

Criteria for selecting and reporting mediation effects sizes

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Abstract

Purpose – This paper aims to provide guidance on applying, assessing and reporting mediation effect sizes within the context of Partial Least Squares Structural Equation Modeling (PLS-SEM) for social science researchers. Despite the growing popularity of PLS-SEM and mediation analysis in the social sciences in general and organizational research specifically, existing literature indicates inadequate reporting of mediation analysis results.

Design/methodology/approach – To address a methodology gap, the authors present a collection of guidelines for selecting and assessing mediation effect sizes to enhance the reporting of PLS-SEM mediation results. These guidelines are exemplified through an empirical application to illustrate how future studies can enhance the reporting of mediation models.

Findings – By aligning post hoc analysis of indirect and direct paths with research goals, researchers can achieve more nuanced insights into their mediation models. This research reviewed the types of mediation, goals of PLS-SEM models and mediation effect sizes to produce guidelines that allow researchers to determine which effect sizes are appropriate and useful to report.

Originality/value – To the best of the authors' knowledge, this paper is the first to present a collection of mediation effect sizes in a PLS-SEM context to explain how research should apply effect sizes that align with both the scope and goal of the mediation model.

Keywords Reporting, PLS-SEM, Mediation, Effect size, Empirical example

Paper type Research paper

Introduction

Mediation analysis has received substantial scholarly attention in recent years (Aguinis, Edwards & Bradley, 2017; Aguinis, Ramani & Villamor, 2019; Cheung, 2008; Taylor, MacKinnon & Tein, 2008; Zhang, Zyphur & Preacher, 2009). Notably, a recent review of



mediation-focused studies published between 2016 and 2022 revealed that over half of the articles in leading management and information systems journals used Partial Least Squares Structural Equation Modeling (PLS-SEM) to assess mediation models (Sabol, Hair, Cepeda & Roldan, 2023). This finding highlights the growing prominence of PLS-SEM as a preferred analytical approach in empirical research. Despite its widespread use, there is increasing recognition that mediation analyses conducted using PLS-SEM often fall short in terms of methodological rigor – particularly in the reporting of effect sizes (Memon, Ting, Ramayah, Chuah & Cheah, 2017). Scholars have called for researchers to move beyond reporting only the statistical significance of mediation effects and to incorporate robust effect size metrics that offer deeper insights into the strength and practical relevance of mediated relationships (Latan, Hair, Noonan & Sabol, 2023; Miočević, O'Rourke, MacKinnon & Brown, 2018; Olivier, May & Bell, 2017; Trafimow & Marks, 2015). As the availability of advanced statistical software and computational tools continues to expand (Cepeda et al., 2025; Hair, Sarstedt, Matthews & Ringle, 2016), researchers are now better equipped to apply and report these more sophisticated metrics. This paper responds to these calls by offering guidance on selecting and reporting mediation effect sizes within the PLS-SEM framework.

Despite the widespread use of mediation analysis, recent methodological reviews have raised concerns about the limited attention given to effect size reporting in mediation models – particularly those estimated using PLS-SEM. Scholars have emphasized that relying solely on statistical significance can obscure the practical importance of mediation effects and hinder cumulative theory development (Hayes & Scharkow, 2013; Preacher & Kelley, 2011; Miočević et al., 2018). As mediation models become more central to organizational and behavioral research, there is a growing consensus that effect size metrics are essential for interpreting the magnitude and relevance of indirect effects (Gaskin, Ogbeibu & Lowry, 2023; Sarstedt & Moisesescu, 2024). These metrics not only enhance transparency but also allow for meaningful comparisons across studies and contexts. Calls for improved reporting standards have been echoed in recent methodological contributions, which advocate for the integration of effect size benchmarks, confidence intervals and context-specific interpretation guidelines (Latan et al., 2023; Lachowicz, Preacher & Kelley, 2018). In response to these developments, this paper aims to provide researchers with practical guidance for selecting and reporting mediation effect sizes in PLS-SEM, thereby contributing to more rigorous and informative mediation research.

To support this effort, this paper outlines a structured approach for selecting and reporting mediation effect size metrics within the PLS-SEM framework. We begin by examining common research objectives in PLS-SEM mediation studies and demonstrate how specific effect size measures can be aligned with those goals to enhance interpretability and rigor. We further review the typology of mediation models and offer guidance on how to align the type of mediation with different effect size measures. Finally, we describe the computation of four mediation effect size measures found in the literature and demonstrate the recommended effect size reporting guidelines using an empirical example.

In this article, appropriate effect size measures are highlighted for researchers to use in the reporting of mediation analysis in PLS-SEM. These insights provide a series of practical methodological implications. First, the insights provide consumers of research with greater clarity and a deeper understanding of the mediated relationship. This clarity allows readers to contemplate the results more fully, leaving less doubt about the viability and implications. Second, the insights into mediation reporting enable future researchers to compare and contrast their results with greater specificity, enhancing precision in describing the mediated

relationship. Finally, guidelines offer an approachable toolset to help guide researchers when determining how to report the results of mediation in the context of PLS-SEM.

Partial least squares structural equation modeling and mediation analysis

PLS-SEM is a powerful multivariate analysis technique that has gained significant traction across various fields of business and social science research. Unlike covariance-based SEM, which emphasizes model fit and theory testing, PLS-SEM is a variance-based approach that prioritizes prediction and theory development. This makes it particularly well-suited for exploratory research, complex model structures and situations where data may not meet the assumptions of normality or where sample sizes are relatively small (Hair, Risher, Sarstedt & Ringle, 2019; Mateos-Aparicio, 2011; Sarstedt, Radomir, Moisescu & Ringle, 2022).

One of the key strengths of PLS-SEM is its ability to estimate complex models involving multiple dependent and independent variables simultaneously. It enables researchers to assess both direct and indirect effects within a single analysis, while also accounting for measurement error through the use of latent constructs. This integrated approach eliminates the need for multiple *ad hoc* regression analyses and enhances the robustness of mediation testing (Hair, Hult, Ringle & Sarstedt, 2022; Legate, Hair, Chretien & Risher, 2023).

In the context of mediation analysis, PLS-SEM estimates all structural relationships by running a series of ordinary least squares regressions for each endogenous construct. This allows for the simultaneous evaluation of mediation pathways, including the estimation of indirect effects through mediators. While the method offers several advantages – such as flexibility, predictive accuracy and ease of use – it also underscores the importance of rigorous reporting practices. Specifically, researchers are encouraged to go beyond statistical significance and include effect size metrics that provide deeper insights into the strength and practical relevance of mediation effects (Memon et al., 2017).

Because this study is focused specifically on mediation effect sizes in PLS-SEM, attention will be paid to metrics which provide useful and meaningful interpretations of mediation that are relevant to PLS-SEM research goals. Furthermore, the effect sizes put forth in this study will align with both the research goal and the type of mediation. For the sake of parsimony, the strengths and weaknesses of the effect sizes put forth will be discussed briefly and at a high level.

Aligning research goals with effect size metrics

The first step in addressing this issue of lackluster reporting of mediation analysis results is to take a look at research goals as stated by authors using PLS-SEM. The argument is made here-in that the goal of the research should be a primary consideration in determining which mediation effect sizes to report. A recent review of PLS-SEM studies found that maximizing variance explained in the dependent variable (DV), prediction and exploratory research are some of the top reasons why researchers use PLS-SEM (Sabol et al., 2023).

Maximizing explained variance with variance accounted for and upsilon

A hallmark of PLS-SEM is maximizing variance explained in the DV. A mediation effect size that focuses on explained variance is a ratio known as the Variance Accounted For value which assesses the proportion mediated. According to the literature, the Variance Accounted For value is useful because it determines the extent to which the mediation model explains the variance of the DV (Nitzl, Roldan & Cepeda, 2016).

A novel measure of effect size for mediation was proposed by Lachowicz et al. (2018) to capture explained variance in the DV considering only the indirect effect. The measure Upsilon (υ) is “equivalent to the sample squared standardized indirect effect, and represents

the variance in an outcome explained indirectly by a predictor through a mediator” (Lachowicz et al., 2018, p. 256). Because Upsilon values are a metric of variance explanation, the magnitude of Upsilon can be benchmarked against R^2 as detailed in Cohen (2013), thereby creating a meaningful interpretation of the magnitude of the indirect effect.

Prediction and predictive contribution of the mediator

In addition to maximizing explaining variance, a key characteristic of PLS-SEM is prediction (Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). The predictive power of a PLS-SEM model is commonly assessed using out of sample predictive metrics such as the mean absolute error (i.e. MAE) or the root mean square error (i.e. RMSE). The MAE is the average absolute difference between the prediction and actual observation. RMSE is the square root of the average of the squared differences between the prediction and actual observation. Although both statistics measure the differences between predictions and observations, the RMSE is the preferred metric because of how weights are assigned to errors (Hair et al., 2022).

Recently, Danks (2021) proposed using RMSE or MAE in calculating the Predictive Contribution of the Mediator (i.e. PCM) statistic. This statistic indicates the increase in the predictive accuracy of the model because of the addition of the mediator. The PCM takes the difference between the out of sample predictive metric for the Earliest Antecedent (i.e. EA) predicting the DV (c') and the out of sample predictive metric for the direct antecedents predicting the DV (b, c') in the mediation model. This difference is divided by the direct antecedents predicting the DV (b, c'). In Danks' (2021) analysis of using earliest versus direct antecedents, it was suggested that in simple, partial mediation models, it is appropriate to simply determine the difference in root mean square error with and without the mediator, and the result will be representative of the PCM.

Exploration and the total effect

In addition to explanation of variance and prediction, exploratory research is another motivation for researchers to pursue a PLS-SEM approach. Exploratory research benefits from a PLS-SEM approach because it allows for the interplay between theory and data when researchers are examining less developed theory. This approach is suitable for examining all possible relationships rather than constraining the analysis to achieve model fit. As such, in exploratory research, it is important to assess all aspects of mediation in a PLS-SEM model.

While a majority of mediation analysis research focuses on the size and significance of the indirect path (Lachowicz et al., 2018), assessing the Total Effect (i.e. TE) can be useful in providing information on the entire mediation model, especially in exploratory studies and studies with multiple mediators (Hair et al., 2022). The TE is the sum of the direct and indirect effects. Although scholars have mostly dismissed assessing the TE to determine the presence of mediation (Loeys, Moerkerke & Vansteelandt, 2015), reporting TE size sheds light on the contribution of the independent variable in the mediation model and, as such, is a useful metric to provide in mediation analysis reporting.

While there is a lack of consensus in the literature on the most useful mediation effect size metrics, whether it be Variance Accounted For, $\bar{u}$, Mean Absolute Error, Root mean square error or TE most methods scholars agree on the fundamental statistics for recognizing and reporting mediation (Hayes & Scharkow, 2013; Lachowicz et al., 2018; MacKinnon, Lockwood & Williams, 2004). The presence of mediation is determined by the statistical significance of the indirect effect. Fundamental effect sizes reported for mediation analysis are the beta coefficient of the indirect path and t statistic. In addition to those two metrics, Bias-Corrected Bootstrapping Confidence Intervals (i.e. BCBCIs) are

generally accepted as a trustworthy metric for reporting the mediation effect size of the indirect path (Dutta & Pullig, 2015; Fritz, Taylor & MacKinnon, 2012; Hayes & Scharkow, 2013; MacKinnon et al., 2004). BCBCI is a method that relies on sampling with replacement to generate empirical distributions of parameter estimates. These estimates can be used for testing the significance of mediated effects by creating confidence intervals from the sampling distribution. The BCBCIs approach is recognized for having the most statistical power of the bootstrap methods although there are concerns about Type 1 error rates.

Fundamental effect sizes are important to report in mediation research. However, the recommendation is made for researchers take an additional step of reporting effect sizes that align with both the research goal and the identified mediation type. The next step in addressing the issue of mediation analysis reporting is to consider the type of mediation occurring in the research model. However, it is prudent to first briefly review what mediation is before discussing types of mediation.

Aligning mediation types with effect size metrics

Mediation occurs when the effect of the predictor variable on the outcome variable is explained fully or partially by an intervening variable, otherwise, a mediator. A simple mediation model contains at least three variables: an independent variable (X), a mediator variable (M) and a DV (Y). Figure 1 depicts the relationship between these three variables in a simple mediation model and provides a demonstration of how the presented effect sizes are calculated.

Mediation analysis may show that a mediator construct accounts for none, all or some of the observed relationship between two latent variables. When a mediating effect is present, it can be classified as complementary, competitive or indirect only mediation (Zhao, Lynch & Chen, 2010). Complementary mediation depicts a mediation model in which the product of a significant indirect effect and the significant direct effect is positive. Competitive mediation is present when the product of the significant direct and significant indirect effects is negative. Indirect only mediation is present when the indirect path is significant, but the direct path is not significant (Cain, Zhang & Bergeman, 2018). We depict the different types of mediation in further detail to describe and explain how the different types of mediation should drive a researcher’s choice in reporting mediation effect sizes that are the most relevant to the mediation type and research goal.

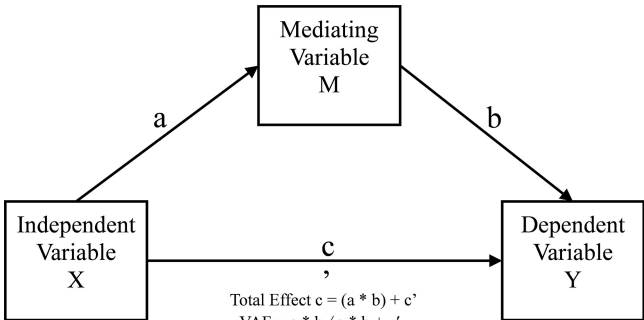


Figure 1. Simple mediation model
Source(s): Created by the authors

Complementary mediation

Complementary mediation is present when both the direct and indirect paths are significant and the product of the two paths is positive. A common example of complementary mediation in business research is the relationship between employee development practices, employee engagement and turnover intention. Both the direct effect (from development support to turnover intention) and the indirect effect (through engagement) are significant and in the same direction (i.e. both reduce turnover intention), which characterizes complementary mediation.

The direction of the paths in part determines the type and presence of mediation; therefore, selecting mediation effect sizes that align with the type of mediation is important. For example, Variance Accounted For values greater than one can indicate a suppressive effect of intensifying the predictive power of the independent variable relevant to the DV. Therefore, Variance Accounted For should only be used in cases of complementary mediation because suppression is also indicated when the directionalities of the direct and indirect path are different. A simple mediation model Variance Accounted For value ratio is defined as follows:

$$a * b / (a * b) + c'$$

Complementary mediation is identified by considering both the direct and indirect effects; therefore, it is important to report effect size metrics that also consider both the direct and indirect paths such as the TE which is the sum of the direct and indirect effects. However, when the direct effect and indirect effect have opposite signs, the effects can offset each other leading to a small TE (Hair et al., 2022); therefore, TE should be used for complementary mediation only.

Complementary mediation, where both the direct and indirect effects are significant and point in the same direction, may indicate the presence of an unidentified alternative mediator influencing the relationship (Zhao et al., 2010). In such cases, the PCM metric can be particularly informative. PCM quantifies the added predictive value of the mediator in the model, and lower PCM values may signal that the mediator contributes little to prediction, suggesting the possibility of an omitted variable in the direct path. Similarly, the Variance Accounted For metric can also help identify underspecified models. According to established thresholds, Variance Accounted For values below 20% suggest negligible mediation, values between 20% and 80% indicate partial mediation and values above 80% reflect strong mediation effects (Hair, Sarstedt, Ringle & Gudergan, 2017). When evaluating complementary mediation, researchers are encouraged to report effect size metrics such as Variance Accounted For, TE and PCM to provide a more comprehensive understanding of the mediation mechanism. Given that root mean square error is the preferred out-of-sample predictive metric in PLS-SEM, the PCM is typically calculated using the following formula:

$$PCM = RMSE_{c'} - RMSE_b$$

where root mean square error (c') represents the prediction error without the mediator, and root mean square error (b') represents the prediction error with the mediator included.

Competitive mediation

Complementary and competitive mediations are both theoretically meaningful and empirically plausible outcomes, particularly in models where one or more mediators may be unidentified or omitted. In complementary mediation, the direct and indirect effects are both

significant and point in the same direction, reinforcing the overall relationship. In contrast, competitive mediation arises when the direct and indirect effects are both significant but have opposite signs – indicating that the mediator transmits an effect that counteracts the direct path. This pattern can reveal complex or even conflicting mechanisms within a model, making it especially important to explore further.

A classic example of this phenomenon is the relationship between intelligence and work performance (McFatter, 1979; Nitzl et al., 2016). Intelligence may enhance error detection and problem-solving, thereby improving performance – an example of complementary mediation. However, intelligence may also increase boredom or disengagement in routine tasks, which can reduce performance – illustrating competitive mediation. When both mechanisms are present, the indirect effect ($a \times b$) and the direct effect (c') may work in opposing directions, resulting in competitive mediation.

Because competitive mediation may signal the presence of an omitted or alternative mediator, it is essential to report effect size metrics that can help identify such model underspecification. The PCM is particularly useful in this context. A low PCM value suggests that the mediator contributes little to the model's predictive accuracy, which may indicate that other relevant mediators have not been accounted for. Including PCM alongside other metrics such as the TE and bias-corrected confidence intervals can provide a more complete picture of the mediation process and help researchers detect competing mechanisms that might otherwise go unnoticed.

Indirect only mediation

Indirect only mediation occurs when the indirect path ($a \times b$) is significant, but the direct path (c) is not significant. A common example of indirect-only mediation (sometimes referred to as “full mediation”) in business research is the relationship between training investment, employee engagement and job performance. In this case, the direct effect of training investment on job performance is not significant, but the indirect effect through employee engagement is significant. This indicates that the effect of training on performance operates entirely through its influence on engagement, making it a clear example of indirect-only mediation. This type of mediation is especially useful in understanding mechanisms where the influence of an independent variable is not immediately observable in the outcome but operates through a meaningful intermediate process.

Researchers have referred to indirect only mediation as full mediation, yet other researchers advocate for not using the terminology of full versus partial to describe mediation (Nitzl et al., 2016; Suder, Duda, Kusa & Mora-Cruz, 2024). In this paper, we refrain from using the terms full and partial mediation. Regardless of the terminology used to identify indirect only mediation, indirect effects for mediation are commonly reported in mediation studies. However, effect size metrics for indirect effects are not yet firmly established in the literature (Preacher & Kelley, 2011).

The Upsilon statistic υ introduced by Lachowicz et al. (2018) offers a standardized population measure of the variance in the DV that is explained indirectly through a mediator. It is calculated as the squared product of the sample's standardized path coefficients from the independent variable to the mediator (a) and from the mediator to the DV (b). Because the population parameter for Upsilon (υ) corresponds to the squared product of the standardized path coefficients in a three-variable mediation model, a natural estimator is the sample-based squared standardized indirect effect ($\hat{\upsilon}$) expressed as follows:

$$\hat{\upsilon} = a^2 b^2$$

Unlike R^2 , which captures the total variance explained in an outcome variable, $\hat{v}$ isolates the portion of variance attributable specifically to the indirect path. While it is not interpreted as a percentage, $\hat{v}$ can be benchmarked using Cohen's (1988) guidelines for R^2 effect sizes (e.g. 0.01 = small, 0.09 = medium and 0.25 = large) to provide a sense of magnitude. Currently, $\hat{v}$ is not a default output in most standard statistical software packages and must be calculated manually using the standardized path coefficients obtained from the model output. Because Upsilon presents a specific measure of the indirect effect that can be benchmarked against extant measures of magnitude (Lachowicz et al., 2018), the suggestion is made that studies focused on indirect-only mediation should include Upsilon values in the reported mediation analysis results.

Aligning mediation effect size with research goals and mediation types

To summarize the recommendations so far, a contingency grid is presented in Table 1. The table depicts the appropriate mediation effect size metrics according to the research goal and mediation type.

For example, the use of Table 1 allows a researcher with an exploratory focus that identifies complementary mediation to see that the mediation results should report TE size in addition to BCBCIs to assess if the model is underspecified, whereas research that is focused on maximizing explained variance and only assesses indirect only mediation should report Upsilon in addition to BCBCIs. In doing so, the mediator can have a variance focused benchmark similar to the DV benchmark R^2 .

Empirical example of mediation effects

To further illustrate these recommendations, a simple mediation model to demonstrate effect size measures in PLS-SEM is presented (Figure 2). The empirical example uses established relationships found in the human resources literature. For the empirical example, this research replicates an original mediation study by Shuck, Twyford and Reio (2014) conducted using regression analysis and a follow-up mediation study by Fulmore, Fulmore, Mull and Cooper (2022) conducted using Covariance-Based Structural Equation Modeling. Both studies found support for employee emotional engagement (EE) serving as a mediator in the relationship between an employee's perceived support for participation in human resource development practices (PSs) and turnover intention (TI).

Data collection. Data was collected from a sample of 399 service sector employees using the online survey platform Qualtrics. The demographics of the sample consisted of 55.4% females and 44.6% males. Respondent tenure at their current company ranged from less than 1 year to 35 years, with an average of 7.14 years ($SD = 6.3$). In total, 56.1% of the

Table 1. Mediation effect size guideline grid

Model goal	Complementary	Mediation type	
		Competitive	Indirect only
Explain DV variance	VAF, BCBCI	BCBCI	$\hat{v}$, BCBCI
Prediction	PCM, BCBCI	PCM, BCBCI	PCM, BCBCI
Exploration	TE, BCBCI	BCBCI	BCBCI

Notes(s): DV = Dependent Variable, VAF = Variance Accounted For, BCBCI = Bias-Corrected Bootstrap Confidence Intervals, PCM = Predictive Contribution of the Mediator, TE = Total Effect and $\hat{v}$ = upsilon

Source(s): Created by the authors

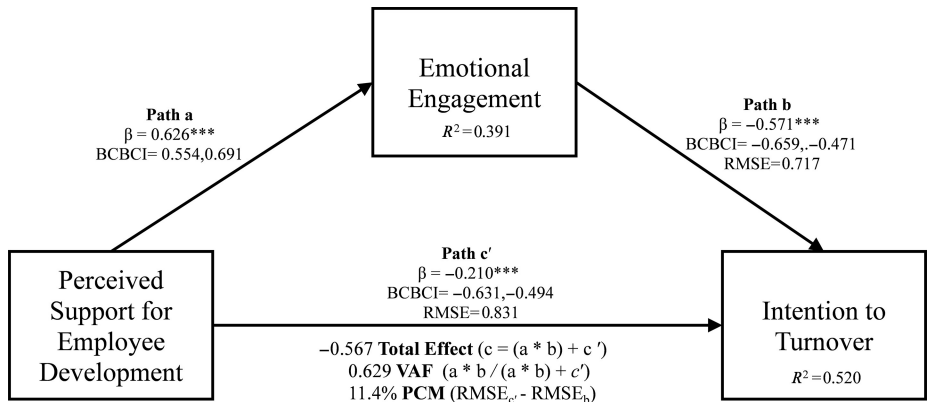


Figure 2. Mediation model results example
Source(s): Created by the authors

respondents worked at organizations with between 1 and 499 employees, while 43.9% were employed in organizations with 500 or more employees.

Measurement. To investigate mediation analysis using PLS-SEM, three constructs were examined:

- (1) perceived investment in employee development (PS);
- (2) employee engagement (EE), specifically its emotional engagement dimension; and
- (3) turnover intention (TI).

These measures were selected for two primary reasons. First, their psychometric properties – validity and reliability – are well-established in the literature (Colarelli, 1984; Fulmore et al., 2022; Lee & Bruvold, 2003; Rich, LePine & Crawford, 2010; Shuck et al., 2014; Shuck, Nimon & Zigarmi, 2017). Second, prior research has consistently demonstrated a mediated relationship among these constructs, with employee engagement serving as a key mechanism linking perceived support to turnover intention (Fulmore et al., 2022; Shuck et al., 2014). This strong theoretical and empirical foundation allows the present study to focus on evaluating mediation effect sizes rather than re-establishing construct validity or the existence of the mediation pathway.

The PS scale consists of nine items that ask respondents to assess their organizations’ commitment to employee learning and training for movement to new positions (Lee & Bruvold, 2003). Respondents indicate their agreement with statements such as “My organization allows employees to have the time to learn new skills that prepare them for future jobs.” Emotional engagement was measured with a six-item sub-scale of the Job Engagement Scale (Rich et al., 2010), which evaluates how willing employees are to use personal resources such as energy, pride and emotion in the workplace, with statements like “I am enthusiastic in my job.” The Intention to Turnover Scale (Colarelli, 1984) assesses an employee’s intention to leave their current employment through three items where respondents indicate their agreement with statements such as “I am planning to search for a new job during the next 12 months.” All measures were anchored on a five-point Likert-type scale ranging from 1 (“strongly disagree”) to 5 (“strongly agree”). Means and standard deviations for each construct

(PS = 3.28, SD = 1.23; EE = 3.66, SD = 1.13; and TI = 2.34, SD = 1.28) were comparable to those in the original and replicated studies.

Mediation analysis. Data were analyzed using SmartPLS 4 software (Ringle, Wende & Becker, 2015). After the measurement and structural models were assessed to confirm the validity and reliability of the model, mediation analysis was conducted. The product of the significant indirect and significant direct paths was positive, meaning the presented model is one of complementary mediation. In the original study and the replication, the authors' stated goal was to contribute to underrepresented research in the area of employee turnover and to develop a model to predict turnover. These findings aligned with those in the original study by Shuck et al. (2014) and the replication study by Fulmore et al. (2022) and suggests that emotional engagement mediates the relationship between perceived support for development and turnover intention. The model results are presented in Figure 2.

The fundamental effect sizes as well as three of the mediation effect sizes put forth by this research are presented in Table 2. The effect sizes presented in the table are aligned with the research goals of exploration and prediction. The reported metrics are appropriate for complementary mediation.

Because this paper focuses on mediation effect size, the discussion is constrained to the results related to mediation effect size. The BCBCIs for the direct and indirect effects are narrow indicating the sample provides a precise representation of the population mean. The TE is -0.567 which is different enough from the indirect effect of -0.357 to indicate there could be additional mediators of the relationship between PS and TI. The Variance Accounted For value is 0.629 meaning the mediation model explains a limited amount of variance in turnover intention. The PCM metric is 0.114 indicating a strong PCM (Danks, 2021) meaning that the mediator, employee engagement, strongly influenced the predictive accuracy of the model.

The results from this demonstration align with extant research on the mediating role of employee engagement in the relationship between perceived support and turnover intention. The mediation effect sizes reported for this relationship provide additional information above and beyond that of traditional mediation analysis. The following discussion explores how these metrics provide useful information for post hoc assessment of mediation results when mediation is present.

Discussion and conclusion

This research reviewed the types of mediation, goals of PLS-SEM models and mediation effect sizes to generate guidelines for researchers to use in determining which effect sizes are

Table 2. Mediation analysis

Relationships	β	<i>t</i> -statistic	<i>p</i> -value	BCBCI 2%	BCBCI 97.5%	TE	VAF	PCM
Effects						0.567	0.629	0.114
<i>Direct effects</i>								
(a) PS → EE	0.626	17.707	0.000	0.554	0.691			
(b) EE → TI	-0.571	12.052	0.000	-0.659	-0.471			
(c') PS → TI	-0.210	16.437	0.000	-0.631	-0.494			
<i>Indirect effect</i>								
(ab) PS → EE → TI	-0.357	9.944	0.000	-0.432	-0.291			

Notes(s): BCBCI = Bias-Corrected Bootstrap Confidence Interval, TE = Total Effect, VAF = Variance Accounted For and PCM = Prediction Contribution of the Mediator

Source(s): Created by the authors

appropriate and useful to report when undertaking mediation analysis using a PLS-SEM approach. A review of the literature on mediation effect sizes revealed there is not a one size fits all metric for reporting mediation effect size. The effect size researchers choose to report should be reflective of both the type of mediation and the goal of the research model. Appropriate effect size measures presented by this research are categorized accordingly and the composition of each suggested metric is provided.

With the advancement of technology and computational power, the numerous calls for findings to go beyond merely recognizing the existence of mediation can and should be answered by both researchers and journal reviewers. This review and explanation of mediation effect sizes for PLS-SEM aims to help authors better understand and apply mediation analysis techniques, thereby enhancing the robustness and transparency of their research. By aligning post hoc analysis of indirect and direct paths with research goals using statistics such as Variance Accounted For, Estimated Variance ($\hat{v}$), TEs and the PCM, researchers can gain more nuanced insights into their mediation models.

This article provides researchers with a range of effect size metrics for reporting mediation analysis in PLS-SEM that can improve theory development across organizational research. By incorporating post hoc analysis of the indirect and direct paths using statistics such as Variance Accounted For, $\hat{v}$, TEs and PCM, researchers can move beyond merely recognizing a mechanism to understanding the magnitude and practical significance of that mechanism. These metrics offer a more comprehensive view of the mediation effects, facilitating a clearer distinction between complementary and competitive mediation. This expanded understanding is crucial, as it can illuminate potential issues such as an underspecified model or spurious correlations that may otherwise go unnoticed (Preacher & Hayes, 2008). Additionally, it opens up opportunities for enhancing the predictive power of mediation models, ultimately leading to more accurate and reliable research findings.

Furthermore, incorporating these advanced statistical measures encourages researchers to perform more thorough and precise analyses, ultimately leading to higher-quality publications. Enhanced reporting procedures, including detailed effect size calculations and clear justification for the chosen mediation paths, will improve the reproducibility and credibility of the research. This, in turn, fosters greater confidence among peers and reviewers, facilitating the dissemination and acceptance of findings within the academic community. By using these advanced effect size metrics, researchers are better equipped to conduct detailed and nuanced analyses, which can contribute to more sophisticated theory development and practical applications in organizational settings. This approach not only enhances the rigor of individual studies but also promotes the adoption of standardized and robust practices in the field of PLS-SEM mediation analysis, driving the overall quality and impact of research in organizational sciences.

Limitations

As with most research, this work has limitations. First, theory suggests that engagement levels fluctuate over time because of environmental variations (Shuck et al., 2017). While cross-sectional designs are common in engagement research (Rich et al., 2010), tests of mediation rely on causal modelling techniques to data from nonexperimental studies that can create issues (Stone-Romero & Rosopa, 2008). The design used in this study did not allow for demonstrating construct stability over time. Interpretations related to causality would best be supported by research methods that incorporate statistical controls for measured variables (e.g. longitudinal designs; Maxwell & Cole, 2007).

Second, the research models and effect size metrics presented focused specifically on PLS-SEM, and the guideline grid was constructed for this context, limiting its

generalizability to other methodological approaches. Additionally, the guidelines are not appropriate in all research settings; researchers should consider the previous literature and the unique framework of their study when interpreting effect sizes.

Third, our demonstration was limited to a simple three-variable mediation model, so the guidelines may not apply to more complex models. While the statistical measures investigated are supported in the literature as useful for mediation, future research could assess appropriate effect size metrics for other methodological approaches and expand upon the guidelines suggested here.

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