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A REVIEW OF THE USE OF PLS-SEM IN NEUROMARKETING RESEARCH

REVISIÓN DEL USO DEL PLS-SEM EN LAS INVESTIGACIONES SOBRE NEUROMARKETING

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Abstract: The methodology applied for the statistical analysis for understanding, explaining and predicting consumer behavior represents an important issue for neuromarketing research. This research analyses the use of the PLS-SEM method in this area. A total of 20 articles, which employed at least one neuromarketing method and performed PLS-SEM analysis, were found in the main data bases (*i.e.*, WOS, Scopus, and others). A lack of an adequate approach for sampling and treatment of small samples was generally found. Problems with the proper application of the common PLS-SEM analysis procedures for the assessment of the outer and inner models, as well as with the application of advanced PLS-SEM approaches. Future studies should assess the suitability of using a PLS-SEM approach, depending on the research objective supporting the method, the conditions supporting its use, and its limitations. Guidelines are provided to researchers on when PLS-SEM is an appropriate research tool for neuromarketing research, which analytical method to use, and how to validate and communicate the results.

Keywords: Statistical Methods; Structural Equation Modelling; Neuromarketing, PLS-SEM; Neuromarketing Techniques; Review.

Resumen: Una parte importante en las investigaciones en neuromarketing es la metodología utilizada para el análisis estadístico con el fin de comprender, explicar y predecir el comportamiento de los consumidores. Esta investigación analiza el uso del método PLS-SEM en este ámbito. Un total de 20 artículos, que emplearon al menos una técnica de neuromarketing y realizaron análisis PLS-SEM, se encontraron en las principales bases de datos (*i.e.*, WOS, Scopus y otros). Se observa que a menudo no se utiliza enfoque adecuado para el muestreo y el tratamiento de muestras pequeñas. También se encuentran problemas con la aplicación apropiada de los procedimientos comunes de análisis PLS-SEM para la evaluación de los modelos externo e interno, así como con la aplicación de métodos avanzados. Los futuros estudios deberían evaluar la idoneidad de utilizar un enfoque PLS-SEM, según el objetivo de investigación que apoye dicho método, las condiciones que apoyen su uso y sus limitaciones. Se proporcionan directrices a los investigadores sobre cuándo el PLS-SEM es una herramienta de investigación apropiada en neuromarketing, qué herramientas analíticas deben utilizar y cómo validar y comunicar los resultados.

Palabras clave: métodos estadísticos; modelos de ecuaciones estructurales; *neuromarketing*; PLS-SEM; técnicas de *neuromarketing*; revisión.

1. Introduction

One of the main goals of marketing research is to understand, explain, and predict consumer behavior. Theoretical models and self-report techniques have been traditionally used by marketing scholars to evaluate consumers' feelings, attitudes, intentions and behavior (Casado-Arando & Sanchez-Fernandez, 2021). However, traditional techniques allow to measure consumers' cognitive and emotional response only as verbally or written expressed at the conscious level (Cherubino et al., 2019). The technological advances of the last decade have enabled researchers to analyze consumers' neural and/or physiological responses to the marketing stimuli in order to understand and explain the unconscious processes that influence consumer behavior (Bell et al., 2018). Moreover, these measurement techniques, also known as neuromarketing techniques, had a great impact on marketing research.

Neuromarketing techniques can be classified into three groups (Cherubino et al., 2019). The first group includes the technologies for recording metabolic activity in the brain, such as positron emission tomography (PET) and functional resonance imagining (fMRI). The second group is comprised by the following technologies used for recording electrical activity in the brain: transcranial magnetic stimulation (TMS), electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), steady-state topography (SST), and magnetoencephalography (MEG). Finally, technologies that do not measure brain activity but body and physiological responses are included in the third group (facial coding, skin conductance, heart rate, facial electromyography, implicit association test, eye tracking, and other technologies for recording physiological response). According to Rawnaque et al. (2020), the most used neuromarketing techniques in research are EEG, fMRI, eye tracking, galvanic skin response, electrocardiogram, fNIRS, and electromyography (EMG).

Casado-Aranda & Sanchez-Fernandez (2021) point out that one of the main differences between neuromarketing and traditional techniques resides in the measures they use. Neuromarketing technologies measure consumers' response in terms of changes in the central nervous system (blood oxygenation-dependent level, neural electrical activity, or hemoglobin flux) or the peripheral nervous system (eccrine sweating, facial muscle contractions, heart rate, pupil size, etc.). On the contrary, traditional techniques collect data for qualitative measures, but also statistical measures (Royo Vela & Verga, 2022), such as comparative scales (Constant Sum Scale, Guttman Scale, Scale of paired comparison, etc.) and non-comparative scales (Likert, Semantic Differential, Stapel, etc.).

Traditional data collection methods are subject to individual biases such as social desirability, subjectivity or language issues that can produce inaccurate results (Casado-Aranda & Sanchez-Fernandez, 2021). These limitations are overcome by neuromarketing techniques as they measure processes that are difficult to be manipulated by the experimental participants. Additionally, the measurement is performed during the exposure to the marketing stimuli, allowing for a temporal match between the stimuli and the neurophysiological response (Byrne et al., 2022). In contrast, traditional techniques usually collect data after the participants are exposed to the stimuli.

Despite the advantages, neuromarketing research faces challenges in the collection of data because of the high cost of the technology used and its intrusive nature, making the recruitment of participants more complex. Thus, the studies have typically included small size samples raising concerns about the reliability of the neuromarketing findings and their potential to predict consumer behavior (Casado-Aranda & Sanchez-Fernandez, 2021). In some cases, the issue of the sample size can be solved by using new technologies that enable large data scale data collection in real-life consumer environments (Bell et al., 2018). In order to provide evidence that physiological and brain changes can be used to predict consumers' behavior, scholars have also recommended the joint use of neurophysiological measures and self-report behavior measures, as well as suitable statistical tools for improving interpretation of results (Cherubino et al., 2019; Byrne et al., 2022).

A statistical method that is widely used for prediction statistical analysis in marketing research is PLS-SEM (Hair et al., 2012; Sarstedt, Hair, Pick, Liengaard, Radomir & Ringle, 2022; Guenther et al., 2023). The method enables researchers to estimate and assess hypothesized relationships between constructs displayed in a path model. The measurement model of the constructs, which represent conceptual variables, is one component of the path model. The other component is represented by the structural model that specifies the casual-predictive relationships between the constructs. Measurement models are also referred to as outer models, while the structural model is also known as the inner model. PLS-SEM differs from other SEM approaches in the way it estimates the model, relying on composites regardless of the measurement model specification (Sarstedt et al., 2021, Sarstedt, Hair & Ringle, 2022; Ringle et al., 2023). In addition, PLS-SEM algorithm computes the measurement and structural model separately, making possible the identification of path models for both reflective and formative measurement models without issues.

The attractiveness of this method relies on the possibility to estimate complex models with many constructs, indicator variables and structural paths relaxing the assumption of multivariate normality and minimal sample requirements (Hair et al., 2022). PLS-SEM is also recommended for exploratory research with the objective of developing established theories, for path models that include one or more formatively measured constructs, research that uses ratios or similar type of data, and follow-up analyses requiring variable scores (Hair et al., 2019; Sarstedt et al., 2021; Becker et al., 2023).

Several review articles (Bell et al., 2018; Cherubino et al., 2019; Rawnaque et al., 2020; Casado-Aranda & Sanchez-Fernandez, 2021) show that the analysis of data obtained from mixed measures using neuromarketing techniques or traditional methods (e.g. surveys) and the use of new statistical tools represent an increased trend in neuromarketing research. However, replication issues resulted from data characteristics and the overuse of frequentist statistics are relevant concerns in neuromarketing research. Byrne et al. (2022) recommend as a solution for these issues the use of statistical methods that allow the achievement of high predictive accuracy in data analysis, such as machine learning algorithms. PLS-SEM follows a prediction-oriented paradigm and, unlike machine learning algorithms, it allows to test as well models developed on the basis of theory and logic (Liengaard et al., 2021). This ability makes PLS-SEM a useful method for marketing research (Sarstedt, Hair, Pick, Liengaard, Radomir & Ringle, 2022).

Thus, the purpose of this paper is to identify to which extent PLS-SEM has been adopted in neuromarketing research and how it is used. Additionally, it aims to provide researchers with guidelines on when PLS-SEM is an appropriate research tool in neuromarketing, which analytical tools they should use and how to validate and report the results. After the introduction, the systematic review methodology is explained, followed by the systematic review results on the PLS-SEM use, the assessment of the outer and the inner model, and reporting, as well as a general discussion and recommendations for further PLS-SEM application in neuromarketing researches.

2. Methodology

A full text research in Thomson Reuters Web of Knowledge, Scopus, Science Direct, Proquest, EBSCO databases was performed using PLS-SEM as a keyword in combination with each neuromarketing technique (e.g., PLS-SEM + electroencephalography, PLS-SEM + eye tracking, and PLS-SEM + electromyography). To ensure the maximum numbers of neuromarketing studies were collected, searches in additional databases, such as Emerald Insight, Sage, Willey Online Library and Taylor and Francis Online as well as online versions of the journals, were performed.

Articles were screened to identify those that have used at least one neuromarketing technique for the collection of data and have performed PLS-SEM analysis. A total of 20 studies published between 2014 and 2023 met this selection criterion, which are listed in Table 1.

Table 1. PLS-SEM studies in neuromarketing

Journal	Authors
Journal of Brand Management	Felix & Borges (2014)
Scientific Annals of Economics and Business	Grigaliunaite & Pileleine (2016)
Journal of Travel Research	Li et al. (2017)
Journal of Business Research	Bettiga, Lamberti & Noci (2017)
Aslib Journal of Information Management	Qu, Guo & Duffy (2017)
Journal of Organizational Behavior Research	Ahmadpour et al. (2019)
Journal of Hospitality & Tourism Research	Li (2019)
Behaviour and Information Technology	Yen & Chiang (2020)
Frontiers in Psychology	Bettiga & Lamberti (2020)
International Journal of Wine Business Research	Monteiro, Guerreiro & Correia Louireiro (2020)
Telematics and Informatics	González-Rodríguez, Díaz-Fernández, & Pacheco-Gómez (2020)
Advances in Tourism, Technology and Systems	Garzón-Paredes & Royo-Vela (2021)
Decision Support Systems	Brand & Reith (2022)
The Retail and Marketing Review	Ersöz & Schröder (2022)
Psychology & Marketing	Badenes-Rocha, Bigne & Ruiz (2022)
Asia Pacific Journal of Marketing and Logistics	Herrando, Jiménez-Martínez & Martín-De Hoyos (2022)
International Journal of Sports Marketing & Sponsorships	Uhm, Ham & Kim (2022)
Vegueta	Garzon-Paredes & Royo-Vela (2023)
Journal of Positive Psychology	Royo Vela & Garzón Paredes (2023)
Journal of Heritage Tourism	Garzón-Paredes & Royo-Vela (2023)

Source: Own elaboration.

Several articles have been published in top interdisciplinary journals that cover marketing, psychology, business, tourism, and technology areas (e.g., Psychology & Marketing, Journal of Positive Psychology, Journal of Business Research, Journal of Travel Research, Decision Support Systems, and Telematics and Informatics). As it can be observed in Table 1, the use of PLS-

SEM as an analysis technique in neuromarketing is relatively new, 65 % of the articles being published in the last three years.

By exploring the articles selected for analysis, it was possible to categorize the use of PLS-SEM in three groups:

- Group 1: Studies that collect data using neuromarketing techniques as well as survey, but apply PLS-SEM for analyzing only the survey data.
- Group 2: Studies that include in the PLS-SEM model path constructs measured using neuromarketing techniques during experiments as well as Likert scale items from survey questionnaires.
- Group 3: Studies that apply PLS-SEM analysis to path models with constructs that have been measured only with data collected via neuromarketing techniques.

Next, each article was evaluated by applying several criteria which allow to identify PLS-SEM's critical issues, most frequent approaches used in neuromarketing and common misapplications. The criteria are applied to the following issues: reasons for using PLS-SEM, data collection, data characteristics, outer model evaluation, inner model evaluation, and advanced PLS-SEM approaches. The results of the analysis of the reviewed papers and a detailed discussion are presented in the next sections.

3. Results

The results obtained according to the different sections are shown below.

3.1. Reasons for Using PLS-SEM in Neuromarketing Research

More than half of the reviewed studies (55 %) do not motivate their use of PLS-SEM. The most frequent author-provided rationales are related to common modelling issues, such as restricted sample size and non-normal data distribution (35 %). Some authors also mention the use of constructs with both reflective and formative measurement, the exploratory nature of the research, the complexity of the structural model, and the use of observational data combined with self-report.

Sample size is a common problem for neuromarketing studies because of the cost and invasive nature of the technologies used for the collection of data (Casado-Aranda & Sánchez-Fernández, 2021). Therefore, it is not surprising that it is the most frequent mentioned motivation for applying PLS-SEM in neuromarketing research. While statistical power and convergence are better achieved with PLS-SEM compared to other methods when the sample size is small, only the nature of population can support this motivation (Sarstedt, Hair, Pick, Liengaard, Radomir & Ringle, 2022). In addition, some of the studies report that they have deleted observations with missing values instead of using methods for data missing treatment. Techniques, like the mean replacement or regression imputation methods, could help preserve the sample size (Kock, 2018; Wang, Lu, & Liu, 2022).

Another frequent argument for choosing PLS-SEM mentioned in the reviewed studies is the non-normal distribution of the data. Although research has confirmed PLS-SEM's robustness in the estimation of models with non-normal data, highly skewed data increase bootstrap errors and reduce statistical power (Hair et al., 2012). Therefore, researchers should analyze data's skewness and kurtosis (only one study reported skewness). Some options that could offer some improvements are the use of a bias-corrected and accelerated (Bca) bootstrapping routine, the treatment of outliers or the use of consistent PLS-SEM (Guenther et al., 2023). Additionally, distributional assumptions should not be cited as a reason to prefer PLS-SEM over CB-SEM (Gefen et al., 2011).

Even though, all the rationales mentioned above are valid arguments, the most recent guidelines recommend researchers to take in consideration other aspects when motivating the use of PLS-SEM (Sarstedt, Hair, Pick, Liengaard, Radomir & Ringle, 2022). PLS-SEM is a composite-based method and, therefore, it should be used when the objective of research is to estimate a model of composites (Rigdon et al., 2017). Two of the analyzed studies (10 %) mention the estimation of constructs as composites as a primary motivation for the use of PLS-SEM.

Furthermore, PLS-SEM's use of composites makes the method a suitable tool for prediction (Sarstedt et al., 2021), which is the research objective that motivates PLS-SEM use in only 10 % of the total sample of studies. If the objective is theory confirmation or the comparison of alternative theories, researchers should apply a CB-SEM approach (Hair et al., 2022). Researchers may also seek to estimate a model that includes a mix of factors and composites. In this case, researchers can use the consistent PLS approach (Dijkstra & Henseler, 2015). We have identified two studies that have applied consistent PLS instead of the traditional PLS-SEM approach.

In addition, future PLS-SEM applications in neuromarketing research must take into account the following considerations when motivating the use of PLS-SEM (Guenther et al., 2023):

- The indicator residual variances have meaning for the focal constructs or the additional constructs in the structural model. The presence of meaningful may be determined by assessing the interaction between indicators when forming the construct.

– The measurement error is large. The impact of indicators' measurement error on the construct proxy is mitigated by the PLS-SEM's weighting procedure based on correlations and by the estimation of the proxy's variances.

3.2. Data Collection

All the studies included in the review have been used survey as a complement data collection method to neuromarketing techniques. Eye tracking is the most popular technique for data collection (35 %), followed by EEG (30 %), devices that record facial movements (25 %), and techniques for heart rate variability measurement (10 %). Only one study has collected data of electrodermal activity by using a skin conductance device. Table 2 presents the neuromarketing techniques used by group studies and the sample sizes of the observations collected with the help of these techniques as well as from surveys.

Table 2. Data collection instruments and sample size

Group	Number of articles	Neuromarketing technique (NT)	Sample size
Group 1	6	Eye tracking (3) EEG (1) Electrocardiogram (1) Facial expression reader (1)	Different samples: NT: 10-50 Survey: <100 (1) 101-200 (2) > 200 (3)
Group 2	10	Eye tracking (3) EMG (2) EEG (1) Skin conductance (1) Facial expression reader (2) Eye tracking + biometric (1)	One sample (NT + Survey) >100 (3) 101-200 (6) > 200 (1)
Group 3	4	EEG (4)	Different samples: NT: 25 (3) Survey: 642 (1)
Total	**20**		

Source: Own elaboration.

Eye tracking is one of most used neuromarketing techniques for both Group 1 and Group 2 studies. The objective of these studies is to measure visual attention (fixation duration and fixation count) in the presence of marketing stimuli, such as online video or text reviews (Brand & Reith, 2022), Instagram posts (Badenes-Rocha et al., 2022), advertising (Felix & Borges, 2014), Grigaliunaite & Pipeleine, 2016; Ahmadopour et al., 2019), and wine labels (Monteiro et al., 2020). In the case of one study, eye-tracking was combined with a biometric technology used to measure heart rate variability for evaluating web usability (Qu et al., 2017).

Electroencephalography (EEG) seems to be also a frequently chosen technique, especially for studies in Group 3. However, it must be mentioned that 80 % of the studies that have used this technique have been performed by the same researchers and, therefore, the analysis may have been done over the same samples. EEG is used to evaluate brain responses to different stimuli, such as the use of chatbots in webpages (Yen & Chian, 2022) or virtual images of tourist destinations (e.g., Royo-Vela & Garzón Paredes, 2023).

Data regarding facial movements are collected with the help of electromyography technology or software that interpret facial movements from video recordings or photos. These techniques are frequently used by studies from Group 2 to evaluate emotional states of consumers when they are exposed to stimuli, such as advertising (Li et al., 2017; Li, 2019), or website (Ersöz & Schröder, 2022). This type of techniques has also been used to evaluate its effectiveness in assessing tourist satisfaction during guided tours (González-Rodríguez et al., 2020). Electrocardiogram and skin conductance devices are other techniques used for the evaluation of emotional response in online interactions (Herrando et al., 2022), or a product's website navigation (Bettiga et al., 2017).

3.3. Data Characteristics

Important differences are observed in the characteristics of the samples used for PLS-SEM analysis among the three groups of studies depending mainly on the methods applied for data collection.

Group 1 studies collect two samples, one using neuromarketing techniques and the other one through survey. Constructs included in PLS-SEM models are generally measured with multiple items, each based on Likert scales and the data is obtained by performing surveys among customers. This group of studies generally use samples ranging from 80 to 585.

More than half (67 %) of Group 1 studies collect the data during the neuromarketing experiment, whereas the survey is applied in a different context (e.g., online surveys). Then, the samples are analyzed using different statistic methods, PLS-SEM being applied only for analyzing the survey data. One of the objectives of these studies is to evaluate if self-reported measures confirm the effects of stimuli found during the neuromarketing experiment. However, the comparison of results raises some issues because of the differences that may exist between the two samples. Only two research study select both samples using the same criteria (*i.e.*, experience with the product, age) and expose them to the same marketing stimuli (Bettiga & Lamberti, 2020; Brand

& Reith, 2022). However, sample's heterogeneity detected during the experiment as well as unobserved heterogeneity in both samples are not fully assessed. This may explain why PLS-SEM analysis reported different results compared with those found in the analysis of the data collected during the neuromarketing experiment.

The other 33 % studies applied instead a questionnaire to the participants before or after experiment and the sample is completed with answers from other individuals. This type of studies performs better in reporting the same results in the analysis of experimental data as well as PLS-SEM analysis. Additionally, a larger selection criteria is used to ensure homogeneity of the sample. Nevertheless, a total sample much larger than the one used for the experiment can add observed and unobserved heterogeneity, which researchers should assess because it can lead to less accurate interpretation of the results.

Group 2 studies collect data during a neuromarketing experiment and use it to measure the constructs reflectively or formatively, which are later included in the path model as independent, dependent, or mediator variables together with constructs measured with survey data obtained from the same sample. In addition, some studies use neuromarketing technique to identify heterogeneity in the sample according to their response to the marketing stimuli, and use the results to create a grouping variable, and then perform a multigroup analysis. Sample sizes in these studies are smaller compared to Group 1 studies, ranging from 36 to 230.

PLS-SEM analysis performed to samples that have been obtained only through neuromarketing techniques have been included in Group 3. The sample size used includes only 25 observations. However, some of these papers add a second PLS-SEM analysis applied to path model with variables measured only with survey data.

Some of the reviewed neuromarketing papers with very small sample sizes mention that the rule of thumb recommended by Barclay et al. (1995) has been used to determine the minimum required sample size for applying PLS-SEM in their study. This common rule suggest using a minimum sample size of ten time the number of indicators or paths aiming at any construct in the outer model or the inner model. However, the lack of accuracy of estimates based on this rule has been in debate for a long time (Marcoulides Chin & Saunders, 2009) and, thus, more suitable approaches should be considered to determine sample size. Additionally, some researchers mention that usually neuroscience and psychological studies are grounded on small sample sizes (e.g., Li et al., 2017; Bettiga & Lamberti, 2020). While this argument may be valid for performing an experimental study, it can not be used as a motivation for PLS-SEM analysis – unless the population is small- because a reduced number of observation can lead to increased standard and type II errors (Sarstedt, Hair, Pick, Liengaard, Radomir & Ringle, 2022; Guenther et al., 2023). Researchers should consider additional aspects, such as the population's characteristics (only one study determines sample based on population's nature), expected effect size and the significance level (Sarstedt et al., 2021). In addition, researchers could use other methods, such as the Monte Carlo-based power analysis for PLS-SEM, the inverse square root and the gamma exponential method (Hair et al., 2022; Guenther et al., 2023).

3.4. Outer Model Evaluation

An important advantage of the PLS-SEM method is that it allows the incorporation in the structural model construct measured reflectively as well as formatively (Hair et al., 2022). The indicators of a reflective outer model represent effects or manifestations of the construct and can be considered as a representative sample of all possible items of the theoretical construct. In contrast, in formatively measurement models the relationship is from the indicators to the construct. Thus, in this type of measurement indicators exhibit conceptual unity and the omission of one indicator may change its definition. Therefore, researchers must take into account the type of measurement when evaluating how well constructs are measured. Table 3 presents the measures usually applied for the assessment of the outer model and their use in neuromarketing studies.

Table 3. Review of the outer model assessment

Outer model assessment	Group 1	Group 2	Group 3
Formative			
Redundancy analysis (convergent validity)		0.0 %	
Variance inflation factor (collinearity)		100 %	
Statistical significance of weights		100 %	
Relevance of weights		100 %	
Reflective			
Loadings (indicator reliability)	50.0 %	77.7 %	100 %
Composite reliability ρ_A (composite reliability	16.6 %	11.1 %	0.0 %
Composite reliability ρ_c (composite reliability)	100 %	100 %	50.0 %
Cronbach's α (composite reliability)	50.0 %	55.5 %	0 %
AVE (convergent (validity)	100 %	100 %	100 %
HTMT ratio (discriminant validity)	66.60 %	44.40 %	0 %
Fornell-Larcker criterion (discriminant validity)	100 %	66.67 %	100 %
Total	**6**	**10**	**4**

Source: Own elaboration.

Formatively specified constructs involve the assessment of convergent validity, indicator collinearity, and statistical relevance and significance of the indicator weights (Sarstedt et al., 2021). Two studies that have incorporated formatively measurement models were identified in Group 2 articles. Both studies assess indicator multicollinearity using VIF values, reporting the recommended maximum cut value of 3. For the evaluation of weights, researchers must analyze if their values are significantly different from zero and establish statistical significance by using the bootstrapping approach. The assessment of indicator's loading, which must reach a minimum value of 0.50 or superior, is recommended when the weight is not significant (Hair et al., 2022). In this case, the indicator can be retained, on the contrary it should be delated, unless its inclusion is essential from a measurement theory perspective. One of the studies has also reported indicator's loadings and significance even though the weights shown relevant and significant values. However, none of the studies reported the results of the convergent validity assessment, also known as redundancy analysis, which represents a major omission according to the literature (Guenther et al., 2023). Convergent validity is established when the correlation between the formatively specified constructs and an alternative measure (a single-item measure which captures the essence of the construct) have a value of at least 0.708.

For reflectively measured constructs, the literature recommends the examination of individual indicator reliability, the reliability of each construct's composite of measures (internal reliability), as well as convergent and discriminant validities (Hair et al., 2022). The individual indicator reliability is established when its loading reaches the 0.708 value or higher. For the measurement of internal reliability, researchers can assess composite reliability (ρ_A and ρ_c) and Cronbach's α. A value of 0.70 is considered being satisfactory for the three criteria. However, values above 0.95 are problematic, indicating that items are almost identical or redundant (Sarstedt et al., 2021). Average extracted variance (AVE) is the measure used for assessing convergent validity and the recommended threshold is a minimum value of 0.50, meaning that construct explains at least half of indicators' variance. According to Henseler et al. (2015), discriminant validity should be assessed using the HTMT ratio, which values should not be below the conservative threshold of 0.85 or the more liberal one of 0.90. As using these cut values could lead to false positive results, the use of percentile-based bootstrap confidence intervals to assess the HTMT ratio is recommended (also see HTMT+; Ringle et al., 2023).

All the reviewed studies omitted at least one of the measures recommended by the literature with some small differences between groups. Group

1 studies usually register a high frequency of discriminant validity assessment, but do not establish indicator reliability (loadings were not reported in 50 % of the articles). Group 2 studies rarely omit indicator's loading assessment, but a higher proportion do not report discriminant validity. The higher lack of assessment of the recommended measures is found in Group 3 studies, as they incorporate in their model indicators and constructs that have not met the reliability and validity criteria. In addition, sometimes they use weights instead of loadings for indicator's assessment and report AVE for constructs with only two indicators, even though it is not a useful measure for convergent validity in this case (Guenther et al., 2023). Overall, studies usually report composite reliability ρ_c for the internal validity assessment. However, literature recommends the use of composite reliability ρ_A (only 16.6 % of Group 1 studies and 11.1 % of Group 2 studies assessed this measure), while Cronbach's alpha and composite reliability ρ_c and Cronbach's α can be used as the lower and the upper bounds of the composite reliability (Hair et al., 2022). Fornell-Larcker criterion is widely used for assessing discriminant validity, and in less extent the recommended HTMT ratio. Only one study assessed HTMT ratio using the percentile bootstrap confidence interval, which is an option that helps to assess better discriminant validity compared to the threshold values.

3.5. Inner Model Evaluation

If the outer model assessment provides evidence of reliability and validity, researchers can perform the next step of PLS-SEM analysis: the evaluation of the inner model. When estimating the relationships established in the theoretical model, the PLS-SEM algorithm minimizes the unexplained variance of both indicators and dependent constructs, prioritizing prediction over explanation (Guenther et al., 2023). First, researchers must check for potential collinearity issues, which as it can be observed in Table 4 is rarely addressed in the review studies. Then, the significance and relevance of structural model relationships as well as the model's in-sample and out-sample predictions must be assessed. The evaluation of prediction is very important in neuromarketing research as its main objective is to understand and predict consumer behavior (Bell et al., 2018).

Table 4. Review of the inner model assessment

Inner model assessment	Group 1	Group 2	Group 3
Variation inflation factor *(collinearity)*	50 %	0 %	0 %
Statistical significance of path coefficients	100 %	100 %	100 %
Effect size f^2 (relevance of path coefficients)	16.7 %	30 %	0 %

R^2 value (in-sample prediction)	100 %	80 %	100 %
Stone Geiser's Q^2 (out-of-sample prediction)	16.7 %	40 %	25 %
PLSpredict	0 %	0 %	0 %
CVPAT of a predictive model assessment	0 %	0 %	0 %
Model fit			
SRMR or other criteria (model fit)	16.6 %	30 %	0 %
Total	**6**	**10**	**4**

Source: Own elaboration.

Path coefficients and the corresponding significance level represent the only predictor that has been reported in all reviewed studies, but the applied bootstrap samples for the bootstrapping procedure were of only 5000. The recommended minimum for the bootstrapping resample method is 10 000 samples (Streukens & Leroi-Werelds, 2018). Researchers should also asses in the bootstrapping results the bias-corrected confidence intervals of the coefficients for significance testing. The size of the coefficients that take values between -1 and 1, can be used to assess and rank the relevance of the predictors for the target construct. R^2 and f^2 values are also useful to rank predictors (Guenther et al., 2023).

The primary criterion for in-sample prediction is the coefficient of determination (R^2), which shows the amount of explained variance of each dependent construct (Hair et al., 2022). However, R^2 has the tendency to overfit in complex models where the dependent construct is explained by several independent constructs. Therefore, R^2 values are considered as acceptable depending on the model's complexity and the context of the study. Additionally, researchers can evaluate changes in R^2 values when a specified exogenous construct is omitted from the model. This measure is known as the f^2 effect size and values of 0.02, 0.15 and 0.35, respectively, represent small, medium and large effects (Cohen, 1988).

For the out-of-sample prediction assessment, literature recommends the use of the $PLS_{predict}$ procedure proposed by Shmueli et al. (2019). This approach offers several prediction statistics. One of these measures is $Q^2_{predict}$ and it is used to compare prediction errors to a benchmark of naïve prediction alternatives. $Q^2_{predict}$ values superior of 0 mean that PLS-SEM has small prediction errors and, therefore, superior predictive capabilities than the naïve mean value prediction benchmark. Other statistics, such as the root mean squared error (RMSE) and the mean absolute error (MAE) can be used to compare PLS-SEM prediction with the benchmark results of the linear model (LM). The default statistic is RMSE, while MAE is recommended when the prediction error distribution is highly nonsymmetric. When the PLS-SEM results show lower RMSE (or MAE) values for all, majority, minority, or none of the construct indicators, the model has high, moderate, weak, or lacks predictive power.

A relatively new approach for the assessment of out-of-sample prediction assessment is the cross-validated predicted ability test (CVPAT) presented by Liengaard et al. (2021) and Sharma et al. (2022). Researchers can use this test to establish if the model has a higher predictive power than the prediction benchmarks, by statistically comparing the model with a naïve mean value benchmark and a more demanding linear model benchmarking. The approach can be used to assess one specific endogenous construct in isolation or multiple relevant endogenous constructs simultaneously.

None of the reviewed studies have applied $PLS_{predict}$ or CVPAT to assess out-of-sample prediction. In turn, 30 % of the reviewed studies use the Stone-Geisser's Q^2 as an out-of-sample prediction criterion. This measure is obtained by applying the blindfolding procedure, which has the advantage that it does not require a holdout sample. However, this advantage makes the criterion unsuitable for the out-of-sample prediction in PLS-SEM (Shmueli et al., 2016). Thus, future research in neuromarketing should use methods recommended by the literature for the assessment of out-of-sample prediction.

Model fit criteria are useful for those studies that seek to support the explanation of their theoretically established model. However, PLS-SEM follows a casual-prediction modelling perspective, which aims to minimize the combination of bias and error variance. In this case, well specified model can yield to poor results in terms of prediction power (Hair et al., 2022). Overall model fit can be assessed by means of inference statistics and by using fit metrics (Henseler et al., 2016). Researchers can use the bootstrap-based test and SRMR index for the assessment of model fit (Benitez et al., 2020). Few neuromarketing studies have assessed model fit, being SRMR the most reported measure. Researchers can use this measure, which should be below the threshold 0.08, when they use a confirmatory approach and, additionally perform the bootstrap-based test, but considering the limitations related to their applicability (Benitez et al., 2020; Schuberth et al., 2022; Ringle et al., 2023).

3.6. Advanced PLS-SEM Approaches Used in Neuromarketing Research

A variety of approaches have been developed in recent years to expand the usefulness of PLS-SEM as a research tool in marketing. Some approaches help researchers to analyze deeper relationships into the data, such as mediation, nonlinear effects, and necessary condition analysis (Guenther et al., 2023). Other approaches can be used to assess endogeneity, observed heterogeneity (moderation and multigroup analysis, see Becker et al. 2023) and unobserved heterogeneity (finitude mixture partial least squares and prediction-oriented segmentation, see Hair et al., 2016; Hair et al., 2017). All these advanced approaches serve marketing researchers as tools for making more accurate predictions. As it can be observed in Table 5, 70 % of the studies used at least one advanced modelling approach.

Table 5. Assessment of the advanced modelling approaches

Advanced modelling approaches	Group 1	Group 2	Group 3	Total
Higher-order constructs	**0**	**1**	**0**	**1**
Conceptual justification of the measurement of the lower- and higher-order constructs		0 %		0 %
Reliability and validity of the lower constructs		0 %		0 %
Reliability and validity of the higher-order constructs		100 %		100 %
Comparison of the model predictive power with and without modelling the higher construct		0 %		0 %
Mediation	**2**	**5**	**0**	**7**
Effects' significance	100 %	100 %		100 %
Bias-corrected confidence intervals	0 %	0 %		0 %
Mediation type	100 %	16.67 %		42.86 %
Moderation	**1**	**1**		**2**
Effects' significance	100 %	100 %		100 %
Effect size f^2	0 %	0 %		0 %
Multigroup analysis	**2**	**3**	**1**	**5**
Measurement invariance	50 %	33.3 %	0 %	40 %
Permutation-based test MGA	0 %	33.3 %	0 %	20 %
Bootstrapped-test MGA	100 %	33,3 %	0 %	60 %
Parametric test	0 %	0 %	100 %	20 %
Model comparison				**1**
BIC or GM	0 %	0 %	0 %	0 %
CVPAT for a predictive comparison	0 %	0 %	0 %	0 %
				15
Total	**6**	**10**	**4**	**20**

Source: Own elaboration.

Mediation is the most common approach applied by neuromarketing researchers that have used PLS-SEM (35 % of the total sample). This approach is used by 50 % of studies in Group 2. Usually, these studies measure the mediator variable using survey data, with the exception of one study that has used visual attention, measured with an eye-tracking technique (see Monteiro et al., 2020). The mediation effect occurs when an independent construct causes a change in the mediator variable which, in turn, results in a change in the dependent construct of the path model. The presence of the mediator variable can completely change the nature of relationships in the established theoretical model. Therefore, this type of analysis requires of a strong theoretical or conceptual fundament (Hair et al., 2022). Researchers must analyze total, direct and indirect effects in a mediation analysis by using the bootstrapping procedure. All the seven studies have assessed the significance of the coefficients corresponding to the direct and indirect effects of the mediation relationships. For the assessment of mediation, researchers should also use R^2 and f^2 values. Mediation can be complementary (when the direct effect as well as the indirect have the same sign (positive or negative)), competitive (direct effect and indirect effect have opposite signs) and only direct (the indirect effect is significative, but not the indirect effect). Some studies use the VAF value (*i.e.*, the indirect-total effect ratio), which can be applied to assess the effect size of a complementary mediation (Henseler, 2020). According to VAF values, the effect can be classified as no mediation (VAF less than 20 percent), partial mediation (between 20 and 80 percent) and full mediation (above 80 percent) (Nitzl et al., 2016).

Heterogeneity is frequently addressed in neuromarketing research. Even in the Group 1 studies, a comparison between the individuals that registered neurophysiological responses to marketing stimuli and those without significant effects are performed to the small samples collected during the experiments. However, only two of these studies apply PLS-SEM approaches for assessing heterogeneity, and none seeks to address the unobserved heterogeneity. Group 2 studies seem a better fit for analyzing heterogeneity in neuromarketing research using a PLS-SEM approach, but only three of them have addressed this issue. The relatively small sizes used in Group 2 studies could be the reason, as it represents a high limitation for applying PLS-SEM approaches for the analysis of the heterogeneity.

Two approaches can be used in PLS-SEM for analyzing observed heterogeneity: moderation and multigroup analysis. Only two studies have performed a moderation analysis. The researchers have assessed the significance of the moderation coefficients using the bootstrapping procedure, however they did not report the effect size f^2. As a rule of thumb, Kenny (2018) proposed 0,005, 0,01 and 0,025 as standard values for the assessment of small, medium and high moderation effects.

Neuromarketing studies usually use multigroup analysis for identifying heterogeneity. Before performing a multigroup analysis, researchers should evaluate the measurement invariance. The measurement invariance of composite models (MICOM) is the recommended procedure to establish measurement invariance (Henseler et al., 2016). The MICOM procedure requires the evaluation of the configurational invariance, compositional invariance, and the equality of composites and means. If configurational invariance is met, the path coefficients of group can be compared by means of multigroup analysis. If all the criteria are met, researchers can pool the data of the different groups and perform the PLS-SEM analysis. Only 40 % of the analyzed studies have assessed the invariance measurement and not all of them have applied the MICOM procedure, as one study only established the configurational variance.

PLS-SEM offers several methods for multigroup analysis (MGA), both parametric (parametric t-test and Welch-Satterthwaite t test) or non-parametric (permutation-based MGA and bootstrap-based MGA), Literature recommends the use of permutation-based MGA because it is a two-side testing procedure with a non-parametric nature (Chin & Dibbern, 2010). However, when one group's sample is more than double the size of the other group, the analysis should be performed using bootstrapped-based MGA, which allows testing one-sided hypothesis (Hair et al., 2024). Researchers can use a multimethod approach if they want to confirm with a higher level of confidence their results. In addition, if the objective is to test heterogeneity across multiple groups, researchers can use the permutation test based on the average geodesic distance and the average squared Euclidean distance (Klesel et al., 2019). The non-parametric distance-based test is also recommended to compare the complete structural model, whereas the permutation-based MGA perform better for the comparison of one path coefficient (Klesel et al., 2022).

More than half (60 %) of the studies that have performed a multigroup analysis have chosen the bootstrapped-based MGA regardless the differences on sample sizes between groups. It must be mentioned that one of the Group 2 studies has used visual attention (measured with an eye tracking device) as grouping variable (see Badenes-Rocha et al., 2022). The other studies have used variables, such as age, gender, type of add, nationality, consumption situation, and type of arousal. Therefore, future studies should consider the benefits of using other methods, such as the permutation-based MGA and the distance-based test.

Higher-order constructs (HCM) is an advanced approach especially used in highly complex models (Sarstedt et al., 2019; Becker et al., 2023). Researchers need to develop and use a proper operational definition for establishing

HCM. This definition serves as a guide for the identification of the lower-order constructs. HCM constructs can have a reflective as well as a formative measurement model. Thus, the outer model must be assessed according to the type of measurement model used to estimate the construct (see Table 3). Additionally, researchers must also report and evaluate the measurement model of the lower-order constructs (Hair et al., 2017). This type of constructs has been estimated only in one study, but researchers have only assessed the reliability and validity of the higher-order construct.

Researchers can choose between several methods that have been proposed for predictive model comparison. The Bayesian information criterion (BIC) and Geweke-Meese criterion (GM) help researchers to compare models in terms of model fit and predictive power without having to use a holdout sample, which is particularly useful for PLS-SEM analyzes performed on small samples (Danks et al., 2020; Sharma et al., 2021). Another approach to a predictive model comparison is CVPAT which, in contrast with the other two measurers, allows researchers to test if the theoretically alternative model has significantly higher power than the original model (Guenther et al., 2023). None of the reviewed studies have used these methods for model comparison. Nevertheless, it has been found a study that use adjusted R^2 and another one that has made the comparison on the model fit. If the adjusted R^2 value can be used to compare models when different numbers of explanatory variables are used to explain the dependent variable, researchers should never use model fit if their objective is prediction.

4. Discussion and Conclusions

One of the main goals of marketing research is to understand, explain and predict consumer behavior. The use of PLS-SEM in neuromarketing research is recent, nevertheless it is observed a higher number of publications in the last three years. Our review shows that PLS-SEM can be a suitable analysis method in studies that complement neuromarketing procedures for data collection, such as eye tracking, facial movement recognition, and EEG technologies, with self-report methods (e.g., survey). However, researchers must follow the most recent best practices proposed by the literature for the application of PLS-SEM and the reporting of their results.

The less adoption of PLS-SEM analysis compared to other marketing research areas can be explained by the relatively small samples used in neuromarketing research. Regarding this issue, our review of 20 PLS-SEM applications in neuromarketing has revealed that researches do not use an adequate approach for sampling and dealing with small samples. PLS-SEM perform well with small sample analysis, but it cannot solve the problems of an inadequate sampling method or the lack of sample's representativeness for the target population. Therefore, researcher must address issues regarding sample sizes, missing data treatment, and data characteristics in future applications of PLS-SEM.

We have also found issues with the appropriate application of common PLS-SEM analysis procedures for the assessment of the outer and inner models, as well as with reporting. These issues are frequently present in the reviewed papers. Thus, we have used our review not only to identify the most critical issues, but also to develop guidelines to help researchers to use the appropriate tests and threshold values, as well as advances application approaches that have raised the interest of neuromarketing researchers.

PLS-SEM revealed to be a proper tool to analyze the heterogeneity previously observed with use of neuromarketing techniques. The use of neuromarketing techniques to detect differences in consumer response to marketing stimuli offers new opportunities for further research. Thus, neuromarketing experiments should be used to measure customers' response to marketing stimuli and after apply a questionnaire to the participants or vice versa. Next, researchers can analyze the heterogeneity obtained from both data collection methods by applying the most suitable PLS-SEM multigroup analysis approach for the objective of their research. In addition, the questionnaire can also be applied to a control group that has not be exposed to the stimuli to check if results remain the same when increasing sample size. However, researchers must ensure that the control group has the same characteristics (e.g., age, gender, nationality) as the experiment's sample to avoid increasing heterogeneity. In this way, researchers can not only better understand and predict consumers' behavior, but also increase the sample size (if measurement invariance is established).

This paper is a review of the use of PLS-SEM analysis in combination with the most frequent neurophysiological techniques applied in neuromarketing research. Other techniques, such as implicit association test, should be considered by further research. Moreover, our search of studies that have performed PLS-SEM analysis have resulted in a small sample of papers, mostly published in the last three years. Nevertheless, we expect that the new technology development in neuroscience area, that allow the collection of data in a less intrusive manner from larger samples will lead to an increase on the use of PLS-SEM in neuromarketing research as well as to opportunities to apply more advanced approaches.

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