figure B1 and Table B1 depict outcome values for depression when neuroticism and stress both simultaneously increase by 1.

Table B2 and Figure B1 show that a regression equation without an interaction term is the function of a linear slope. However, when an interaction term is introduced the nature of the regression equation changes because it now includes multiplication of variables that are not constant. The standard for a regression equation with an interaction term is as follows:

Equation 2

$$Y = b_0 + b_1(X) + b_2(Z) + b_3(X)(Z) + e$$

While the regression coefficient b_3 is indeed a constant, X and Z are not constants. Because X and Z change and they are being multiplied, regressions that include interactions form a nonlinear function. In a hypothetical circumstance where X and Z were to simultaneously increase by 1, the outcome variable Y will change at a nonlinear rate. To illustrate this, we add an interaction term to the hypothetical neuroticism, life stress, and depression example giving us: Y = 2 + 0.5(neuroticism) + 0.75(stress) + 0.2(neuroticism; stress). Figure B1 and Table B1 show how the function is nonlinear.

Figure B2 and Table B2 illustrate how the interaction is curved when neuroticism and life stress increase at equal values and how this appears in 2-D space. When this relationship is extended across the full range of values for both predictors it forms a curved plane in 3-D space, which is emphasized in the main body of the article.

Table B1
Predicted Values From Regression With Two Continuous Predictors and No Interaction Term

Neuroticism	Life stress	Depression
−3	−3	−1.75
−2	−2	−0.50
−1	−1	0.75
0	0	2.00
1	1	3.25
2	2	4.50
3	3	5.75

Table B2
Predicted Values From Regression With Two Continuous Predictors and Their Interaction

Neuroticism	Life stress	Depression
−3	−3	0.05
−2	−2	0.30
−1	−1	0.95
0	0	2.00
1	1	3.45
2	2	5.30
3	3	7.55

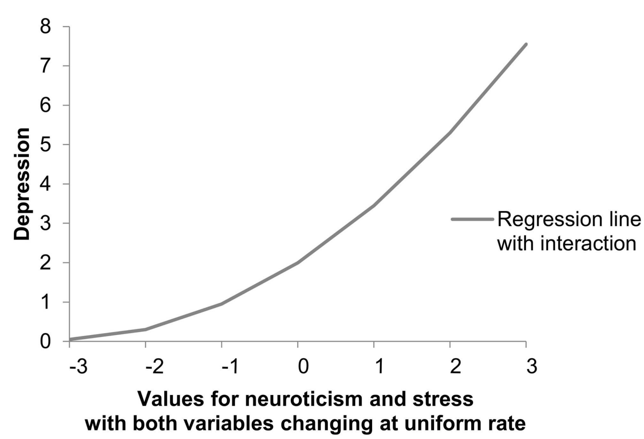

Figure B2. Regression with two continuous predictors and their interaction is curved.

(*Appendices continue*)

Appendix C

Step-By-Step Directions for Plotting and Interpreting the Interaction

This guide uses the simulated data found at https://github.com/mfinsaas/jnthreedimint. We also encourage researchers to follow these steps using their own data to become more familiar with the tool.

Setting up the plot:

1. Upload the data by clicking the browse button. This data file must have unique variable names at the top of the file, should not contain missing data indicators (but blanks are okay; the program handles missing data using listwise deletion based on variables in the model), and must be a comma-separated (.csv), or SPSS (.sav) file. All variables in the model must be numeric. When the file has been properly uploaded, the dropdown menus for the predictors and outcome will automatically populate with the variable names in the file. Researchers also have the option to input parameter estimates and asymptotic covariances obtained from another statistical software program (a good option for researchers who use SEM software to handle missing data or to examine interactions of latent variables).

2. Select "LifeStress" for X1, "Neuroticism" for X2, and "Depression" for Y. Alternatively, one can delete "–" and type in the variable names. The radio buttons "Center," "Standardize," and "Raw" allow the user to transform these variables. For this exercise, keep them as the default of "Center." The user can also input covariates, which are always centered at their means, but are not needed for this example.

3. Uncheck the "Limit false discovery rate for Johnson-Neyman?" box. Keep the gray scale option unchecked. The latter option is useful for print publications.

4. Click "Run/Update." The 3-D plot of the regression plane with raw data overlaid as a scatterplot will appear.

Scatterplot and predicted values confidence interval:

5. The scatterplot of raw data is overlaid on the plane. The user can also add 95% confidence intervals around the predicted values by checking the corresponding box. These confidence intervals will appear as semiopaque planes floating above and below the regression plane. For the purposes of the exercise, uncheck both boxes before moving to the next step.

Regions of significance:

6. Options for depicting both regions of significance will appear, along with output describing them. Begin by adding a solid region of significance for life stress as the moderator by selecting "Solid ROS" in the top box. Rotate the plot by clicking on it and dragging it so that neuroticism is on the X-axis and life stress is on the Z-axis, (providing depth to the figure). The green shaded rectangle covers the portion of the regression plane for which the relationship between Neuroticism and depression is significantly positive. This rectangle can also be construed as a series of simple slopes. This concept may be best understood by looking at the edge of the rectangle closest to the viewer; this edge is a diagonal line indicating the positive relationship between neuroticism and depression when life stress is as its maximum. The slopes become shallower, or less positive, as one moves away from this edge until one reaches the other edge of the region of significance where life stress equals .27. This is the lower bound and marks where the relationship between neuroticism and depression transitions to being nonsignificantly different from zero. The interpretation of this region of significance is that neuroticism and depression are positively related when life stress is at .27, or about at its mean, through its maximum. In the output, one can see that the region includes 35.4% of the sample. Select "No ROS" before moving to the next step.

7. To view the region of significance when neuroticism is the moderator, select "Solid ROS" in the lower box. Again, rotate the plot so that the primary predictor, life stress, is on the X-axis and the moderator, neuroticism, on the Z-axis. Note that the scale for neuroticism goes high to low. This blue rectangle is the region of significance for neuroticism as the moderator and can again be construed as a series of slopes. The far edge is the slope depicting a significantly positive relationship between life stress and depression when neuroticism is at its maximum. As one moves away from that edge, "closer" to the viewer, the slopes become less positive, until neuroticism equals −.95, at which point the relationship between life stress and depression is no longer significantly different from zero. The interpretation of this region of significance is that life stress and depression are positively related when neuroticism is at −.95 through its maximum. This region includes 80.6% of the sample.

(*Appendices continue*)

8. Now we will add information about the reliability of the life stress-depression slope estimate to the plot. Select "Gradient ROS" (Slope 95% CB) in the lower box and rotate back to the same orientation described in Step 6. This option shades the region of significance according to the width of the confidence bands around the slope estimates. Bluer shading corresponds to narrower bands and whiter shading to wider bands. One can see that the estimate is more reliable at the mean of neuroticism than at its highest values. A table containing all slope and lower and upper confidence band estimates is also available under the Johnson-Neyman tab.

9. Researchers who wish to avoid binary tests of significance may wish to select the "Gradient All" option, which shades the entire regression plane according to the confidence bands. When this option is applied, one can see that the reliability of the estimate is lower at extreme values of neuroticism.

10. Finally, visualize both regions of significance simultaneously by selecting "Solid ROS" for both variables. The rectangles are semitranslucent so they can be viewed at the same time. While researchers may be tempted to focus on the darker rectangle where the two regions overlap, this rectangle is simply a byproduct of visualizing both regions of significance at once and does not have additional interpretive value to our knowledge.

Crossover points:

11. Check the "Crossover" box for life stress as moderator to overlay a green line at the point on life stress (−1.49) where the relationship between neuroticism and depression equals zero, or where the slope transitions from positive to negative.

12. Check the "Crossover" box for neuroticism as moderator to overlay a blue line at the point on neuroticism (−2.49) where the relationship between life stress and depression equals zero.

Appendix D

Conceptual Building Blocks for 3-D Interaction Plots

Understanding 3-D interaction plots requires students and researchers to integrate and build on existing knowledge about linear regression and interactions. We outline the key concepts that must be mastered before the 3-D plot will be comprehensible. We recommend working through these concepts in order, as they build on one another. The answers here are not exhaustive and are unlikely to help students master these concepts if they are not already familiar with them. If students do understand the concepts based on prior learning, however, recognizing that each of these key concepts tie to interactions in general, and 3-D plots in particular, may facilitate deeper understanding. This guide can also be used by statistics teachers to guide and assess student learning.

1. Ordinary Least Squares (OLS) Linear Regression

What is the "aim" of a regression model?

To identify parameters (also known as betas or coefficients) that make up an equation or function which minimizes the difference between the observed data points and the model-estimated solution.

What do the coefficients mean in terms of the outcome variable (also known as the dependent variable, or Y)?

For every one unit increase in the predictor, Y changes by the value of the coefficient. For example, if the beta for predictor X is .5, then for every one unit increase in X, Y increases by .5 units.

In general, how are the terms in linear regression combined (when an interaction term is not included)?

Additively, or linearly. That is, the betas are multiplied by the corresponding predictor variables and then all product terms are added together.

Why might a linear regression model with two predictors be depicted as a 3-D plane, rather than a regression line, and what is the defining characteristic of this plane when an interaction term is not included?

A plane is able to show the change in the outcome given a one-unit change in both predictors simultaneously. Without an interaction term, the plane is flat (although it may be tilted), such that the change in the outcome given a one-unit change in either or both predictors is constant across the entire surface.

2. Interactions in Linear Regression

What does it mean when an interaction term in linear regression is significant? (two complementary answers)

(*Appendices continue*)

The strength and direction of the relationship between a predictor and the outcome depends on the value of a second predictor.

AND

Combining the terms additively was not sufficient for minimizing the difference between the observed data points and the model-estimated solution. Including a new term—the interaction—significantly improves the model-estimated solution by further minimizing this difference.

What are the two slope components that make up the simple slopes representing the relationship between one predictor and the outcome in a model <u>*with*</u> *an interaction term? (These components can be seen when simplifying the regression model at different moderator values.)*

The two slope components are (a) the predictor's beta (also known as its coefficient or conditional effect), which is the same regardless of moderator values; plus (b) the product of the interaction beta and a moderator value, which necessarily differs across different moderator values.

What is the shape of the regression plane when an interaction term <u>is</u> *included?*

The plane is curved.

What makes up the curved regression plane?

A series of simple slopes.

How is the Johnson-Neyman test compatible with a 3-D regression plane?

The Johnson-Neyman technique returns the point on the moderator that the predictor-outcome relationship becomes significantly different from zero. All simple slopes that are significantly different from zero make up the region of significance. Because the regression plane is also made up of simple slopes, the region of significance can be identified on the regression plane.

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Correction to Finsaas and Goldstein (2020)

In the article "Do Simple Slopes Follow-Up Tests Lead Us Astray? Advancements in the Visualization and Reporting of Interactions," by Megan C. Finsaas and Brandon L. Goldstein (*Psychological Methods*, advance online publication. April 20, 2020. http://dx.doi.org/10.1037/met0000266), Figure 5 contained an error.

The second sentence of the caption of Figure 5 should read: "The left plot depicts the region of significance when life stress is acting as the moderator, and the right when neuroticism is acting as the moderator."

All versions of this article have been corrected.

http://dx.doi.org/10.1037/met0000369