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Simple and parallel mediation: A tutorial exploring anxiety sensitivity, sensation seeking, and gender

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Abstract ■ In this tutorial, we demonstrate how to conduct simple and parallel mediation analyses using the PROCESS macro for SPSS (Hayes, 2013). We begin by describing the principles of mediation. We then present a step-by-step tutorial describing how to test statistical assumptions and conduct a simple and a parallel mediation using data from a project exploring whether anxiety sensitivity mediates the relationship between gender and sensation seeking in a sample of 295 undergraduate students. Results of these analyses showed that anxiety sensitivity, and more specifically the belief that bodily sensations are dangerous, explains part of the relationship between gender and sensation seeking. Finally, we interpret these results as if we are presenting the findings in a research article. The tutorial serves as a concrete and need-to-know introduction to simple and parallel mediation.

Keywords ■ mediation, gender differences, anxiety sensitivity, sensation seeking. **Tools** ■ SPSS, PROCESS macro.

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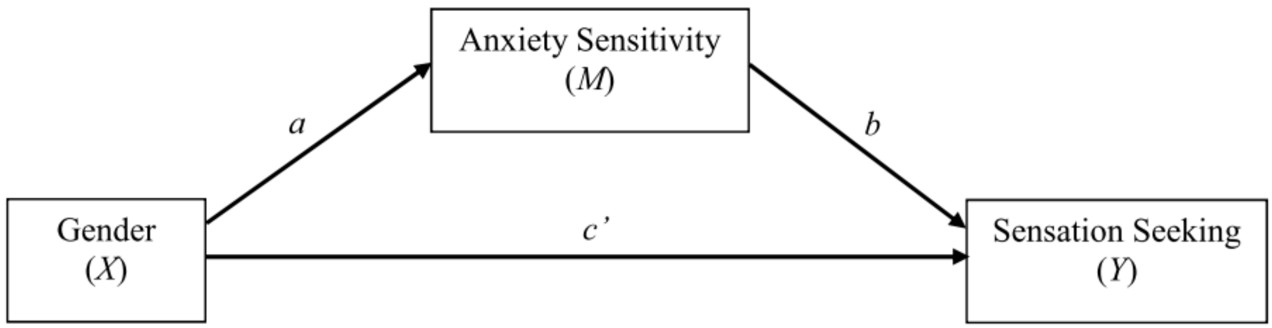
Introduction

In psychology, researchers are often interested in examining whether variables are related to one another. To achieve this, they can conduct regression-based analyses. Although causality cannot be inferred from this type of analysis, researchers anchor themselves in a theoretical framework to determine which variable is said to be the outcome and which is said to be the cause of this outcome. For instance, one might wonder if gender is related to various personality characteristics like impulsivity or sensation seeking. Conceptually, it would make more sense to test whether gender predicts these characteristics than the other way around. However, it would also be possible to examine if these characteristics predict gender. A theoretical framework will help determine which option is the most probable and useful way of conceptualising the relationship.

Moreover, theory may also guide researchers to postulate that the relationship between two variables is more complex than meets the eye. To illustrate this, we will use the example of gender and sensation seeking. Sensation seeking refers to a personality trait implicating the search for novel, intense, and complex sensations through various experiences (Zuckerman, 1994). It has also been conceptualized as a motivating need for novelty and intensity (Roth & Hammelstein, 2012). In a meta-analysis, Cross, Copping, and Campbell, 2011 determined that men scored significantly higher on measures of sensation seeking than women ($d = 0.41$). However, various factors may account for the relationship between gender and sensation seeking. Indeed, the underlying processes are certainly anything but simple.

In cognitive-behavioural models of psychological phenomena, behaviours, thoughts, and emotions mutually influence each other (Hofmann, Asmundson, & Beck, 2013). A person may therefore choose to engage, or to not engage, in activities that produce new and exciting sensations for

Figure 1 ■ Simple mediation using the mediating effect of anxiety sensitivity on the relationship between gender and sensation seeking. Notes: a is effect of gender on anxiety sensitivity; b is effect of anxiety sensitivity on sensation seeking; c' is direct effect of gender on sensation seeking.



many reasons. Indeed, if a person interprets sensations, such as rapid heart beat, sweating, and racing thoughts, in a negative way (i.e., they do not like those feelings), then they will likely seek less of these sensations. Many individuals fear sensations like these because of their possible negative consequences, a construct know as anxiety sensitivity (Taylor, Zvolensky, Cox, Deacon, & Heimberg, 2007). Anxiety sensitivity has three dimensions: Physical Concerns (the beliefs that bodily sensations are life-threatening), Cognitive Concerns (the belief that difficulties concentrating are dangerous), and Social Concerns (the belief that others will reject or laugh at observable anxiety symptoms; Taylor et al., 2007). Women report higher anxiety sensitivity than men (Stewart, Taylor, & Baker, 1997). Consequently, women may seek exciting sensations less frequently than men. It would be interesting therefore to see whether gender affects sensation seeking through its effect on anxiety sensitivity. More specifically, perhaps gender affects levels of anxiety sensitivity, which in turn may influence the tendency to seek novel and intense sensations.

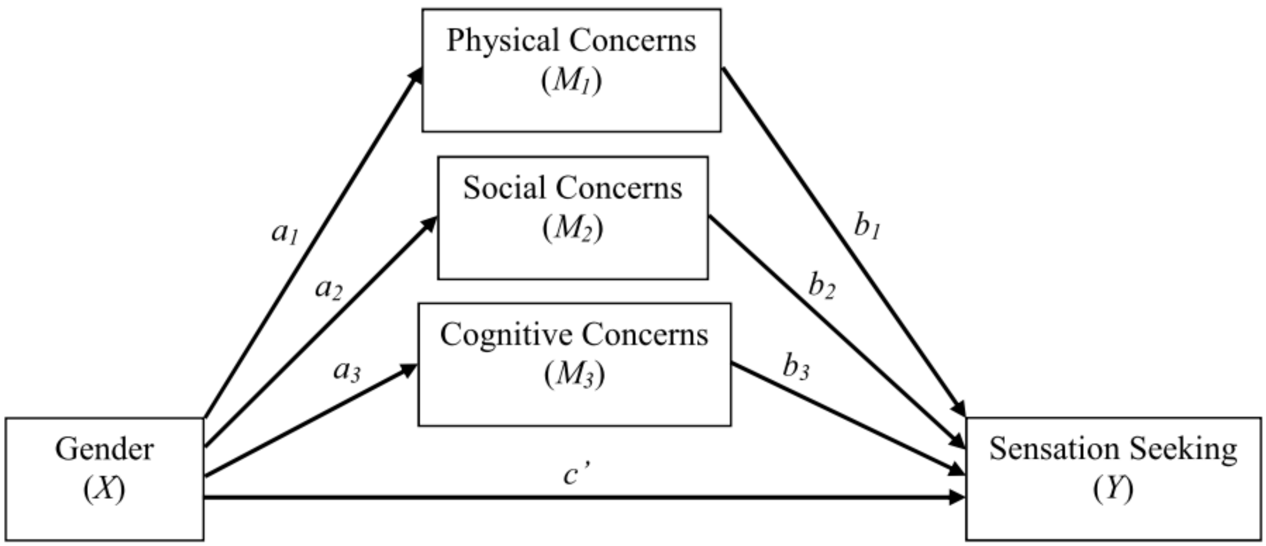
This kind of hypothesis can be tested using mediation analysis (e.g., Hayes, 2013; MacKinnon, Fairchild, & Fritz, 2007; Preacher & Hayes, 2004; Rucker, Preacher, Tormala, & Petty, 2011), wherein a mediator (M; anxiety sensitivity) is proposed to explain the relationship between an independent variable (X; gender) and an outcome variable (Y; sensation seeking; see Figure 1). This model is a simple mediation because there is only one mediator.

In this example, gender is proposed to influence anxiety sensitivity (a), which in turn would affect sensation seeking (b). This is called the indirect effect (ab) of gender on sensation seeking through anxiety sensitivity. This indirect effect is obtained by multiplying a and b, the two effects associated with this pathway (Hayes, 2013). In addition, there is the direct effect (c'), which is the effect of gender on sensation seeking while keeping levels of anxiety sensitivity constant (Rucker et al., 2011). When combining the indirect and the direct effects, you obtain the total effect (c), which is in fact the result you would get by simply regressing sensation seeking on gender (Hayes, 2013; Rucker et al., 2011). The coefficients associated with the various pathways (i.e., a, b, ab, c', and c) are essentially unstandardized regression coefficients. We will see more on their interpretations later in the tutorial.

The strength of the indirect and the direct effects will determine the result of the mediation analysis (MacKinnon et al., 2007). If the indirect effect is significant, then it is considered to be successful mediation (MacKinnon et al., 2007). When this occurs, the direct effect may disappear or remain significant. If it disappears, then there is complete mediation (i.e., the effect of X on Y is entirely due to M), whereas if it remains, then there is partial mediation (i.e., M does account for part of the relationship between X and Y, but, X still predicts Y even when taking into account M; MacKinnon et al., 2007).

This conceptualisation of partial versus complete mediation is very wide-spread in the scientific community (Hayes, 2013). However, it does have its critics. Hayes (2013) presents various arguments against the use of this nomenclature. For instance, he posits that partial mediation is bound to occur because something will mediate all effects; it is simply a question of finding it (Hayes, 2013). The process behind variable associations is too complex and is bound to be mediated by some factor or another. Moreover, discovering that a variable completely mediates the relationship between two others does not exclude the possibility that other constructs, not assessed in the

Figure 2 ■ Parallel mediation using the mediating effect of three anxiety sensitivity dimensions in the relationship between gender and sensation seeking. Notes: a_n is effect of gender on anxiety sensitivity dimensions, women are coded as 0 and men as 1; b_n is effect of anxiety sensitivity dimensions on sensation seeking; c' is direct effect of gender on sensation seeking.



study, may also play a role in the relationship (Hayes, 2013; Rucker et al., 2011). In essence, just because a researcher finds evidence for one mediator does not mean that it is the whole story. Therefore, readers should be cautioned if they choose to report their analyses using the partial-complete view of mediation. However, given that it is widely used in scientific articles, it is necessary to comprehend its definitions to better identify its pitfalls.

Furthermore, simple mediation is the simplest of mediation models. More complex models, such as parallel mediation, can include more than one mediator (Hayes, 2013). In parallel mediation, two or more variables (M_1, M_2, etc.) are proposed to mediate the relationship between X and Y (see Figure 2). These mediators are allowed to correlate with one another, but not to influence each other in causality (Hayes, 2013). In parallel mediation, there are as many indirect effects as there are mediators. With three mediators, there are the a_1b_1, a_2b_2, and a_3b_3 pathways using M_1, M_2, and M_3 respectively. This model is useful since it allows for a more complex assessment of the processes through which X affects Y. For example, anxiety sensitivity is a multidimensional construct assessing three related but distinct beliefs: the belief that bodily sensations are life-threatening (Physical Concerns), the belief that difficulties concentrating are dangerous (Cognitive Concerns), and the belief that others will reject or laugh at observable anxiety symptoms (Social Concerns; Taylor et al., 2007). These dimensions may play different roles in the relationship between gender and sensation seeking. Using parallel mediation, we can test the mediating effects of all three anxiety sensitivity dimensions (see Figure 2). We would then have three possible indirect effects: one through each anxiety sensitivity dimension.

Well written and comprehensive books regarding mediation analysis are available for the interested reader (e.g., Hayes, 2013). This paper will more so act as a concrete and need-to-know tutorial on simple and parallel mediation by extending the gender, anxiety sensitivity, and sensation seeking example introduced above. After introducing the research question and briefly discussing the data and the methods used to collect them, we will describe and test the statistical assumptions of mediation. We will then present a step-by-step on how to conduct the analyses. Finally, we will interpret the results as if we are presenting the findings in a research article.

Example Mediation Analyses

To illustrate a mediation analysis, we will be using data from a study examining anxiety sensitivity. Briefly, 297 undergraduate students from the University of Ottawa participated in an online study for course credit. One participant did not identify a clear gender and was therefore eliminated considering our interest in gender differences. One case with missing data was also deleted listwise, creating a final sample of 295 participants consisting of 148 women and 147 men. Since the statistical analyses themselves are of current focus, further sociodemographic characteristics will not be discussed. All study procedures were in accordance with the Research Ethics Board of the University of Ottawa and with the 1964 Helsinki declaration and its later amendments.

Following informed consent, participants completed the UPPS-P (negative Urgency, Premeditation, Perseverance, Sensation seeking, Positive urgency), a questionnaire assessing impulsive behaviour (Lynam, Smith, Whiteside, & Cyders, 2006). The UPPS-P has five subscales; Sensation Seeking, Negative Urgency, Positive Urgency, (lack of) Premeditation, and (lack of) Perseverance. For the current study, we were interested in the Sensation Seeking subscale (`SSs`), which conceptualizes sensation seeking as a disposition to impulsive behaviour (Cyders, 2013).

Participants also completed the Anxiety Sensitivity Index-3 (ASI-3; Taylor et al., 2007). The ASI-3 has three subscales measuring to Physical Concerns (i.e., the belief that bodily sensations are life-threatening; `ASI.PHY`), Cognitive Concerns (i.e., the belief that difficulties concentrating are dangerous; `ASI.COG`), and Social Concerns (i.e., the belief that others will reject or laugh at observable anxiety symptoms; `ASI.SOC`; Taylor et al., 2007). Therefore, the supplemental dataset includes the following variables: `gender`, `ASI.TOT` (ASI-3 total scale score), `ASI.PHY`, `ASI.COG`, `ASI.SOC`, and `SSs`.[1]

In the introduction, we wondered if gender influences levels of sensation seeking through its effect on anxiety sensitivity. Considering that we have a total scale and three subscale scores for anxiety sensitivity, we could go about testing the mediating effect of anxiety sensitivity in many different ways. The option that appears the most appropriate is to begin by conducting a simple mediation using the ASI-3 total scale as our mediator. If this analysis provides support for our hypothesis, we could then do a parallel mediation with the three subscale scores to determine which dimension of anxiety sensitivity is driving the mediation.

To conduct our analyses, we will be using version 23 of SPSS (IBM Corp., 2015) and the PROCESS macro for SPSS (Hayes, 2013), which uses a regression-based approach to mediation. This macro can be downloaded at the following address: http://processmacro.org/download.html. As a side-note, it is important to know that the PASTE option in SPSS (which allows you to save your syntax, or method, for later) cannot be used in the PROCESS macro. Therefore, we suggest writing down all the steps taken and the selected options to ensure that you can redo your analyses at a later time.

Simple Mediation

Before running the analysis, we must first examine our variables to determine if mediation is appropriate. You may have noticed that gender, our independent variable, is dichotomous. Thankfully, it is completely correct to conduct a mediation analysis with a dichotomous independent variable (Hayes, 2013). In fact, the interpretation that we will be able to make of the coefficients will be even more informative, as we will see later on when we examine our results. Our other variables, anxiety sensitivity and sensation seeking, are on a Likert-type scale, which should lend itself well to regression.

Assumptions.

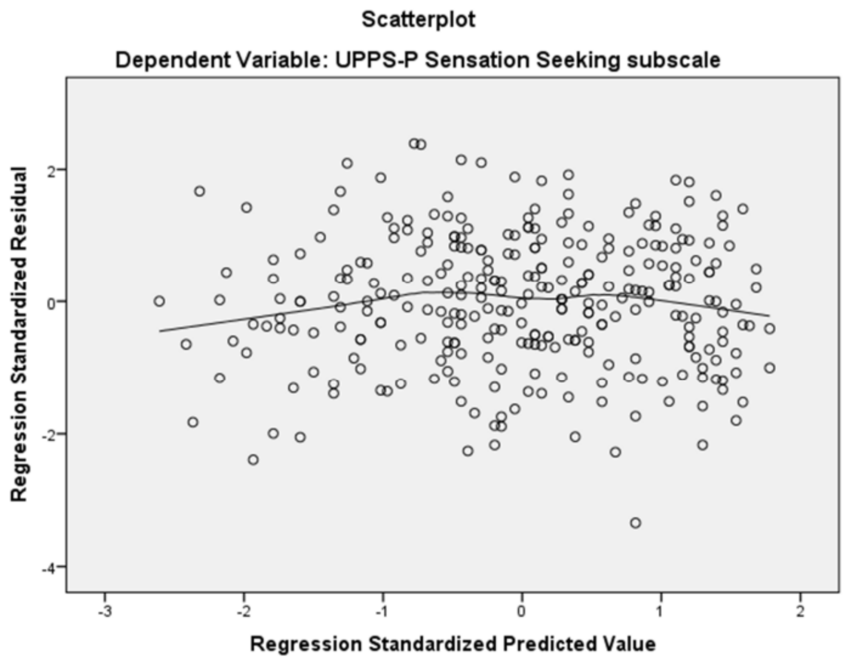
We first need to consider statistical assumptions. We will provide examples of assumption testing using our data (for more details, see Field, 2013; Hayes, 2013).

Linearity. In regression analysis, the relationship between X and Y should be linear to minimize error (Hayes, 2013). To our knowledge, no guidelines suggest a way of assessing overall model linearity in mediation. However, a mediation can be broken down into simple and multiple regressions, which each need to fulfil the assumption. The indirect effect should also be linear, which means that its constituting effects (a and b) need to be linear. To examine these criteria for a simple mediation, you need to plot residuals against predicted values in four regressions: X predicting Y (c), X predicting M (a), M predicting Y (b), and X and M predicting Y (combined linearity of b and c'). Should a or b be nonlinear, Hayes and Preacher (2010) outline procedures for determining and testing indirect effects.

We will follow this procedure by running a series of regressions (`Analyze > Regression > Linear`). For the sake of time and space, we will only present results relating to the X and M predicting Y regression (note: all other relationships respected the assumptions). First, enter `gender` and `ASI.TOT` as the independent variables and `SSs` as the outcome variable. In the Save tab, select the standardized residuals. Then, in the Plots tab, select the standardized regression residuals (`ZRESID`) for the Y axis and standardized predicted values (`ZPRED`) for the X axis. Optionally, after you have run the analysis, you may add a Loess curve to the scatterplot by double-clicking on the plot, and then going under `Elements > Fit Line at Total > Loess > Apply`. Loess fits a non-parametric curve that represents the relationship between variables

[1] In the discussion, we will briefly discuss serial mediation. Therefore, we also included the Negative Urgency subscale (NUs) of the UPPS-P in the dataset to provide readers with the possibility of conducting a serial mediation.

Figure 3 ■ Checking the linearity and homoscedasticity assumptions using the multiple regression standardized predicted and residual values: The influence of gender and anxiety sensitivity on sensation seeking.



(Jacoby, 2000). As can be seen in Figure 3, the regression appears fairly linear since the Loess curve centers close to zero along the entire X axis.

Homoscedasticity. Estimation error should be relatively equal across all predicted Y values. If it varies, then we have heteroscedasticity, which affects the standard error of the regression coefficients (Hayes, 2013). To check homoscedasticity, return to the same plot that we created to examine linearity, but this time look for consistency in vertical range across the X axis. In other words, see if the data spreads on the Y axis consistently and equally throughout the plot, resembling a rectangle. Our data in Figure 3 shows a relatively constant vertical range.

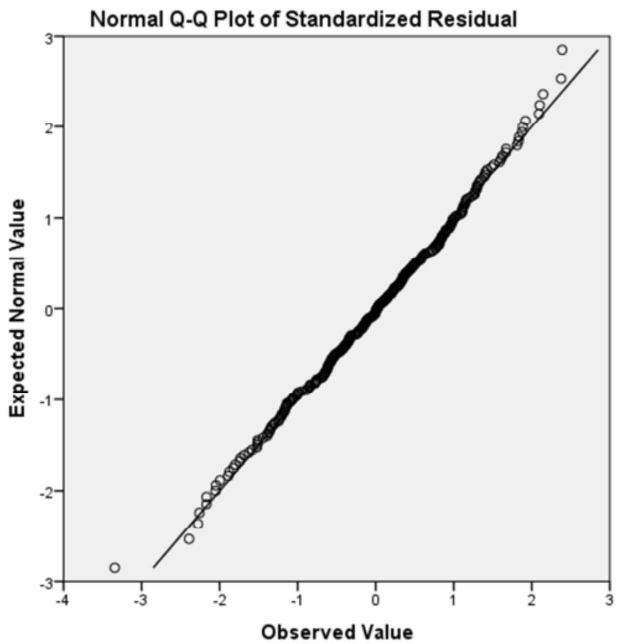
Normality of estimation error. Estimation error should be normally distributed (Hayes, 2013). To examine this assumption, we can create a Q-Q plot with the residuals we saved from the regression by going under `Analyze > Descriptive Statistics > Q-Q Plots`. The resulting plot for the X (gender) and M (anxiety sensitivity) predicting Y (sensation seeking) multiple regression can be seen in Figure 4. Our data fit well with the diagonal line, indicating normality. When there are minor violations to this assumption, the results of the analysis should not be affected unless the sample size is very small (Hayes, 2013).

Independence of observations. The error associated with each data point (i.e., one case) should be independent from the error of all other cases (Hayes, 2013). This is especially relevant for studies using cluster sampling procedures or dyadic data research (Hayes, 2013), wherein cases may be related to each other on the outcome because they share some characteristics or context. In the presence of nonindependence of observations, the standard error of the regression coefficients could be either smaller or larger than what it should be (Hayes, 2013). Only knowledge of one's own data collection method will allow a person to determine if their data meets the independence assumption. Given that we sampled our participants from an undergraduate participant pool at the same university, it is unlikely that we have underlying common characteristics that would compromise the independence of our estimation error.

The analysis.

Now that we have determined that our data respects multiple regression assumptions relatively well, we can conduct our simple mediation. Once the PROCESS macro has been installed on SPSS, you may access it by going under `Analyze > Regression > PROCESS`. You will be greeted with the window shown in Figure 5. You will need to use the center arrows to guide your variables to the appropriate boxes. We want `gender` as the independent variable, `ASI.TOT` as the M Variable, and `SSs` as the out-

Figure 4 ■ Checking the normality of estimation error assumption using the multiple regression standardized residuals: The influence of gender and anxiety sensitivity on sensation seeking.

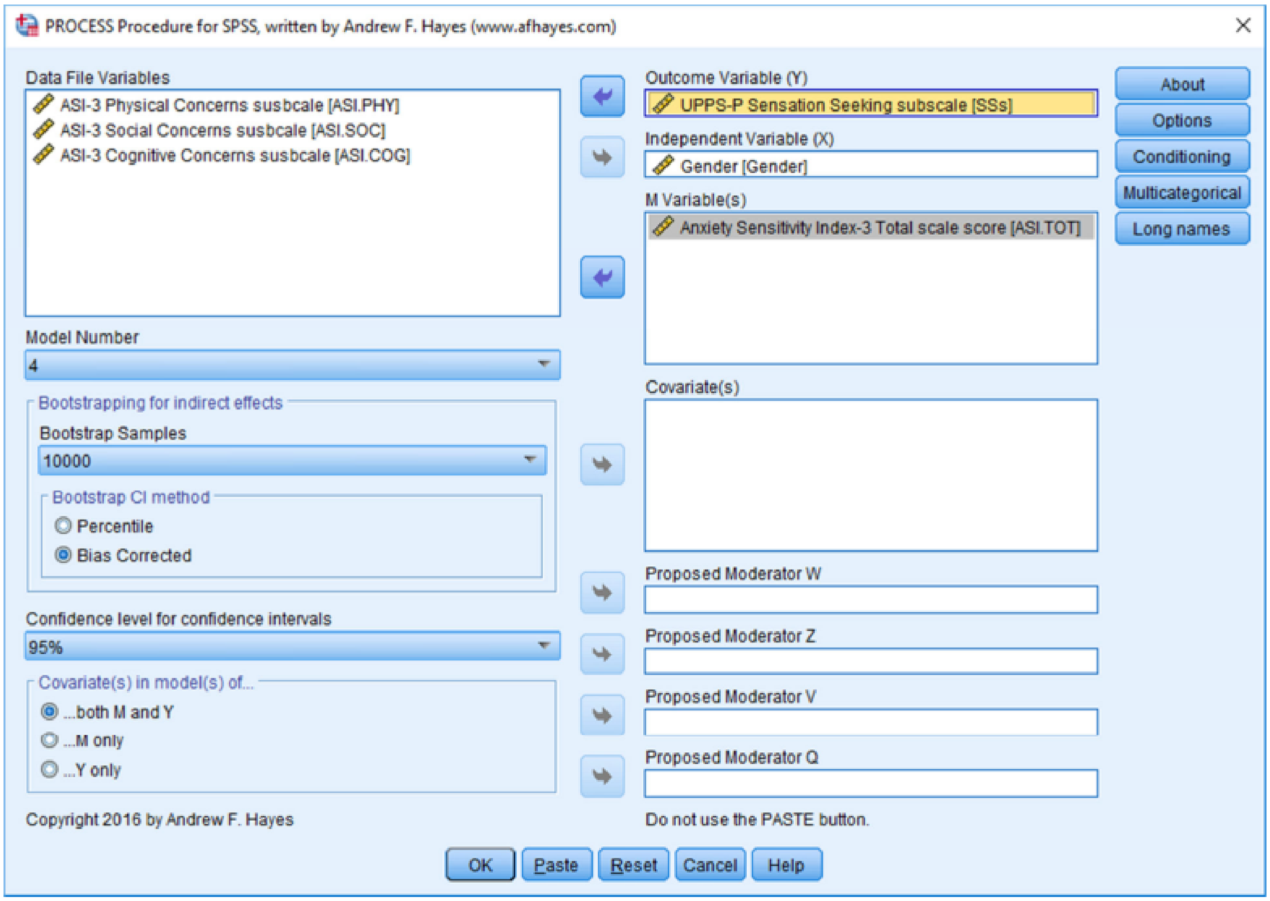


come variable. On the left-hand side, you will see various options. First, Model Number refers to the type of analysis we want to run. The default setting is 4, which is the one we want since it is for simple and parallel mediation (for the use of other model numbers, the interested reader can refer to Hayes, 2013). Second, we must decide which type of bootstrapping to use for the indirect effects. This technique merits explanation before we continue with the analysis.

Bootstrapping is an alternative way to perform null hypothesis testing that can be applied to the test of the indirect effect (ab) to determine if it is different from zero (Hayes, 2013). When using null hypothesis testing for an indirect effect, one assumption is that ab is normally distributed (i.e., if we were to redo the study multiple times, determining ab for each, the distribution of ab should be normal). Bootstrapping does not assume that ab is normal and therefore is preferable since we cannot really know the shape of the indirect effect's distribution in the population. Bootstrapping is a resampling method (Hayes, 2013). The goal is to construct a confidence interval around the examined effect (in our case, around the indirect effect ab). To achieve this, the current sample (of size n) is used as a mini population. We have 295 participants, who we believe adequately represent the population from which they came, the undergraduate students of the University of Ottawa. The computer will take a random bootstrap sample of observations (of size n) within this mini population with replacement. This means that some observations may be selected multiple times or not at all within each bootstrap sample. The computer will repeat this process thousands of time, each bootstrap sample being slightly different. Hayes (2013) recommends and uses 10,000 bootstrap samples. The analyses are then run on all these bootstrap samples to obtain the desired statistic for every one of them. Hence, if there are 10,000 bootstrap samples, there will be 10,000 computed indirect effects. These effects are then placed in ascending order to determine the lower and upper bounds of the confidence interval (CI), usually a 95% CI. An example 95% CI may resemble -0.023 to 0.265, -0.416 to -0.146, or 0.024 to 0.137. In the first case, the CI includes zero, which would indicate that the indirect effect is not significant because zero is in the realm of possible values for the effect. In the latter two cases, the CIs do not include zero and are entirely below or above zero. We can therefore say with 95% confidence that the indirect effect is negative in the second case and positive in the third case.

For our analysis, we will use 10,000 bootstrap samples and select the Bias Corrected method of bootstrapping. Examining the pros of bias-corrected bootstrap CIs over other methods is beyond the scope of this paper; the interested reader may refer to Hayes (2013). Lastly, we will select a

Figure 5 ■ Screen capture of the completed opening PROCESS procedure window in SPSS (version 23).



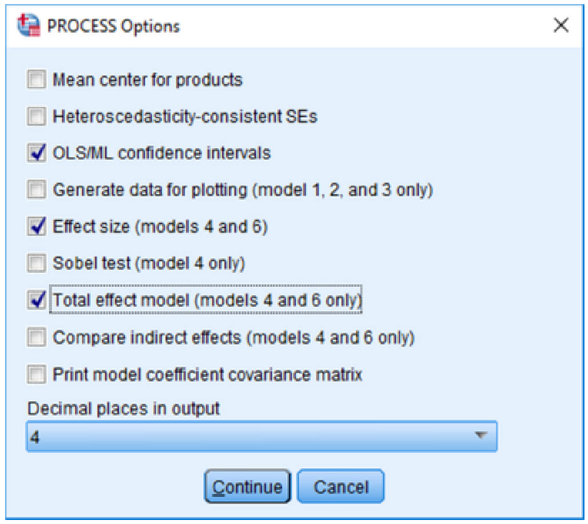
95% confidence level. If we had covariates, we could also select which variables we would like them to influence (M and/or Y). Since we do not have any covariates, it does not matter which option is selected. The screen should resemble the window shown in Figure 5.

Next, under the Options tab, we will select Ordinary Least Square/Maximum Likelihood (OLS/ML) confidence intervals to obtain CIs for effects other than the indirect effect which uses bootstrapping (optional if you do not wish to present these), Effect size, and Total effect model (see Figure 6). Additionally, PROCESS by default only allows for variables that are eight characters or less to be entered in the analysis. If your variable names are longer than eight characters, you may go in the Long Name tab and allow long variable names.

We are now ready to click OK on the main window. It may take some time before results appear in the output window. This is normal considering the work the computer must do to compute the bootstrap CIs. The output from PROCESS should resemble Listing 1 given at the end of the article.

Several key points should be noted in this output. Lines 8 to 14 remind the researcher of the model (number 4), the variables, the sample size, the number of bootstrap CIs, and the level of confidence. Lines 16 to 39 show the regressions associated with the mediator and the outcome variable. It is these coefficients we will be using to construct a diagram to represent our mediation. We will return to this in the interpretation of our results. Also, all coefficients in this output are unstandardized ones. If you would like to obtain standardized coefficients, you may transform your variables into Z scores before entering them in the mediation. Considering that our independent variable is gender, it would have been inappropriate to standardize as it would have produced coefficients without any real meaning.

Figure 6 ■ Screen capture of the Options menu of the PROCESS macro in SPSS (version 23).



Continuing, Lines 42 to 51 present the total effect model that we requested in the options. As previously explained, the total effect (c) is the result you would obtain by simply regressing sensation seeking on gender without consideration of the mediator. You may notice that these values are identical to those in the next section of the output. The interesting information in the Total Effect Model section is the R-squared, which tells us how much variance in sensation seeking our model can explain. In our case, we are explaining 4% with our model, which indicates that many other factors are influencing sensation seeking.

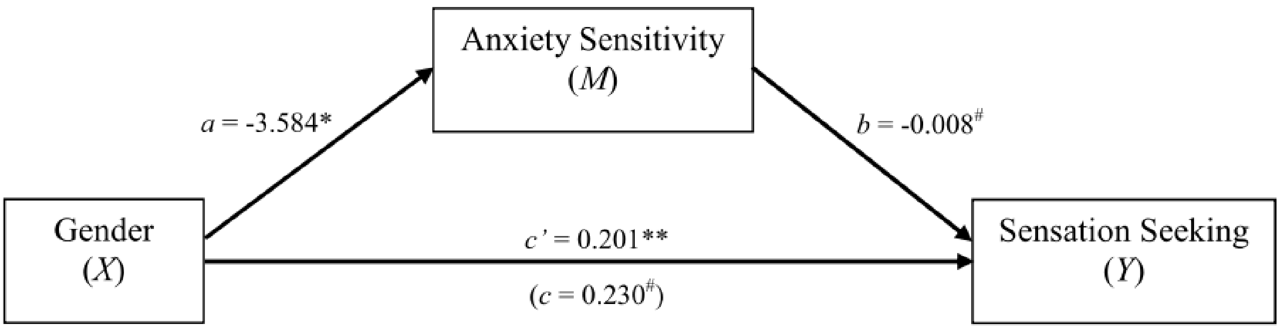
Direct effect. Finally, Lines 52 to 85 give information on the direct and indirect effects. Recall that, in our dataset, our X is coded by a unit difference (women coded as 0; men coded as 1), which means that the effects can be interpreted as mean differences between women and men (Hayes, 2013). It appears that men scored 0.201 points higher on sensation seeking than did women when levels of anxiety sensitivity were kept constant. However, if we had coded men as 0 and women as 1, we would then say that women scored 0.201 points lower on sensation seeking than did men when levels of anxiety sensitivity were kept constant.

Indirect effect. You will notice that the output presents three versions of the indirect effect: the indirect effect, the partially standardized indirect effect, and the completely standardized indirect effect. The indirect effect, similar to the direct effect, is presented using the metrics of X and Y, such that for every increase in one unit on X, there is a change of ab units on Y (Hayes, 2013). For example, we can say here that men scored 0.029 points higher than women on sensation seeking as a result of the indirect effect through anxiety sensitivity. However, what does 0.029 mean? Is it a small or a large increase in sensation seeking? The bootstrap CI is completely above 0, so we know with 95% confidence that the indirect effect is positive, but we still do not know if the increase in sensation seeking is notable. In addition, scores on the `SSs` vary from 1 to 4, but these are arbitrary values that carry no real meaning.

Partially standardized indirect effect. It is possible to change part or all of the metrics used to describe the indirect effect to add to its interpretation. The partially standardized indirect effect expresses ab using the original metric of X, but the standard deviation of Y (Hayes, 2013). In our case, men scored 0.048 standard deviations higher on sensation seeking than women as the result of the indirect mechanism of anxiety sensitivity.

Completely standardized indirect effect. It is possible to even further standardize the indirect effect by expressing ab using the standard deviations of both X and Y (Hayes, 2013). As such, we could say that an increase by one standard deviation on gender produced an increase of 0.024 standard deviations on sensation seeking through the indirect effect of anxiety sensitivity. However, considering that our X variable is dichotomous, this makes little sense. Indeed, the values we associated with men and with women were arbitrary. An increase in one standard deviation in gender therefore is uninterpretable. Completely standardized indirect effect can be used with other types of variables, but it is not appropriate for dichotomous ones

Figure 7 ■ The mediating effect of anxiety sensitivity in the relationship between gender and sensation seeking. Notes: *$p < .05$, **$p < .01$, # $p < .001$; All presented effects are unstandardized; a is effect of gender on anxiety sensitivity, women are coded as 0 and men as 1; b is effect of anxiety sensitivity on sensation seeking; c' is direct effect of gender on sensation seeking; c is total effect of gender on sensation seeking.



(Hayes, 2013). Thus, for our analyses we may use either the unstandardized indirect effect or the partially standardized indirect effect. The important thing will be to specify which one we choose in the text or in a figure note.

Interpretation of results.

To finish the section on simple mediation, we will present the results of our analysis as we would in a manuscript. All information comes from the PROCESS output.

> *Results from a simple mediation analysis indicated that gender is indirectly related to sensation seeking through its relationship with anxiety sensitivity. First, as can be seen in Figure 7, men reported less anxiety sensitivity than women (*$a = -3.584, p = .042$*), and lower reported anxiety sensitivity was subsequently related to more sensation seeking (*$b = -0.008, p =< .001$*). A 95% bias-corrected confidence interval based on 10,000 bootstrap samples indicated that the indirect effect (*$ab = 0.029$*) was entirely above zero (0.003 to 0.074). Moreover, men reported greater sensation seeking even after taking into account gender's indirect effect through anxiety sensitivity (*$c' = 0.201, p = .003$*).*

Parallel mediation

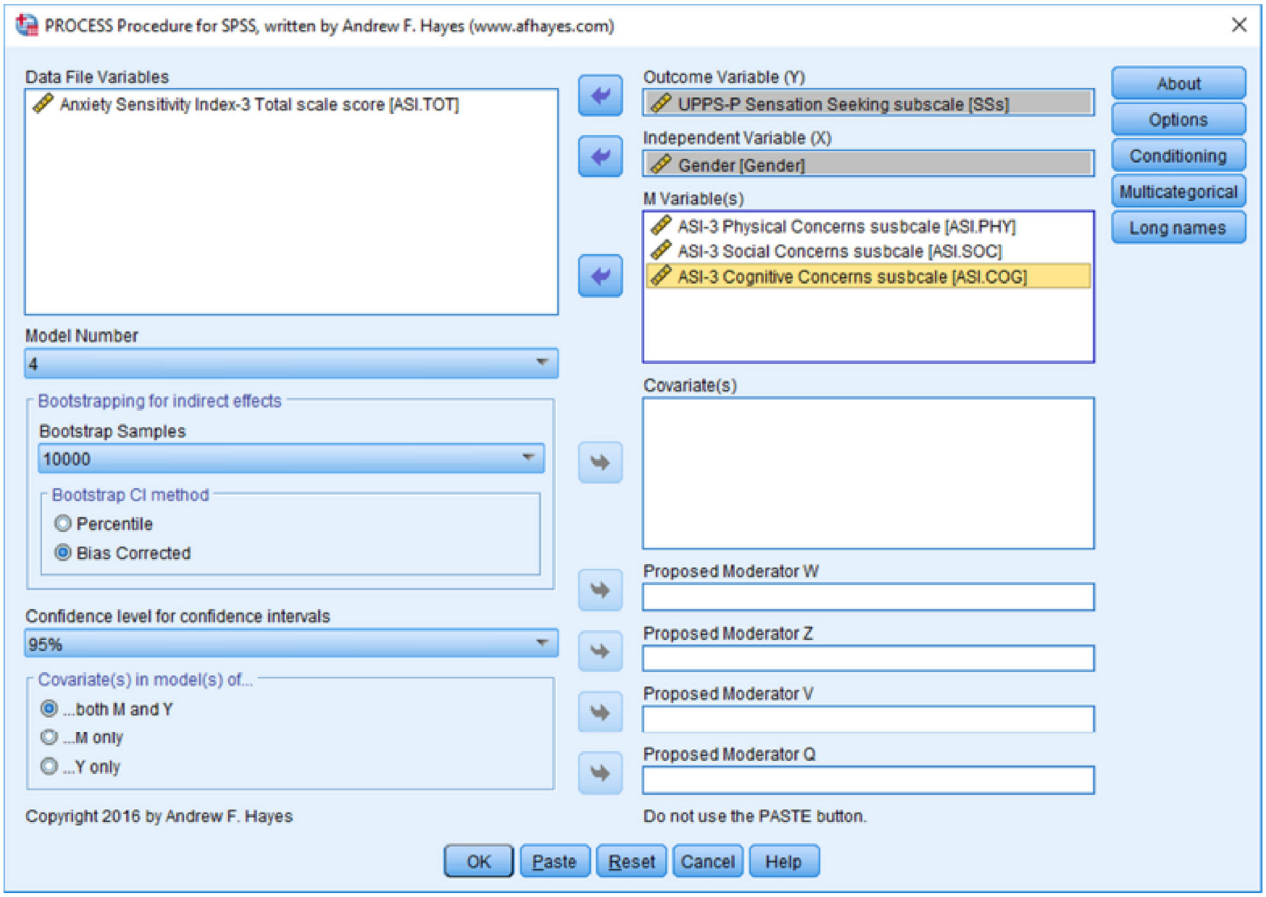
The results of our simple mediation suggest that anxiety sensitivity mediates the relationship between gender and sensation seeking. However, anxiety sensitivity has three dimensions: Physical, Cognitive, and Social Concerns (Taylor et al., 2007). It would be interesting to know if any of these dimensions drive the mediation more than the others, or if all three contribute to it. We can answer this question using parallel mediation. Recall that mediators in a parallel mediation are allowed to correlate, but not to causally influence each other. Considering that all three dimensions are assessed in one questionnaire and that we have no theoretical reason to believe that one dimension would lead to another, parallel mediation is appropriate. On the other hand, if we believed that one dimension led to another then serial mediation (see the conclusion for a more in-depth description of serial mediation) would be the appropriate choice. With parallel mediation, we can test each proposed mediator while accounting for the shared variance between them (Hayes, 2013). However, mediators that are too highly correlated may create multicollinearity, which affects the estimation of their partial relationships with the outcome variable (Hayes, 2013).

Assumptions. We verified the assumptions using the same methods we used for simple mediation, only this time we conducted seven additional regressions (i.e., X [gender] predicting each mediator [the three anxiety sensitivity dimensions]; each mediator predicting Y [sensation seeking]; X and all three mediators predicting Y; note: we already had regressed Y on X for the simple mediation). We noted no major assumption violations.

The analysis. To conduct our parallel mediation, we will go to the same PROCESS window as before, which should resemble Figure 8. The order in which you place the mediators will not affect the results of the parallel mediation.

Next, under the Options tab, we will select OLS/ML confidence intervals, Effect size, Total effect model, and Compare indirect effects. Once again, if your variable names are longer than eight characters, you may also go in the

Figure 8 ■ Screen capture of the completed opening PROCESS procedure window in SPSS (version 23).

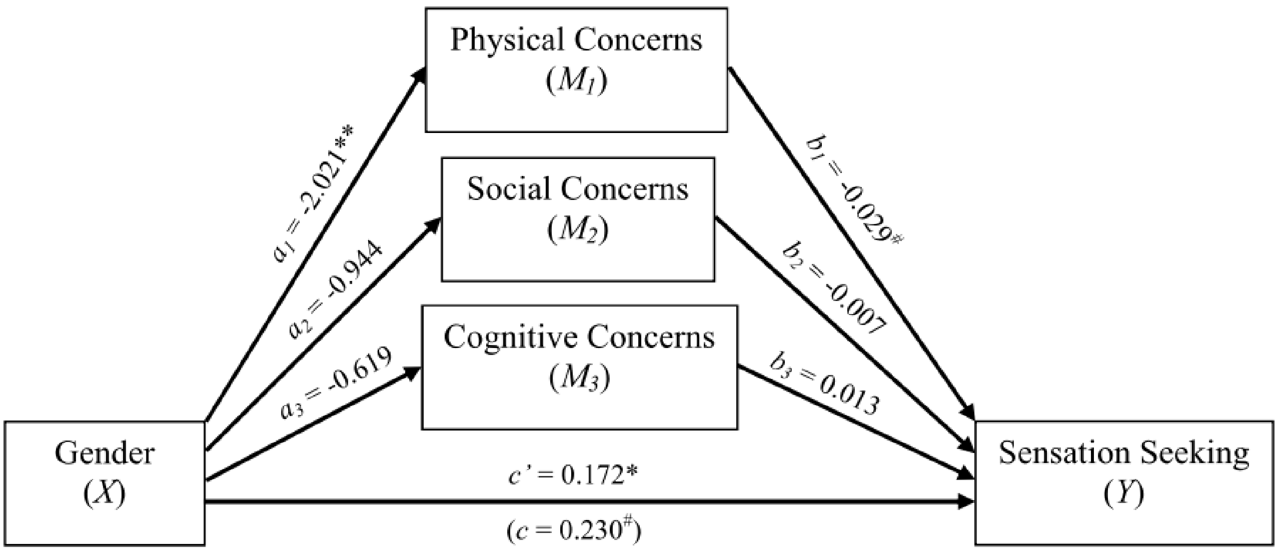


Long Name tab and allow long variable names. Click OK on the main PROCESS window to obtain the output in Listing 2.

This output is very similar to the simple mediation analysis, with some key differences. First, there is a section that presents the unstandardized coefficients for each "outcome", that is for each mediator and the final outcome variable (sensation seeking). Then, we have once again the total effect model, which is the same as for the simple mediation we ran earlier since, if you recall, the total effect is the result obtained by simply regressing sensation seeking on gender. Next, we can see information on the direct effect of gender on sensation seeking. The results are slightly different than they were for the simple mediation because we have different mediators entered in the model (i.e., three separate mediators versus one combined mediator) that account for a different proportion of the total effect. Here, men scored 0.172 points higher on sensation seeking than did women when levels of the three dimensions of anxiety sensitivity were kept constant. In addition, if you examine the indirect effect section of the output, you will see the total indirect effect, which is the sum of all indirect effects. This statistic is often not of interest because we usually want to look at the specific indirect effects (Hayes, 2013). Indeed, it appears that the only indirect effect that is different from zero with 95% confidence is the Physical Concerns subscale of the ASI-3, as evidenced by the bootstrap CI for Physical Concerns that is completely above zero. Thus, we can say here that men scored 0.058 points higher than women on sensation seeking as a result of the indirect effect through the physical concerns of anxiety sensitivity, holding all other mediators constant.

Next, you will find pairwise comparisons between the specific indirect effects (denoted by C_1, C_2, and C_3). The legend for these contrasts is at the end of the output. It should be noted, however, that these comparisons do not

Figure 9 ■ The mediating effect of three anxiety sensitivity dimensions in the relationship between gender and sensation seeking. Notes: *$p < .05$, **$p < .01$, #$p < .001$; All presented effects are unstandardized; a_n is effect of gender on anxiety sensitivity dimensions, women are coded as 0 and men as 1; b_n is effect of anxiety sensitivity dimensions on sensation seeking; c' is direct effect of gender on sensation seeking; c is total effect of gender on sensation seeking.



allow to test if one indirect effect is larger than another; they simply tell us if the effects are different (Hayes, 2013). For example, if one indirect effect is .20 and another is $-.20$, the contrast would probably identify these effects as being different, which they are because one is positive and the other is negative even if they are of the same strength. However, if both indirect effects are of the same sign, then a significant contrast may be interpreted as one effect being larger than the other (Hayes, 2013). Here, we can see that C_1 and C_2 are significant. With the help of the legend, we can determine that the indirect effect through the Physical Concerns subscale is larger than the two other indirect effects. For other analyses wherein more than one effect is significant, the contrasts may also provide additional interesting information.

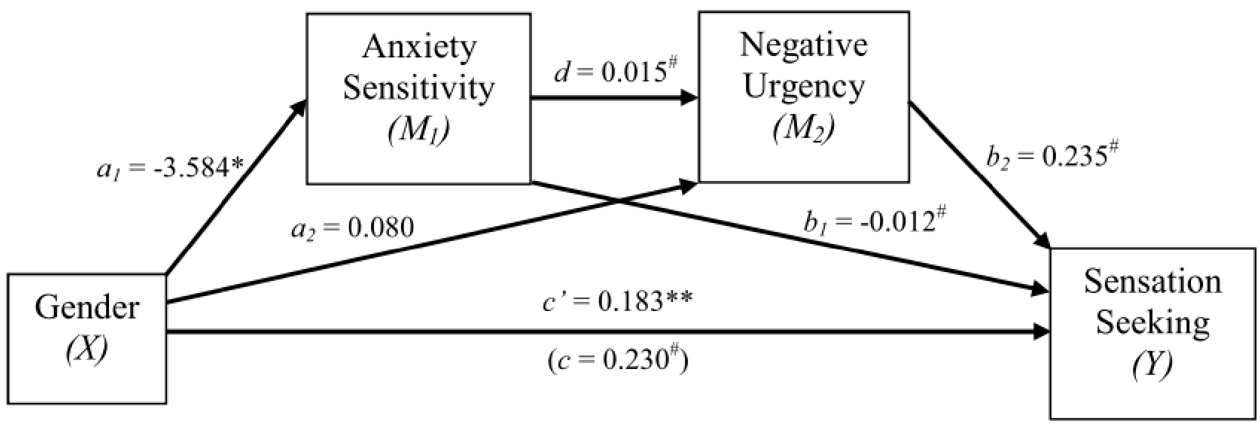
Interpretation of results. Once again, we will present the results of our parallel mediation as we would in a manuscript.

> *Results from a parallel mediation analysis indicated that gender is indirectly related to sensation seeking through its relationship with the Physical Concerns subscale of anxiety sensitivity. This dimension pertains to the fear of physiological sensations because of the belief that they may have negative consequences and are life-threatening. First, as can be seen in Figure 9, men reported less fear of physiological sensations than women ($a_1 = -2.021, p = .004$), and lower reported fear of physiological sensations was subsequently related to more sensation seeking ($b_1 = -0.029, p < .001$). A 95% bias-corrected confidence interval based on 10,000 bootstrap samples indicated that the indirect effect through fear of physiological sensations ($a_1b_1 = 0.058$), holding all other mediators constant, was entirely above zero (0.017 to 0.132). In contrast, the indirect effects through both the Social and the Cognitive Concerns subscales of anxiety sensitivity were not different than zero (-0.004 to 0.038 and -0.047 to 0.005, respectively; see Figure 9 for the effects associated with these pathways). Moreover, men reported greater sensation seeking even when taking into account gender's indirect effect through all three dimensions of anxiety sensitivity ($c' = 0.172, p = .011$).*

Discussion and Conclusion

Mediation analysis enables researchers to examine the processes through which one variable affects another. Although complex, modern computers and software make conducting mediations much more approachable. Using

Figure 10 ■ The serial mediating effect of anxiety sensitivity and negative urgency in the relationship between gender and sensation seeking. Notes: $*p < .05$, $**p < .01$, $\#p < .001$; All presented effects are unstandardized; a_n is effect of gender on mediators, women are coded as 0 and men as 1; b_n is effect of mediators on sensation seeking; c' is direct effect of gender on sensation seeking; c is total effect of gender on sensation seeking; d is effect of anxiety sensitivity on negative urgency.



the PROCESS macro for SPSS (Hayes, 2013), we were able to determine that anxiety sensitivity explains part of the relationship between gender and sensation seeking. More specifically, men reported less anxiety sensitivity than women, and less anxiety sensitivity was associated with more sensation seeking. We did not stop there, however. We then wondered which dimension of anxiety sensitivity was driving the mediation. Using parallel mediation, we found that the Physical Concerns dimension of anxiety sensitivity was the only significant mediator of the relationship. Men reported less fear of physiological sensations than women, which in turn led to more sensation seeking. Considering the three dimensions of anxiety sensitivity (Physical, Social, and Cognitive Concerns), it makes sense that it is the Physical Concerns that played the greatest role. Sensation seeking produces many physiological sensations. A person who fears these sensations would likely score high on the Physical Concerns subscale and also engage in less activities that produce strong physiological sensations.

In the introduction, we alluded to the fact that regression-based analyses (including mediation) imply causality, but that it is in fact a false sense of causality. Researchers choose which variable is the outcome and which is the predictor of this outcome, but the analyses could also be run the other way around. In our simple mediation example, we decided that anxiety sensitivity would be the mediator in the relationship between gender and sensation seeking. However, we could have also tested if sensation seeking mediates the relationship between gender and anxiety sensitivity. We chose the former because we based ourselves in a cognitive-behavioural framework, which suggests that beliefs (anxiety sensitivity) influence behaviour (sensation seeking).

But what if we want to see if this sequence of elements truly operates in this causal order? We could try running the mediation analysis with the mediator and the outcome in both possible configurations and see if the indirect effect holds in each model. We could also conduct a longitudinal study where we would measure anxiety sensitivity some time before sensation seeking to establish evidence of temporal precedence. However, to really determine if anxiety sensitivity causally influences sensation seeking, we would need to conduct an experiment where we would manipulate anxiety sensitivity (by either inducing or inhibiting it by, say, telling people that anxiety-related sensations are either dangerous or harmless) and see how this manipulation affects level of sensation seeking on a standardized task. Trait levels of sensation seeking would also need to be statistically controlled for in this experiment.

Furthermore, simple and parallel mediation are not the only possible mediation models. In parallel mediation, we saw that the mediators are allowed to correlate but not to causally influence each other. If it is believed that one mediator leads to another, then a serial mediation would be the preferred model (see Figure 10). Briefly, in serial mediation the a or b pathway is mediated by a second mediator. There are then indirect effects through each of the mediators (a_1b_1 and a_2b_2) and an indirect effect through both mediators (a_1db_2). Essentially, it is like conducting a parallel mediation, but with an added pathway that tests the causal relationship between the mediators. For instance, maybe anxiety sensitivity affects a person's tendency to act rashly when faced with negative emotions, a construct known as negative urgency (Cyders & Smith, 2007). Essentially, a person who is afraid of the sensations associated with negative emotions may act impulsively in order to escape these sensations. Negative urgency could then affect levels of sensation seeking. Figure 10 shows this example of serial mediation.[2] The material we covered in this tutorial can easily be applied to serial mediation and you may practice this technique using the supplemental dataset (note: in PROCESS, the model number for serial mediation is Model 6). The interested reader can refer to Hayes (2013) to learn about serial mediation in more detail.

This paper presents only the tip of the iceberg regarding mediation. It is based in our previous experiences with this type of analysis, complemented with information from much more comprehensive resources (e.g., Hayes, 2013). We hope it will prove useful to researchers who are new to the field or who require a quick refresher. Mediation is a great tool to have in a statistical toolbox, whether it be to conduct it yourself or to better understand the literature that uses the technique.

Authors' note

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[2] 95% bias-corrected confidence intervals based on 10,000 bootstrap samples indicated that the indirect effects through fear of physiological sensations alone and including negative urgency ($a_1b_1 = 0.042$ and $a_1db_2 = -0.013$) were entirely above or below zero (0.004 to 0.098 and -0.032 to -0.002, respectively). However, the indirect effect through only negative urgency (a_2b_2) was not different than zero (-0.008 to 0.058), suggesting that gender influences levels of negative urgency only through its effect on anxiety sensitivity.

Listing 1: Output from the PROCESS procedure in SPSS (version 23) for the gender, anxiety sensitivity, and sensation seeking simple mediation analysis.

```
Run MATRIX procedure:
************* PROCESS Procedure for SPSS Release 2.16.1 ******************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 4
    Y = SSs
    X = Gender
    M = ASI.TOT

Sample size
        295
**************************************************************************
Outcome: ASI.TOT

Model Summary
          R       Rfsq        MSE          F        df1        df2          p
      ,1188      ,0141   225,9784     4,1923     1,0000   293,0000      ,0415

Model
              coeff         se          t          p       LLCI       ULCI
constant    26,1351     1,2357    21,1506      ,0000    23,7032    28,5671
Gender      -3,5841     1,7505    -2,0475      ,0415    -7,0292     -,1390

**************************************************************************
Outcome: SSs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,2822      ,0796      ,3244    12,6292     2,0000   292,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,8641      ,0744    38,4869      ,0000     2,7176     3,0105
ASI.TOT      -,0080      ,0022    -3,6364      ,0003     -,0124     -,0037
Gender        ,2012      ,0668     3,0127      ,0028      ,0698      ,3327

************************** TOTAL EFFECT MODEL ****************************
Outcome: SSs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1948      ,0379      ,3379    11,5530     1,0000   293,0000      ,0008

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,6537      ,0478    55,5384      ,0000     2,5597     2,7478
```

```
Gender         ,2301      ,0677     3,3990      ,0008      ,0969      ,3633

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,2301      ,0677     3,3990      ,0008      ,0969      ,3633

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,2012      ,0668     3,0127      ,0028      ,0698      ,3327

Indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,0288      ,0177      ,0027      ,0738

Partially standardized indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,0488      ,0296      ,0043      ,1226

Completely standardized indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,0244      ,0148      ,0022      ,0614

Ratio of indirect to total effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,1254      ,1295      ,0085      ,4062

Ratio of indirect to direct effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,1434      ,5763      ,0083      ,6730

R-squared mediation effect size (R-sq_med)
            Effect    Boot SE   BootLLCI   BootULCI
ASI.TOT      ,0093      ,0066      ,0010      ,0294

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
    10000

Level of confidence for all confidence intervals in output:
    95,00

NOTE: Kappa-squared is disabled from output as of version 2.16.

------ END MATRIX -----
```

***Listing 2:** Output from the PROCESS procedure in SPSS (version 23) for the gender, anxiety sensitivity, and sensation seeking parallel mediation analysis.*

```
Run MATRIX procedure:
```

```
************* PROCESS Procedure for SPSS Release 2.16.1 ******************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 4
    Y = SSs
    X = Gender
   M1 = ASI.PHY
   M2 = ASI.SOC
   M3 = ASI.COG

Sample size
        295
**************************************************************************
Outcome: ASI.PHY

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1657      ,0274    36,4396     8,2676     1,0000   293,0000      ,0043

Model
              coeff         se          t          p       LLCI       ULCI
constant     7,8919      ,4962    15,9047      ,0000     6,9153     8,8685
Gender      -2,0211      ,7029    -2,8753      ,0043    -3,4046    -,6377

**************************************************************************
Outcome: ASI.SOC

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0867      ,0075    29,6116     2,2199     1,0000   293,0000      ,1373

Model
              coeff         se          t          p       LLCI       ULCI
constant    11,2162      ,4473    25,0753      ,0000    10,3359    12,0965
Gender       -,9441      ,6337    -1,4899      ,1373    -2,1912      ,3030

**************************************************************************
Outcome: ASI.COG

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,0524      ,0027    34,9672      ,8078     1,0000   293,0000      ,3695

Model
              coeff         se          t          p       LLCI       ULCI
constant     7,0270      ,4861    14,4568      ,0000     6,0704     7,9837
Gender       -,6189      ,6886     -,8988      ,3695    -1,9740      ,7363

**************************************************************************
```

```
Outcome: SSs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,3187      ,1016      ,3188     8,1959     4,0000   290,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,8771      ,0829    34,7125      ,0000     2,7140     3,0402
ASI.PHY      -,0289      ,0084    -3,4265      ,0007     -,0455     -,0123
ASI.SOC      -,0074      ,0075     -,9909      ,3225     -,0222      ,0073
ASI.COG       ,0125      ,0088     1,4223      ,1560     -,0048      ,0299
Gender        ,1724      ,0671     2,5693      ,0107      ,0403      ,3045

************************** TOTAL EFFECT MODEL ****************************
Outcome: SSs

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,1948      ,0379      ,3379    11,5530     1,0000   293,0000      ,0008

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,6537      ,0478    55,5384      ,0000     2,5597     2,7478
Gender        ,2301      ,0677     3,3990      ,0008      ,0969      ,3633

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS ********************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,2301      ,0677     3,3990      ,0008      ,0969      ,3633

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1724      ,0671     2,5693      ,0107      ,0403      ,3045

Indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
TOTAL        ,0577      ,0235      ,0199      ,1152
ASI.PHY      ,0584      ,0278      ,0168      ,1320
ASI.SOC      ,0070      ,0096     -,0044      ,0384
ASI.COG     -,0078      ,0114     -,0466      ,0053
(C1)         ,0514      ,0288      ,0090      ,1268
(C2)         ,0662      ,0362      ,0149      ,1665
(C3)         ,0148      ,0169     -,0069      ,0665

Partially standardized indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
TOTAL        ,0975      ,0386      ,0341      ,1897
ASI.PHY      ,0987      ,0460      ,0287      ,2168
ASI.SOC      ,0119      ,0161     -,0074      ,0651
ASI.COG     -,0131      ,0191     -,0772      ,0092
```

```

Completely standardized indirect effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
TOTAL          ,0488      ,0193      ,0172      ,0952
ASI.PHY        ,0495      ,0230      ,0144      ,1086
ASI.SOC        ,0059      ,0080     -,0037      ,0325
ASI.COG       -,0066      ,0096     -,0386      ,0046

Ratio of indirect to total effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
TOTAL          ,2507      ,5783      ,0811      ,6446
ASI.PHY        ,2539      ,9142      ,0679      ,7241
ASI.SOC        ,0305      ,0607     -,0230      ,1913
ASI.COG       -,0337      ,3114     -,2309      ,0288

Ratio of indirect to direct effect of X on Y
             Effect    Boot SE   BootLLCI   BootULCI
TOTAL          ,3346     7,9496      ,0838     1,5885
ASI.PHY        ,3388     9,9316      ,0708     1,8026
ASI.SOC        ,0407     1,6297     -,0330      ,4503
ASI.COG       -,0450     1,4064     -,6041      ,0410

Specific indirect effect contrast definitions
(C1)   ASI.PHY   minus     ASI.SOC
(C2)   ASI.PHY   minus     ASI.COG
(C3)   ASI.SOC   minus     ASI.COG

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
    10000

Level of confidence for all confidence intervals in output:
    95,00

------ END MATRIX -----
```

Open practices

The *Open Data* badge was earned because the data of the experiment(s) are available on the journal's web site.

Citation

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