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A Scoping Review of Latent Moderated Structural Equations and Recommendations

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Abstract ■ Structural equation modeling involving latent interaction has garnered much attention from researchers in many disciplines. Interestingly, Becher & Trowler (2001) described academics as living in a tribe sharing a common set of practices and led by a stable elite. To provide an overview of psychological and educational studies using the latent moderated structural equations approach (LMS), we produced a scoping review from three databases (ERIC, PsychInfo, and Érudit) and selected 78 articles. The goal of this study is to examine the nature and extent of practices regarding the use of the LMS method in order to recommend good practices. Our results show that there are some discrepancies in the way researchers analyze data using LMS.

Keywords ■ Structural equation model; Interaction; Practice; Psychology; Education.

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Introduction

"Interaction effects are central to theory and practice in the social sciences" (Marsh, Wen, Nagengast, & Hau, 2012, p. 437). In fact, objects that interest scientists in these fields are generally shaped by interrelated variables: "[social] researchers that adopt a complex systems perspective have argued that, rather than focusing on a single causal relationship at a time, we need to investigate how the interaction or combination of different factors generates specific outcomes" (Quintana, 2022). However, the ability to detect moderation effects is often low, owing to the measurement error in the observed variables (Aiken & West, 1991; Holmbeck, 1997; Jose, 2013; Marsh et al., 2012). Therefore, using latent variable moderation represents an efficient strategy to increase the chances of detecting interaction effects (Klein & Moosbrugger, 2000; Little, Bovaird, & Widaman, 2006; Marsh et al., 2012). Moreover, it provides an opportunity to evaluate the interaction between continuous latent variables, which is not possible with multigroup invariance testing (Marsh et al., 2012).

To formally illustrate the concept of latent interaction in structural equation modeling (SEM), suppose that four items (X_1 to X_4) measure the exogenous latent variable ξ_1, two items (X_5 and X_6) measure the exogenous latent variable ξ_2, four items (X_7 to X_{10}) measure the exogenous latent variable ξ_3, and three items (Y_1 to Y_3) measure the endogenous latent variable η. Figure 1 graphically illustrates this model.

For didactic purposes, we focus on the notation of the structural model. Mathematically speaking, the relationship between these manifest and latent variables takes the form

$$\eta = \alpha + \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_3\xi_3 + \gamma_4\xi_1\xi_3 + \zeta \qquad (1)$$

where α is the intercept of the model, γ are the slopes (known as factor loadings), η and ξ are the latent variables, and ζ is the error term. This study focuses on the interaction $\xi_1\xi_3$. Therefore, γ_4 is of great interest because we aim to evaluate its significance, among other things. It is also interesting to rewrite (1) after removing α, as follows:

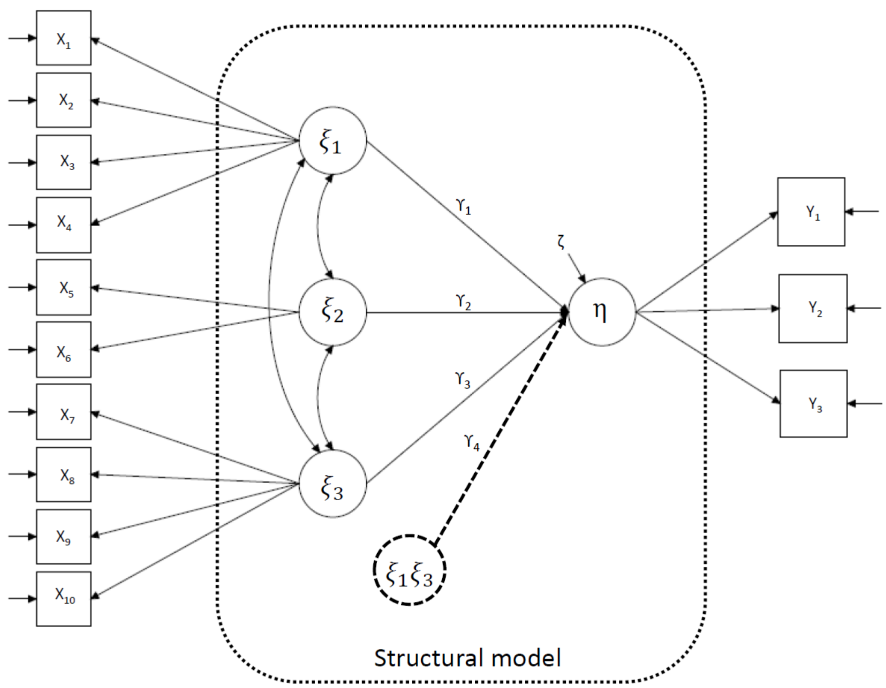
$$\eta = (\gamma_1 + \gamma_4\xi_3)\,\xi_1 + \gamma_2\xi_2 + \gamma_3\xi_3 + \zeta \qquad (2)$$

to understand that $(\gamma_1 + \gamma_4\xi_3)$ is clearly a "moderator function" (Klein & Moosbrugger, 2000).

Interaction in Structural Equation Modeling

There are two general steps to assessing the interactions in SEM. First, we need to estimate a SEM model without interaction (called Model 0). The second step requires the

Figure 1 ■ Example of a structural model of a SEM



estimation of an SEM model with latent interaction (called Model 1). To compute the added value of the interaction, we must compare the information from these two models. Given that the numerical integration algorithm ensures that standard errors are robust but prevents the calculation of fit indices (Kelava et al., 2011; Wang & Wang, 2012), the log-likelihood ratio test can be used to assess the fit of the SEM model with the latent interaction (Klein & Moosbrugger, 2000; Muthén, 2012). Mathematically,

$$D = -2\Big(\ell(\text{Model } 0) - \ell(\text{Model } 1)\Big) \quad (3)$$

where ℓ stands for the log-likelihood, Model 0 is the more restricted model. This test is asymptotically distributed as χ^2 and the degrees of freedom are calculated by subtracting the number of free parameters in Model 0 from the number of free parameters in Model 1. If D is significant, it can be concluded that Model 0 results in a significant loss of fit compared to Model 1.

Additionally, the variance explained by the interaction, which also represents the effect size, is very useful. According to Harring, Weiss, and Li (2015): "(...) effect size associated with the interaction effect represents the additional variance that the interaction explains in η above and beyond that which can be explained by the first-order effects." Following Maslowsky, Jager, and Hemken (2015), we can use R^2 to assess the additional variance from the interaction:

$$\Delta R^2 = R^2_{Model1} - R^2_{Model0} \quad (4)$$

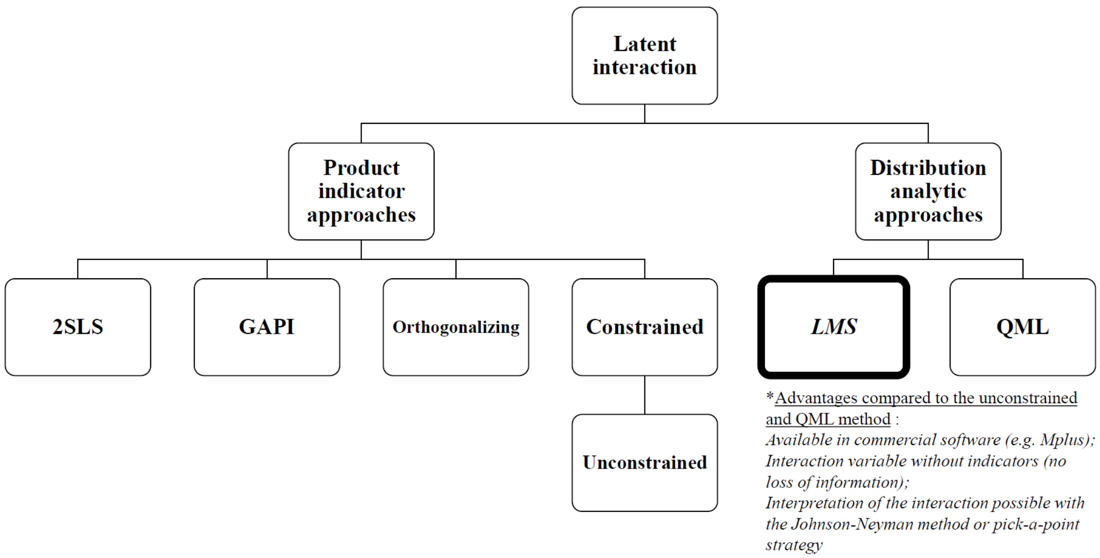
where R^2 for η in (1) and (2) can be defined as $\left[Var\left(\eta\right) - Var\left(\zeta\right)\right] / Var\left(\eta\right)$.

Finally, one can plot the interaction for interpretation using different strategies. Examples are the pick-a-point strategy (Rogosa, 1980) and Johnson and Neyman (1936) plot technique. For more information about these techniques, see Girard, Béland, Lemoyne, and Caron (2020).

Classification of Methods to Test Interaction

Several methods have been developed to compute interaction effects in structural equation models (Kenny & Judd, 1984; Klein & Moosbrugger, 2000; Klein & Muthén, 2007; Little et al., 2006; Marsh, Wen, & Hau, 2004; Marsh et al., 2007; Moosbrugger, Schermelleh-Engel, Kelava, & Klein, 2009) and, over the years, have become increasingly accessible and easier to use by researchers in the social science field (Girard & Béland, 2017; Girard et al., 2020; Lorah & Wong, 2018; Maslowsky et al., 2015). As depicted in Figure 2, these methods can be categorized into two approaches: product indicator and distribution analytic (Marsh et al.,

Figure 2 ■ Overview of latent interaction methods in SEM and advantages of the LMS method.



2012).

In the product indicator approaches, the interaction variable is a latent variable with indicators (manifest variables). These indicators are created by multiplying the indicators of the latent variables that interact together. Historically, the constrained approach was the most influential and was originally proposed by Kenny and Judd (1984). However, this approach involves many restrictive assumptions that can lead to potential complications (Kline, 2016). Consequently, other product indicator approaches have been developed: two-stage least squares (2SLS; Bollen, 1996), the generalized appended product indicator method (GAPI; Wall & Amemiya, 2001), orthogonalizing (Little et al., 2006), and partially constrained and unconstrained (Marsh et al., 2004; Marsh et al., 2012). Among these methods, the unconstrained approach presents many advantages for applied researchers (Marsh et al., 2004, 2006): ease of implementation, elimination of complicated constraints, efficacy with non-normal data, and the possibility of using different statistical software (e.g., AMOS and Mplus). Nonetheless, when using this approach, many precautions must be taken. First, the researcher must create product indicators among several options: all possible products, matched-pair products, or one-pair product (Marsh et al., 2004, 2006; Marsh et al., 2007; Y. Wu, Wen, Marsh, & Hau, 2013). Second, prior to creating product indicators, the double-mean centering strategy needs to be applied to avoid using the mean structure (Lin, Wen, Marsh, & Lin, 2010). Third, to obtain appropriate standardized estimates for the significant moderating effects, an additional mathematical transformation is required (Marsh et al., 2012; Wen, Hau, & Marsh, 2008; Wen, Marsh, & Hau, 2010). Finally, only the sign of the interaction can be used to interpret its meaning (Marsh et al., 2012). Although the Aiken and West (1991) procedure is often used to decompose the interaction effect in regression, it is not appropriate for product indicator approaches because it is based on the estimation of predicted effects for specific values of the independent and moderating variables (Aiken & West, 1991). However, with the product indicator approaches, the values of the independent variable and the moderator do not define the "true" value of the interaction because it is a different latent variable formed by its own indicators. Consequently, the only way to interpret the interaction is to interpret the sign (Marsh et al., 2012).

Distribution analytic approaches have been developed to eliminate the necessity of forming product indicators (Klein & Moosbrugger, 2000; Klein & Muthén, 2007). Therefore, in these approaches, the interaction variable has no indicators; it represents the product of two latent variables interacting together. Moreover, unlike previous approaches, they do not require linear constraints, and they model the implied non-normality of the latent product term (Kelava et al., 2011; Marsh et al., 2012). More precisely, the latent moderated structural equations (LMS) method analyzes raw data using “an iterative ML estimation procedure tailored for the type of non-normality induced by interaction effects” (Klein & Moosbrugger, 2000,

p. 473) and calculates the estimates using an expectation-maximization (EM) algorithm adapted to the mixture density (Klein & Moosbrugger, 2000). Quasi-maximum likelihood (QML) estimation represents a simpler version of the LMS method that provides similar results (Klein & Muthén, 2007). However, even though some authors claim that the QML method is implemented in Mplus (Kline, 2016; Lorah & Wong, 2018), Mplus product support confirmed that it is the LMS method that is used by this software (**mm19**).

Tutorials to apply the LMS method using Mplus are currently available in English (Maslowsky et al., 2015) and French (Gucciardi, Stamatis, & Ntoumanis, 2017; Girard et al., 2020). For users familiar with R, the "nlsem" package allows for the estimation of latent interaction terms using both approaches (LMS and QML; Umbach, Naumann, Brandt, & Kelava, 2017). However, its current implementation requires certain technical aspects of the user interface that are not addressed here. Instead, this study focused on the application of the LMS method given its many advantages (e.g., availability in commercial software, no loss of information, and the possibility of interpreting the interaction effect).

Aim of This Study

SEM models are used in a broad range of disciplines (Kline, 2016), but we can hypothesize that the methods of doing things can differ among groups of researchers from different fields. For this reason, (**bt01**) explained that academics live in a type of tribe, where they share common sets of practices and comprise a stable elite. These communities are characterized by their own epistemic cultures (Knorr-Cetina, 1999), which is probably true when people analyze their data.

How do people in social science, especially those in psychology and education, analyze their data? Fundamentally, humans are very bad Homo statisticus (Kahneman, 2011). Further, it is well known that many researchers in social science are not well trained in statistics and psychometric, which is a common ground for errors (Sijtsma, 2015). Unsurprisingly, courses in quantitative methods are not very popular among students of these disciplines (Cui, Zhang, Guan, Zhao, & Si, 2019).

Is this difficult relationship between statistics and psychometrics reflected by bad practices when the LMS method is used by social scientists? Unfortunately, little is known about how people work with this model in specific social science disciplines, such as psychology and education.

In this paper, we specifically study the use of the LMS method, which has many advantages such as being available in commercial software (e.g., Mplus), interaction variable without indicators (no loss of information), and the possibility of interpretation of the interaction with the Johnson–Neyman method or pick-a-point strategy. To our knowledge, this is the first study to produce a scoping review of latent interactions from a disciplinary point of view. Our goal is to examine the nature and extent of practices regarding the use of the LMS method in social science to formulate recommendations on good practices in the light of our results.

Method

Given the possibility of applying the LMS method using Mplus and its potential contribution to evaluating interactions between latent variables, a scoping review allowed the identification of studies in social science by applying it, considering its availability. We followed Arksey and O'Malley's (2005) method, which consists of five steps: 1) defining a research question, 2) identifying relevant studies, 3) selecting studies, 4) extracting data, and 5) synthesizing results.

Defining a Research Question

To examine the nature and extent of practices regarding the use of the LMS method in social science in order to recommend good practices, three exploratory research questions oriented this scoping review:

1. Who in the social science field uses the LMS method to analyze latent interactions in their scientific studies?
2. What are the aims of these scientific studies?
3. How do researchers report their application of the LMS method?

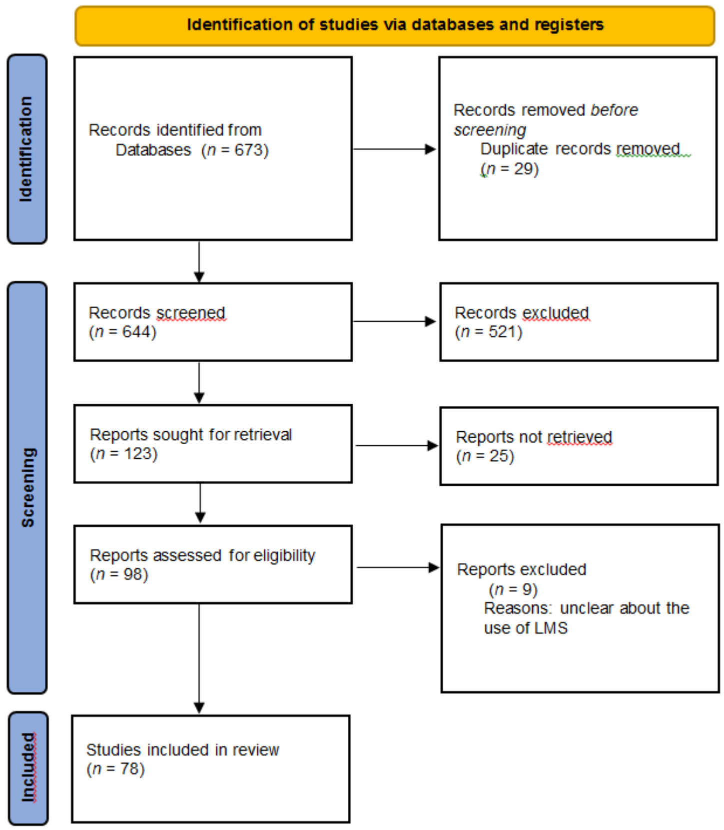
Identifying Relevant Studies

To develop an overview of social science studies using the LMS method to evaluate latent interaction, we screened three databases (ERIC, PsychInfo, and Érudit) in January 2021 for articles written between January 1st, 2006 and December 31st, 2020. We selected these databases because ERIC is the largest online library of educational research, PsychInfo is the largest library of psychological research, and Érudit is the largest library of publications in the French language in the fields of humanities, social sciences, and letters. The keywords used for the research were latent, interaction, moderated, structural, OR equation.

Selecting Studies

The inclusion criteria were as follows: 1) studies in the social sciences (mainly psychology and education), 2) analyzing latent variable interaction with the LMS method, and 3) written in English or French. The exclusion criteria were as follows: 1) studies outside social science fields and/or 2) analyzing latent variable interaction without using LMS.

Figure 3 ■ Flow chart



This identification strategy enabled us to locate 673 references, including 425 from PsycINFO, 184 from ERIC, and 64 from Érudit, including duplicates. The flowchart in Figure 3 shows the screening process used to identify eligible studies.

The selected articles were transferred to EndNote to identify duplicates. Once duplicates were filtered out, one member of the research team read the titles and abstracts to keep the most relevant articles based on our exclusion criteria. In the case of uncertainty about relevance, the full texts were screened for additional information. All selected and rejected articles were also analyzed by a second member of the research team. In case of uncertainty or disagreement, a third member of the research team was consulted. One member of the research team then read the articles to retain the most relevant articles. After applying the inclusion and exclusion criteria, 78 articles were retained.

Extracting Data

Relevant information for each article was collected and transcribed into an extraction grid available on the journal's web site to document the following aspects: 1) authors and their university, 2) sample size for the analysis, 3) dependent variable of the SEM model, 4) variables involved in interaction, 5) variance explained by the interaction or effect size, 6) statistical software, 7) fit of the SEM model, 8) fit of the latent interaction, 9) interpretation and visualization of the latent interaction, 10) general aim of the study, 11) results and elements of the interaction, and 12) information about missing data.

Synthesizing Results

Data from the extraction grid were synthesized according to each study question. To identify "who" used the LMS method to analyze latent variable interaction in social science, we used the first author's university, department, and country. Descriptive statistics were used to portray the people behind the bodies of the articles under inves-

Figure 4 ■ Number of articles using LMS published by year among our body of texts

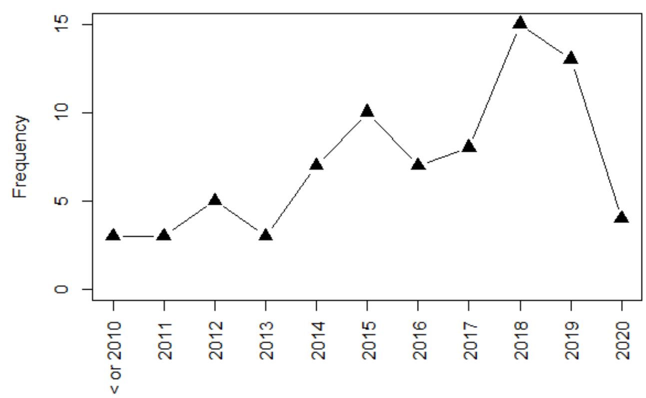


Table 1 ■ Number of authors by article

Number of authors	1	2	3	4	5	6	7	8	12
Frequency	3	14	22	17	10	6	3	2	1

tigation. To identify "what" the topic of these SEM interactions was, we used the study samples and more when available, such as the dependent variable in the SEM model, variables involved in the interaction, aim of the study, and results from the interaction. Finally, to explore "how" researchers apply the LMS method and associate analysis (Gucciardi et al., 2017; Girard et al., 2020), we used explained variance or effect size, significance of the interaction, statistical software, fit of the SEM model without latent interaction, interpretation of the latent interaction, and missing data treatment.

Results

Who?

Figure 4 shows the number of articles using LMS that have been published each year since 2006.

We observe an upward trend, especially after 2013. However, the number of articles involving latent variable interactions ($n = 78$) has been limited since the publication of the LMS method (Klein & Moosbrugger, 2000). Next, we extracted the number of authors per article.

Table 1 shows that 81% of the articles had between two and five authors. In addition, the three largest producers of latent interaction articles among our body of text were as follows: 33% (26/78) of the first authors were affiliated with an American university, 22% (17/78) with a German university, and 9% (7/78) with a British university. As expected, most authors were affiliated with a department of psychology or education, but some authors were affiliated with fields such as agriculture and rural policy, business and marketing, physiotherapy and exercise science, and public health.

What?

Among all the studies, 81% (63/78) were classified in the fields of psychology and education. We also found a few articles in other fields, such as health, psychiatry and gerontology (10/78), criminology (2/78), sports (2/78), and marketing (1/78). Among these articles, we were able to identify some common research objects. In the following, we present the three most popular subjects based on the dependent variable of the SEM model.

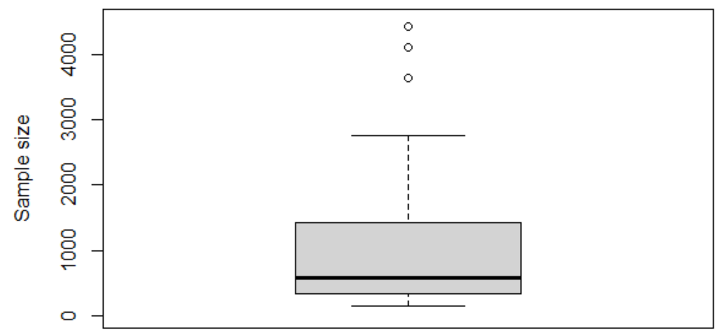
First, 13 studies used at least one dependent variable related to constructs such as anxiety, depression, or burnout. For example, Van Zalk and Tillfors (2017) examined whether corumination with online friends buffered the link between social anxiety and depressive symptoms over time. They considered depressive symptoms (η in equation 1) influenced by social anxiety (ξ in equation 1) and co-rumination (ξ in equation 1) and the interaction between these latent variables. (L. Wu, Zhang, Cheng, & Hu, 2018) predicted social anxiety using the interaction trait between resilience and bullying victimization in their SEM model. In the context of education, Hoferichter, Raufelder, and Eid (2015) predicted test anxiety using many interactions, such as representations of student–student relationships and associations of achievement drive.

Another group of nine articles attempted to predict educational achievement using interaction. Ning and Down-

Table 2 ■ Descriptive statistics about the sample of 78 articles

Min	1st Quantile	Median	Mean	3rd Quantile	Max
155	334	583	4,761	1420	257,273

Figure 5 ■ Boxplot of reported sample sizes (without the study with $n = 257,273$)



ing (2012) predicted cumulative GPA using an interaction between learning experience and motivation and an interaction between learning experience and self-regulation. In one of their analyses, Trautwein et al. (2012) calculated an interaction between expectancy and attainment to predict Math and English achievement.

A cluster of seven articles was related to problematic substance use (e.g., alcohol and cannabis) and eating disorders. For example, Blanchard, Stevens, Cann, and Littlefield (2019) attempted to predict alcohol and cannabis consumption and other related problems with an interaction between reappraisal and protective behavioral strategies. In addition, Maslowsky and Schulenberg (2013) studied the use of cigarettes, alcohol (including binge drinking), and marijuana using an interaction term between conduct problems and depressive symptoms. As a last example, Martins et al. (2018) studied alcohol use and heavy drinking using a SEM model with an interaction between executive functions and drinking motives.

How?

Table 2 and Figure 5 show the descriptive statistics of the sample sizes reported in all the articles. The smallest sample is $N = 155$, and the largest is $N = 257,273$, which explains the large difference between the median and mean.

Score reliability has generally been reported using Cronbach's alpha. Few authors have used McDonald's omega (e.g., Duan & Mu, 2018; Huard Pelletier, Girard, & Lemoyne, 2020; Putwain, Wood, & Pekrun, 2020; Sandrin et al., 2019), but none of them specified the nature of this coefficient explicitly (e.g., computed from a EFA or CFA; use of total omega or hierarchical omega; value of fit indices).

When estimating the SEM model without interaction, more than 95% of the articles also mention fit indices (e.g., χ^2, CFI, TLI, RMSEA) in their articles. The article that did not report this information only focused on latent interaction (see Hammond, Sibley, & Overall, 2014).

As stated in the Introduction, when estimating the SEM model without interaction, the log-likelihood ratio test can be used to compare the relative fit of the structural model excluding latent interaction and the structural model including latent interactions. Out of our 78 articles, 53 clearly reported using this test to assess the fit of the model with the interaction, whereas the others did not report how they managed the absence of fit indices to evaluate the quality of the SEM model with the latent interaction about this test.

The ΔR^2 was reported in 31% of articles (24/78). For example, Bardach, Lüftenegger, Oczlon, Spiel, and Schober (2019) explained an additional 2.3% of the variance by latent interaction. This additional percentage of variance was between 1% and 4% in Diestel and Schmidt (2010), 4% in (Girard, St-Amand, & Chouinard, 2019), between 2% and 5% in Gucciardi et al. (2017), between 3% and 5% in Racine and Martin (2016), and 11% in Barbaranelli et al. (2018).

From our body of text, 82% (64/78) offered a plot or table to help interpret the interaction. Here, only a few articles interpreted significant interactions with the Johnson–Neyman plots (see Huard Pelletier et al., 2020, for a scarce example). Most studies (58/78) used the pick-a-point strategy (Rogosa, 1980).

Finally, 60% (47/78) of our studies utilized full information maximum likelihood (FIML), an estimation method that can handle missing data. However, not all of these studies formally discuss the treatment of missing data. Among all articles, 26% (20/78) did not discuss (or remain unclear) the treatment of missing data. According to Cham, Reshetnyak, Rosenfeld, and Breitbart (2017), FIML works well when the indicators are missing completely at random (MCAR) or missing at random (MAR) and are normally distributed. Only a few authors have investigated the type of missing data. For example, Mohammad, Shapiro, Wainwright, and Carter (2015) used the Little test (Little, 1988). In addition, two studies reported using listwise deletion, three used multiple imputation, two used the EM algorithm, one used mean imputation, and three had no missing data.

Discussion and conclusion

This article is a scoping review of studies focusing on psychological and educational variables using the LMS method to analyze latent interaction. After extracting articles from three social sciences databases (ERIC, PsychInfo, and Érudit), 78 articles were selected. The body of the text was analyzed to answer three questions: Who used the LMS method to analyze their data? What research questions are addressed using the LMS method? How do researchers apply and present the LMS method in their articles?

Despite the interest of scientists in education and psychology in using LMS, the number of articles remains limited, according to our scoping review. In line with the first two research questions, the results indicated that 64% of the first authors of the analyzed articles were related to American, German, and English universities, although all were published in English.

In addition to the three groups of articles discussed in the results, a wide variety of subjects can be analyzed using the LMS: worry about crime (Jackson, 2015), sport and exercise behaviors (Huard Pelletier et al., 2020), creativity (Silvia, Nusbaum, Berg, Martin, & O'Connor, 2009), sexism (Hammond et al., 2014), right-wing authoritarism (Dallago, Mirisola, & Roccato, 2012), and intention to drop out of university (Bardach et al., 2019), etc. It is not surprising that fields such as psychiatry, criminology, sports, and marketing have also used this method to analyze their data. This diversity, even though not high in terms of the number of articles, points to the versatility of the LMS method and its relevance to a wide range of researchers. Therefore, sharing best practices should be of interest in an increasing number of studies in the near future.

In line with our third research question, we observed some discrepancy in the way researchers analyze data using LMS in our 78 analyzed articles. Some have good practices, but others seem to omit important information. To help researchers use the LMS method correctly, we propose a list of 10 recommended practices (see Table 3).

First, preparation of the data under investigation is essential before analysis. Thus, the researcher needs to understand these data, and the distribution of variables must be investigated. As Li et al. (1998) reminds us, "test statistics such as standard errors and the chi-square goodness-of-fit statistic for maximum likelihood estimation method are not asymptotically correct in the presence of nonnormality, and should be taken as rough guidelines" (p. 14). In addition, it is important to investigate the score reliability. If McDonald's omega is used, it is important to explain whether this coefficient is at least based on EFA or CFA and the category of omega (Revelle & Condon, 2019).

If there are missing data, the researcher needs to study whether they are MCAR, MAR, or not missing at random. This step is important to ensure the effectiveness of data treatment. Cham et al. (2017) show that FIML estimation can handle missing data for LMS to produce unbiased parameter estimates. However, this result holds only if the data are MCAR or MAR, which is also the case for multiple imputation (van Buuren, 2012).

The next step involves estimating the SEM model without interaction. Our body of texts shows that researchers used fit indices such as χ^2, RMSEA, SRMR, CFI, and TLI as a type of "quality measure". However, people should not be blinded by their values: fit indices are imperfect (Peugh & Feldon, 2020). According to Preacher (2006, p. 254):

> The good fit of a hypothesized model to observed data, although desirable, can result from the model's inherent ability to predict data patterns and may have little to do with its value as a scientific tool. Cherished models may have to be abandoned or replaced if their past successes can be ascribed more to [fitting propensity, FP] than to any insight they lend into the process that actually generated the data. Adopting a model selection perspective and explicitly considering FP can help researchers avoid these problems.

After that, the estimated SEM model with the interaction term follows and all the information to better understand the marginal benefit of the significant interaction is reported. The log-likelihood ratio test provides information on the effects of the model with interactions. Therefore, without this information, we cannot assess whether the interaction improves the model, which is essential for interpreting the results.

Finally, to improve the interpretation of the interaction effect, a recent methodological exemplification (Girard et al., 2020) suggested that the Johnson–Neyman plot had an important benefit compared to the pick-a-point strategy,

Table 3 ■ Ten "must-do's" in latent variable interaction using LMS

Preparation of the data
1. "Cleaning" and standardization of the data if necessary.
Understanding the data
2. Assessing and reporting information concisely about assumptions behind the SEM model (e.g., computation of the skewness and kurtosis of the variables).
3. Arguing the psychometric properties of the scales.
4. Assessment of the missing data to see if they are MCAR, MAR, or MNAR.
Estimation of the SEM model without interaction (model 0)
5. Estimation and interpretation of the parameters for model 0.
6. Interpretation of the fit indices (χ^2,CFI, TLI, SRMR, RMSEA) and explained variance R^2.
Estimation of the SEM model with interaction (model 1)
7. Estimation and interpretation of the parameters for model 1.
8. Computation and interpretation of the log-likelihood ratio test.
9. Computation and interpretation of ΔR^2 to assess the percentage of variance explained by the latent interaction.
10. Plot and interpret the interaction using the pick-a-point strategy or the Johnson-Neyman plot technique.

showing a confidence interval area for the significant interaction. However, as seen in the present scoping review, the pick-a-point strategy remains the most commonly used strategy in scientific literature.

Limits

This scoping review has some limitations. First, it focused mainly on psychology and education. Other disciplines, such as sociology, economics, and political science, must be surveyed more thoroughly using other databases. The second limitation concerns the nature of the criteria under investigation. Other choices could have included different types of information, such as the measurement of the scale under investigation.

Take away message

It is important to study how people in specific disciplines analyze data to understand their strengths and weaknesses. For example, we have observed that articles in psychology and education need to clarify the information about data preparation before the analyses, as in the case of the treatment of missing data and the reporting of the size effect. However, information regarding the estimation of the SEM model without interaction is generally satisfactory.

This study is only the first step toward enhancing our understanding of LMS practices from a disciplinary point of view. The next step was to produce a systematic review involving other disciplines. In addition, everyone knows that English is the lingua franca of science. All 78 articles analyzed in this study were in English. Although we only found two articles using latent interaction in French (not used in this article because they were not relevant for our purpose), it would be interesting to search for articles about latent interaction in other languages because many professionals and students are more inclined to read in their own language to understand complex topics such as LMS. As Oreskes (2019, p. 4) says, "In diversity there is epistemic strength!"

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Appendix: Studies included in the scoping review

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