RAM

Recherche et Applications en Marketing
2015, Vol. 30(4) 88–128

DOI: 10.1177/2051570715606278
rme.sagepub.com
SAGE

Analysing moderated mediation effects: Marketing applications

Sylvie Borau
Université de Toulouse, Toulouse Business School, France

Assâad El Akremi
Université Toulouse 1 Capitole, Centre de Recherche en Management (CRM, UMR 5303 CNRS), France

Leila Elgaaied-Gambier
Université de Cergy-Pontoise, THEMA (UMR CNRS 8184), France

Linda Hamdi-Kidar
IUT A, Université Paul Sabatier, LGCO - Laboratoire de Gouvernance et Contrôle Organisationnel, France

Charlotte Ranchoux
Université Toulouse 1 Capitole, Centre de Recherche en Management (CRM, UMR 5303 CNRS), France

Abstract

The purpose of this article is to explain and illustrate the methodological approach used to test moderated mediation effects (conditional indirect effects) in marketing. A moderated mediation effect indicates the presence, in a single model, of one or more mediating variables and one or more moderating variables. Having first described the main methodological approaches used to test moderated mediation effects, with an emphasis on their respective advantages and disadvantages, we go on to recommend the method used by Hayes, which we illustrate through several marketing applications. This method makes it possible rigorously and simultaneously to test both mediating and moderating effects. Recommendations are also made to guide marketing researchers in the analysis of moderated mediation.

Keywords

bootstrap, conditional indirect effects, mediated moderation, methodology, moderated mediation

Introduction

Mediating and moderating effects are often tested by marketing researchers (Caceres and Vanhamme, 2003; Zhao et al., 2011). A mediating effect, also known as an indirect effect, is defined by the presence of one or more variables that intervene to transmit the influence of variable X on variable Y (Baron

Corresponding author:
Sylvie Borau, Toulouse Business School, Université de Toulouse, 20 Boulevard Lascrosses, 31068 Toulouse, France.
Email: s.borau@tbs-education.fr

and Kenny, 1986; MacKinnon, 2008; MacKinnon et al., 2012; Shrout and Bolger, 2002; Zhao et al., 2010, 2011). A moderating effect is defined by the presence of one or more variables that modulate the influence of variable X on variable Y by impacting the nature, direction and/or strength of this influence, which can vary in accordance with the values of the moderating variable (Aguinis and Gottfredson, 2010; Baron and Kenny, 1986; Caceres and Vanhamme, 2003; Dawson, 2014; Jaccard and Turrisi, 2003; Sharma et al., 1981). Edwards (2008) uses the term conditional effect to describe a moderating effect. The procedures used to test mediating and moderating effects separately and rigorously are increasingly stable and widely adopted (Aguinis and Gottfredson, 2010; Aiken and West, 1991; Preacher and Hayes, 2004, 2008; Zhao et al., 2011). However, the considerable advances being made in marketing research now encourage researchers to move beyond the separate analysis of mediating and/or moderating effects and instead to understand the simultaneous mechanisms underlying these effects ('*how*') and the conditional limits of these effects ('*when*' or '*under what conditions*'; Edwards and Lambert, 2007; Hayes, 2013a, 2013b).

Marketing researchers currently face an increasing number of models that use both mediating and moderating variables, giving rise to so-called *moderated mediation*, *mediated moderation* (Edwards and Lambert, 2007) or *conditional indirect effects* (Preacher et al., 2007). The term 'moderated mediation' is conventionally used as a generic term to describe multiple effects (Edwards and Lambert, 2007; Fairchild and McQuillin, 2010; Muller et al., 2005; Preacher et al., 2007). Indeed, the methodological approach presented herein applies to all of these effects. We therefore use the term 'moderated mediation' to refer to all cases in which the moderating effect is transmitted via one or more mediating variables. In other words, moderated mediation is present when the magnitude, size or direction of the indirect effect of variable X on variable Y via a mediating variable M varies in accordance with the value of a moderating variable Z (Preacher et al., 2007). For example, Sellier and Dahl (2011) demonstrated that the impact of a greater rather than a limited choice of inputs on consumer creativity is mediated by the pleasure associated with the creative process and that this indirect impact varies according to the consumer's level of expertise. By studying the partnerships between buyers and sellers, Celuch et al. (2011) found that the indirect effect of a partner's communication on conflict resolution via the attribution of responsibility is determined by the level of trust between the buyer and seller. Bibliographical research covering the period from early January 2007 to late December 2014 in marketing journals ranked 1 and 2[1] reveals a growing interest among researchers in the analysis of moderated mediation effects (see Appendix 1). However, the number of articles that use rigorous analytical approaches remains limited (from a sample of several hundred articles, we identified 118 which explicitly deal with moderated mediation), which might generate a risk that inadequate methods will be used leading to incorrect results and conclusions. The majority of these 118 articles (61, or 51.7%) were based on the approach recommended by Preacher et al. (2007). Although recent, Hayes (2013a, 2013b) updated version of this approach has already been used in 49 articles (41.5%), no more than 8 articles (6.8%) make reference to the method suggested by Edwards and Lambert (2007; see Appendix 1). It is worth noting that, since it was first revealed, Hayes' method (2013a, 2013b) has taken on significant importance in the marketing literature. In 2013, 14 articles used this method (compared to 20 in which that of Preacher et al., 2007 was used). This rose to 33 in 2014 (compared to 23 for Preacher et al., 2007). So, while the method proposed by Preacher et al. (2007) continues to dominate in terms of the overall number of studies between 2007 and 2014, Hayes' method (2013a, 2013b) was used more often in 2014. This rising influence suggests that this method, which we recommend, is currently becoming the dominant approach in marketing research.

Many authors have recently emphasised that traditional procedures are insufficient and inadequate when it comes to simultaneously and rigorously testing moderated mediation effects (Edwards and Lambert, 2007; Hayes, 2013a, 2013b; Preacher et al., 2007). These procedures often involve initially testing for mediating effects and then for moderating effects, before reaching a conclusion about the presence of moderated mediation effects. In other cases, a multi-group analysis is used: the sample is first split into subgroups according to various values of the moderating variable, after which the significance of the mediating effect is tested in each subgroup (Wegener and Fabrigar, 2000). Most of these methods do not allow the user to formally test for conditional indirect effects, therefore making it impossible to formulate clear statistical inferences in this regard (see Table 1). It is also possible to use structural equations to simultaneously test an overall model of moderated mediation (Dabholkar and Bagozzi, 2002; Hayes and Preacher, 2013). However, the use of structural equation methods to test this type of model is complex and sometimes runs the risk of breaching the conditions for normal probability and linearity distribution of the tested effects,[2] especially when the sample size is insufficient (Cortina et al., 2001; Edwards, 2008). Different authors emphasise the importance of (1) using robust methods such as bootstrapping which allow the user to rigorously test for non-linear effects and, in the case of non-normal distribution, to calculate confidence intervals (CIs); (2) testing the significance of indirect effects for various values of the moderating variable and (3) making methods for testing moderated mediation effects more intuitive and easy to use by developing macros that can be readily used by researchers (Hayes, 2013a; Preacher et al., 2007).

The objective of this article is to present, explain and illustrate the methodological approach to be adopted when testing moderated mediation effects. Having first clarified what is meant by moderated mediation, mediated moderation and conditional indirect effects, we outline the main methods used to study these effects, highlighting the contributions and limitations of each analytical procedure. We then provide an illustration of this approach in the context of marketing through several applications of our recommended method, that of Hayes (2013a, 2013b), before finally concluding with a series of recommendations for marketing researchers who want to test moderated mediation effects.

Definition and fundamental principles of moderated mediation

In order to understand moderated mediation effects, one must first grasp what is meant by mediation and moderation. Despite the advanced state of methods with which to analyse mediation and moderation effects, there remains some confusion between the two, although they represent distinct processes and require different methods of analysis (Hayes, 2013a, 2013b).

Mediation effects: Direct and indirect effects

A mediation effect relates to the mechanism through which an independent variable X has an impact on a dependent variable Y via an intermediary variable M located between X and Y (MacKinnon, 2008). The mediation effect can often be broken down into *direct* and *indirect* effects. Two regression equations can be used as a simplified method to test these effects. The first links the independent variable X and the mediating variable M

$$M = b_{\mathrm{M}} + aX + e_{\mathrm{M}} \quad (1)$$

The second equation represents the estimation of Y by both X and M, thereby enabling the impact of M on Y to be tested while controlling for X

$$Y = b_{\mathrm{Y}} + c'X + bM + e_{\mathrm{Y}} \quad (2)$$

The *indirect effect* is represented by the product $(a \times b)$ in equations (1) and (2). The *total effect* of X on Y is the sum of the direct and indirect effects $(a \times b + c')$, whereby c' represents the *direct effect* in the presence of M.

Several methods are used to test mediating effects: (1) the causal steps approach developed by Baron and Kenny (1986), (2) the Sobel (1982) test and the significance of the indirect effect (MacKinnon et al., 2007) and (3) the bootstrapping method (Preacher and Hayes, 2004, 2008). It is not the purpose of this article to present these methods; the strengths and weaknesses of each one are summarised in Table 1. We direct the reader to a range of excellent studies that provide a critical overview of the methods used to test mediation effects (Hayes, 2013a; MacKinnon, 2008; MacKinnon et al., 2012; Zhao et al., 2010, 2011).

The following is an overview of the contributions made by these recent studies:

Table 1. Summary of the main methods for estimating relationships with both mediation and moderation links.

	Procedures and methods	References	Tools	Advantages	Disadvantages
First approach: test for mediation and moderation separately	Mediation analyses using the method developed by Baron and Kenny (1986; with or without Sobel's test), followed by a moderation test often with moderated hierarchical regression (or multi-group analysis)	Baron and Kenny (1986) Sobel (1982) Aiken and West (1991) Jaccard and Turrisi (2003) Wegener and Fabrigar (2000)	Very often with SPSS/SAS	Easy to implement Popular approach frequently used in journals since 1986, when Baron and Kenny published their article	Procedure challenged in respect of mediation test. The causal steps approach developed by Baron and Kenny (1986) may produce erroneous results, especially due to step 1. You are strongly advised against using this approach (Zhao et al., 2010, 2011), nor does it allow you to quantify indirect effect or test for the significance of this effect (Edwards and Lambert, 2007; Muller et al., 2005; Preacher et al., 2007) Sobel's test is based on the assumption that the indirect mediation effect is normally distributed. This assumption is very rarely verified, implying a risk of biased results (Edwards and Lambert, 2007) This procedure does not permit statistical inferences on conditional indirect process by testing for mediation and moderation separately.
	Mediation analyses using the bootstrapping method followed by a moderation test often with moderated hierarchical regression (or multi-group analysis)	Preacher and Hayes (2004, 2008) Zhao et al. (2010, 2011) MacKinnon (2008) Aiken and West (1991) Jaccard and Turrisi (2003) Wegener and Fabrigar (2000)	SPSS/SAS+suitable macro (downloadable)	As a non-parametric test, bootstrapping removes the assumption of normal distribution, as it is robust regardless of distribution Bootstrapping allows you to calculate a confidence interval for the indirect effect that is significant if this interval does not include zero (Preacher and Hayes, 2008) The procedure is more reliable and more robust when testing for mediation than the method developed by Baron and Kenny (1986) or Sobel's test. It is based on a formal test of the significance of the indirect effect using bootstrap (Hayes, 2013a) This method is applicable when the dependent variable is dichotomous (the macro's script adapts automatically and changes from linear to logistic regression when it detects a binary dependent variable)	Because the mediation and moderation tests are carried out independently, they do not permit statistical inferences on conditional indirect links If the moderated hierarchical regression is not backed up by a bootstrapping procedure, its analysis may be biased (Edwards and Lambert, 2007) When a multi-group analysis is used to test the moderating effect, there is a risk of bias if the variable must be discretised (Cadario and Parguel, 2014) and a risk of reduced statistical power if the initial sample is split

(Continued)

Table 1. (Continued)

	Procedures and methods	References	Tools	Advantages	Disadvantages
Second approach: testing for mediation and moderation simultaneously	Multi-group analyses using structural equation methods	Dabholkar and Bagozzi (2002) Dittmar, et al. (2009)	Structural equation software (Amos, Lisrel, Mplus, EQS, Stata, PLS)	Using structural equation methods, this procedure allows you to test the model as a whole, irrespective of the number of mediating and dependent variables The multi-group analyses are adapted to process qualitative moderating variables with more than two modalities This procedure carries the advantages of structural equation methods in terms of accounting for measurement errors, imprecise estimations and errors in evaluating adjustment quality This procedure is compatible with bootstrap. It is therefore possible to generate confidence intervals for the effects estimated by the structural equation software	Unless you systematically impose a series of equality constraints between the different groups – leaving only the mediation link to be tested constraint-free (see Dabholkar and Bagozzi, 2002) – this procedure does not allow you to account formally for conditional indirect links and may be comparable to separate mediation and moderation tests (Hayes, 2013a) Dividing the overall sample into subsamples may reduce statistical power This procedure does not always offer a formal test of the differences in direct and indirect effects between the groups (Hayes, 2013a) If the moderating variable is quantitative/continuous, it must be discretised in order to form groups; this may result in a loss of information and a risk of bias (Cadario and Parguel, 2014) Discretising the moderating variable reduces statistical power and makes it more difficult to detect interaction effects (Dawson, 2014) If the groups are significantly different in terms of size, there is a risk that statistical power will differ from one model to another, inducing a risk of error in the comparison between mediating effects (Hayes, 2013a)
	Moderated mediation analyses (conditional indirect effect) using bootstrap	Preacher et al. (2007) Edwards and Lambert (2007) Hayes (2013a, 2013b)	SPSS/SAS+suitable macro (downloadable)	This is the only approach that allows you to make formal and clear estimates of conditional indirect links: it enables analysis of a mediation effect as well as its variations in terms of the different values of the moderating variable The bootstrapping method is very robust regardless of the distribution of the variables analysed and sample size Because of confidence intervals, this procedure generates statistical inferences on conditional indirect links Recent advances in this approach (Hayes, 2013a, 2013b) now make it possible to process both quantitative/continuous and qualitative/dichotomous variables	Certain procedures such as that of Edwards and Lambert (2007) may potentially be laborious to implement SPSS/SAS macros can only process one dependent variable at a time. To overcome this limitation, Hayes and Preacher (2013) developed a version of this approach that can be used with structural equation methods (specifically with Mplus) These procedures cannot be used to process dichotomous mediating variables. Such cases can only be processed by structural equation software such as Mplus

- Zhao et al. (2010, 2011) propose a new typology of mediating effects, notably by drawing a distinction between *complementary mediation* (the indirect effect ($a \times b$) and direct effect (c') are significant and have the same signs) and *competitive mediation* (the indirect effect ($a \times b$) and the direct effect (c') are significant but of opposite signs). This typology moves beyond the traditional distinction between *complete mediation* and *partial mediation*, which has increasingly been criticised for its trivial if not unrealistic nature (Hayes, 2013a).
- There is now unanimous agreement that the causal steps approach developed by Baron and Kenny (1986) should be rejected. Several authors have demonstrated its significant limitations and the risk of incorrect results (Zhao et al., 2010, 2011; see also Table 1). There is also consensus to support the use of bootstrapping when testing mediation effects (Hayes, 2013a; Preacher and Hayes, 2004, 2008; Shrout and Bolger, 2002). The only condition for the existence of a significant indirect effect is based on a bootstrap test with a CI that excludes zero.
- Structural equation methods can be combined with bootstrapping to test mediating effects (Iacobucci et al., 2007; Zhao et al., 2010, 2011). It is recommended to use these methods when the mediating variable is categorical/dichotomous – the software program *Mplus* is well suited to this scenario (Muthén and Muthén, 2011).

Moderation effects: Interaction effects and conditional effects

A moderation effect refers to the interaction between two or more variables that have an influence on another variable. This effect occurs when the impact of independent variable X on dependent variable Y varies in accordance with the value of a third variable Z (Aiken and West, 1991; Edwards and Lambert, 2007; Jaccard and Turrisi, 2003). Variable Z may be a continuous variable (or an ordinal Likert-type variable with equidistant intervals), such as involvement, or a categorical variable, such as gender (Aguinis, 2004; Aguinis and Gottfredson, 2010). Preacher et al. (2007) recommend using the term *conditional effect* to describe a moderating effect, given that the moderating variable plays a role as a contingency factor[3] that has an influence on the strength, direction and/or significance of the relationship between two variables. Analysing moderating effects is important as it allows us to understand the conditions for generalisation under which the relationship between the independent variable and the dependent variable can be verified (Fairchild and McQuillin, 2010). Accounting for moderating effects also reflects the level of maturity and sophistication of a research field (Aguinis et al., 2001).

Several methods such as analysis of variance (ANOVA) or multi-group analysis can be used to test moderating effects. Moderated hierarchical regression is also often used to test these effects. This involves testing the significance of the regression coefficient for the product of the independent variable X with variable Z, after the direct effects of X and Z have been introduced to the regression equation. The product XZ represents the interactive term

$$Y = b_Y + \beta_1 X + \beta_2 Z + \beta_3 XZ + e_Y \qquad (3)$$

Z has a moderating effect on the relationship between X and Y if the coefficient β_3 is significant ($p < 0.05$). It should be noted that the moderating variable Z is not necessarily directly linked to the dependent variable Y; in other words, while it is essential from a statistical point of view to include in one's analysis the direct link between the moderating variable and the dependent variable (Dawson, 2014), the significance of this direct link (β_2) is not a requisite condition for the existence of a moderating effect (Carte and Russell, 2003). When adding the interactive term XZ, it is also important to have a significant variation in the explained variance R^2. The value of ΔR^2 (F test) indicates the extent to which the moderating effect improves the explanatory power of the model beyond the direct linear effects (Aguinis, 2004; Aiken and West, 1991; Fairchild and McQuillin, 2010).

Despite the recent debate on the appeal and necessity of centring variables X and Z before calculating XZ and of carrying out a moderated hierarchical regression to reduce multicollinearity (Dalal and Zickar, 2012; Echambadi and Hess, 2007; Hayes, 2013a), it is still recommended to centre[4] the variables in order to facilitate the interpretation

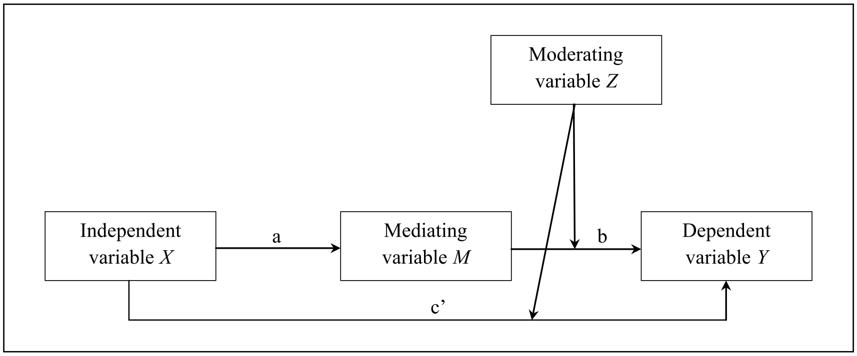


Figure 1. Moderated mediation: a sample model.

of one's results (Dawson, 2014). Note that dependent variable *Y* need not be centred (Dawson, 2014). Finally, to make it easier to interpret the direction and size of interaction effects, it is necessary to produce a graphic representation (*plot*)[5] of these effects using the method recommended by Aiken and West (1991). This representation also makes it possible to compare the significance of the relationship between *X* and *Y* in respect of focal values of *Z* or where the value of *Z* is low (typically considered to be equal to the mean value of *Z* minus its standard deviation) or high (typically considered to be equal to the mean of *Z* plus its standard deviation). Although this so-called spotlight approach (based on an interpretation of the effects in respect of the focal values of the moderating variable) continues to be dominant, some recent studies have recommended the so-called floodlight approach, which involves interpreting the effects using all of the moderating variable's values so as to limit the potentially arbitrary choice of focal values (Cadario and Parguel, 2014; Spiller et al., 2013). This approach is based on the identification of *regions of significance* (all of the values of moderating variable *Z* for which the relationship between *X* and *Y* is significant) according to the procedure developed by Johnson–Neyman which is embedded in macros such as PROCESS (Hayes, 2013a, 2013b).[6]

Moderated mediation: Conditional indirect effects

The advances made in marketing research mean that researchers are increasingly confronted with complex models that combine both mediation and moderation effects. Yet some authors process and analyse these effects separately, while others approach them simultaneously (see Table 1). In these models, referred to as *conditional process* models (Hayes and Preacher, 2013), the indirect and/or direct effects of an independent variable *X* on a dependent variable *Y* via one or more mediating variables *M* are moderated by one or more moderating variables *Z*. A simple example is given in Figure 1, which shows that both the direct and indirect effects of *X* on *Y* via *M* are moderated by *Z*. Ultimately, the influence of the independent variable on the dependent variable is determined by the interaction between the mediating and moderating variables.

Moderated mediation models can be highly varied (Hayes, 2013a, 2013b). This explains the many different terms used to refer to them. According to Edwards and Lambert (2007), *mediated moderation* refers to a scenario in which the moderating effect is localised within the first sequence of the mediation process, that is, before the mediating variable, around (*a*) in Figure 1. They consider mediated moderation to be a specific case of moderated mediation. It is, nonetheless, worth noting that this concept is subject to debate. For other authors such as Muller et al. (2005), mediated moderation instead refers to a scenario in which it is the direct link between *X* and *Y* that is moderated. Finally, Hayes (2013a) challenges the relevance of the very notion of mediated moderation and advises against using this term. Hayes and Preacher (2013) refer to *conditional indirect effects* when the moderating variable has an influence on the indirect impact of the independent variable on the dependent variable via the mediating variable ((*a*) and/or (*b*) in Figure 1) and to *conditional direct effects* when the impact of the moderating variable is localised on the direct link between the independent variable and the dependent variable ((*c′*) in Figure 1).

Simultaneous analysis of these different effects is needed to produce reliable and robust results (Edwards and Lambert, 2007; Hayes, 2013a, 2013b; Preacher et al., 2007). It offers several advantages: (1) it overcomes the limitations of traditional sequential approaches which test for mediation and moderation effects separately, (2) it leads to more rigorous and precise results using the bootstrapping procedure (see Box 1), (3) it can be used both with conventional multiple regressions and with structural equation methods (Hayes and Preacher, 2013) and (4) it has been made increasingly simple and accessible through ready-to-use macros.[7]

Box 1. The advantages of bootstrapping to test for moderated mediation.

The various ways of analysing moderated mediation effects have one common feature: the use of bootstrapping. Bootstrapping is a sample estimation procedure using repeated resampling (random sampling with replacement) based on an original sample (Efron and Tibshirani, 1993).

It is a robust procedure that is equally suited to non-normal distributions and small samples. It is particularly useful when analysing moderated mediation, given that indirect and interaction effects very often have non-normal distributions (Edwards and Lambert, 2007). Bootstrapping therefore provides a more precise estimation of conditional indirect effects using a reliable statistical test and generating a confidence interval for the lower and upper limits of the moderated mediation effect (this interval must exclude zero in order to be significant).

The bootstrapping procedure is now embedded in various software programs such as SPSS and SAS or structural equation-type applications (Mplus, Lisrel, Stata or Amos). It has been directly integrated into the macro used in this article (Hayes, 2013a). Finally, it is generally recommended to produce at least 1,000, if not 5,000 or 10,000 resamples and to opt for the percentile, bias-corrected or accelerated bootstrap procedures (Hayes and Scharkow, 2013; Preacher et al., 2007).

The main bootstrapping procedures for simultaneously testing moderated mediation effects

A review of the literature on moderated mediation (see Appendix 1) reveals three analytical approaches which are increasingly used: that of Edwards and Lambert (2007), that of Preacher et al. (2007) and, more recently, that of Hayes (2013a, 2013b). We outline these methods in the following section; it should be noted that the last two are grouped together (one is an improved version of the other). Table 2 provides details of the main advantages and disadvantages of each method.

Edwards and Lambert (2007)

The approach developed by Edwards and Lambert (2007) is based on the principle that in a model of moderated mediation, the moderating effect can have an impact on the indirect effect, the direct effect or the overall effect. Moderated mediation is therefore expressed in direct, indirect and overall terms. As Figure 2 illustrates, in each approach the moderating effect of variable Z is tested at several different levels each time: (1) in the first sequence between independent variable X and mediating variable M (first stage), (2) in the second sequence between mediating variable M and dependent variable Y (second stage) and (3) in the direct link between independent variable X and dependent variable Y. According to Edwards and Lambert (2007), in moderated mediation modelling, any sequence of the direct effect between X and Y or the indirect effect via M can be moderated by Z. It is the mediating relationship as a whole that is considered to be moderated (Muller et al., 2005). This is an analytical rather than a theoretical vision of moderated mediation. One's theoretical arguments must,

Table 2. Summary of methods for simultaneous analysis of moderated mediation using *bootstrap*.

	Procedure to follow	Advantages	Disadvantages
Edwards and Lambert (2007)	Download MODMED file[a] (see dedicated website for detailed steps to follow)	This method allows you to generate detailed results both at a specific level for each link in the model and at an overall level in order to interpret indirect effects and total effect based on the different values of the moderating variable It provides estimations of the indirect effect transmitted via the mediating variable according to different values of the moderating variable, both between the independent variable *X* and the mediating variable *M* (first sequence) and between the mediating variable *M* and the dependent variable *Y* (second sequence). You can also test for the moderating effect on the direct link between *X* and *Y*	Requires SPSS syntax to be programmed in order to set the parameters for the links between the variables The procedure can prove laborious when conducted in several stages (it is quite time-consuming to generate confidence intervals for bootstrap using the Excel file) This method only allows you to study simple models with one moderator and one mediator
Preacher et al. (2007)	Download MODMED macro[b]	The approach is quite simple due to the SPSS/SAS macros directly installed in the software as a dialogue box Confidence intervals are directly generated for indirect effects with different focal values of the moderating variable (in spotlight analysis, focal values equal mean±standard deviation) It is possible to use Johnson–Neyman's method to generate values for the moderating variable so as to construct regions of significance using a floodlight approach (Cadario and Parguel, 2014; Spiller et al., 2013)	If the personalised dialogue box is not installed, you will need to program the SPSS/SAS syntax in order to set the parameters for the links between the variables This procedure does not process binary dependent variables With the MODMED macro, the number of models that can be tested is limited to 5
Hayes (2013a, 2013b)	Download and install the PROCESS macro[c] Once the installation is completed, a new PROCESS option will appear in the SPSS/SAS regression tab. By clicking on this, a dialogue box opens in which you select your variables and specify the type of model being tested using the *template* provided with the macro as a guide (see our sample application for an illustration of the steps to follow)	PROCESS is a more intuitive macro that is easy to use The *template*, which comes with the macro, offers 76 different possible scenarios PROCESS allows you to test models with several mediators and several moderators It is possible to process qualitative/dichotomous dependent variables The PROCESS macro can do everything that the MODMED macro can, but you can estimate a larger number of models for conditional indirect effects	Despite the high number of models that can be tested (76), it is possible that the model the researcher would like to test will not appear in the list, in which case it is necessary to use a more complex approach such as that developed by Hayes and Preacher (2013)

[a]http://public.kenan-flagler.unc.edu/faculty/edwardsj/downloads.htm
[b]http://www.processmacro.org/
[c]http://www.processmacro.org/download.html

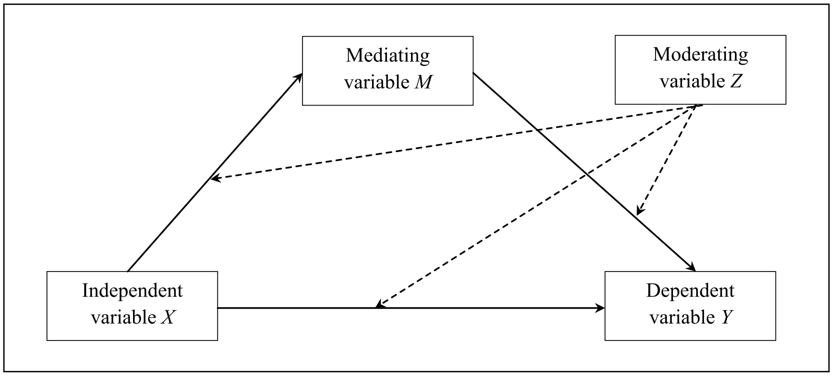


Figure 2. Moderated mediation: general model based on Edwards and Lambert (2007).

however, be presented beforehand in a specific and precise manner, thereby making it possible to demonstrate at what level the moderating effect has an impact on the overall process.

Edwards and Lambert (2007) developed a MODMED macro[8] that allows the user to test for moderated mediation effects. This macro can be used with continuous or categorical moderating variables. Given the limited number of marketing studies that have used the approach developed by Edwards and Lambert (see Appendix 1), we will not be developing this approach any further, instead directing the reader to the authors' 2007 article as well as the explanation and application of this approach on the website dedicated to our article.[9]

Preacher et al. (2007) and Hayes (2013a, 2013b)

The approach developed by Preacher et al. (2007) to test for conditional indirect effects was recently reworked by Hayes (2013a, 2013b) in a new macro known as PROCESS,[10] which can be downloaded free of charge from Andrew Hayes' website. The new macro comes in the form of a syntax or dialogue box that operates under SPSS or SAS. It can be used with quantitative/continuous or qualitative/categorical dependent variables. It can also test moderated mediation models with one or more mediating and moderating variables. This new macro makes it possible to analyse a large number of models, with up to 10 mediating variables and 4 moderating variables in a single model (Hayes, 2013a, 2013b). It is also advisable to download the templates document 'process.pdf' from the same website, in which 76 possible combinations of moderated mediation are modelled, with their respective scripts (detailed for each model below).

Given the level of refinement and ease of use of the PROCESS macro developed by Hayes (2013a, 2013b), as well as the frequency with which it is used by researchers whose work has been published in the highest ranking marketing journals (see Appendix 1 and Table 2), we recommend using this tool when testing for conditional indirect effects. The user procedure is explained in detail as part of the marketing applications provided in the following section. It should, nonetheless, be noted that one's choice of method may also depend on the nature of the variables being studied. Valeri and VanderWeele (2013) recently demonstrated the importance of taking into account whether the mediating variables in one's analysis are of a continuous or categorical nature. Building on these previous studies, we have extended the analysis to the case of moderated mediation, considering the various alternatives based on the nature of the different variables in the model, whether independent, dependent, mediating or moderating. Table 3 indicates the appropriate method(s) for quantitative/continuous or qualitative/categorical variables (dichotomous or binary where variables have no more than two modalities).[11]

Table 3. Summary of appropriate methods for moderated mediation analysis based on the nature of variables.

Most common scenarios	Appropriate method(s)
X, Y, M and *Z* are quantitative/ continuous variables	The simplest scenario. All methods of moderated mediation analysis can be used and all of the macros presented in this article can be applied to this scenario
Dependent variable *Y* is a qualitative/categorical variable (also described as dichotomous or binary in the case of two modalities)	• Unlike the MODMED macro (Preacher et al., 2007), Hayes' PROCESS macro (2013a, 2013b) can be used to process categorical/dichotomous dependent variables (the macro automatically changes from linear regression to logistic regression when a categorical dependent variable is detected) • It is possible to use the method developed by Edwards and Lambert (2007) by conducting a binary logistic regression during the first stage (or a multinomial logistic regression if the dependent variable is qualitative and has more than two modalities)
Independent variable *X* is a qualitative/categorical variable	• All methods that can be used with qualitative/categorical independent variables • If *X* is a qualitative variable with more than two modalities, it must be recoded as indicator (dummy) variables and the analysis must be repeated for each one, specifying the other variables in the 'covariates' box in Hayes' PROCESS macro (2013a, 2013b)
Mediating variable *M* is a qualitative/categorical variable	• Only the method developed by Edwards and Lambert (2007) can be used with a qualitative mediating variable (simply include the variable as an independent variable in equation (20) and use a binary logistic regression for equation (5) in the syntax proposed by the authors). • The methods developed by Preacher et al. (2007) and Hayes (2013a, 2013b) cannot be used to study non-quantitative mediating variables. In the case of a qualitative mediating variable, it is recommended to use structural equation methods based on the procedure proposed by Hayes and Preacher (2013), using *Mplus*
Moderating variable *Z* is a qualitative/categorical variable	• All methods of moderated mediation analysis can be used with qualitative moderating variables. The PROCESS macro is well suited to this scenario • However, only a multi-group analysis using structural equation methods can be used to study a scenario in which *Z* is a qualitative variable with more than two modalities • In order to use a bootstrapping procedure, the moderating variable must be transformed into several indicator (dummy) variables

Developing marketing applications

This section illustrates moderated mediation through several applications in the field of marketing. A website dedicated to our article (see Note 9) further develops these applications and makes the relevant databases available. The first is a simple example of moderated mediation (one mediator and one moderator), with one continuous or dichotomous moderating variable. The second example illustrates a more complex case of moderated mediation, with two mediators and two moderators.

Example 1: Moderated mediation with one mediator and one moderator

Conditional indirect effect hypothesis. This application involves the study of the process through which

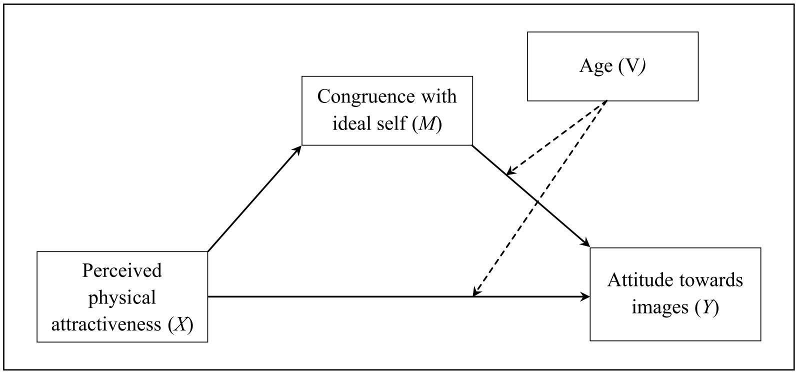


Figure 3. Conceptual research model (Example 1).

the perceived physical attractiveness of female models represented in the media (*X*) has an effect on the perceived congruence with one's ideal self (*M*), which in turn affects women's attitude towards these images (*Y*). However, the link between congruence with one's ideal self and attitude towards these images – the second mediation segment – is supposed to be moderated by age (*V*). The direct link between perceived physical attractiveness and attitude towards the images is also thought to be moderated by age (*V*). The tested conceptual model is presented in Figure 3.

The proposed hypothesis for the conditional indirect effect is formulated as follows:

> ***H1***. The respondents' age moderates the strength of the indirect relationship between the perceived physical attractiveness of the female models and attitude towards the images via the congruence with one's ideal self in such a way that the mediated relationship is weaker (or stronger) when the respondents' age is high (or low).

Sample and measurement scales. A sample of 509 women aged between 15 and 50 years were interviewed online (average age = 27.3 years; standard deviation = 7.72). Before answering the questionnaire, the respondents were shown a series of images comprising six visual representations of females taken from magazines. All of the measurement scales used are unidimensional and can be considered reliable (Cronbach's $\alpha > 0.80$). The ages were provided directly by respondents.

The confirmatory factor analysis, carried out using Amos 17, reveals that the measurement model tested produces very good adjustment indices (Chi-squared/df=1.974 ; RMSEA = 0.044; SRMR = 0.023 ; NFI = 0.986 ; CFI =0.993 ; GFI = 0.975; AGFI = 0.958; AIC = 109/ 4640).

During the data collection, precautions were taken to limit method bias (anonymity and confidentiality were guaranteed and the variables were distributed within the questionnaire). Nonetheless, because the sets of data were collected on a single occasion from the same people, it was necessary to ensure the absence of common method variance bias (Podsakoff et al., 2003). A method factor was therefore introduced and linked to all of the indicators for the model's latent variables. The results reveal that the additional proportion of total variance (1.97%) falls below the threshold recommended by Williams et al. (1989), therefore ruling out the risk of common method variance bias.

Testing moderated mediation with the PROCESS macro (Hayes, 2013a, 2013b). In Table 2, we have emphasised the advantages of the approach developed by Hayes (2013a, 2013b) for the analysis of conditional indirect effects. This approach, which provides an easy way to process a large number of moderated mediation models, is used in a PROCESS macro with a bootstrapping procedure (Hayes, 2013a, 2013b) that can be carried out under SPSS (and SAS). The following example illustrates this application under SPSS 19.00:

1. Download the PROCESS macro (see the detailed procedure in Appendix 2).
2. Once the macro has been installed, open the SPSS database.

3. To conduct the moderated mediation analyses, open the PROCESS macro dialogue box ('Analyses'>'Regression'>'PROCESS').
4. In the dialogue box, *choose your model*: In the document entitled '*templates.pdf*',[12] find the conceptual model to be tested from the 76 models provided, and then choose this model by replacing the default value '4' with the corresponding '*Model Number*'. For the purposes of our example, the model number is 15 (see Figure 3). Therefore, '*Model Number*' = 15.
5. *Specifying your variables*. If the dialogue box is being used, drag the variables to the box, ensuring that the name of each variable in the model is respected; these are specified in '*templates.pdf*' as variables *Y, X, M, W, Z, V* or *Q* (see Appendix 2). The '*Covariates*' box is reserved for control variables.[13] It is important to ensure that the names of the variables in the SPSS file do not contain more than eight characters. In our example, in accordance with the tags used in Model 15 and Figure 3, we specified the dependent variable by dragging 'Attitude' to the '*Outcome variable (Y)*' box, 'Attractiveness' to the '*Independent variable (X)*' box, the mediating variable(s) (in this case there is just one mediating variable: 'Congruence') to the '*M variables*' box and finally the continuous or categorical moderating variable (in this case 'Age') to the '*Proposed Moderator V*' box (as indicated in Model 15 mentioned above). Regarding the moderating variable(s), note the importance of ensuring that the tag indicated in '*templates.pdf*' representing the chosen model accurately corresponds to that which appears in the dialogue box (*W, Z, V* or *Q* and sometimes *M* in Models 1, 2 and 3). One final point in relation to the control variables '*Covariates*' is as follows: as indicated in the bottom right of the dialogue box (tab entitled '*Covariate(s) in Model(s) of*'), the default decision is to control for these variables in respect of both dependent variable *Y* and mediating variable *M*. The decision to control only for *M* or *Y* must be based on theoretical arguments and will therefore depend on the theory and model tested by the researchers. In our example, we have no control variables so this does not arise.
6. *Setting the number of resamples produced using bootstrap and the level of the CI*. By default, the number of resamples is set to 1,000 in the dialogue box. This should be increased to 5,000 or 10,000. The default value for the CI is 95% in the dialogue box. It is generally recommended to leave this unchanged. Note that while the default proposed bootstrapping method is 'Bias corrected and accelerated', it is possible to choose the 'Percentile' method, which was recently recommended by Hayes and Scharkow (2013). However, the 'Bias corrected and accelerated' method is considered robust and can be used without difficulty (Edwards and Lambert, 2007).
7. *Specifying options and conditions of analysis*. If you decide to center the variables, this can be done automatically by the PROCESS macro. To do this, again using the dialogue box, click on the '*Options*' tab and tick the box entitled '*Mean center for products*'. Other options such as calculating '*Effect size*' or comparing '*Indirect effects*' can be chosen if they correspond to the model being tested. Finally, for some models but not for all, the macro offers the possibility of generating regions of significance for a floodlight analysis (Cadario and Parguel, 2014; Spiller et al., 2013). To choose this option, tick 'Johnson–Neyman' in the '*Conditioning*' tab. For the purposes of our example, we only chose '*Mean center for products*'. The other options and conditions are not available for Model number 15.
8. *To conduct the analysis, click on OK in the dialogue box.*

Analysing the results of conditional indirect effects using bootstrap: Two illustrations. We will now present two possibilities, depending on whether the moderating variable is quantitative/continuous or qualitative/dichotomous. When the PROCESS macro is launched as explained above, the results of the moderated mediation will be automatically displayed in the SPSS results window (see Appendices 2 and 3). For the purposes of this application, the products of the variables were centred by ticking the box entitled '*Mean center for products*' in the '*Options*' tab within the dialogue box, as already explained. The number of resamples was set at 10.000.

Case 1. Testing for conditional indirect effect in the case of one continuous moderating variable (age declared by respondents in years) (see Table 4 and Figure 4).

a. In the case of Model 15, with one continuous moderating variable, the moderated mediation index is displayed explicitly in the results (Appendix 3). This is the 95% CI in section '*Moderated mediation index*' at the bottom of the page. The moderated mediation effect is significant as the CI excludes zero [−0.0222; −0.0033]. H1 is therefore validated.
b. It is now possible to localise the moderating effect: on the second mediation segment or on the direct effect, as specified in the model tested (see Figure 3). This involves observing the significance and CIs of the interactive terms (in the SPSS output, look at **Int_1** which corresponds to $(M \times V) \rightarrow Y$, that is, the moderating effect of age on the second segment of the mediating relationship between the congruence with one's ideal self and attitude towards the images): this term is significant (*coeff.*=−0.0169, p=0.0015) with a CI=[−0.0273; −0.0065] that excludes zero. The following line displays the results of **Int_2** which corresponds to $(X \times V) \rightarrow Y$, that is, the moderating effect of age on the direct link between perceived physical attractiveness and attitude towards the images: the second term is not significant (*coeff.*=0.0086, p=0.1330) with a CI=[−0.0026; 0.0198] that includes zero. We can therefore see that only the CI for **Int_1** excludes zero, indicating that the moderator (Age) has an influence on the second half of the mediation $(M \rightarrow Y)$, that is, the link between the congruence with one's ideal self and attitude towards the images.
c. The final step is to observe the results of the 95% CI in section '*Conditional indirect effects of X on Y for the different moderator values*' at the bottom of the page. Three CIs are given for each moderator value: (1) mean minus standard deviation, (2) mean and (3) mean plus standard deviation. This application produced the following intervals:
    - Mean minus standard deviation (lower age group): CI=[0.1531; 0.3358];
    - Mean (average age group): CI=[0.0849; 0.2135];
    - Mean plus standard deviation (upper age group): CI=[−0.0554; 0.1522].

These results show that the conditional indirect effect is significant in the lower and average age groups since the 95% CI excludes zero. In the case of the upper age group, the conditional indirect effect is not significant as the CI includes zero.

Case 2. Testing for conditional indirect effects in the case of one dichotomous moderating variable (in this example, two age groups have been artificially created for the purposes of illustration by discretising the continuous variable previously used[14]) (see Table 5 and Figure 5).

a. In order to establish the presence of moderated mediation, you need to observe the result for the 95% CI in section '*Moderated mediation index*' (in Appendix 4). The moderated mediation effect proves to be significant as the CI excludes zero [−0.3592; −0.1057]. H1 is therefore validated.
b. Since the moderation hypothesis once again relates to the second mediation segment $(M \rightarrow Y)$ and the direct effect $(X \rightarrow Y)$ that corresponds to Model 15, it is important to identify in which case the moderation is significant. To do this, look at the significance and CIs of the interactive terms. In the SPSS output, look at the results for **Int_1** which corresponds to $(M \times V) \rightarrow Y$, that is, the moderating effect of age on the second segment of the relationship between the congruence with one's ideal self and attitude towards the images: this term is

Table 4. Testing for conditional indirect effect: the case of a continuous moderating variable (Example 1, Case 1).

Moderator *V* (Age)	Mediating variable *M* (Congruence with ideal self)		Dependent variable *Y* (Attitude towards images)	
	Coeff.	*t*	*t*	*Coeff.*
X: Phys. attract.	0.723	16.432***	0.310	6.429***
V: Age			−0.018	−2.318**
$X \times V$ (Int 2)			0.008	1.504 *ns*
M: Congr. ideal			0.204	5.211***
$M \times V$ (Int 1)			−0.016	−3.190**
R^2	0.347		0.284	
ΔR^2			0.015 ($\Delta F(2, 503) = 5.21$, $p < 0.01$)	

Conditional indirect effect for different age values (=0 and ±standard deviation)[a]
95% confidence interval for conditional indirect effect using bootstrap. Bias corrected and accelerated (BCa)

Age	Effect	Confidence interval	
		Lower limit	Upper limit
−7.7236	0.242	0.153	0.335
0	0.147	0.084	0.213
7.7236	0.053	−0.055	0.152
Moderated mediation index	−0.012	−0.022	−0.003

[a]The average age here is equal to 0 as the variable was centred before the interactive term was created and the analyses were carried out.
***p <0.001; **p <0.01.

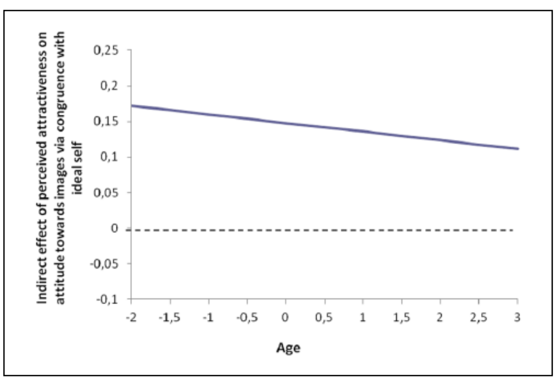


Figure 4. Visual representation of the linear function in relation to the effect of age (continuous variable) on the indirect effect of perceived physical attractiveness on attitude towards images via congruence with ideal self (Example 1, Case 1).

significant (*coeff.* = −0.3113, p = 0.0001) with a CI = [−0.4639; −0.1587] that excludes zero. The following line displays the results for **Int_2** which corresponds to $(X \times V) \rightarrow Y$, that is, the moderating effect of age on the relationship between perceived physical attractiveness and attitude towards the images. This second term is not significant (*coeff.* = 0.1748, p = 0.0672) with a CI = [−0.0124; 0.3620]. Only the CI of **Int_1** excludes zero, which confirms that the moderator clearly acts on the second half of the mediation $(M \rightarrow Y)$.

c. In order to interpret these results, we must now look at the CIs obtained when testing for the conditional indirect effect of X on Y for the two moderator values (in the case of this

Table 5. Testing for conditional indirect effect: the case of a categorical/dichotomous moderating variable (Example 1, Case 2).

Moderator *V* (Age)	Mediating variable *M* (Congruence with ideal self)		Dependent variable *Y* (Attitude towards images)	
	Coeff.	*t*	*Coeff.*	*t*
X: Phys. attract.	0.723	16.432***	0.301	6.293***
V: Age			−0.230	−1.907 *ns*
X × *V* (Int 2)			0.174	1.834 *ns*
M: Congr. ideal			0.219	5.637***
M × *V* (Int 1)			−0.311	−4.007***
R^2	0.347		0.293	
ΔR^2			0.023 ($\Delta F(2, 503) = 8.23$, $p < 0.001$)	

Conditional indirect effect for different age values (1 = low; 2 = high)
95% confidence interval for conditional indirect effect using bootstrap. Bias corrected and accelerated (BCa)

Age	Effect	Confidence interval	
		Lower limit	Upper limit
1 (−0.4853)	0.267	0.190	0.351
2 (0.5147)	0.042	−0.056	0.137
Moderated mediation index	−0.225	−0.359	−0.105

***p <0.001.

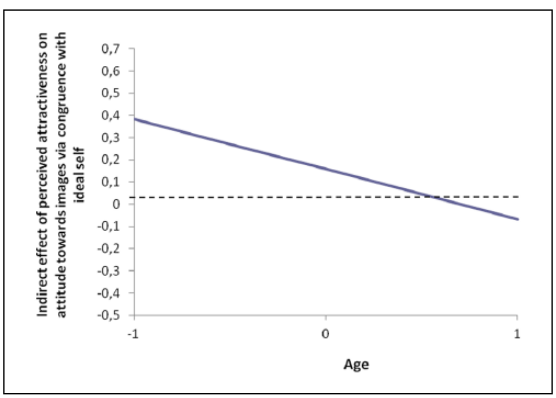


Figure 5. Visual representation of the linear function in relation to the effect of age (binary variable) on the indirect effect of perceived physical attractiveness on attitude towards images via congruence with ideal self (Example 1, Case 2).

study, CI=[0.1900; 0.3514] for the lower moderator value and [−0.0564; 0.1373] for the higher value). These results indicate that when the moderator has a low value (in the case of the lower age group here), the conditional indirect effect is significant as the CI excludes zero. In contrast, when the moderator has a high value (upper age group), the conditional indirect effect is not significant as the CI includes zero.

Interpreting the results. The proposed hypothesis was that the indirect effect of physical attractiveness on attitude towards the images via the congruence with one's ideal self is positive. We also postulated that this link is reinforced (or attenuated) when the age of the respondents is low (or high). In both cases analysed above (continuous or dichotomous moderator), the conditional indirect effect is verified. The age of respondents therefore significantly moderates the indirect effect. The indirect effect is only significant in the lower age group (youngest respondents). Regarding the localisation of the moderating effect, our observation of the interaction effects shows that the interactive term 'Congruence × Age' does indeed have a negative and significant effect on attitude towards the images (continuous moderating variable: *coeff.* = −0.0169, $p < 0.01$/dichotomous moderating variable: *coeff.* = −0.3113, $p < 0.001$). Therefore, as the age falls, the relationship between the congruence with one's ideal self and attitude towards the images is strengthened.

Our model also postulated a moderating effect on the direct link between perceived physical attractiveness and attitude towards the images. However, the factor 'Attractiveness × Age' has no impact on attitude towards the images. In other words, age does not moderate the link between perceived attractiveness and attitude towards the images (continuous moderating variable: *coeff.* = 0.0086, $p = ns$/ dichotomous moderating variable: *coeff.* = 0.1748, $p = ns$).

To summarise, when considering our model without accounting for a potential mediation effect, we found that age moderated the second half of the model but not the direct effect. In order to complete the analysis, it is important to calculate the R^2 variation (ΔR^2), which represents the proportion of explained variance through the interactive term beyond the direct and main effects of the other variables. The PROCESS macro only provides ΔR^2 for certain models but not for all of the existing models. In our example, and for Model 15, this value is not given automatically; we obtained it by carrying out a simple moderated hierarchical regression using SPSS (Aguinis, 2004; Aiken and West, 1991; Cohen et al., 2003). In Case 1, when age was taken as a continuous variable, ΔR^2 was equal to 0.015 [$\Delta F[2, 503] = 5.21$, $p < 0.01$]. In Case 2, when age was taken as a dichotomous variable, ΔR^2 was equal to 0.023 [$\Delta F[2, 503] = 8.23$, $p < 0.001$]. These values are significant although they may seem reduced; they correspond to the standard R^2 variation in analyses of interaction effects (Dawson, 2014).

Graphic representation. To make it easier to interpret the results, it is always useful to plot the moderating effects (Aguinis and Gottfredson, 2010; Aiken and West, 1991; Dawson, 2014; Hayes, 2013b). Graphic representations of the moderated mediation were produced using Hayes' approach (2013b). This involves tracing a simple straight line ($y = ax + b$) that corresponds to a linear function which establishes a link between the indirect effect and the moderator. To determine this equation, simply refer to the *Templates* file provided with the macro. Depending on the model being studied (Models 1–76 in the *Templates* file), the gradient of this line is obtained differently. The appropriate equation is therefore indicated under each model in the *Templates* file. In the case of Model 15, the equation for conditional indirect effect is as follows: $a_i(b_{1i} + b_{2i}V)$. This equation can be reformulated as follows:

$$\omega = a \times b_1 + a \times b_2 V$$

In this equation, V is the moderator (continuous variable), $(a \times b_1)$ is the intercept point and $(a \times b_2)$ is the gradient. The gradient represents the weight of the function that links the indirect effect to the moderator; this is the moderated mediation index (*index* in the results output under SPSS). So, for the purposes of our application, if age is taken as a continuous moderating variable, we can represent the moderated mediation using the following equation (see boxes in SPSS outputs – Appendices 3 and 4 – to find the following values)

$$\begin{aligned}\omega &= 0.7234(0.2043) + 0.7234(-0.0169) \\ &= 0.147 + (-0.012)V\end{aligned}$$

However, when the moderating variable is dichotomous, even though the same model is used, the index (or gradient) is not obtained in the same way. According to Hayes (2013b), if the two figures used to code the groups of a dichotomous moderator are only one point apart (e.g. 1 and 2), the moderated mediation index corresponds to the difference between the two conditional indirect effects. In this case, the index was obtained by calculating the difference between the conditional indirect effect for the upper age group (0.042) and the conditional indirect effect for the lower age group (0.267). This gives us the following equation

$$\omega = 0.7234(0.219) + (0.042 - 0.267)V$$
$$= 0.158 + (-0.225)V$$

According to our results, the two moderated mediation indices are negative, indicating that the indirect effect of perceived physical attractiveness (X) on attitude towards the images (Y) via the perceived congruence with one's ideal self (M) is a decreasing function of age (V). The higher the age, the weaker the indirect effect, as is illustrated by the gradient in the previous two graphs. It should, nonetheless, be noted that the gradient is steeper when the moderator is binary; this is in line with recent studies that have criticised the dichotomisation of moderating variables, as this tends to exacerbate the results obtained (see Cadario and Parguel, 2014).

Example 2: Moderated mediation with two mediators and two moderators

Conditional indirect effect hypothesis. In this second application, we study the process through which the perceived originality of an advertisement (X) has an effect on both attitude towards the advertisement ($M1$) and attitude towards the brand ($M2$), which in turn affect purchasing intentions (Y). Furthermore, the links between X and M (1 and 2) – the first mediation segments – and the links between M (1 and 2) and Y – the second mediation segments – appear to be moderated by resistance to advertising in general (W) and one's involvement in the medium in which the advertisement appeared (Z). It is important to point out that this model only includes two-way interactions and not three-way interactions. The conceptual model tested is presented in Figure 6.

The proposed hypothesis for the conditional indirect effect is formulated as follows:

> *H1*. Resistance to advertising and involvement in the medium concerned moderate the strength of the indirect links between the originality of the advertisement and purchasing intentions via attitude towards the advertisement and attitude towards the brand, in such a way that the relationships of mediation are stronger (or weaker) where resistance to advertising and involvement in the medium are high (or low).

Sample and measurement scales. A sample of 373 individuals participated in an online questionnaire. Before providing their answers, the respondents were shown an advertisement. The measurement scales used are all unidimensional and can be considered reliable (Cronbach's $\alpha > 0.90$).

The confirmatory factorial analysis, carried out using Amos 17, shows that the model tested produces very good adjustment indices (Chi-squared/df= 1.828, RMSEA=0.047, SRMR=0.041, NFI=0.969, CFI=0.986, GFI=0.936, AGFI=0.912 and AIC= 356/8,205).

During the data collection phase, the same precautions were taken as in the previous example in order to limit common method variance bias (Podsakoff et al., 2003).

Testing moderated mediation with the PROCESS macro (Hayes, 2013a, 2013b). To test for moderated mediation using the PROCESS macro, all eight stages detailed above in Example 1 must be repeated. Based on the conceptual model being tested, Model 75 was chosen from the document entitled '*templates.pdf*', and the corresponding variables were specified in the macro: independent variable 'Originality' (*Independent variable X*), mediating variables 'Attitude towards the advertisement' and 'Attitude towards the brand' (*M variables*), dependent variable 'Purchasing intention' (*Outcome variable Y*) and finally moderating variables 'Resistance to advertising' (*Proposed Moderator W*) and 'Involvement in the medium' (*Proposed Moderator Z*; as indicated in Model 75). Again, only the option '*Mean center for products*' has been ticked to centre the products of the variables. Note once again that it is essential to ensure that the names of the variables do not include more than eight characters in the SPSS file.

Analysing the results of conditional indirect effects using bootstrap

1. In the case of Model 75, the moderated mediation index is not explicitly displayed in the SPSS results (Appendix 5). The conditional indirect effects for each

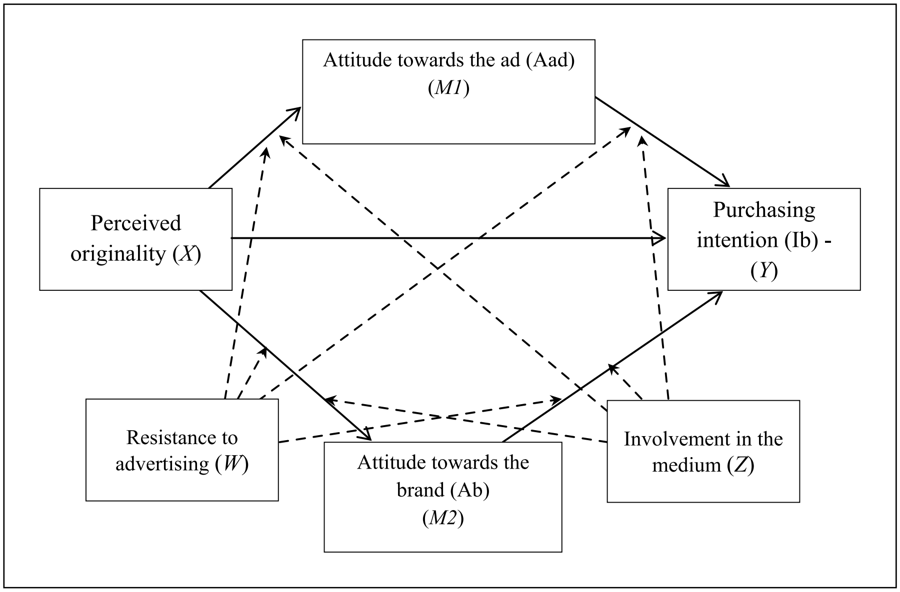


Figure 6. Conceptual research model (Example 2).

mediator and each moderator can be seen in section '*Conditional indirect effects of X on Y for the different moderator values*' at the bottom of the results page (see Step 3).

2. Before commenting on the results of the conditional indirect effects, and following the same logic as in Example 1, it is possible to localise the moderating effects on the various segments, as specified in the model tested (see Figure 6). To do this, simply look at the significance and CIs of the interactive terms. For the model tested (Model 75 with two mediators and two moderators), a total of six interaction effects are estimated. For example, in the SPSS output, **Int_1** corresponds to $(X \times W) \rightarrow M1$, that is, the moderating effect of resistance to advertising on the first segment of the mediation relationship between the originality of and attitude towards the advertisement: this term is significant (*coeff.* = 0.0992, $p < 0.001$) with a CI = [0.0514; 0.1470] that excludes zero.
3. It is during the final step that the results of the conditional indirect effects can be observed. A total of 18 CIs are specified within two blocks, corresponding to the 18 possible combinations between the different mediators and moderators: nine combinations for the first mediator (*M1*: Attitude towards the advertisement) and nine others for the second mediator (*M2*: Attitude towards the brand). Within each block, you can see the interaction effects of the two moderators in terms of their respective levels: low (mean minus standard deviation), mean, and high (mean plus standard deviation). In this application, the following intervals can be observed in the first block (where the mediating variable (*M1*) is Attitude towards the advertisement):

- When the level of resistance is low, regardless of the level of involvement in the medium (see first three lines of block 1), the indirect effect is not significant as the CI includes zero ($CI_{\text{low involvement in medium}} = [-0.0449; 0.1697]$, $CI_{\text{average involvement in medium}} = [-0.0108; 0.1355]$ and $CI_{\text{high involvement in medium}} = [-0.0042; 0.1479]$).
- When the level of resistance to advertising is average or high, regardless of the level of involvement in the medium (see last six lines of block 1), the conditional indirect effects are all significant as the 95% CIs exclude zero.

Table 6. Testing for conditional indirect effects (Example 2).

ModeratorsZ and W	Mediating variable M1 (Attitude towards the ad)		Mediating variable M2 (Attitude towards the brand)		Dependent variable Y (Purchasing intention)	
	Coeff.	*t*	*Coeff.*	*t*	*Coeff.*	*t*
X: Originality	0.4288	11.4744***	0.2788	7.5898***	0.1561	3.3668***
W: Resistance	−0.3429	−7.9186***	−0.3539	−8.3130***	−0.0654	−1.2375 *ns*
Z: Involvement medium	0.1813	4.0917***	0.1473	3.3805***	−0.0013	−0.0271 *ns*
X × *W* (Int 1)	0.0992	4.0795***	0.0966	4.0408***		
X × *Z* (Int 2)	0.0087	0.3336 *ns*	0.0518	2.0157*		
M1: Aad					0.3160	4.5666***
M2: Ab					0.3742	5.3475***
M1 × *W* (Int 3)					0.0796	1.9753*
M2 × *W* (Int 4)					−0.1179	−2.6447**
M1 × *Z* (Int 5)					0.0136	0.2988 *ns*
M2 × *Z* (Int 6)					0.0394	0.4145 *ns*
R^2	0.526		0.435		0.513	
ΔR^2	0.026 ($\Delta F(2, 367) = 9.91$, $p < 0.01$)		0.025 ($\Delta F(2, 367) = 8.17$, $p < 0.01$)		0.020 ($\Delta F(4, 363) = 3.71$, $p < 0.01$)	

Example for mediator 1: attitude towards the advertisement.[a] Conditional indirect effect for different resistance and involvement values (=0 and ±standard deviation)[b]
95% confidence interval for conditional indirect effect using bootstrap. Bias corrected and accelerated (BCa)

Resistance	Involvement in medium	Effect	Confidence interval	
			Lower limit	Upper limit
−1.5439	−1.4496	0.0456	−0.0449	0.1697
−1.5439	0	0.0532	−0.0108	0.1355
−1.5439	1.4496	0.0613	−0.0042	0.1479
0	−1.4496	0.1233	0.0047	0.2444
0	0	0.1355	0.0705	0.2116
0	1.4496	0.1482	0.0606	0.2514
1.5439	−1.4496	0.2387	0.0966	0.3837
1.5439	0	0.2555	0.1652	0.3697
1.5439	1.4496	0.2727	0.1294	0.4503

X: Originality; *M1*: Attitude towards the ad; *M2*: Attitude towards the brand; *Y*: Purchasing intention; *W*: Resistance to advertising generally; *Z*: Involvement in the medium.
[a]In the interest of economy, only those results that relate to the first mediator (attitude towards the ad) are reproduced in the table. The presentation of the results for the second mediator is identical.
[b]The mean for the moderating variable here is equal to 0 as the variable was centred before the interactive term was created and the analyses were carried out.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

The exact same logic is used to analyse the results of the conditional indirect effects via the second mediator (*M2*: Attitude towards the brand). This gives us the following:

- When involvement in the medium is low combined with a low or high level of resistance (see the first and seventh lines of block 2), the indirect effect is not significant as the CI includes zero ($CI_{low\ resistance} = [-0.0519; 0.1322]$ and $CI_{high\ resistance} = [-0.0134; 0.1355]$).
- In all other cases, the conditional indirect effects are significant as the 95% CIs exclude zero.

Interpreting the results. The moderated mediation hypothesis formulated above is based on the indirect effect of the advertisement's perceived originality on purchasing intentions via attitude towards the advertisement and attitude towards the brand. We also postulated that mediation links are strengthened (or attenuated) when resistance to advertising and involvement in the medium are high (or low). These conditional indirect effects are partly verified.

Regarding mediation via attitude towards the advertisement, only resistance to advertising generally moderates the indirect effect via attitude towards the advertisement. This indirect effect is only significant when resistance is average or high, regardless of the level of involvement in the medium. This involvement does not therefore moderate the indirect effect. Regarding mediation via attitude towards the brand, resistance to advertising and involvement in the medium both play a moderating role. The indirect effect is significant in all cases, except where involvement in the medium is low and resistance is low or high.

Regarding the localisation of the moderating effects on the first segments (between the independent variable and the mediating variables), the observation of interaction effects shows that interactive term 1, **Int_1** 'Originality × Resistance', has a positive and significant effect on attitude towards the advertisement (*coeff.* = 0.0992, $p<0.001$) and on attitude towards the brand (*coeff.* = 0.0966, $p<0.001$). This means that as resistance increases, the relationships between perceived originality and the two mediators (attitude towards the advertisement and attitude towards the brand) are reinforced. Interactive term 2, **Int_2** 'Originality × Involvement in the medium', has no significant effect on attitude towards the advertisement (*coeff.* = 0.0087, $p=0.7389$) but does have a significant effect on attitude towards the brand (*coeff.* = 0.0518, $p<0.05$). This means that when involvement in the medium increases, the link between the advertisement's perceived originality and attitude towards the brand is reinforced. Whether in the case of attitude towards the brand or attitude towards the advertisement, the complementary analyses based on hierarchical regressions highlight a significant R^2 variation once the interaction effects have been integrated into the model ($\Delta R^2=0.026$, $[\Delta F[2, 367]=9.91, p<0.01]$ and $\Delta R^2=0.025$, $[\Delta F[2, 367]=8.17, p<0.01]$, respectively).

The localisation of the moderating effects on the second segments (between the mediating variables and the dependent variable) is done in the same way. Interactive term 3, **Int_3** 'Attitude towards the advertisement × Resistance', has a significant and positive effect on purchasing intentions (*coeff.* = 0.0796, $p<0.05$), whereas interactive term 4, **Int_4** 'Attitude towards the brand × Resistance', has a significant and negative effect on purchasing intentions (*coeff.* = −0.1179, $p<0.01$). Finally, interactive terms 5, **Int_5** 'Attitude towards the advertisement × Involvement in the medium', and 6, **Int_6** 'Attitude towards the brand × Involvement in the medium', have no significant effect on purchasing intentions. Nonetheless, accounting for interaction effects improves the model's overall predictive ability ($\Delta R^2=0.020$, $[\Delta F[4, 363]=3.71, p<0.01]$).

To summarise, when moderating effects alone are considered (and not conditional indirect effects), resistance to advertising moderates both the first and second halves of the model, irrespective of which mediator is taken into account (attitude towards the advertisement or towards the brand). However, the involvement in the medium only moderates the first half of the model between the originality of the advertisement and attitude towards the brand.

Graphic representation. In order to graph the conditional indirect effects, you must first identify the appropriate equation for the model treated in the *Templates* file. The coefficients must then be replaced by the values obtained in the results on moderated mediation. In the case of Model 75, there were two moderators (W and Z), which means using an equation with two unknowns. Hayes (2014)[15] recommends setting different values one by one for W followed by different values for Z. This gives us six different equations. The first three illustrate the link between Z and the indirect effect for three W values (low, average and high); the following three represent the effect of W for three Z values (low, average and high). It is important to note that unlike the plots in application 1, those produced here do not represent straight lines but rather curves. This is due to the fact that Model 15 (*Example 1*) deals with a linear effect between a moderator and an indirect effect, which is not the case in Model 75, which simultaneously uses two moderators. Furthermore, each plot indicates the indirect effect based only on the first mediator (attitude towards the advertisement), only on the second mediator (attitude towards the brand) or both mediators (Figures 7–12).

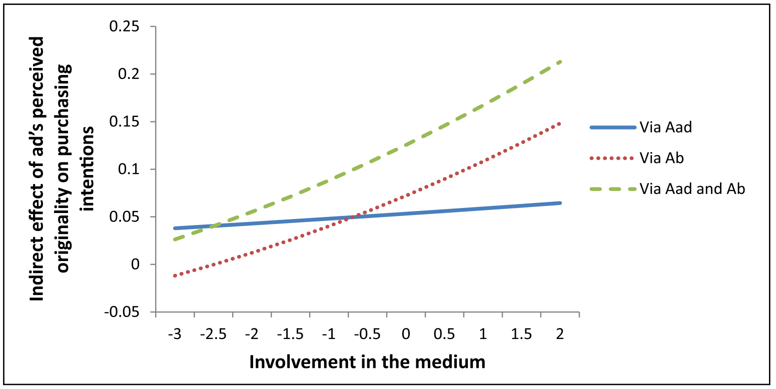


Figure 7. Graphic representation of moderating effects of involvement in the medium on the indirect link between perceived originality and purchasing intention (conditional indirect effect based on *Z* (involvement in medium) when W (resistance to advertising) is low).

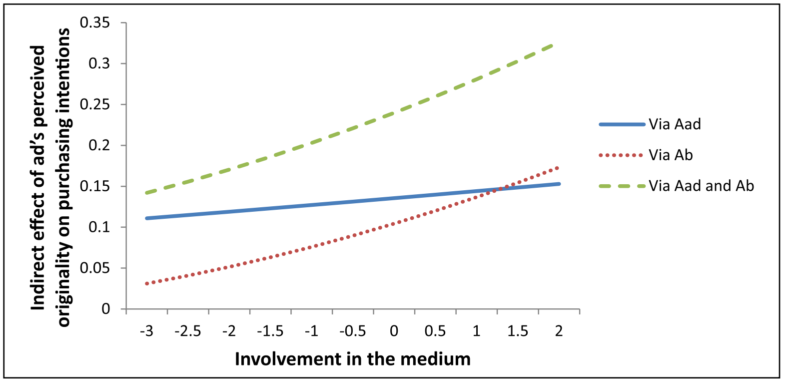


Figure 8. Graphic representation of moderating effects of involvement in the medium on the link between perceived originality and purchasing intention (conditional indirect effect based on *Z* (involvement in medium) when *W* (resistance to advertising) is average).

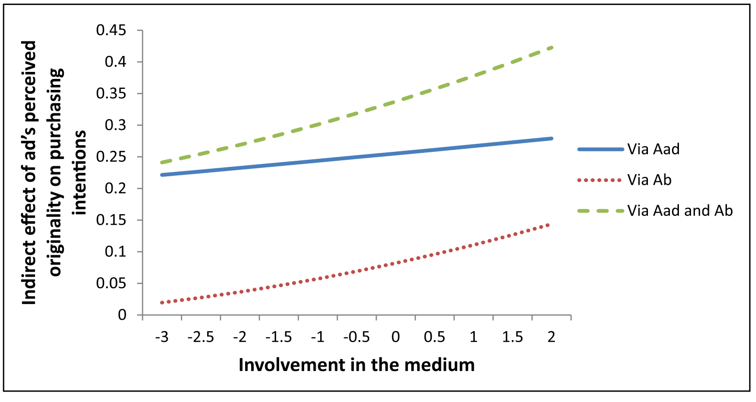


Figure 9. Graphic representation of moderating effects of involvement in the medium on the link between perceived originality and purchasing intention (conditional indirect effect based on *Z* (involvement in medium) when *W* (resistance to advertising) is high).

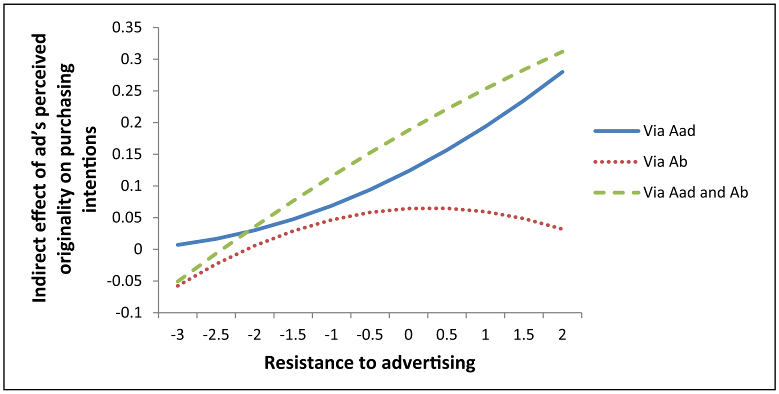


Figure 10. Graphic representation of moderating effects of resistance to advertising on the link between perceived originality and purchasing intention (conditional indirect effect based on *W* (resistance to advertising) when *Z* (involvement in medium) is low).

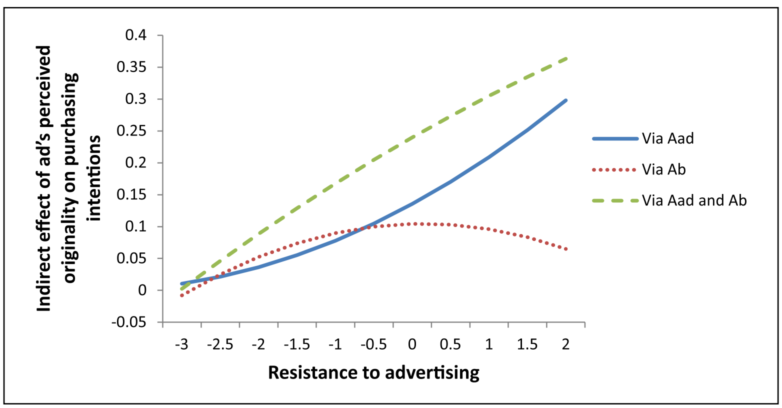


Figure 11. Graphic representation of moderating effects of resistance to advertising on the link between perceived originality and purchasing intention (conditional indirect effect based on *W* (resistance to advertising) when *Z* (involvement in medium) is average).

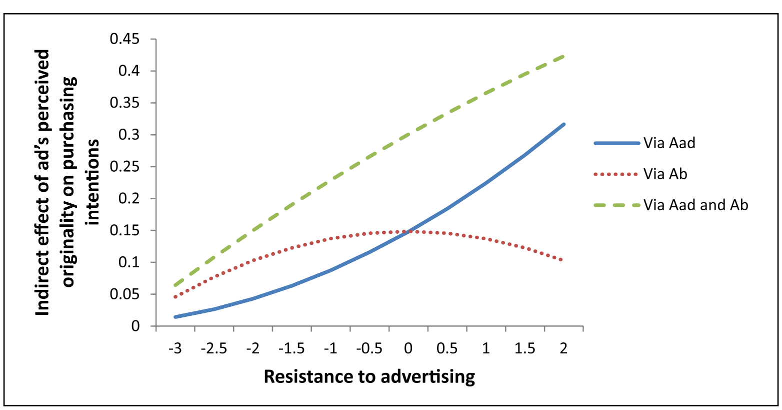


Figure 12. Graphic representation of moderating effects of resistance to advertising on the link between perceived originality and purchasing intention (conditional indirect effect based on *W* (resistance to advertising) when *Z* (involvement in medium) is high).

Conclusion and recommendations

The purpose of this article is to shed light on certain methodological aspects of testing for relationships of moderated mediation, otherwise known as conditional indirect effects. It provides an overview of current knowledge of this question and also develops several applications to the field of marketing, which as yet is relatively unfamiliar with these techniques. While tests for mediation and moderation are commonplace when conducted separately, very few marketing studies have employed methods to test for moderated mediation effects. Yet, models that include both mediating and moderating variables (and therefore moderated mediation effects) are increasingly frequent in marketing. The methods we have presented, developed by Edwards and Lambert (2007), Preacher et al. (2007) and Hayes (2013a, 2013b) and detailed in-depth herein, provide robust and precise results to the extent that they simultaneously include the different effects, providing an overall vision of the process studied. Moderated mediation therefore allows us to evaluate conditional indirect effects, which is not the case when mediation and moderation are tested independently of one another. It should also be pointed out that the implications of this over-arching approach are not only methodological but also theoretical in nature. If a researcher expects to find that an indirect link between two variables will be attenuated or amplified by another factor, he or she may decide to formulate a moderated mediation hypothesis, provided the theoretical basis is solid and the research design is adapted. Box 2 summarises recommendations for correctly analysing conditional indirect effects. While some of these apply to all marketing research, they are particularly important in the case of moderated mediation.

Box 2. Main recommendations for analysing moderated mediation (conditional indirect effects).

Recommendations when developing your test model and collecting data

Recommendation 1. It is essential to form a clear and robust theoretical basis for conditional indirect effects. Each mediation and/or moderation link must be founded and rooted in a theoretical framework that is clearly outlined in the study. The theoretical rigour of the test model is the only gauge of the quality of the research; the statistical tools presented herein, no matter how robust and effective, in no way undermine the central importance of the theoretical foundation.

Recommendation 2. The omission of important variables can limit the scope of the results. A detailed review of the literature is necessary to identify the main mediating, moderating and control variables to be included in the test model.

Recommendation 3. It is important to encourage marketing researchers to use experimental and longitudinal research designs when testing for conditional indirect effects – a longitudinal research design is recommended when testing for indirect effects (MacKinnon et al., 2012).

Recommendation 4. It is essential to monitor the reliability and validity of variable measurements. Measurements must be considered very reliable (high Cronbach's α) in order to detect conditional indirect effects. Researchers are also recommended to first test the validity of their measurements using confirmatory factorial analyses (e.g. Lisrel, Amos, Mplus).

Recommendation 5. The detection of conditional indirect effects, as in the case of moderation, requires high statistical power in order to avoid Type II errors (Dawson, 2014; Hayes, 2013a). To achieve this, the sample size[16] must be high, especially when the test model is complex. There is no rule that can be applied to all cases. The reader may wish to refer to Aguinis (2004; categorical moderating variables) and Shieh (2009; continuous moderating variables) for further information.

Recommendation 6. It is essential to account for the quantitative/continuous or qualitative/categorical nature of dependent, mediating and moderating variables (see Table 3).

Box 2. (Continued)

Recommendation 7. Centring (or standardising) variables can make it easier to interpret the results (Aguinis and Gottfredson, 2010). The decision whether or not to centre the variables will in no way change the results in terms of interactions nor will it reduce multicollinearity, it will simply facilitate interpretation of the results. It is important not to centre either dependent or dichotomous variables (Dawson, 2014).

Recommendation 8. Testing for moderated mediation effects requires the introduction of the main (direct) effects of all variables, even where hypotheses specifically relating to these direct links have not been explicitly formulated (Carte and Russell, 2003). It is therefore important to convey all of these effects in the results tables and not to limit one's findings to interaction effects alone.

Recommendation 9. In order to better interpret and present one's results, it is important to produce a graphic representation (plot) of the conditional indirect effect using the method developed by Hayes (2013b). For certain models processed using PROCESS, it is possible to generate regions of significance using a spotlight or floodlight analysis (Cadario and Parguel, 2014; Spiller et al., 2013).

Recommendation 10. When presenting your results, it is important to note the scale of the conditional indirect effect by indicating the variation in the determination coefficient (ΔR^2); this value is provided by PROCESS for most models.

Major advances have been made in the analysis of moderated mediation effects over the last 10 years or so. The research approaches that marketing researchers are encouraged to pursue in this area mainly relate to (1) the use of so-called Bayesian methods when analysing conditional indirect effects (see Wang and Preacher, 2015) and (2) the development of multi-level analyses with mediation and moderation effects (Bauer et al., 2006). These advances offer marketing researchers new perspectives both in theoretical and methodological terms.

Acknowledgements

All authors contributed equally to this work and are listed in alphabetical order.

Notes

1. Centre national de la recherche scientifique (CNRS) ranking, November 2014.
2. In the case of complex models and/or which show signs that multi-normality constraints have been violated, it may be appropriate to adopt a PLS approach.
3. The term *boundary condition* is increasingly used from a conceptual point of view to refer to contingency factors that reflect the existence of moderating variables.
4. To centre your variables, simply subtract the mean from their raw scores. It is also possible to standardise them, that is, centre and reduce: *z* scores under SPSS, for example. Your choice will not change the results in terms of the significance of the moderating effect.
5. Several websites provide support for researchers in graphing interaction effects. Jeremy Dawson's website offers several Excel files to produce and interpret graphic representations of these effects: http://www.jeremydawson.co.uk/slopes.htm. These files have been recommended in articles published in peer-reviewed journals (Dawson, 2014). A specific file must be used when the moderating variable is dichotomous/categorical.
6. Analysis of moderating effects alone is not the subject of this article; we direct the reader towards Dawson's recent article (2014 and another by Aguinis and Gottfredson (2010), who provide an excellent review of the analysis of interaction effects (including three-way interaction effects)).
7. These macros are always based on articles published in peer-reviewed journals. That of Edwards and Lambert (2007) was published in *Psychological Methods*, that of Preacher et al. (2007) in *Multivariate Behavioral Research* and that of Hayes (2013a) is included in a book entitled *Introduction to Mediation, Moderation, and Conditional Process Analysis*. They can be accessed via the websites of these journals or those of the authors themselves in order to facilitate dissemination.
8. The MODMED macro can be downloaded directly from Jeffrey Edwards' website: http://public.kenan-flagler.unc.edu/faculty/edwardsj/downloads.htm.

9. The website dedicated to this article (https://sites.google.com/site/medmodmarketing/home) includes both a marketing application of the approach developed by Edwards and Lambert (2007) and databases used for the two applications detailed herein.
10. The PROCESS macro can be downloaded from Andrew Hayes' website: http://www.processmacro.org/download.html.
11. We would like to thank an anonymous reader for drawing our attention to the importance of this question.
12. Model Templates for PROCESS for SPSS and SAS, Andrew F. Hayes (2013), http://www.processmacro.org/.
13. Control variables are variables that are not directly central to the model studied but which may have an influence on the phenomenon being explored. In many cases, accounting for these variables can avoid bias in estimating the model (Spector and Brannick, 2011). For example, certain socio-demographic variables can be controlled in order to verify that the effect of variable X remains significant independently of the effects of these variables. In this case, we decided not to include control variables so as not to complicate our sample applications, but we encourage readers to include the most important control variables when analysing moderated mediation effects (often in the '*Covariates*' box in the PROCESS macro).
14. Note that you are advised strongly against discretising a continuous variable in order to transform it into a dichotomous variable when conducting moderated mediation analyses. This reduces the statistical power and may produce biased results in terms of interaction effects (see Cadario and Parguel, 2014; Hayes, 2013a). This example was chosen so as to illustrate a case in which the moderating variable is dichotomous. Because our sample comprised women only, we were unable to use a traditional dichotomous variable such as gender to illustrate our example.
15. These graphs were produced based on personal exchanges between the authors and Andrew Hayes. We remind the reader that it is important not to confuse two-way interaction plots (as in Example 2, Model 75 in the *templates* (Hayes, 2013a)) with three-way interaction plots (Model 3 or Model 73 in the *templates* (Hayes, 2013a)).
16. The use of a bootstrapping procedure does not negate the importance of having a large sample. Koopman et al. (2014) very recently showed that bootstrap is more robust when used with sample sizes that exceed 80 and even 100 observations.

References

Aguinis H (2004) *Regression Analysis for Categorical Moderators*. New York: Guilford Press.

Aguinis H and Gottfredson RK (2010) Best-practice recommendations for estimating interaction effects using moderated multiple regression. *Journal of Organizational Behavior* 31: 776–786.

Aguinis H, Boik RJ and Pierce CA (2001) A generalized solution for approximating the power to detect effects of categorical moderator variables using multiple regression. *Organizational Research Methods* 4: 291–323.

Aiken LS and West SG (1991) *Multiple Regression: Testing and Interpreting Interactions*. Thousand Oaks, CA: SAGE.

Auh S, Spyropoulou S, Menguc B et al. (2014) When and how does sales team conflict affect sales team performance? *Journal of the Academy of Marketing Science*. Epub ahead of print 17 January. DOI: 10.1007/s11747-014-0368-7.

Avnet T, Laufer D and Higgins ET (2013) Are all experiences of fit created equal? Two paths to persuasion. *Journal of Consumer Psychology* 23(3): 301–316.

Aydınoğlu NZ and Cian L (2014) Show me the product, show me the model: Effect of picture type on attitudes toward advertising. *Journal of Consumer Psychology*. Epub ahead of print April 2014. DOI: 10.1016/j.jcps.2014.04.002.

Bagchi R and Davis D (2012) $29 for 70 items or 70 items for $29? How presentation order affects package perceptions. *Journal of Consumer Research* 39: 62–73.

Baron RM and Kenny DA (1986) The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology* 51(6): 1173–1182.

Bauer DJ, Preacher KJ and Gil KM (2006) Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: New procedures and recommendations. *Psychological Methods* 11: 142–163.

Baxter S, Ilicic J and Kulczynski A (2014) What's in a name? Examining the effect of phonetic fit between spokesperson name and product attributes on source credibility. *Marketing Letters*. Epub ahead of print March. DOI: 10.1007/s11002-014-9287-0.

Bellezza S and Keinan A (2014) Brand tourists: How non-core users enhance the brand image by eliciting pride. *Journal of Consumer Research* 41(2): 397–417.

Bellezza S, Gino F and Keinan A (2014) The red sneakers effect: Inferring status and competence from signals of nonconformity. *Journal of Consumer Research* 41(1): 35–54.

Berger J and Fitzsimons G (2008) Dogs on the street, pumas on your feet: How cues in the environment influence product evaluation and choice. *Journal of Marketing Research* 45: 1–14.

Bhattacharjee A, Berger J and Menon G (2014) When identity marketing backfires: Consumer agency in identity expression. *Journal of Consumer Research* 41(2): 294–309.

Biswas A, Bhowmick S, Guha A et al. (2013) Consumer evaluations of sale prices: Role of the subtraction principle. *Journal of Marketing* 77(4): 49–66.

Bolton LE and Mattila AS (2014) How does corporate social responsibility affect consumer response to service failure in buyer-seller relationship? *Journal of Retailing*. Epub ahead of print October. DOI: 10.1016/j.jretai.2014.10.001.

Buechel EC and Janiszewski C (2014) A lot of work or a work of art: How the structure of a customized assembly task determines the utility derived from assembly effort. *Journal of Consumer Research* 40: 960–972.

Bullard O and Manchanda RV (2013) Do sustainable products make us prevention focused? *Marketing Letters* 24: 177–189.

Burton S, Cook LA, Howlett E et al. (2014) Broken halos and shattered horns: Overcoming the biasing effects of prior expectations through objective information disclosure. *Journal of the Academy of Marketing Science*. Epub ahead of print March. DOI: 10.1007/s11747-014-0378-5.

Caceres CR and Vanhamme J (2003) Les processus modérateurs et médiateurs: Distinction conceptuelle, aspects analytiques et illustrations. *Recherche et Applications en Marketing* 18(2): 67–100.

Cadario R and Parguel B (2014) Reconsidering the practice of discretizing quantitative variables: Towards a new analysis of moderation in experimental research. *Recherche et Applications en Marketing* 29(4): 1–18.

Campbell MC, Mohr GS and Verlegh PWJ (2013) Can disclosures lead consumers to resist covert persuasion? The important roles of disclosure timing and type of response. *Journal of Consumer Psychology* 23(4): 483–495.

Carte TA and Russell CJ (2003) In pursuit of moderation: Nine common errors and their solutions. *MIS Quarterly* 27(3): 479–501.

Carvalho SW and Luna D (2014) Effects of national identity salience on responses to ads. *Journal of Business Research* 67(5): 1026–1034.

Cavanaugh LA (2014) Because I (don't) deserve it: How relationship reminders and deservingness influence consumer indulgence. *Journal of Marketing Research* 51(2): 218–232.

Celuch K, Bantham JH and Kasouf CJ (2011) The role of trust in buyer–Seller conflict management. *Journal of Business Research* 64(10): 1082–1088.

Chae B and Zhu R (2014) Environmental disorder leads to self-regulatory failure. *Journal of Consumer Research* 40(6): 1203–1218.

Chen Z and Berger J (2013) When, why, and how controversy causes conversation. *Journal of Consumer Research* 40: 580–593.

Chen Z and Lurie NH (2013) Temporal contiguity and negativity bias in the impact of online word of mouth. *Journal of Marketing Research* 50: 463–476.

Choi J, Li YJ, Rangan P et al. (2014) The odd-ending price justification effect: The influence of price-endings on hedonic and utilitarian consumption. *Journal of the Academy of Marketing Science*. Epub ahead of print January. DOI: 10.1007/s11747-014-0369-6.

Cian L, Krishna A and Elder RS (2014) This logo moves me: Dynamic imagery from static images. *Journal of Marketing Research* 51(2): 184–197.

Cohen J, Cohen P, West SG et al. (2003) *Applied Multiple Regression/Correlation Analysis for the Behavioral Sciences*, 3rd edition. Hillsdale, NJ: Lawrence Erlbaum Associates.

Connell PM, Brucks M and Nielsen JH (2014) How childhood advertising exposure can create biased product evaluations that persist into adulthood. *Journal of Consumer Research* 41(1): 119–134.

Cortina JM, Chen G and Dunlap WP (2001) Testing interaction effects in LISREL: Examination and illustration of available procedures. *Organizational Research Methods* 4: 324–360.

Coulter KS and Grewal D (2014) Name-letters and birthday-numbers: Implicit egotism effects in pricing. *Journal of Marketing* 78(3): 102–120.

Coulter KS and Roggeveen AL (2014) Price number relationships and deal processing fluency: The effects of approximation sequences and number multiples. *Journal of Marketing Research* 51(1): 69–82.

Cutright KM and Samper A (2014) Doing it the hard way: How long control drives preferences for high-effort products and services. *Journal of Consumer Research* 41(3): 730–745.

Dabholkar PA and Bagozzi RP (2002) An attitudinal model of technology-based self-service: Moderating effects of consumer traits and situational factors. *Journal of the Academy of Marketing Science* 30(3): 184–201.

Dalal DK and Zickar MJ (2012) Some common myths about centering predictor variables in moderated multiple regression and polynomial regression. *Organizational Research Methods* 15(3): 339–362.

Dawson J (2014) Moderation in management research: What, why, when and how. *Journal of Business and Psychology* 29(1): 1–19.

Devezer B, Sprott DE, Spangenberg ER et al. (2014) Consumer well-being: Effects of subgoal failures and goal importance. *Journal of Marketing* 78(2): 118–134.

Dittmar H, Halliwell E and Stirling E (2009) Understanding the impact of thin media models on women's body-focused affect: The roles of thin-ideal internalization and weight-related self-discrepancy activation in experimental exposure effects. *Journal of Social and Clinical Psychology* 28: 43–72.

Echambadi R and Hess JD (2007) Mean-centering does not alleviate collinearity problems in moderated multiple regression models. *Marketing Science* 26: 438–445.

Edwards JR (2008) To prosper organizational psychology should … overcome methodological barriers to progress. *Journal of Organizational Behavior* 29: 469–491.

Edwards JR and Lambert LS (2007) Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychological Methods* 12(1): 1–22.

Efron B and Tibshirani R (1993) *An Introduction to the Bootstrap*. New York: Chapman & Hall/CRC Press.

Ein-Gar D (2014) Committing under the shadow of tomorrow: Self-control and commitment to future virtuous behaviors. *Journal of Consumer Psychology*. Epub ahead of print. DOI: 10.1016/j.jcps.2014.08.006.

Ertürk A and Vurgun L (2015) Retention of IT professionals: Examining the influence of empowerment, social exchange, and trust. *Journal of Business Research* 68(1): 34–46.

Fairchild AJ and McQuillin SD (2010) Evaluating mediation and moderation effects in school psychology: A presentation of methods and review of current practice. *Journal of School Psychology* 48(1): 53–84.

Ferraro R, Kirmani A and Matherly T (2013) Look at me! Look at me! Conspicuous brand usage, self-brand connection, and dilution. *Journal of Marketing Research* 50: 477–488.

Gao L, Wheeler SC and Shiv B (2009) The 'shaken self': Product choices as a means of restoring self-view confidence. *Journal of Consumer Research* 36(1): 29–38.

Gatignon-Turnau A-L and Mignonac K (2015) (Mis) Using employee volunteering for public relations: Implications for corporate volunteers' organizational commitment. *Journal of Business Research* 68(1): 7–18.

Giebelhausen M, Robinson SG, Sirianni NJ et al. (2014) Touch versus tech: When technology functions as a barrier or a benefit to service encounters. *Journal of Marketing* 78: 113–124.

Grappi S, Romani S and Bagozzi RP (2013a) Consumer response to corporate irresponsible behavior: Moral emotions and virtues. *Journal of Business Research* 66: 1814–1821.

Grappi S, Romani S and Bagozzi RP (2013b) The effects of company offshoring strategies on consumer responses. *Journal of the Academy of Marketing Science* 41: 683–704.

Gu Y, Botti S and Faro D (2013) Turning the page: The impact of choice closure on satisfaction. *Journal of Consumer Research* 40: 268–283.

Guo W and Main KJ (2012) The vulnerability of defensiveness: The impact of persuasion attempts and processing motivations on trust. *Marketing Letters* 23: 959–971.

Hada M, Grewal R and Lilien GL (2014) Supplier-selected referral. *Journal of Marketing* 78(2): 34–51.

Hadi R and Valenzuela A (2014) A meaningful embrace: Contingent effects of embodied cues of affection. *Journal of Consumer Psychology*. Epub ahead of print February. DOI: 10.1016/j.jcps.2014.02.001.

Haws KL and Winterich KP (2013) When value trumps health in a supersized world. *Journal of Marketing* 77(3): 48–64.

Haws KL, Winterich KP and Naylor RW (2014) Seeing the world through GREEN-tinted glasses: Green consumption values and responses to environmentally friendly products. *Journal of Consumer Psychology*. Epub ahead of print July. DOI: 10.1016/j.jcps.2013.11.002.

Hayes AF (2013a) *Introduction to Mediation, Moderation, and Conditional Process Analysis – A Regression-Based Approach*. New York: Guilford Press.

Hayes AF (2013b) PROCESS: A versatile computational tool for observed variable mediation, moderation, and conditional process modeling. Available at: http://www.afhayes.com/public/process2012.pdf. Epub ahead of print.

Hayes AF (2014) An index and test of linear moderated mediation. *Multivariate Behavioral Research*. Epub ahead of print 17 February. DOI: 10.1080/00273171.2014.962683.

Hayes AF and Preacher KJ (2013) Conditional process modeling: Using structural equation modeling to examine contingent causal processes. In: Hancock GR and Mueller RO (coord.) *Structural Equation Modeling: A Second Course*. Greenwich, CT: Information Age Publishing, pp. 219–266.

Hayes AF and Scharkow M (2013) The relative trustworthiness of inferential tests of the indirect effect in statistical mediation analysis: Does method really matter? *Psychological Science* 24(10): 1918–1927.

Huang S-C and Zhang Y (2011) Motivational consequences of perceived velocity in consumer goal pursuit. *Journal of Marketing Research* 48(6): 1045–1056.

Humphreys A and Latour KA (2013) Framing the game: Assessing the impact of cultural representations on consumer perceptions of legitimacy. *Journal of Consumer Research* 40: 773–795.

Iacobucci D, Saldanha N and Deng X (2007) A meditation on mediation: Evidence that structural equations models perform better than regressions. *Journal of Consumer Psychology* 17(2): 139–153.

Irmak C, Wakslak CJ and Trope Y (2013) Selling the forest, buying the trees: The effect of construal level on seller-buyer price discrepancy. *Journal of Consumer Research* 40: 284–297.

Jaccard J and Turrisi R (2003) *Interaction Effects in Multiple Regression*, 2nd edition. Thousand Oaks, CA: SAGE.

Jiang L, Hoegg J and Dahl DW (2013) Consumer reaction to unearned preferential treatment. *Journal of Consumer Research* 40: 412–427.

Jin L and He Y (2013) Designing service guarantees with construal fit effects of temporal distance on consumer responses to service guarantees. *Journal of Service Research* 6(2): 202–215.

Jin L and Huang Y (2014) When giving money does not work: The differential effects of monetary versus in-kind rewards in referral reward programs. *International Journal of Research in Marketing* 31(1): 107–116.

Jin L, Hu B and He Y (2014) The recent versus the outdated: An experimental examination of the time-variant effects of online consumer reviews. *Journal of Retailing* 90(4): 552–566.

Kachersky L (2011) Reduce content or raise price? The impact of persuasion knowledge and unit price increase tactics on retailer and product brand attitudes. *Journal of Retailing* 87(4): 479–488.

Kan C, Lichtenstein DR, Grant S et al. (2014) Strengthening the influence of advertised reference prices through information priming. *Journal of Consumer Research* 40(6): 1078–1096.

Khajehzadeh S, Oppewal H and Tojib D (2014) Consumer responses to mobile coupons: The roles of shopping motivation and regulatory fit. *Journal of Business Research* 67(11): 2447–2455.

Kim H, Kulow K and Kramer T (2014) The interactive effect of beliefs in malleable fate and fateful predictions on choice. *Journal of Consumer Research* 40(6): 1139–1148.

Kim J and Gupta P (2012) Emotional expressions in online user reviews: How they influence consumers' product evaluations. *Journal of Business Research* 65(7): 985–992.

Kim S and Labroo AA (2011) From inherent value to incentive value: When and why pointless effort enhances consumer preference. *Journal of Consumer Research* 38: 712–742.

Koopman J, Howe M, Hollenbeck JR et al. (2014) Small sample mediation testing: Misplaced confidence in bootstrapped confidence intervals. *Journal of Applied Psychology* 100(1): 194–202.

Kronrod A and Danziger S (2013) 'Wii will rock you!' The use and effect of figurative language in consumer reviews of hedonic and utilitarian consumption. *Journal of Consumer Research* 40: 726–739.

Lacey R, Kennett-Hensel PA and Manolis C (2014) Is corporate social responsibility a motivator or hygiene factor? Insights into its bivalent nature. *Journal of the Academy of Marketing Science*. Epub ahead of print May. DOI: 10.1007/s11747-014-0390-9.

Lacoste-Badie S, Malek F and Droulers O (2013) Influence of a sad program context on the process of advertising persuasion among younger and older adults. *Recherche et Applications en Marketing* 28(1): 5–26.

Laran J, Dalton AN and Andrade EB (2011) The curious case of behavioral backlash: Why brands produce priming effects and slogans produce reverse priming effects. *Journal of Consumer Research* 37(6): 999–1014.

Leal-Rodríguez AL, Ariza-Montes JA, Roldán JL et al. (2014) Absorptive capacity, innovation and cultural barriers: A conditional mediation model. *Journal of Business Research* 67(5): 763–768.

Lee S, Winterich KP and Ross WT Jr (2014) I'm moral, but I won't help you: The distinct roles of empathy and justice in donations. *Journal of Consumer Research* 41(3): 678–696.

Lefroy K and Tsarenko Y (2014) Dependence and effectiveness in the nonprofit-corporate alliance: The mediating effect of objectives achievement. *Journal of Business Research*. Epub ahead of print September. DOI: 10.1016/j.jbusres.2013.11.003.

Liao J, O'Brien AT, Jimmiesson NL et al. (2014) Predicting transactive memory system in multidisciplinary teams: The interplay between team and professional identities. *Journal of Business Research*. Epub ahead of print May. DOI: 10.1016/j.jbusres.2014.09.024.

Lisjak M and Lee AY (2014) The bright side of impulse: Depletion heightens self-protective behavior in the face of danger. *Journal of Consumer Research* 41(1): 55–70.

Luna D, Carnevale M and Lerman D (2013) Does brand spelling influence memory? The case of auditorily presented brand names. *Journal of Consumer Psychology* 23(1): 36–48.

Ma Z, Yang Z and Mourali M (2014) Consumer adoption of new products: Independent versus interdependent self-perspectives. *Journal of Marketing* 78(2): 101–117.

MacKinnon DP (2008) *Introduction to Statistical Mediation Analysis*. New York: Lawrence Erlbaum Associates.

MacKinnon DP, Coxe S and Baraldi AN (2012) Guidelines for the investigation of mediating variables in business research. *Journal of Business and Psychology* 27(1): 1–14.

MacKinnon DP, Fairchild AJ and Fritz MS (2007) Mediation analysis. *Annual Review of Psychology* 58: 593–614.

Mariadoss BJ, Johnson JL and Martin KD (2014) Strategic intent and performance: The role of resource allocation decisions. *Journal of Business Research* 67(11): 2393–2402.

Mariadoss BJ, Milewicz C, Lee S et al. (2014) Salesperson competitive intelligence and performance: The role of product knowledge and sales force automation usage. *Industrial Marketing Management* 43(1): 136–145.

Mathur P, Block L and Yucel-Aybat O (2014) The effects of goal progress cues: An implicit theory perspective. *Journal of Consumer Psychology*. Epub ahead of print March. DOI: 10.1016/j.jcps.2014.03.003.

May F and Irmak C (2014) Licensing indulgence in the present by distorting memories of past behavior. *Journal of Consumer Research* 41(3): 624–641.

Mehta R, Zhu RJ and Meyers-Levy J (2014) When does a higher construal level increase or decrease indulgence? Resolving the myopia versus hyperopia puzzle. *Journal of Consumer Research* 41(2): 475–488.

Michaelis B, Wagner JD and Schweizer L (2015) Knowledge as a key in the relationship between high-performance work systems and workforce productivity. *Journal of Business Research* 68(5): 1035–1044.

Mochon D, Norton MI and Ariely D (2012) Bolstering and restoring feelings of competence via the IKEA effect. *International Journal of Research in Marketing* 29: 363–369.

Moldovan S, Steinhart Y and Ofen S (2014) ‘Share and scare’: Solving the communication dilemma of early adopters with a high need for uniqueness. *Journal of Consumer Psychology*. Epub ahead of print June. DOI: 10.1016/j.jcps.2014.06.001.

Moore SG (2012) Some things are better left unsaid: How word of mouth influences the storyteller. *Journal of Consumer Research* 38: 1140–1154.

Morhart F, Malär L, Guèvremont A et al. (2014) Brand authenticity: An integrative framework and measurement scale. *Journal of Consumer Psychology*. Epub ahead of print. DOI: 10.1016/j.jcps.2014.11.006.

Mourali M and Yang Z (2013) The dual role of power in resisting social influence. *Journal of Consumer Research* 40: 539–554.

Muller D, Judd CM and Yzerbyt VY (2005) When moderation is mediated and mediation is moderated. *Journal of Personality and Social Psychology* 89(6): 852–863.

Muro F and Noseworthy TJ (2013) Money isn’t everything, but it helps if it doesn’t look used: How the physical appearance of money influences spending. *Journal of Consumer Research* 39: 1330–1342.

Muthén LK and Muthén BO (2011) *Mplus User’s Guide*, 6th edition. Los Angeles, CA: Muthén & Muthén.

Nguyen HP and Munch JM (2011) Romantic gift giving as chore or pleasure: The effects of attachment orientations on gift giving perceptions. *Journal of Business Research* 64(2): 113–118.

Noseworthy TJ and Trudel R (2011) Looks interesting, but what does it do? Evaluation of incongruent product form depends on positioning. *Journal of Marketing Research* 48(6): 1008–1019.

Onur Bodur H, Klein NM and Arora N (2014) Online price search: Impact of price comparison sites on offline price evaluation. *Journal of Retailing*. Epub ahead of print October. DOI: 10.1016/j.jretai.2014.09.003.

Orth UR and Crouch RC (2014) Is beauty in the aisles of the retailer? Package processing in visually complex contexts. *Journal of Retailing* 90(4): 524–537.

Orth UR, Bouzdine-Chameeva T and Brand K (2013) Trust during retail encounters: A touchy proposition. *Journal of Retailing* 89(3): 301–314.

Pandelaere M, Briers B, Dewitte S et al. (2010) Better think before agreeing twice mere agreement: A similarity-based persuasion mechanism. *International Journal of Research in Marketing* 27(2): 133–141.

Podsakoff PM, MacKenzie SM, Lee J et al. (2003) Common method variance in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology* 88(5): 879–903.

Preacher KJ and Hayes AF (2004) SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments & Computers* 36: 717–731.

Preacher KJ and Hayes AF (2008) Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods* 40(8): 879–891.

Preacher KJ, Rucker DD and Hayes AF (2007) Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research* 42(1): 185–227.

Rego LL, Morgan NA and Fornell C (2013) Reexamining the market share-customer satisfaction relationship. *Journal of Marketing* 77(5): 1–20.

Salerno A, Laran J and Janiszewski C (2014) Hedonic eating goals and emotions: When sadness decreases the desire to indulge. *Journal of Consumer Research* 41(1): 135–151.

Samper A and Schwartz JA (2013) Price inferences for sacred versus secular goods: Changing the price of medicine influences perceived health risk. *Journal of Consumer Research* 39: 1343–1358.

Schumann JH, Wünderlich NV and Evanschitzky H (2014) Spillover effects of service failures in coalition loyalty programs: The buffering effect of special treatment benefits. *Journal of Retailing* 90(1): 111–118.

Scott ML, Mende M and Bolton LE (2013) Judging the book by its cover? How consumers decode conspicuous consumption cues in buyer-seller relationships. *Journal of Marketing Research* 50: 334–347.

Sellier A-L and Dahl DW (2011) Focus! Creative success is enjoyed through restricted choice. *Journal of Marketing Research* 48(6): 996–1007.

Shapiro SA and Nielsen JH (2013) What the blind eye sees: Incidental change detection as a source of perceptual fluency. *Journal of Consumer Research* 39: 1202–1218.

Sharma S, Durand RM and Gur-Arie O (1981) Identification and analysis moderator variables. *Journal of Marketing Research* 18: 291–300.

Shieh G (2009) Detecting interaction effects in moderated multiple regression with continuous variables: Power and sample size considerations. *Organizational Research Methods* 12: 510–528.

Shrout PE and Bolger N (2002) Mediation in experimental and nonexperimental studies: New procedures and recommendations. *Psychological Methods* 7(4): 422–445.

Sirianni NJ, Bitner MJ, Brown SW et al. (2013) Branded service encounters: Strategically aligning employee behavior with the brand positioning. *Journal of Marketing* 77(6): 108–123.

Sobel ME (1982) Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological methodology* 13: 290–312.

Spector PE and Brannick MT (2011) Methodological urban legends: The misuse of statistical control variables. *Organizational Research Methods* 14: 287–305.

Spiller SA, Fitzsimons GJ, Lynch JG Jr et al. (2013) Spotlights, floodlights, and the magic number zero: Simple effects tests in moderated regression. *Journal of Marketing Research* 50(2): 277–288.

Steinhart Y, Kamins M, Mazursky D et al. (2014) Effects of product type and contextual cues on eliciting naive theories of popularity and exclusivity. *Journal of Consumer Psychology*. Epub ahead of print April. DOI: 10.1016/j.jcps.2014.04.004.

Strizhakova Y, Tsarenko Y and Ruth JA (2012) 'I'm mad and I can't get that service failure off my mind': Coping and rumination as mediators of anger effects on customer intentions. *Journal of Service Research* 15(4): 414–429.

Sundar A and Noseworthy TJ (2014) Place the logo high or low? Using conceptual metaphors of power in packaging design. *Journal of Marketing* 78(5): 138–151.

Thompson DV and Chandon Ince E (2013) When disfluency signals competence: The effect of processing difficulty on perceptions of service agents. *Journal of Marketing Research* 50: 228–240.

Thompson DV and Malaviya P (2013) Consumer-generated ads: Does awareness of advertising co-creation help or hurt persuasion? *Journal of Marketing* 77(3): 33–47.

Trudel R and Argo JJ (2013) The effect of product size and form distortion on consumer recycling behavior. *Journal of Consumer Research* 40: 632–643.

Trudel R and Murray KB (2011) Why didn't I think of that? Self-regulation through selective information processing. *Journal of Marketing Research* 48(4): 701–712.

Uhrich S, Koenigstorfer J and Groeppel-Klein A (2014) Leveraging sponsorship with corporate social responsibility. *Journal of Business Research*. Epub ahead of print September. DOI: 10.1016/j.jbusres.2013.10.008.

Ulkümen G and Cheema A (2011) Framing goals to influence personal savings: The role of specificity and construal level. *Journal of Marketing Research* 48(6): 958–969.

Valeri L and VanderWeele TJ (2013) Mediation analysis allowing for exposure-mediator interactions and causal interpretation: Theoretical assumptions and implementation with SAS and SPSS macros. *Psychological Methods* 18(2): 137–150.

Verlegh PWJ, Ryu G, Tuk MA et al. (2013) Receiver responses to rewarded referrals: The motive inferences framework. *Journal of the Academy of Marketing Science* 41: 669–682.

Walsh D (2014) Attenuating depletion using goal priming. *Journal of Consumer Psychology*. Epub ahead of print May. DOI: 10.1016/j.jcps.2014.05.001.

Wan EW and Rucker DD (2013) Confidence and construal framing: When confidence increases versus decreases information processing. *Journal of Consumer Research* 39: 977–992.

Wang L and Preacher KJ (2015) Moderated mediation analysis using Bayesian methods. *Structural Equation Modeling: A Multidisciplinary Journal* 22(2): 249–263.

Wang X, Sun L and Tat Keh H (2013) Consumer responses to variety in product bundles: The moderating role of evaluation mode. *International Journal of Research in Marketing* 30: 335–342.

Wang Y and Griskevicius V (2014) Conspicuous consumption, relationships, and rivals: Women's luxury products as signals to other women. *Journal of Consumer Research* 40: 834–854.

Ward MK and Broniarczyk SM (2011) It's not me, it's you: How gift giving creates giver identity threat as a function of social closeness. *Journal of Consumer Research* 38: 164–181.

Wegener DT and Fabrigar LR (2000) Analysis and design for nonexperimental data – addressing causal and noncausal hypotheses. In: Reis HT and Judd CM (coord.) *Handbook of Research Methods in Social and Personality Psychology*. New York: Cambridge University Press, pp. 412–450.

Whang J, Zhu RJ and Shiv B (2012) The lonely consumer: Loner or conformer? *Journal of Consumer Research* 38: 1116–1128.

Whelan J and Dawar N (2014) Attributions of blame following a product-harm crisis depend on consumers' attachment styles. *Marketing Letters*. Epub ahead of print December. DOI: 10.1007/s11002-014-9340-z.

Wiebenga JH and Fennis BM (2014) The road traveled, the road ahead, or simply on the road? When progress framing affects motivation in goal pursuit. *Journal of Consumer Psychology* 24(1): 49–62.

Wilcox K and Stephen AT (2013) Are close friends the enemy? Online social networks, self-esteem, and self-control. *Journal of Consumer Research* 40: 90–103.

Williams L, Cote J and Buckley M (1989) Lack of method variance in self- reported affect and perceptions at work: Reality or artifact? *Journal of Applied Psychology* 74: 462–468.

Williams LE, Stein R and Galguera L (2014) The distinct affective consequences of psychological distance and construal level. *Journal of Consumer Research* 40(6): 1123–1138.

Winterich KP, Mittal V and Aquino K (2013) When does recognition increase charitable behavior? Toward a moral identity-based model. *Journal of Marketing* 77(3): 121–134.

Wong J, Newton JD and Newton FJ (2014) Powerlessness following service failure and its implications for service recovery. *Marketing Letters*. Epub ahead of print June. DOI: 10.1007/s11002-014-9303-4.

Xie C, Bagozzi RP and Gronhaug K (2014) The role of moral emotions and individual differences in consumer responses to corporate green and non-green actions. *Journal of the Academy of Marketing Science*. Epub ahead of print July. DOI: 10.1007/s11747-014-0394-5.

Xu AJ and Labroo AA (2014) Incandescent affect: Turning on the hot emotional system with bright light. *Journal of Consumer Psychology* 24(2): 207–216.

Xu J, Liu Y and Guo Y (2014) The role of subordinate emotional masking in leader–Member exchange and outcomes: A two-sample investigation. *Journal of Business Research* 67: 100–107.

Yang LW, Cutright KM, Chartrand TL et al. (2014) Distinctively different: Exposure to multiple brands in low-elaboration settings. *Journal of Consumer Research* 40: 973–992.

Yoshida DT, Sendjaya S, Hirst G et al. (2014) Does servant leadership foster creativity and innovation? A multi-level mediation study of identification and prototypicality. *Journal of Business Research*. Epub ahead of print. DOI: 10.1016/j.jbusres.2013.08.013.

Zhao X, Lynch JG Jr and Chen Q (2011) Reconsidérer Baron et Kenny: mythes et vérités à propos de l'analyse de médiation. *Recherche et Applications en Marketing* 26(1): 81–95. [original publication: Zhao X, Lynch JG Jr and Chen Q (2011) Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*, 37: 197–206.]

Appendix 1. Marketing research studies that have used one of the three moderated mediation methods.[a]

	Edwards and Lambert (2007)	Preacher et al. (2007)	Hayes (2013a, 2013b)[b]
Journal of Marketing		Haws and Winterich (2013), Winterich et al. (2013), Biswas et al. (2013), Rego et al. (2013), Thompson and Malaviya (2013), Devezer et al. (2014), Hada et al. (2014)	Sirianni et al. (2013), Ma et al. (2014), Coulter and Grewal (2014), Giebelhausen et al. (2014), Sundar and Noseworthy (2014)
Journal of Consumer Psychology		Avnet et al. (2013), Campbell et al. (2013), Luna et al. (2013), Haws et al. (2014), Moldovan et al. (2014), Steinhart et al. (2014), Wiebenga and Fennis (2014)	Aydınoğlu and Cian (2014), Ein-Gar (2014), Hadi and Valenzuela (2014), Mathur et al. (2014), Morhart et al. (2014), Walsh (2014), Xu and Labroo (2014)
Journal of Consumer Research	Moore (2012), Bellezza et al. (2014), Bellezza and Keinan (2014)	Gao et al. (2009), Ward and Broniarczyk (2011), Kim and Labroo (2011), Laran et al. (2011), Whang et al. (2012), Bagchi and Davis (2012), Jiang et al. (2013), Wan and Rucker (2013), Wilcox and Stephen (2013), Gu et al. (2013), Chen and Berger (2013), Shapiro and Nielsen (2013), Yang et al. (2014), Chae and Zhu (2014), Bhattacharjee et al. (2014), Connell et al. (2014), Lisjak and Lee (2014), Mehta et al. (2014)	Muro and Noseworthy (2013), Samper and Schwartz (2013), Irmak et al. (2013), Trudel and Argo (2013), Kronrod and Danziger (2013), Humphreys and Latour (2013), Mourali and Yang (2013), Buechel and Janiszewski (2014), Wang and Griskevicius (2014), Kan et al. (2014), Kim et al. (2014), Cutright and Samper (2014), Lee et al. (2014), May and Irmak (2014), Salerno et al. (2014), Williams et al. (2014)
Journal of Marketing Research		Berger and Fitzsimons (2008), Huang and Zhang (2011), Noseworthy and Trudel (2011), Sellier and Dahl (2011), Trudel and Murray (2011), Ulkümen and Cheema (2011), Thompson and Chandon Ince (2013)	Scott et al. (2013), Chen and Lurie (2013), Ferraro et al. (2013), Cavanaugh (2014), Cian et al. (2014), Coulter and Roggeveen (2014)
Industrial Marketing Management		Mariadoss et al. (2014)	

(Continued)

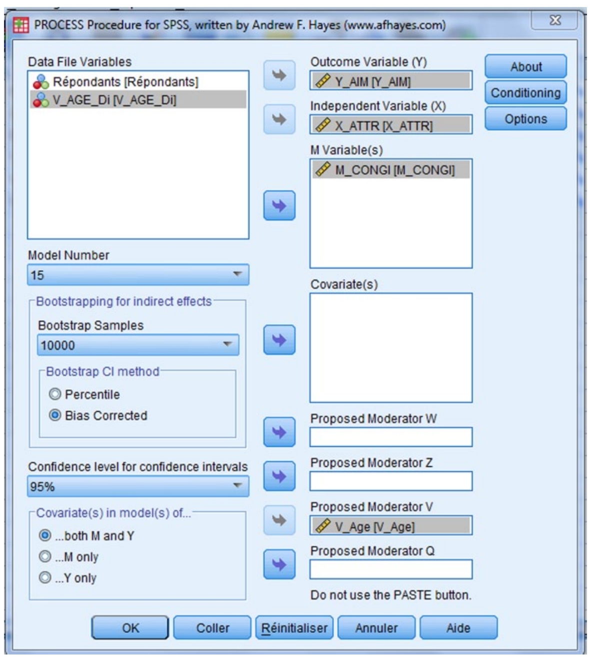
Appendix 1. (Continued)

	Edwards and Lambert (2007)	Preacher et al. (2007)	Hayes (2013a, 2013b)[b]
International Journal of Research in Marketing		Pandelaere et al. (2010), Mochon et al. (2012), Jin and Huang (2014)	Wang et al. (2013)
Journal of Business Research	Liao et al. (2014), Uhrich et al. (2014), Xu et al. (2014), Gatignon-Turnau and Mignonac (2015)	Nguyen and Munch (2011), Kim and Gupta (2012), Grappi et al. (2013a), Carvalho and Luna (2014), Yoshida et al. (2014), Khajehzadeh et al. (2014), Mariadoss et al. (2014)	Lefroy and Tsarenko (2014), Leal-Rodríguez et al. (2014), Michaelis et al. (2015), Ertürk and Vurgun (2015)
Journal of Retailing		Kachersky (2011), Orth et al. (2013), Schumann et al. (2014), Jin et al. (2014)	Bolton and Mattila (2014), Onur Bodur et al. (2014), Orth and Crouch (2014)
Journal of Service Research		Strizhakova et al. (2012), Jin and He (2013)	
Journal of the Academy of Marketing Science	Auh et al. (2014)	Verlegh et al. (2013), Choi et al. (2014), Lacey et al. (2014)	Grappi et al. (2013b), Burton et al. (2014), Xie et al. (2014)
Marketing Letters		Baxter et al. (2014)	Guo and Main (2012), Bullard and Manchanda (2013), Whelan and Dawar (2014), Wong et al. (2014)
Recherche et Applications en Marketing		Lacoste-Badie et al. (2013)	

[a]List updated in December 2014, covering the period 2007–2014 and including journals ranked 1 and 2 by the Centre national de la recherche scientifique (CNRS) in November 2014 (with the exception of *Marketing Science*, which has an embargo on its databases).
[b]Some authors cite Hayes' (2013a) method as originating in his 2012 working paper, which preceded the article cited herein.

Appendix 2. Procedure to download the PROCESS macro and dialogue box illustration (Hayes, 2013a, 2013b).

To download the PROCESS macro, visit Andrew Hayes' website (http://www.processmacro.org/download.html) and download the latest version of the macro. To install it, you will need to open SPSS as an administrator (right click then 'run as administrator'), then go to 'Utilities' > 'Install a personalised dialogue box', select the 'process.spd' file and click 'OK'. It is also possible to use the 'process.sps' script and adapt the syntax according to each test model. However, we encourage the reader to install the dialogue box, which is much simpler to use.



Model number must be specified (see "templates.pdf" file, available at http://www.processmacro.org/download.html)

Number of iterations using *bootstrap* (min. 5 000)

Y = dependent variable

X = independent variable

M = mediating variable(s)

Covariates = control variable(s) (optional)

W, Z, V et Q = moderating variable(s) to be determined based on test model (see "templates.pdf" file, which lists 76 possible moderated mediation models).

Appendix 3. Example 1, Case 1: Results for conditional indirect effect with a continuous moderating variable using Hayes' method (2013a, 2013b)

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Release 2.13 ***************

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

**************************************************************************
Model = 15
    Y = Y_AIM
    X = X_ATTR
    M = M_CONGI
    V = V_Age

Sample size
        509

**************************************************************************
Outcome: M_CONGI

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5895      ,3475     2,4047   270,0292     1,0000   507,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,0000      ,0687      ,0000     1,0000     -,1350      ,1350
a = 0,7234
X_ATTR        ,7234      ,0440    16,4326      ,0000      ,6369      ,8099

**************************************************************************
Outcome: Y_AIM

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,5334      ,2846     1,8175    40,0117     5,0000   503,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,8388      ,0612    46,3868      ,0000     2,7186     2,9591
b1 = 0,2043
M_CONGI       ,2043      ,0392     5,2113      ,0000      ,1273      ,2813
X_ATTR        ,3102      ,0482     6,4293      ,0000      ,2154      ,4049
V_Age        -,0186      ,0080    -2,3182      ,0208     -,0344     -,0028
b2 = –0,0169
int_1        -,0169      ,0053    -3,1900      ,0015     -,0273     -,0065
int_2         ,0086      ,0057     1,5047      ,1330     -,0026      ,0198

Interactions:

 int_1    M_CONGI     X     V_Age
 int_2    X_ATTR      X     V_Age

******************* DIRECT AND INDIRECT EFFECTS *************************

Conditional direct effect(s) of X on Y at values of the moderator(s):
    V_Age     Effect         SE          t          p       LLCI       ULCI
  -7,7236      ,2437      ,0708     3,4415      ,0006      ,1046      ,3828
    ,0000      ,3102      ,0482     6,4293      ,0000      ,2154      ,4049
   7,7236      ,3766      ,0595     6,3285      ,0000      ,2597      ,4935
```

```
Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
              V_Age      Effect     Boot SE    BootLLCI    BootULCI
M_CONGI     -7,7236       ,2422       ,0465       ,1531       ,3358
M_CONGI       ,0000       ,1478       ,0331       ,0849       ,2135
M_CONGI      7,7236       ,0534       ,0527     -,0554       ,1522
```

Confidence interval for the conditional indirect effect at different moderator values

```
Values for quantitative moderators are the mean and plus/minus one SD from
mean.
Values for dichotomous moderators are the two values of the moderator.

******************* INDEX OF MODERATED MEDIATION ***********************

Mediator
              Index    SE(Boot)    BootLLCI    BootULCI
M_CONGI      -,0122       ,0048     -,0222      -,0033
```

a* b2 = –0,012

Confidence interval for moderated mediation index

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

Number of bootstrap samples for bias corrected bootstrap confidence inter-
vals:
    10000

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

NOTE: The following variables were mean centered prior to analysis:
 X_ATTR   M_CONGI  V_Age

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

A4. – Exemple 1, cas 2 : Résultats de l'effet indirect conditionnel avec une variable modératrice dichotomique suivant la méthode de Hayes (2013a, 2013b)

```
Run MATRIX procedure:

**************** PROCESS Procedure for SPSS Release 2.13 **************

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

**********************************************************************
Model = 15
    Y = Y_AIM
    X = X_ATTR
    M = M_CONGI
    V = V_AGE_Di

Sample size
        509

**********************************************************************
Outcome: M_CONGI

Model Summary
    R       R-sq        MSE          F        df1        df2          p
  ,5895      ,3475     2,4047   270,0292     1,0000   507,0000      ,0000
```

```
Model
                  coeff         se          t          p       LLCI       ULCI
constant          ,0000       ,0687      ,0000     1,0000     -,1350      ,1350
X_ATTR            ,7234       ,0440    16,4326      ,0000      ,6369      ,8099

**************************************************************************
Outcome: Y_AIM

Model Summary
     R       R-sq        MSE          F        df1        df2          p
  ,5415      ,2932     1,7955    41,7390     5,0000   503,0000      ,0000

Model
                  coeff         se          t          p       LLCI       ULCI
constant         2,8400       ,0603    47,1167      ,0000     2,7215     2,9584
M_CONGI           ,2193       ,0389     5,6371      ,0000      ,1429      ,2958
X_ATTR            ,3013       ,0479     6,2939      ,0000      ,2072      ,3954
V_AGE_Di        -,2301       ,1206    -1,9079      ,0570     -,4671      ,0068
int_1           -,3113       ,0777    -4,0072      ,0001     -,4639     -,1587
int_2            ,1748       ,0953     1,8341      ,0672     -,0124      ,3620

Interactions:

 int_1    M_CONGI     X     V_AGE_Di
 int_2    X_ATTR      X     V_AGE_Di

******************** DIRECT AND INDIRECT EFFECTS *************************

Conditional direct effect(s) of X on Y at values of the moderator(s):
 V_AGE_Di      Effect         SE          t          p       LLCI       ULCI
   -,4853       ,2165       ,0723     2,9959      ,0029      ,0745      ,3585
    ,5147       ,3913       ,0621     6,3006      ,0000      ,2692      ,5133

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
           V_AGE_Di      Effect    Boot SE   BootLLCI   BootULCI
M_CONGI      -,4853       ,2679      ,0409      ,1900      ,3514
M_CONGI       ,5147       ,0427      ,0496     -,0564      ,1373

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** INDEX OF MODERATED MEDIATION ************************

Mediator
              Index   SE(Boot)   BootLLCI   BootULCI
M_CONGI      -,2252      ,0644     -,3592     -,1057

When the moderator is dichotomous, this is a test of equality of the
conditional indirect effects in the two groups.

******************** 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: The following variables were mean centered prior to analysis:
 X_ATTR    M_CONGI   V_AGE_Di

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

a = 0,7234

b1 = 0,2193

Confidence interval for the conditional indirect effect at two moderator values

0,042–0,267 = –0,225

Confidence interval for moderated mediation index

A5. – Exemple 2 : Résultats de l'effet indirect conditionnel avec deux variables médiatrices et deux modérateurs suivant la méthode de Hayes (2013a, 2013b)

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Release 2.13 ***************

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

**************************************************************************
Model = 75
    Y = Y_Ib
    X = X_Origin
   M1 = M1_Aad
   M2 = M2_Ab
    W = W_Resist
    Z = Z_ImpSup

Sample size
        373

**************************************************************************
Outcome: M1_Aad

Model Summary
     R       R-sq        MSE          F        df1        df2          p
   ,7252      ,5259     1,2533    81,4300     5,0000   367,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,0886       ,0615     1,4424      ,1500     -,0322      ,2095
X_Origin      ,4288       ,0374    11,4744      ,0000      ,3553      ,5023
W_Resist     -,3429       ,0433    -7,9186      ,0000     -,4281     -,2578
int_1         ,0992       ,0243     4,0795      ,0001      ,0514      ,1470
Z_ImpSup      ,1813       ,0443     4,0917      ,0001      ,0942      ,2684
int_2         ,0087       ,0261      ,3336      ,7389     -,0427      ,0601

Interactions:

 int_1    X_Origin    X     W_Resist
 int_2    X_Origin    X     Z_ImpSup

**************************************************************************
Outcome: M2_Ab

Model Summary
     R       R-sq        MSE          F        df1        df2          p
  ,6594      ,4347     1,2113    56,4527     5,0000   367,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,0637       ,0604     1,0549      ,2922     -,0551      ,1825
X_Origin      ,2788       ,0367     7,5898      ,0000      ,2066      ,3511
W_Resist     -,3539       ,0426    -8,3130      ,0000     -,4376     -,2702
int_1         ,0966       ,0239     4,0408      ,0001      ,0496      ,1436
Z_ImpSup      ,1473       ,0436     3,3805      ,0008      ,0616      ,2329
int_2         ,0518       ,0257     2,0157      ,0446      ,0013      ,1023
```

```
Interactions:

 int_1    X_Origin    X     W_Resist
 int_2    X_Origin    X     Z_ImpSup

***************************************************************************
Outcome: Y_Ib

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,7165      ,5134     1,4799    42,5501     9,0000   363,0000      ,0000

Model
               coeff         se          t          p       LLCI       ULCI
constant      2,8174      ,0718    39,2487      ,0000     2,6763     2,9586
M1_Aad         ,3160      ,0692     4,5666      ,0000      ,1799      ,4521
M2_Ab          ,3742      ,0700     5,3475      ,0000      ,2366      ,5119
X_Origin       ,1561      ,0464     3,3668      ,0008      ,0649      ,2473
W_Resist      -,0654      ,0529    -1,2375      ,2167     -,1693      ,0385
int_3          ,0796      ,0403     1,9753      ,0490      ,0004      ,1589
int_4         -,1179      ,0446    -2,6447      ,0085     -,2056     -,0302
Z_ImpSup      -,0013      ,0494     -,0271      ,9784     -,0986      ,0959
int_5          ,0136      ,0455      ,2988      ,7653     -,0759      ,1031
int_6          ,0394      ,0483      ,8170      ,4145     -,0555      ,1343

Interactions:

 int_3    M1_Aad      X     W_Resist
 int_4    M2_Ab       X     W_Resist
 int_5    M1_Aad      X     Z_ImpSup
 int_6    M2_Ab       X     Z_ImpSup

******************* DIRECT AND INDIRECT EFFECTS ************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      ,1561      ,0464     3,3668      ,0008      ,0649      ,2473

Conditional indirect effect(s) of X on Y at values of the moderator(s):

Mediator
          W_Resist   Z_ImpSup     Effect    Boot SE   BootLLCI   BootULCI
M1_Aad     -1,5439    -1,4496      ,0456      ,0520     -,0449      ,1697
M1_Aad     -1,5439      ,0000      ,0532      ,0366     -,0108      ,1355
M1_Aad     -1,5439     1,4496      ,0613      ,0378     -,0042      ,1479
M1_Aad       ,0000    -1,4496      ,1233      ,0600      ,0047      ,2444
M1_Aad       ,0000      ,0000      ,1355      ,0352      ,0705      ,2116
M1_Aad       ,0000     1,4496      ,1482      ,0478      ,0606      ,2514
M1_Aad      1,5439    -1,4496      ,2387      ,0739      ,0966      ,3897
M1_Aad      1,5439      ,0000      ,2555      ,0516      ,1652      ,3697
M1_Aad      1,5439     1,4496      ,2727      ,0798      ,1294      ,4503
```

Confidence intervals for conditional indirect effect at low level of moderator 1 (W) and at three levels of moderator 2 (Z)

Mean level of moderator 1 (W) and three levels of moderator 2 (Z)

High level of moderator 1 (W) and three levels of moderator 2 (Z)

```
Mediator
         W_Resist   Z_ImpSup     Effect    Boot SE   BootLLCI   BootULCI
M2_Ab     -1,5439    -1,4496      ,0272      ,0456     -,0519      ,1322
M2_Ab     -1,5439      ,0000      ,0721      ,0370      ,0094      ,1575
M2_Ab     -1,5439     1,4496      ,1256      ,0448      ,0485      ,2238
M2_Ab       ,0000    -1,4496      ,0646      ,0307      ,0209      ,1472
M2_Ab       ,0000      ,0000      ,1043      ,0257      ,0608      ,1623
M2_Ab       ,0000     1,4496      ,1527      ,0494      ,0720      ,2666
M2_Ab      1,5439    -1,4496      ,0477      ,0375     -,0134      ,1355
```

```
M2_Ab     1,5439      ,0000      ,0823      ,0405      ,0122      ,1697
M2_Ab     1,5439     1,4496      ,1255      ,0766      ,0075      ,3091

Values for quantitative moderators are the mean and plus/minus one SD from mean.
Values for dichotomous moderators are the two values of the moderator.

******************** 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: The following variables were mean centered prior to analysis:
 X_Origin M1_Aad   M2_Ab    W_Resist Z_ImpSup

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

RAM

Corrigendum

Recherche et Applications en Marketing
2015, Vol. 30(4) 129

DOI: 10.1177/2051570715606296
rme.sagepub.com

Borau et al., 2015, Analysing moderated mediation effects: Marketing applications, *Recherche et Applications en Marketing* 30(4) 2015.

Regarding the moderated mediation evoked by Muller et al. (2005), there is, first, moderation of the total effect, and then moderation either of the link a, or the link b. Pertaining to the direct effect, it is moderated only in the case of partial moderated mediation.