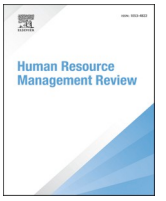
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Drawing more complete and valid interpretations of mediation in human resource management: Beyond the sole focus on indirect effects and their statistical significance

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ABSTRACT

Well-executed mediation research offers unique insights into how well theoretical Human Resource Management (HRM) pathways (mediators, M) can account for observed relationships between an exogenous HRM variable, X, and an endogenous outcome variable, Y. This is central to advancing theory, as well as developing credible policy implications. However, our review shows that the value of mediation research in HRM and in related fields (e.g., organizational behavior) is significantly limited by its typical sole focus on the indirect effect and its statistical significance, often disregarding direct and/or total effects and their practical meanings. We demonstrate the importance of complete reporting and interpretation of all effects—indirect, direct, and total—as well as the percentage mediated. Doing so allows a more complete and valid assessment of the degree to which one or more indirect effects account for the HRM-outcome relationship, a central issue in mediation research. We further highlight that inconsistent mediation (i.e., when the indirect and direct effects carry opposite signs) is often overlooked and misinterpreted. In such cases, a conclusion about the X → Y effect, based solely on the statistical significance of the indirect effect, can be misleading for theory and, in an applied field like HRM, for practice. We illustrate these concerns with examples from empirical work in HRM and related fields and show how more complete reporting and interpretation provides more informed and valid conclusions, thereby better guiding future theory, research, and practice.

A critical effort in human resource management (HRM) theory and research is to explain how and why HRM policies/practices and systems, via intervening mediation mechanisms, influence employee and organizational outcomes. This effort lies at the heart of resolving the longstanding "black box" problem in HRM research areas such as high performance work systems (HPWSs; Becker & Gerhart, 1996; Becker & Huselid, 2006; Jiang et al., 2013) as it helps explain the intervening psychological, motivational, and behavioral processes that transmit these effects (Banks & Kepes, 2015) into valued outcomes. For instance, in the case of HPWSs, "Without intervening variables, one is hard pressed both to explain how HRM influences firm performance and to rule out an

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alternative explanation" (Becker & Gerhart, 1996, p. 793).

Most HRM theoretical frameworks are, explicitly or implicitly, mechanism-centered. At the macro-level, continuing with the HPWS example, the Ability-Motivation-Opportunity (AMO) framework (Appelbaum et al., 2000), posits that HPWSs influence firm outcomes by enhancing employees' knowledge, skills, motivation, and opportunity to contribute (Jiang et al., 2012; Rabl et al., 2014). At the *meso*-level, a key mechanism by which HPWS and other HRM practices are said to become meaningful to employees is through shared perceptions of organizational climate (Bowen & Ostroff, 2004) and the attributions employees make about why HRM practices are used (Nishii et al., 2008). At the micro-level, social exchange theory (Blau, 1964), suggests that HRM practices shape employee attitudes and behaviors through reciprocal perceptions of organizational support (Liao et al., 2009). Many further cross/multi-level examples also exist. Ease and desirability of movement (perceptions) continue as key mechanisms carrying the effect of HRM on voluntary employee turnover. Research on leadership examines what personality traits predict leader effectiveness and seeks to understand the mediating mechanisms (e.g., motivation to lead), which has direct implications for HRM practice (e.g., selection, training/development).

In these and many other areas of study, investigation of mediating mechanisms is central to understanding how HRM influences objectives. Mediation analysis is therefore one of the primary empirical tools for theory testing through which scholars adjudicate between competing theoretical explanations to inform HRM policy/practice. When comprehensively reported and correctly interpreted, mediation analysis using rigorous research designs and statistics (Maxwell & Cole, 2007; Preacher, 2015) is fundamental to the progression of knowledge and causal inference. As Cook and Campbell (1979, p. 35) argue, "Dependable intermediate mediation is involved in all *strong* causal laws."

By way of definition, a *mediator* "transmit[s] the effect of one variable to another variable" and "explain[s] the process or mechanism by which one variable affects another" (MacKinnon et al., 2007, p. 594). In Model 1 of Fig. 1, for example, in addition to the direct effect *c*' of the exogenous variable, X, on the endogenous variable, Y, there is also an indirect effect of X that is transmitted through the mediator variable, M_1, which is the product of paths *a* and *b*. The total effect, *c*, is given by $ab + c$' or by the reduced form regression of Y on X, which includes only purely exogenous variables (X), and not partially endogenous variables (M) as regressors. Of note, Alwin and Hauser (1975, p. 47) emphasized examining the magnitude (absolute and relative) of both indirect effects and direct and/or total effects to answer the question: "How much does mechanism [mediator] Z contribute to the effect of X on Y?"

However, as we will show, current practices in studying, reporting, and interpreting empirical mediation research in HRM (and the related fields that provide much of the theoretical basis for mediation) fall short in following Alwin and Hauser's (1975) recommendations. That can lead to incomplete and/or invalid conclusions about mediation in HRM research.

Consider, for example, a recent study[1] on the effect of pay for performance (PFP), a key HRM practice, on intrinsic motivation where the direct effect was available, but not interpreted. The authors argued, based on self-determination theory, that PFP exerts a controlling effect on workers, which undermines intrinsic motivation. The joint significance test ostensibly supports this hypothesis (*indirect effect* $= -0.03$, *S.E.* $= 0.008$, $p = .001$), and the authors conclude that their study's main contribution is showing that the "negative relationship [of PFP and intrinsic motivation]" can be explained by the controlling effect of PFP. Yet, closer inspection reveals that the *direct effect* of PFP on intrinsic motivation is positive ($b = 0.19$, *S.E.* $= 0.09$, $p = .03$) and over six times larger than the negative *indirect effect*, yielding a positive total effect ($b = 0.16$). Therefore, PFP resulted in an overall increase in intrinsic motivation, which is opposite of the authors' conclusion of a negative relationship between PFP and intrinsic motivation. In this example, taking the authors' conclusion of a negative effect of PFP at face value would suggest that use of PFP is unwise. On the other hand, a more complete interpretation (including the direct and total effect) points to the opposite conclusion that PFP can have an overall positive impact.[2]

We provide further specific examples from empirical studies of the nature of these problematic current practices and identify the serious limitations they can impose against drawing complete and valid conclusions about mediation. We document the broader fieldwide prevalence of these problems with current practice by examining three leading journals for empirical HRM research: *Academy of Management Journal* (AMJ), *Journal of Applied Psychology* (JAP), and *Personnel Psychology* (PP). Across articles in these journals, we found that total effects, direct effects and estimates of the extent of mediation are rarely discussed; small indirect effect sizes are interpreted as substantively important "full mediation" mechanisms on the basis of statistical significance of the indirect effect and statistical non-significance of the direct effect; and inconsistent mediation mechanisms (i.e., where the signs of the indirect and direct effects are opposed) are seldom acknowledged, despite the fact that such inconsistent mediation can result in an invalid conclusion (especially when the sign of the direct effect, and thus of the total effect, is larger and of opposite sign to that of the indirect effect). We also found that the cases where researchers addressed the degree to which mediators explained the X–Y relationship were rare.

These mediation interpretation and reporting gaps are not only serious enough to threaten the validity and informativeness of HRM theory testing; they can also constrain or misdirect theory refinement, integration, correction, and advancement. Improved practice in

[1] We omit the citation information for this study because our goal is to illustrate an important problem with current practice, not to critique specific researchers.

[2] An example from outside of management may help further drive home the problem of looking at only the indirect effect. Consider a drug that in a large sample randomized clinical trial has a positive indirect effect on patient survival via improved cardiovascular function but has a negative total effect on patient survival due to a negative direct (unmediated) effect that is larger than the indirect positive effect. Clearly, the safe (correct) recommendation would be to not prescribe the drug. However, the (incorrect and dangerous) recommendation to prescribe the drug would be made if only the indirect effect were to be used as evidence of the drug's efficacy.

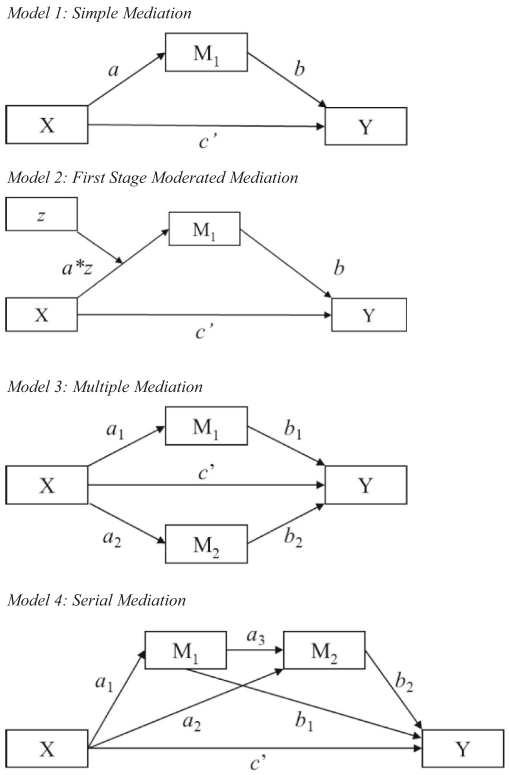


Fig. 1. Illustrative Examples of Mediation Models.
Model 1: Simple Mediation.
Model 2: First Stage Moderated Mediation.
Model 3: Multiple Mediation.
Model 4: Serial Mediation.
Note: In all models, *c*′ represents the direct effect of X on Y. The total effect, *c*, equals *c*′ plus all indirect effects.

mediation analysis can change/correct the interpretation of theory tests by identifying instances in which prior conclusions based solely on the indirect effect may have overstated, understated, or even gotten the direction (sign) of the relationship wrong. It can also advance theory by uncovering and seeking to understand unexpected patterns in mechanisms, previously often overlooked, such as inconsistent mediation (including direct effects that dominate the indirect effect) and/or proportions of the total effect mediated close to 0.00. Doing so can initiate new theoretical directions (e.g., new mediating pathways) in understanding how and why HRM creates value, generates tradeoffs, or operates through competing processes. Evaluating how multiple pathways operate simultaneously and their importance enables scholars to integrate distinct theories within a more complete "ecosystem" account of how HRM operates (Snell et al., 2023).

Valid conclusions about theoretical mechanisms and total effects are necessary not only for theory advancement, but also to more accurately inform HRM policy/practice decisions in organizations. Making sound decisions about how much to invest in HRM and where to invest (e.g., in which policies and practices, or combinations thereof) requires rigorous, empirically supported theoretical logic explaining how and why certain investments are more likely to pay off than others. In this vein, we include research from related fields such as organizational behavior and applied psychology in our review of mediation practices as these fields often contribute substantially to mapping out HRM-relevant mediation processes in more detail than might be found in some more mainstream HRM research. In addition, the concepts studied in these related fields, such as social exchange, leadership, employee attitudes and behaviors are ones that an organization typically seeks to influence by turning to its toolkit of HRM policies/practices. For example, if leadership is causing negative effects on important outcomes, training/development, selection, and compensation are among the HRM policies/practices to revisit and consider using as levers to improve leadership.

Our paper therefore aims to document current mediation interpretation and reporting gaps in the HRM-relevant literature broadly defined and explain how the consequences of these gaps can be serious. We first highlight the serious problems that now occur in current mediation research practice. Second, we describe four general scenarios where mediation analysis problems occur, and their consequences. Third, we provide 11 specific examples from six published studies of conclusions that are materially changed by redoing the mediation analysis following our recommendations on how to obtain more valid conclusions. Fourth, we provide a systematic review of fieldwide prevailing practices in mediation research to more fully document the wider scale and prevalence of the problems we identify. Fifth, we discuss specific recommendations for improving mediation analysis reporting and interpretation that

can help advance HRM theory and practice by providing more valid, complete, and informative interpretations and implications of mediation analysis. Our recommendations are broadly applicable to a wide range of fields related to HRM, including psychology, organizational behavior, strategy, and entrepreneurship—fields in which scholars seek not only to establish whether empirical relationships exist, but also to explain the processes through which they unfold.

1. An overview of mediation analysis problems and consequences in HRM-related research

Mediation analysis builds on the foundational work on path analysis by Sewall Wright (Goldberger, 1972; Wright, 1934), early conceptual works on intervening and mediating variables (MacCorquodale & Meehl, 1948; Rozeboom, 1956), work on the delineation and testing of total, direct and indirect effects and proportion mediated (Alwin & Hauser, 1975; Baron & Kenny, 1986; Duncan, 1966), advances in indirect-effect statistical significance testing and confidence intervals (MacKinnon, 2008; Preacher & Hayes, 2008) and causal identification (Imai et al., 2010).

Mediation is a theoretical concept that explains how the effect of a causal variable, X, on an outcome variable, Y, is transmitted via intervening pathways/mechanisms. To empirically test and estimate theorized mediation concepts, one must choose a statistical definition and operationalization of the mediation concept. Researchers typically operationalize the indirect effect as the primary—and at times the only—statistic of interest, based on their attempt to adhere to what is seen as best practice methodological guidance (Lachowicz et al., 2018; Preacher, 2015; Preacher & Kelley, 2011). For example, Preacher and Kelley (2011, p. 93) note, "Mediation analysis consists of estimating the indirect effect of X on Y via an intervening variable…(M)." Preacher (2015, p. 827) similarly observes that "evidence that M serves as a mediator is often said to exist when the indirect effect…is statistically and practically significant," and Lachowicz et al. (2018, p. 246) state that "the primary statistic of interest is generally the indirect effect." None of these statements precludes examining the direct or total effects, but in practice, these latter effects are often not interpreted or even reported, especially in an accessible manner.

Prior "best practices" pieces have offered important insights into mediation study design (e.g., Podsakoff et al., 2026; Stone-Romero & Rosopa, 2008), as well as contributions to how the indirect effect is estimated and tested—for example, through examinations of *p*-hacking (Götz et al., 2021), causal inference (Nguyen et al., 2021), robust indirect-effect estimators (Alfons et al., 2022; Loh et al., 2022), and R^2-type metrics (Sanchez et al., 2024). Yet, the field's attention remains centered almost exclusively on estimating, testing, interpreting and reporting indirect effects. We next elaborate on how this prevailing practice of focusing on the indirect effect, to the exclusion of direct and total effects, can produce incomplete and/or invalid mediation conclusions.

1.1. Consequences of interpreting and reporting only the indirect effect

The sole focus on the indirect effect while ignoring the direct and total effects diverges from prior classic definitions of mediation (e.g., Alwin & Hauser, 1975; Shrout & Bolger, 2002; Sobel, 1982). The routinization of this practice has created several undesired consequences. First, as noted, ignoring the direct and total effects and focusing exclusively on the indirect effect can render conclusions of the study invalid. Importantly, such a problem is especially likely when the sign of the direct or total effect is opposite to that of the indirect effect (i.e., inconsistent mediation). This type of invalid conclusion above in a study of a key HRM practice, pay for performance (PFP), and this possibility of opposed mechanisms is increasingly being recognized in the pay for performance strand of the HRM literature (e.g., Gerhart et al., 2026; Sayre & Conroy, 2024).

In HRM research broadly, whether studying practices or systems of practices, the problem is often potentially consequential because theory can include multiple simultaneous and opposed mechanisms. For example, HPWS may raise firm performance via enhancing workers' AMO (Jiang et al., 2012; Kang et al., 2025), yet simultaneously depress it by elevating stress (Godard, 2001; Spector, 2016), job strain (Van De Voorde & Beijer, 2015), and/or work intensification (Boxall & Macky, 2016; Mariappanadar, 2014). When a study models only the beneficial pathway (e.g., AMO) as its mediator, the omitted negative countervailing mediation processes (in the form of omitted negative indirect effects) are captured in the direct effect. Yet, as we have noted, the direct effect (and total effect) is often ignored. A positive indirect effect through AMO can thus coexist with a negative direct effect, and the resulting total effect of HPWS can be greatly reduced, nullified, or even change sign to negative. That fact would be missed if only the indirect effect of motivation is reported and interpreted. As such, a statistically significant positive indirect effect, on its own, does not therefore establish that the HPWS has a positive total effect. To draw more valid conclusions from HRM research going forward, these concerns must be better addressed.

A second concern with focusing solely on the indirect effect is that it limits the understanding of the extent of mediation or the relative size of the indirect effect compared to the size of the direct and/or total effects (Alwin & Hauser, 1975). Suppose two HPWS studies both report a statistically significant indirect effect through employee engagement, but in one, engagement accounts for only a small fraction (near 0) of the total effect while in the other it accounts for the great majority of it (near 1.00). With current interpretation and reporting practices, which focus only on the indirect and often only on its statistical significance, both studies would reach the same conclusion: "HPWS improves performance through engagement." Yet their relative practical significance and therefore practical implications may diverge. In the latter instance, the case for investing in HPWS to increase engagement is stronger, whereas in the former, the case is weaker. Thus, in HRM research, determining the relative magnitude of mediating mechanisms is necessary to make better decisions about HRM investments.

Thus, our work argues for a shift in focus from the binary presence or absence of statistical significance of the indirect effect alone to also focusing on the mediation effect size in terms of the relative magnitude of the indirect effect size compared to the total and/or direct effect sizes. Although several other statistics for evaluating degree of mediation have been proposed, such as κ^2 (Preacher &

Kelley, 2011) and υ (Lachowicz et al., 2018), the former has been demonstrated to be nonviable (Wen & Fan, 2015; also acknowledged by Preacher)[3] while the latter only captures the variance explained in the dependent variable by the indirect effect. Although υ provides useful information, it is again entirely focused on the indirect effect. It does not inform us as to the relative magnitude of the indirect effect (compared to the total effect) and thus, also does not inform us as to how much of the X–Y relationship is accounted for by the mediator(s), M.

Rather, the relevant statistic for this mediation effect size is the proportion mediated (P_M), the ratio of the indirect effect to the total effect (Alwin & Hauser, 1975). In Fig. 1, Model 1, for example, P_M is estimated as ab / ($ab + c'$). Despite its limitations, the use of P_M has been recommended as a best practice by numerous scholars (e.g., Alwin & Hauser, 1975; Maxwell & Cole, 2007; Pieters, 2017; Shrout & Bolger, 2002; Sobel, 1982; Wen & Fan, 2015). The benefit of using P_M can be summarized as follows:

> *An important advantage of the index P_M is that it provides a continuous measure of the strength of mediation instead of reducing mediation to a dichotomous yes–no decision. In this sense, P_M is an effect size index and conveys information about the magnitude of the mediated effect.* (Maxwell & Cole, 2007, p. 32).

Likewise, Wen and Fan (2015, p.199) recommend that "reporting P_M together with the total effect c will allow us to meaningfully evaluate the magnitude of the indirect effect." Thus, our central thesis is that precise and complete interpretation and reporting of mediation requires evaluating the relative magnitude of the indirect effect to the direct or total effect using P_M. Yet, as we will see, that is almost never what we see in current practice.

1.2. Four scenarios to illustrate types of incomplete and/or invalid mediation interpretations

To further demonstrate how conclusions about mediation mechanisms can change depending on which effect sizes are reported and interpreted, we have summarized (see Table 1) four different types of generic mediation scenarios that may occur in HRM and related research, where the same indirect effect would lead to different interpretations, depending on the size of the direct and total effects (if included in drawing the interpretation). As part of this, we also created hypothetical direct, indirect, and total effects to help illustrate.[4] Scenarios 1 and 2 represent inconsistent mediation scenarios where the direct and indirect effects have opposite signs. Scenario 1, 'sign-flipping inconsistent mediation', represents the most striking example of why reporting all effects is essential. Reporting only the indirect effect (0.05) may suggest the presence of mediation. However, comprehensive interpretation and reporting reveals a direct effect that is 4 times larger and opposite in direction (−0.20), yielding a total effect of −0.15. In Scenario 2, 'inconsistent mediation; no sign-flips', the focus is solely on the indirect effect (0.05) while ignoring the direct effect, which is negative (−0.025). In this scenario, the total relationship between X and Y is concluded to be stronger than it actually is. Reporting and interpreting all effects reveal that the total effect is half the size of the indirect effect.

In HRM, as we have noted, the theoretical relevance of inconsistent mediation can be seen in terms of possible countervailing effects of HPWS. In what has been referred to as the "dark side" of HPWSs, the same HPWS that fosters a positive mechanism like knowledge sharing or engagement (or AMO) may simultaneously activate countervailing pathways such as work intensification, job strain, or leader anxiety that culminates in abusive supervision (Boxall & Macky, 2016; Mariappanadar, 2014; Van De Voorde & Beijer, 2015; Xi et al., 2022). When the negative direct path outweighs the positive indirect path, reporting only the positive indirect effect yields an incomplete or invalid conclusion about HRM theory and practice implications.

We provide examples (see Table 2) from published studies of Scenarios 1 and 2 where the lack of full reporting caused problems. Before that, however, consider a positive example of comprehensive effect size reporting and interpretation in an inconsistent mediation (sign-flipping) Scenario 1. Huang et al. (2019) proposed a mediation model where general mental ability (GMA) and conscientiousness influence family–work conflict (FWC) and family–work enrichment (FWE) through various pathways. Inconsistent mediation was found in the relationship between GMA and FWE (direct effect = −0.140, $p < .05$; indirect effect = 0.105, $p < .01$), which ultimately produced a statistically non-significant, smaller, and negative total effect ($b = -0.035$), in contrast to the positive indirect effect. Rather than focus on the indirect effect only, which would have resulted in a less accurate conclusion, the authors helpfully noted that "the total effect of GMA on FWE was negative and nonsignificant because the positive indirect effect and negative direct effect, both significant, canceled each other out" and as such, "high GMA may not generate the same level of positive effects in the family domain" as it does in predicting work performance (Huang et al., 2019, pp. 310–311).[5]

Scenarios 3 and 4 in Table 1 are consistent mediation scenarios where all effect signs are the same. In Scenario 3, 'consistent mediation, small P_M', the direct effect (0.20) is 4 times larger than the indirect (0.05). M explains 0.20 of the relationship between X and Y. Without considering the direct and total effect, one might erroneously overestimate the mediator's relative importance. Conversely, in Scenario 4, 'consistent mediation, large P_M', reporting only the indirect effect (0.05) hides the bigger picture that mediation plays a larger role in explaining the relationship. The direct effect is 0.00, meaning that M explains 100% of the X–Y relationship. Again, we will shortly provide an example (see Table 2, Example D) from a published study fitting Scenario 3, where the

[3] This has been acknowledged on Preacher's own website where, if one clicks on the link to the Preacher and Kelley (2011) article (http://quantpsy.org/pubs/preacher_kelley_2011.pdf), one will find (as of May 25, 2025) an annotation on p.106 that states "Important: do not use Kappa^2! See Wen & Fan (2015, Psychological Methods…)"

[4] The effects in Table 1 fall within the range of what we observed in our sample. That can be seen most easily by referring to the examples (drawn from actual studies) of Scenarios 1 and 2 in our Table 2.

[5] The authors did not report P_M *or absolute* P_M.

Table 1
Illustration of How the Total Effect, P_M, and Abs P_M Can Vary, Given a Constant Indirect Effect.

Scenarios	Standardized Effects			Total/Indirect	Proportion Mediated	
	Indirect	Direct	Total		P_M	*Abs* P_M
1. Sign-flipping inconsistent mediation	0.05	−0.2	−0.15	–3x larger (absolute magnitude)	−0.33	0.20
2. Inconsistent mediation; no sign flips	0.05	−0.025	0.025	0.5x as large	2.00	0.67
3. Consistent mediation, small P_M	0.05	0.2	0.25	5x larger	0.20	0.20
4. Consistent mediation, large P_M	0.05	0.0	0.05	1x (same)	1.00	1.00

lack of full reporting caused problems of interpretation. In one instance the ignored total effect was 24.5 times larger than the indirect effect, which was the sole basis for interpretation. This yields a P_M value of 0.04, suggesting that M explained little of the X–Y relationship.

However, let us take a look at a positive example of complete reporting that allows for an accurate interpretation. Jo et al. (2024) examined human capital resources (HCR) as a mediator of the influence of the HR function's relational activities on firm performance. Their results show that HCR carried the majority of the total effect for both outcomes they examined (reported $P_M = 0.53$ for labor productivity and $P_M = 0.71$ for return on assets). Thus, unlike most mediation studies, their full reporting allows one to distinguish between Scenarios 3 and 4 (with support leaning toward Scenario 4).

Another positive example is useful as it relates to HPWSs, which we have used as an ongoing example of mediation in HRM. Jiang et al. (2012) examined (using regression based on a meta-analytic correlation matrix) the mediating mechanisms in the relationship between HPWS and organizational outcomes. They reported the indirect effect sizes for the three AMO dimensions of HPWS—skill-enhancing, motivation-enhancing, and opportunity-enhancing—as 0.08, 0.05, and 0.09, respectively. Notably, they also report the corresponding total effects (0.13, 0.18, and 0.09). Based on these findings, they conclude that "HR systems were related to financial outcomes both directly and indirectly by influencing human capital and employee motivation as well as voluntary turnover and operational outcomes" (p. 1264). They also note that mediation was not 100% (with some results consistent with Scenario 3, others more with Scenario 4): "Moreover, as we expected, there were direct relationships between skill-enhancing HR practices and motivation-enhancing HR practices and financial outcomes that could not be explained by the mediating process." Based on this, they conclude: "The findings of the current study and others suggest that it is meaningful for future research to further explore other mediators of the relationship between HRM and organizational outcomes" (p. 1277).[6]

1.3. Inconsistent mediation: a closer look at specific study examples of incomplete reporting and the negative consequences

Building on our Table 1, and in contrast to a few examples of good mediation reporting practice provided above, we now take a closer look at 11 specific mediation analyses from 6 different published studies (Table 2) that demonstrate how incomplete and, to varying degrees, invalid conclusions were reported. This resulted from overlooking the existence of inconsistent mediation in drawing study conclusions (Scenarios 1 through 2 from Table 1) and/or not reporting P_M. (We also examine one further example relevant to consistent mediation Scenarios 3 and 4). In each example, the indirect effect is reported and interpreted in the article text, whereas the direct and total effects are either not reported or, if reported, are not interpreted. We chose these examples (11 mediation analyses from 6 published studies) not only for their relevance to HRM, but also because each is clear and compelling, allowing us to clearly show the undesirable consequences of overlooking inconsistent mediation and, more generally, not completely reporting and interpreting mediation results. These examples relate to key HRM objectives and have implications for the use of key HRM levers such as selection, training, performance management, and compensation.

Example A in Table 2 shows how the conclusion regarding the effect of pay for performance changed (i.e., the sign/direction of effect flipped). In Example B (Scenario 1), reporting only the indirect effects of Extraversion (−0.16), Conscientiousness (−0.11), and Openness (−0.09) may suggest that these traits represent the dark side of leadership through motivation to lead. However, reporting all effects reveals that the *positive* direct effects of these traits range from three to four times larger than the *negative* indirect effects. Such instances of strongly inconsistent mediation pathways yield the corresponding *positive* total effects of 0.31, 0.38, and 0.18.

In Example C (Scenario 2), focusing solely on the indirect effects through Mental Preoccupation with Work (−0.10) may suggest practically meaningful mediation between top management bottom line mentality and customer incivility. However, it is worth noting

[6] Their comprehensive reporting and interpretation of all effect sizes allows the reader to compute P_M values for the three HPWS dimensions. The resulting P_M values suggest that mediation pathways are best understood for opportunity-enhancing practices ($P_M = 1.00$), followed by skill-enhancing ($P_M = 0.62$), and least well understood for motivation-enhancing practices ($P_M = 0.28$). One issue here is the conclusion that 100% of the effect of opportunity-enhancing practices on financial outcomes is mediated. Taken at face value, it indicates the field of HRM knows all there is to know about the theoretical processes by which opportunity-enhancing practices influence financial outcomes. That seems unlikely. The $P_M = 1.00$ conclusion occurs because a model comparison test showed no significant improvement in fit when the direct effect was included. Thus, the direct effect was taken to be 0.00. Although that may have been best practice at the time, as we have instead recommended that the direct effect always be included and estimated and that estimate (not 0.00) is the best estimate of the direct effect, whether statistically significant or not. Following this recommendation would have likely resulted in less than 100% of the effect of opportunity-enhancing practices being mediated. That would call for a substantial change to the theoretical implications (in terms of the future attention needing to be devoted to these particular mediating mechanisms) in future theory-building and theory-testing.

Table 2
Examples of Incomplete and/or Invalid Conclusions from Focusing Solely on the Indirect Effects.

Example A. Effects of Individual Variable Pay for Performance (PFP) Plan Implementation (Scenario 1. Sign-flipping inconsistent mediation)

Direct Effect of X	Indirect Effect via M	Total Effect on Y	Effect Size Comparison	Interpretation
Reported in figure and text	Reported in text	***Not reported***	***Not reported*** The total effect is 5× larger and the ***sign flips*** $P_M = -0.19$	**Authors' conclusion:** Main contribution of the study is showing that the negative relationship [of PFP and intrinsic motivation] can be explained by the controlling effect of PFP. **Recommended additions:** It is nonetheless important to note that the direct effect of PFP is six times larger in magnitude and positive (i.e., opposite in direction to the negative indirect effect). Consequently, the total effect is positive.
PFP = 0.19*	Controlling Effect = −0.03**	Our calculation indicates a total effect on Intrinsic Motivation = 0.16	$AbsP_M = 0.14$	

Example B. Motivation to Lead (MTL), Based on a Meta-Analytic Correlation Matrix (Scenario 1. Sign-flipping inconsistent mediation)

Direct Effect of X	Sum of all Indirect Effects via M	Total Effect on Y	Effect Size Comparison	Interpretation
Reported in table	Reported in table and text	***Not reported***	***Not reported*** The total effect is 2× larger and the ***sign flips*** $P_M = -0.52$ $AbsP_M = 0.25$	**Authors' conclusion**: Leader traits typically viewed as positive may have a negative effect via MTL. Leader traits may have positive effects through other mechanisms.
Extraversion = 0.47*	via 3 types of MTL = −0.16*	Our calculation indicates a total effect on Leader Emergence = 0.31	The total effect is 3.5× larger and the ***sign flips*** $P_M = -0.29$ $AbsP_M = 0.18$	**Recommended additions:** Although the indirect effects of these three variables are noteworthy, it is important to consider that their direct effects are positive and three to four times larger in magnitude. Consequently, the total effects are positive and substantially larger than the negative indirect effects. Thus, on balance, these leader traits have a positive effect on leader emergence.
Conscientiousness = 0.49*	via 3 types of MTL = −0.11*	Our calculation indicates a total effect on Leader Emergence = 0.38	The total effect is 2× larger and the ***sign flips*** $P_M = -0.50$ $AbsP_M = 0.25$	
Openness = 0.27*	via 3 types of MTL = −0.09*	Our calculation indicates a total effect on Leader Emergence = 0.18		

Example C. Top Management Bottom Line Mentality (TMBLM)'s Effect on Customer Incivility (Scenario 2. Inconsistent mediation; no sign flips)

Direct Effect of X	Indirect Effects via M	Total Effect on Y	Effect Size Comparison	Interpretation
Reported in table	Reported in table and text	***Not reported***	***Not reported*** The total effect is 3/5× of the indirect. Same sign $P_M = 1.67$	**Authors' conclusion**: A sole focus on bottom-line outcomes can be positive for organizations via employee perceptions of TMBLM and resulting lower customer-directed incivility and higher service performance. **Recommended additions:** Additionally, it is worth noting that the direct effect estimate of TMBLM, while not statistically significant, runs counter to the negative signed mediation pathway. This opposing (albeit nonsignificant) direct path produces a smaller total effect (−0.06) relative to the larger negative indirect effect (−0.10), hinting at possible countervailing forces in the relationship. These findings underscore the importance of our mediation analysis since focusing solely on the overall effect would overlook the nuanced interplay between these competing pathways.
Perceived TMBLM = 0.04 (non-stat. significant)	Mental preoccupation with work = −0.10*	Our calculation indicates a total effect on Customer Incivility = −0.06	$AbsP_M = 0.71$	

(*continued on next page*)

Table 2 (*continued*)

Example D. Social Network and Employee Turnover Meta-Analytic Correlation Matrix
(Scenario 1. Sign-flipping inconsistent mediation & Scenario 3. Consistent mediation, small P_M)

Example D. Social Network and Employee Turnover Meta-Analytic Correlation Matrix
(Scenario 1. Sign-flipping inconsistent mediation & Scenario 3. Consistent mediation, small P_M)

Direct Effect of X	Indirect Effects via M	Total Effect on Y	Effect Size Comparison	Interpretation
Reported in table and text	Reported in table and text	***Not reported***	***Not reported***	**Authors' conclusion**: Both instrumental and expressive degree centrality reduced turnover due to more positive work attitudes and job performance. It is suggested that future research investigates additional potential mediators. **Recommended additions:** Although instrumental degree centrality is statistically significant, its standardized total effects are relatively small (0.01 to 0.02). This suggests the need for a more nuanced interpretation of its impact. Furthermore, we propose refining the call to investigate additional mediators with more details. For expressive degree centrality, organizational commitment mediates 4% of the total effect (−0.49) on turnover, while performance mediates 2% of the total effect (−0.46). These findings indicate that these focal mediators provide limited explanation of the mechanisms through which expressive degree centrality influences turnover, more strongly highlighting the importance of identifying additional mediators.
Instrumental degree centrality = 0.04***	Organizational Commitment = −0.02***	Our calculation indicates a total effect on Turnover = 0.02	The total effect is equal to the indirect, but the ***sign flips*** $P_M = -1.00$ $AbsP_M = 0.33$	
	Performance = −0.03***	Our calculation indicates a total effect on Turnover = 0.01	The total effect is 1/3× of the indirect, but the ***sign flips*** $P_M = -3.00$ $AbsP_M = 0.43$	
Expressive degree centrality = −0.47***	Organizational Commitment = −0.02**	Our calculation indicates a total effect on Turnover = −0.49	The total effect is 24.5× larger. Same sign $P_M = 0.04$ $AbsP_M = 0.04$	
	Performance = 0.01	Our calculation indicates a total effect on Turnover = −0.46	The total effect is 46× larger and the ***sign flips*** $P_M = -0.02$ $AbsP_M = 0.02$	

Example E. Predictive Validity and Pathways of Big Five Personality Traits Effect on Outcomes (e.g., Life Satisfaction) via Future Time Perspective (FTP), Based on a Meta-Analytic Correlation Matrix
(Scenario 1. Sign-flipping inconsistent mediation)

Direct Effect of X	Indirect Effect via M	Total Effect on Y	Effect Size Comparison	Interpretation
Reported (but not labeled) in table	Reported in table	Not reported	Not reported	**Authors' conclusion**: As hypothesized, FTP mediates the positive relationship of the big five personality traits and outcomes. In the case of the outcome of life satisfaction, openness to experience had a positive indirect effect, as hypothesized. **Recommended additions**: Although the indirect effect of openness to experience on life satisfaction was positive as hypothesized, the total effect of openness on life satisfaction was actually negative, contrary to our hypothesis. Further, of the 40 (5 personality traits × 8 outcome variables) mediation pathways estimated, 26 took the form of inconsistent mediation, with 21 of those 26 having indirect and direct effects that were both statistically significant (in addition to having different signs). In 17 of those 21 cases, the total effect had a different sign than the indirect effect.[a]
			The total effect is similar in magnitude to the indirect, but the ***sign flips***	
−0.097***	0.047***	Our calculation indicates a total effect = −0.050	$P_M = -0.94$ $AbsP_M = 0.33$	

Example F. Predictive Validity and Pathways of Big Five (Five Factor Model, FFM) Personality Traits Effects on Leadership Effectiveness (LE), Based on a Meta-Analytic Correlation Matrix
(Scenario 2. Inconsistent mediation; no sign flips)

Direct Effect of X	Indirect Effect via M	Total Effect on Y	Effect Size Comparison	Interpretation
Not reported	Reported in text	Not reported	Not reported	**Authors' conclusion**: Support was found for a theoretical model where select leader FFM trait effects on leader effectiveness operate via/are mediated by Consideration and Initiating Structure. For example, the authors reported the indirect effect of Extraversion was 0.119 (0.047 via Consideration +0.072 via Initiating Structure). **Recommended additions**: Although the indirect effect (0.119) of Extraversion on LE was positive as hypothesized, the direct effect (−0.104) of Extraversion on LE was of
−0.104*	0.119*	Our calculation indicates a total effect = 0.015 (non-stat. significant)	The indirect effect is 7.9× larger than the total effect $P_M = 7.93$ $AbsP_M = 0.53$	

(*continued on next page*)

Table 2 (*continued*)

Example F. Predictive Validity and Pathways of Big Five (Five Factor Model, FFM) Personality Traits Effects on Leadership Effectiveness (LE), Based on a Meta-Analytic Correlation Matrix (Scenario 2. Inconsistent mediation; no sign flips)	
	opposite sign (negative). Thus, the total effect of Extraversion on LE was 0.015, or only about 1/8th of the effect estimated by using and reporting only the indirect effect of Extraversion. Stated differently, relying on the indirect effect alone overstates the total effect of Extraversion by a factor of 0.119/0.015 = 7.9×.

Note. The total effect was computed with a reduced form equation (i.e., including only the purely exogenous FFM variables as regressors) using the correlation matrix reported by the authors and the harmonic mean $N = 2525$ reported by the authors. The direct effect was computed as the total effect – indirect effect.

[a]The authors suggested care in interpreting results for 2 of the 8 dependent variables because the sign of the partial regression coefficient differed from the sign of the corresponding bivariate correlation in those cases. The authors did not discuss total effects having different signs than the indirect effects (inconsistent mediation).

that the direct effect (0.04) points to the opposite direction and produces a total effect (−0.06) that is smaller than the indirect effect. While this direct effect estimate is not statistically significant, its coefficient hints at the possibility that there are countervailing forces underlying the overall relationship—a nuance that would otherwise have been missed.

In Example D, there are further examples of inconsistent mediation sign flips (Scenario 1). There is also an example of Scenario 3 (the 3rd row of empirical findings). Here, reporting only the indirect effect (and focusing primarily on its statistical significance) of the expressive degree centrality ➔ organization commitment ➔ turnover pathway (−0.02) may lead one to conclude that organizational commitment is an important mechanism through which expressive degree centrality reduces turnover. It only becomes clear once all effects are considered that the direct effect (−0.47) is 23.5 times larger than the indirect effect—which means that the mediator actually explains only 4% of the relationship ($P_M = 0.04$). Without considering the direct and total effect, readers might erroneously overestimate the mediator's importance.

One might object that inconsistent mediation (conflicting signs) is simply an artifact of small samples. Although differing signs on the indirect and direct effects can occur due to small sample size, one would also need to demonstrate that sampling error makes direct and indirect effects with opposing signs more likely (and to what degree) than effects with the same signs. Moreover, unexpected and unacknowledged inconsistent mediation appears even in mediation analyses based on meta-analytic correlation matrices derived from large samples, which represent four (Examples B, D, E, and F) of the six studies shown in Table 2. Our recommendation is simply that authors provide complete reporting of all effects, including their signs (and whether inconsistent mediation), statistical significance, and magnitude.

In Example E (Scenario 1 again), for example, a large N regression (harmonic mean $N > 5000$) based on a meta-analytic derived correlation matrix examined whether future time perspective mediates the relationships between the Big Five personality traits and various work and well-being outcomes. Relying solely on the statistical significance of the indirect effect, the authors concluded that future time perspective mediates these relationships. Yet of the 40 trait–outcome mediation relationships estimated, 26 took the form of inconsistent mediation, and in 21 of these, the direct and indirect effects were both statistically significant but opposite in sign. The direct effects could be recovered from the published tables, but were never labeled, interpreted, or used to compute P_M, and "suppressor effects" (but not inconsistent mediation, per se) was acknowledged only in a footnote covering two of the eight outcomes. Reporting and interpreting all three effects together would have revealed inconsistent mediation to be pervasive rather than incidental.

In Example F (Scenario 2), a regression based on a meta-analytic derived correlation matrix (harmonic mean $N = 2525$) examined a theoretical model in which leaders' Five-Factor Model personality traits influence leader effectiveness through the mediating behaviors of Consideration and Initiating Structure. For Extraversion, the authors reported a positive indirect effect on leader effectiveness of 0.119 (0.047 via Consideration and 0.072 via Initiating Structure), consistent with their hypothesis. Reporting all effects, however, tells a different story: the countervailing direct effect of Extraversion on leader effectiveness was negative (−0.104), opposite in sign to the indirect effect. The resulting total effect is just 0.015. Thus, relying on the indirect effect alone overstates the total effect of Extraversion by a factor of nearly eight (0.119 /0.015 = 7.933).

Fig. 2 provides a comparison of the indirect effect (the typical point of emphasis) and the total effect for each of the study examples in Table 2. It further drives home the point that emphasizing only the indirect effect provides an incomplete picture of the X ➔ Y total effect. For each study, we computed the absolute value of the difference between the indirect effect and total effect. The median absolute difference = 0.190. The median absolute value of the indirect effect = 0.047. Dividing 0.190 by 0.047 yields a ratio of 4.043, indicating that a more complete interpretation that focuses on the total effect rather than only the indirect effect, leads to a large change in interpreting how X influences Y. As noted, the magnitude, the sign, or both, can change.

2. Documentation of current fieldwide mediation practices

To evaluate current mediation practices, we previously identified 11 specific examples of incomplete and/or invalid conclusions

about mediation hypotheses from 6 published studies. The next question is how pervasive are such problems? Thus, our second step was to conduct a broader analysis with a larger and representative sample of articles appearing in three empirical outlets that are highly influential in HRM and related research fields, each of which publishes research across micro, *meso*, and macro levels, although they differ in the relative mix and disciplinary orientation of the research they publish. We did not limit our sample to only "HRM" articles per se for several reasons. First, the practices we examine are methodological conventions rather than topic-specific ones. HRM research reflects/follows the conventions of the broader management and applied-psychology outlets for "best practice" methodological advice, including on statistical examination of theoretical mediation mechanisms. Thus, documenting current practice warrants sampling those outlets as a whole. Second, HRM research is not cleanly demarcated within these journals. It spans macro, meso, and micro levels of analysis and, as we have shown, is deeply interwoven with adjacent work in organizational behavior, strategy, and applied psychology. HRM policies/practices often seek to achieve valued objectives by influencing mediators informed by work in these related fields.

We started from an initial list of 1215 articles published between 2019 and 2024 across the three journals. We then excluded 55 non-empirical articles such as awards lists, editorials, errata, and review articles, leaving 1160 empirical articles. Next, we excluded articles without statistical mediation analyses by screening for studies containing "*mediation*", "*mediator*", "*mediated*", "*mediating*", "*mediates*", and "*indirect effects*" in titles, abstracts, or keywords. Studies with only moderation (i.e., interaction effects) but no mediation analysis were excluded from the review. We included moderated-mediation and mediated-moderation studies because they test conditional indirect effects. These categories are not mutually exclusive; for example, a study could test both moderated mediation and serial mediation.

After careful screening, 185 articles (16%) remained eligible for sampling. Using Yamane's (1967) sample size formula, we needed to sample and code 126 articles to obtain a $\pm$ 5 percentage points margin of error at 95% confidence.[7] We treated each journal–volume combination as a single stratum and allocated the target sample proportionally to the number of mediation articles within each stratum. Within each stratum, articles were selected at random. This approach of coding a random subset is consistent with recent reviews of mediation practice (e.g., Podsakoff et al., 2026). Our sample included 20 articles from AMJ, 77 from JAP, and 29 from PP. The full article identification, screening, and inclusion process is depicted in the PRISMA diagram (Fig. 3).

Since one article may contain multiple studies, the unit of coding was the study-level (209 studies from 126 articles). The first author coded all studies. To assess coding reliability, the second and third authors coded 46 studies (22%). Before coding this subset, the authors reviewed the coding categories and discussed the operational definitions. Initial agreement across these 46 studies was 96.5% of all coded cells. Disagreements were then resolved through discussion among the authors. For example, when coders disagreed about whether a study had hypothesized inconsistent mediation ex ante, they jointly revisited the article to reach agreement on whether the direct and indirect effects were explicitly theorized in opposite directions. The list of studies and coded data can be found in our online supplemental materials.[8]

As Table 3 shows, the 209 studies tested a range of mediation relationships. Most (65%) tested moderated-mediation or mediated-moderation. Fewer studies tested serial (22%) or multiple (35%) mediation. One takeaway is that contemporary management research increasingly theorizes complex, multi-path mechanisms, and these are precisely the models in which drawing mediation inference by the indirect effect's statistical significance alone most likely obscures how much of the focal effect actually flows through a given mechanism.

2.1. Interpreting and reporting presence of mediation but not its relative magnitude

As shown in Table 3, almost all studies reported the statistical significance of the indirect effect (*ab*). These include studies reporting *ab* with its confidence intervals (92%), *ab* with *p*-value but no confidence interval (3%), or only confidence interval without *ab* estimates (2%). The most common interpretation was limited to a version of, "The effect of X on Y was [or was not] mediated by M," suggesting a 'binary approach' because researchers considered only whether mediation is statistically different from zero—a dichotomous yes/no decision. The magnitude of the indirect effect, while customarily reported, was seldom interpreted. Two approaches to interpreting effect size may be informative: The first is an interpretation of the nature 'a 1-unit (or 1 percent) change in X is associated with xx-units (or xx percent) change in Y'; The second type of interpretation is the *relative* magnitude of the indirect effect to

[7] We also used an alternative means of determining necessary sample size due to Cochran (1977). Cochran's formula, unlike Yamane (1967), takes into account the population proportion for yes/no variables, which are the key results in our Tables 3–5. For example, in Table 3, the proportion of studies that reported $_{PM}$ is 0.04 and the proportion that discussed indirect effects relative to direct/total effects is 0.07. The required sample size with our population of 185 articles necessary to form a 99% confidence interval with a +/− margin of error of 0.05 for a proportion of size 0.10 is 105 articles. We coded a total of 126 articles, which is significantly more than the 105 needed using Cochran's formula.

[8] Link to the supplemental materials: https://researchbox.org/9619

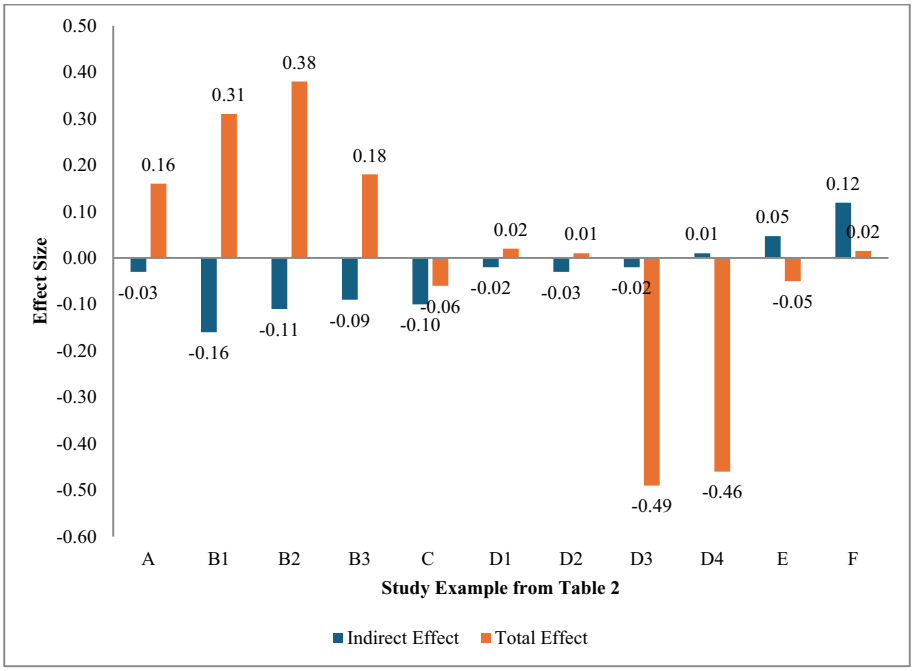


Fig. 2. Comparison of Magnitudes and Signs of Indirect and Total Effects (for studies in Table 2).
Notes. Fig. 2 shows that the indirect effect often differs substantially from the total effect in both magnitude and, in several cases, direction. These differences illustrate why focusing only on the indirect effect can yield an incomplete or potentially misleading interpretation of the overall X–Y relationship.

the total effect, as reported by P_M. We rarely found either type of interpretation in prior research. For example, we found that P_M, was reported in only 4% of sampled studies.

2.2. Not interpreting or reporting direct and/or total effect sizes

Consistent with P_M being rarely reported, Table 3 also shows that it is rare for researchers to compare the magnitude of the indirect, direct, and total effects (7%). In contrast, researchers are far more willing to compare one indirect effect to another indirect effect: among the 136 moderated-mediation / mediated-moderation studies, 76% reported differences between conditional indirect effects across levels of a moderator (Hayes, 2015). Thus, even when scholars quantify how a mechanism's strength shifts across conditions, they typically stop short of quantifying how much of the overall effect that mechanism transmits. A further breakdown of reporting practices for direct, indirect, and total effects in mediation analyses across the three journals (Table 4) reveals that almost all (98%) report indirect effects, whereas 80% report direct effects and only 37% of studies report total effects.

Table 4 also shows a striking difference in the visibility and transparency of the reported effects. Indirect effects are usually emphasized in the text—46% are reported in text only and another 48% in both text and tables—whereas direct effects are largely relegated to tables / figs. (60%) and just 14% are highlighted in both tables and text. Meanwhile, the minority of studies that do report total effects place them in tables / figs. only (9%), text only (9%), or both tables / figures and text (20%). Thus, current practice de-emphasizes or fails to report and interpret the total effect, even though the total effect is the most relevant to understanding, from the policy and practice view central to HRM, what the expected effect of a change in X will be on the outcome variable, Y. Further, current reporting practices often make it laborious, if not impossible, for readers to locate and assess total effect information.[9]

2.3. Not interpreting or reporting inconsistent mediation outcomes

We have shown (e.g., Table 2, Fig. 2) that interpreting mediation using only the indirect effect poses more serious consequences in cases of inconsistent mediation. Across the three journals (Table 5), mediation effects are *consistent* in only 32% of cases. In 46% of cases, there is inconsistent mediation (the direct and indirect effects are opposed). In the remaining 22% of cases, whether mediation is

[9] We remind readers that the bivariate correlation between an X and Y, which is often reported, does not estimate the total effect in the typical multivariate case where there is more than one X variable in the model and the X variables are not statistically independent. Rather, the total effect of each X in this situation is given by the regression coefficient of each X from the reduced form regression equation of endogenous variable Y on the X (i.e., purely exogenous) variables. (See, for example, Alwin & Hauser, 1975)

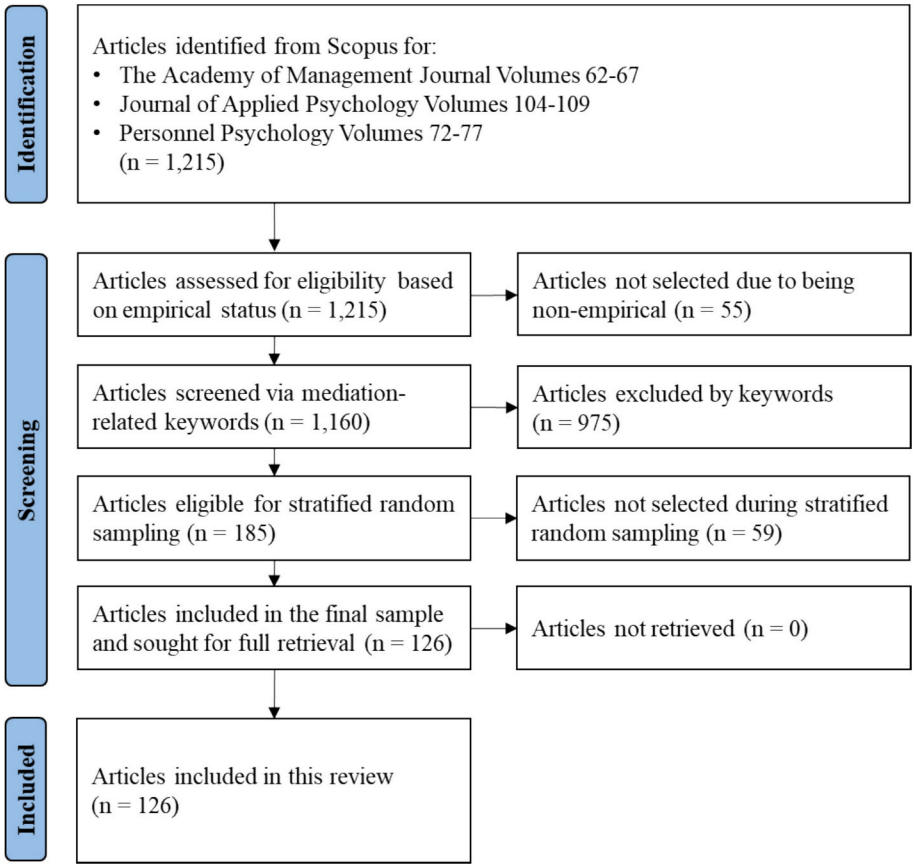


Fig. 3. PRISMA Flow Diagram of the Article Identification, Screening, and Inclusion Process.

consistent or inconsistent (or what the direct effect size is) cannot be determined because of incomplete reporting. Table 5 shows that when the direct effect is reported in inconsistent mediation scenarios, it is often not statistically significant. This is because statistical power for the test of the direct effect is typically much lower than that for the test of the indirect effect (Kenny & Judd, 2014).[10] Nonetheless, the absence of evidence is not evidence of absence (Altman & Bland, 1995), and a lack of statistical significance does not mean the direct effect is 0.00. Rather, the best estimate of the direct effect is the empirical estimate obtained in the study, regardless of whether it reaches statistical significance.

Returning briefly to Table 3, we also found that despite the widespread occurrence of inconsistent mediation, researchers almost never (3% of such cases) hypothesized inconsistent mediation scenarios ex ante and likewise almost never reported or interpreted inconsistent mediation ex post that existed in their studies (4% of the time). Such oversight poses a major concern, given the widespread occurrence of inconsistent mediation. The concern is magnified when the direct effect is larger than and opposite to the indirect effect. To be clear, we are not suggesting that researchers should more often propose inconsistent mediation hypotheses. Rather, we are saying that when mediation is hypothesized to be consistent (as it almost always is based on existing theories), but empirical evidence indicates inconsistent mediation exists, this must be explicitly identified and recognized.

[10] Kirk (1996, p. 747) notes that "because the null hypothesis is always false, a decision to reject it simply indicates that the research design had adequate power to detect a true state of affairs, which may or may not be a large effect or even a useful effect." In the mediation context, Mathieu and Taylor (2006) note that "[statistical] significance tests must be tempered by considerations of power and effect size estimates." Statistical significance testing not only often has low power (Rosnow & Rosenthal, 1989). Different tests can also have different power. In this vein, Kenny and Judd (2014) report that "when there is a direct effect of a causal variable on the outcome controlling for the mediator, the power of the test of the indirect effect is often considerably greater than the power of the test of the direct effect, even when the two are of the same magnitude." For example, their Table 4 shows that when the indirect (*ab*) and direct (*c'*) effect are both 0.09, the power for the test of *ab* is 0.80 versus 0.21 for *c'*—nearly a 4-fold difference. Kenny and Judd (2014, p. 339) conclude that "researchers need to be very cautious about claims of complete mediation" and that "it is especially problematic to trim nonsignificant values of *c'* and report them as zero without at least reporting their value with a standard error or confidence interval." See also Hayes and Rockwood (2017, p. 45) on this point, who worry that "it is to an investigator's advantage to minimize the sample size so that there is sufficient power to detect the indirect effect, but insufficient power to detect the direct effect." See also Götz et al. (2021).

Table 3
Sampled Studies with Mediation Analyses in Academy of Management Journal, Journal of Applied Psychology, and Personnel Psychology (2019–2024).

Categories		*N*
Total number of mediation articles		126
Total number of mediation studies (within articles)		209
Sample Size Statistics	**Level 1**	**Level 2**
25th percentile	183	82
Mean	1861	144
Median	290	100
75th percentile	589	136
	N	**% of studies**
Total number of studies with Level 1 $N > 500$	64	(31%)
Types of Mediation Relationships Tested (out of 206 studies)		
Moderated-Mediation and Mediated-Moderation	136	(65%)
Serial Mediation	46	(22%)
Multiple Mediation	73	(35%)
Mediation Effect Sizes Reported (out of 206 studies)		
Verbal description (e.g., full, partial, and no mediation)	21	(10%)
Indirect effect (*ab*) with confidence interval	192	(92%)
ab with *p*-value but no confidence interval	7	(3%)
Only confidence interval without *ab*	5	(2%)
Changes in variance explained	21	(10%)
Proportion of the total effect mediated (P_M)	8	(4%)
Differences between conditional indirect effects (out of 136 moderated-mediation / mediated-moderation studies)	104	(76%)
Discussed indirect effects relative to direct / total effects	15	(7%)
Inconsistent Mediation	97	(46%)
Authors hypothesized inconsistent mediation ex ante (out of 97 studies)	3	(3%)
Authors did not hypothesize inconsistent mediation ex ante but discussed inconsistent mediation ex post (of 97 studies)	4	(4%)

Notes. Percentage totals can exceed 100% because the same study may report mediation effect sizes in multiple formats. In multilevel studies, Level 1 represents the sample size at the lowest level of analysis, while Level 2 corresponds to the clustering level. For studies involving more than two levels, only Level 1 and 2 statistics are reported. When a study uses different sample sizes for different mediation analyses, we reported the minimum sample size. We excluded studies that tested moderation alone and did not estimate an indirect effect. For studies that '*Discussed indirect effects relative to direct / total effects*', we looked for sentences that explicitly compared effect sizes (e.g., "the direct effect's coefficient is smaller than the indirect"). We exclude studies that only mentioned direct effects being "weakened" or non-statistically significant when mediators are added to the model—an approach typical of Baron and Kenny's (1986) "partial / full mediation" conditions. For studies where '*Authors hypothesized inconsistent mediation ex ante*', we looked for hypotheses and figures of hypothesized models where direct and indirect effects point to opposite directions. For studies where '*Authors did not hypothesize inconsistent mediation ex ante but discussed inconsistent mediation ex post*', we perused the Results and Discussion sections for statements involving "inconsistent mediation", "competitive mediation", "suppression", or general mentions of the direct and indirect effects pointing to opposite directions.

Table 4
Direct, Indirect, and Total Effects Reporting Practices in Academy of Management Journal, Journal of Applied Psychology, and Personnel Psychology (2019–2024).

Reporting Status		Direct Effect (%)		Indirect Effect (%)		Total Effect (%)
Not reported	42	(20%)	4	(2%)	131	(63%)
Reported	167	(80%)	205	(98%)	78	(37%)
Reporting Location		Direct Effect (%)		Indirect Effect (%)		Total Effect (%)
Tables and/or figures only	125	(60%)	7	(3%)	18	(9%)
Text only	12	(6%)	97	(46%)	18	(9%)
Both tables / figures & text	30	(14%)	101	(48%)	42	(20%)

Notes. $N = 209$ studies reported in 126 articles. Percentages are the share of all 209 studies within each column. The "Reporting Location" panel decomposes the "Reported" row above it.

3. Improving mediation reporting and interpretation: using P_M and *Absolute* P_M

We have documented that current mediation interpretation and reporting practice typically relies solely on information (e.g., statistical significance) of the indirect effect to conclude the presence of mediation, rather than reporting the extent of mediation using P_M which reflects the relative size of the indirect effect compared to the total effect. We surmise that authors may choose not to quantify mediation extent using P_M owing to the findings of previous simulation studies (e.g., Lachowicz et al., 2018; Preacher & Kelley, 2011). For example, Lachowicz et al. (2018, p. 246) suggested that "measures [such as P_M] are easy to implement and have some intuitive appeal" while simultaneously arguing that "simulation studies have identified serious problems and their use is generally not recommended". These suggested problems include that it is not bounded between 0 and 1.00, and that it is unstable in small samples. Thus, our next step is to clarify the optimal conditions for the use of P_M in quantifying mediation and to address these

Table 5
Summary of Inconsistent Mediation Scenarios in Academy of Management Journal, Journal of Applied Psychology, and Personnel Psychology (2019–2024).

Mediation Scenarios	N	(%)
Consistent	66	(32%)
Inconsistent	97	(46%)
Direct effect is statistically significant	17	(8%)
Direct effect is not statistically significant	47	(22%)
Due to moderated mediation	33	(16%)
Cannot be determined	45	(22%)
Total	208	(100%)

Notes. The total number of studies is 208 instead of 209 because one study reported non-statistically significant indirect effects, so we excluded that study from the inconsistent mediation scenario count. Inconsistent due to moderated mediation means that the effect sizes are consistent at some level of the moderator and inconsistent at another level. The three rows beneath "Inconsistent" decompose the 97 inconsistent mediation cases.

criticisms through the use of *Absolute* P_M.

3.1. The value added by P_M, its limitations, and using absolute P_M for inconsistent mediation

While we previously included the equation for P_M, *Absolute* P_M differs by re-defining the total effect as the sum of the absolute values of the indirect and direct effects (Alwin & Hauser, 1975). In a basic mediation scenario (Fig. 1, Model 1), *Absolute* P_M can be calculated based on the equations listed on Table 7.

$P_M < 0.00$ or $P_M > 1.00$ in Inconsistent Mediation. Researchers have cautioned that P_M, unlike a true proportion, can fall outside the 0–1.00 interval (Hayes, 2009; Hayes & Rockwood, 2017; Preacher & Kelley, 2011), and some have recommended using P_M only under consistent mediation conditions where values remain within this interval (Shrout & Bolger, 2002). A P_M value *outside* of the 0–1.00 interval indicates "inconsistent mediation" (MacKinnon et al., 2007, p. 602)—also called "competitive mediation" (Zhao et al., 2010), or "suppression" (MacKinnon et al., 2000; Shrout & Bolger, 2002)—which occurs when the indirect (*ab*) and direct (*c'*) effects have opposite signs.

We recommend always reporting both P_M and *Absolute* P_M. In consistent mediation (i.e., the direct and indirect effects have the same signs), P_M and *Absolute* P_M will be identical. In *in*consistent mediation, P_M and *Absolute* P_M provide complementary information on mediation extent. First, reporting P_M serves the important function of efficiently flagging cases of inconsistent mediation (because it will fall outside of the 0–1.00 interval), a situation where focusing only on the indirect effect is especially problematic. Second, reporting *Absolute* P_M provides a meaningful estimate of the extent of mediation in both consistent and inconsistent mediation scenarios. *Absolute* P_M always falls between 0 and 1.00 and is therefore meaningful in quantifying mediation. Also, unlike P_M and other mediation statistics (e.g., k^2), *Absolute* P_M is monotonic such that "a larger absolute value always indicates a stronger effect" (Wen & Fan, 2015, p. 194).

Let us now demonstrate the advantages of combining the use of P_M and *Absolute* P_M to report mediation effect size. Shrout and Bolger (2002) examined how coping behavior mediates the relationship between an environmental stressor and experienced stress. In this case, the indirect effect (*ab*) is negative because it is composed of a positive effect of the stressor on coping behavior and a negative effect of coping behavior on experienced stress. The direct effect (*c'*) of the stressor on experienced stress is positive. Hypothetically, if *ab* was −0.30 and *c'* was 0.40, then the total effect (*ab* + *c'*) would be 0.10. This would result in a P_M estimate of −3.00 (= −0.30/0.10), which would very clearly alert us to evidence of inconsistent mediation. In addition, computing the *Absolute* P_M of 0.43 (= 0.30 / (0.30 + 0.40)) would indicate that 43% of the absolute total effect of the stressor on experienced stress is mediated by coping behavior. Thus, P_M flags inconsistent mediation and *Absolute* P_M accurately quantifies mediation here.

Instability of P_M in Small Samples. As another criticism, Preacher and Kelley (2011, p.98) stated that P_M has "large variances over repeated samples." Previous Monte-Carlo simulations show that P_M estimates are most credible when the predictor is continuous and sample sizes are larger than 500 (e.g., MacKinnon et al., 1995; Miočević et al., 2018). That said, the statistical properties of P_M in small samples contexts do not preclude its usefulness in reporting mediation effect size, just as the instability of commonly reported parameters like *r*, *d*, or *b* in small samples has not led to their dismissal. Rather, it underscores the importance of reporting confidence intervals (CIs) and using larger samples to produce more efficient estimates with less sampling error and narrower CIs. Echoing this view, Wen and Fan (2015), while cautioning that P_M's ratio properties "may magnify the estimation errors of the multiple components involved" (p. 199), nevertheless recommend that P_M be used to interpret mediation effect size.[11]

Returning to our Table 3, we found 64 studies (31%) had sample sizes greater than 500. Thus, roughly one-third of studies in AMJ, JAP, and PP fall within conditions that prior simulations suggest are more favorable for estimating P_M. Moreover, because mediation is increasingly examined using regression based on a meta-analytic correlation matrix where sample size (*N*) almost always significantly

[11] P_M is a ratio. However, it is not used as a variable in regression or other models. Rather, it is more comparable to other well-known ratios that help interpret models such as the *F* statistic, χ^2 statistic, any reliability indices (e.g., Cronbach's α or the intraclass correlation), and R^2.

exceeds 500, sampling error should ordinarily not be a concern for P_M and *Absolute* P_M in such a context.[12] Nevertheless, we found no mediation analyses based on a meta-analytic correlation matrix in our sample that reported P_M.

Other Concerns with P_M. There are concerns with P_M beyond its performance in small samples. First, Preacher and Kelley (2011) stated that P_M is "misleading" because "obtaining P_M =.9 for a relatively small…total effect may not necessarily be as impressive as obtaining P_M = .6 for a relatively large…total effect." (p. 97). We recommend that this concern be addressed by reporting P_M and *Absolute* P_M in conjunction with the magnitude of the total effect. Second, Preacher and Kelley (2011) argue, "It is easy to assume that if P_M seems large…there is no room for additional mediators" (p. 98). Whatever the size of P_M, we recommend that researchers report the P_M, *Absolute* P_M, and the magnitude of total, direct, and indirect effects from models that consider multiple new/alternative mediators simultaneously to draw valid interpretations with theoretical and practical insights. Of course, as Preacher and Kelley (2011), argue, we need to be thoughtful in doing so.

Use of P_M in other Fields. In contrast to the norm in HRM and broader areas of management, the proportion mediated is widely recognized and more frequently used in some other fields.[13] For example, P_M is "a pivotal quantity of interest" in medicine and epidemiology (Ditlevsen et al., 2005), where "mediation analysis is often undertaken to investigate the extent to which the effect of a risk factor on an outcome of interest is mediated by other covariates" (Nevo et al., 2017, p. 1).[14]

3.2. Recommendations for drawing precise and complete conclusions about mediation

We began by emphasizing that theoretical insights and policy implications are often undermined by the manner in which mediation research is currently conducted. We demonstrated that complete and valid mediation interpretations are only possible when all effects, indirect, direct, and total, are fully reported and interpreted. We provided examples of how the current practice of focusing only on the indirect effect results in incomplete and/or invalid conclusions that hinder theory testing/development as well as good decisions about HRM policy/practice.

Table 6 lists our recommended best practices. The most important change we recommend is to not only report and interpret the statistical significance (including confidence intervals) and size of the indirect effect, but to do so also for the direct and total effects (including paying close attention to the *signs* of all effects). A second recommendation is to compute and report both P_M and *Absolute* P_M and their confidence intervals to provide insight into how much of the X–Y relationship is accounted for by M. We note the ready availability of statistical software for these purposes.[15] P_M is also invaluable in clearly and efficiently flagging instances of inconsistent mediation while *Absolute* P_M adds the ability to handle inconsistent mediation scenarios, with its values always falling within the 0–1.00 interval. Consistent with Cohen (1990), p. 1310) assertion that "the primary product of a research inquiry [should be] effect size", explicitly reporting P_M and *Absolute* P_M, together with indirect, as well as direct and total effects, ensures that mediation studies reliably and transparently communicate the degree to which the effect of X on Y is mediated by M.

P_M and *Absolute* P_M are versatile statistics that can be used across different types of mediation models. For moderated-mediation models, the calculation varies by type of moderated-mediation effect, including first-stage, second-stage, both first- and second-stage, direct-effect, or both direct- and indirect-effects (Edwards & Lambert, 2007). In our first-stage example (Fig. 1, Model 2), one computes P_M for various levels of the moderating variable z (Table 7, Eq. 1) such as different groups for categorical moderators or one standard deviation above and below the mean for continuous moderators (Preacher et al., 2007). When multiple mediators are

[12] In the regressions using a meta-analytic correlation matrix in our sample (such as the examples shown in our Table 2), the typical approach was to construct a correlation matrix where the correlations were based on $N > 500$ and the regression analysis used to estimate indirect (and sometimes direct and total) effects likewise has that same $N > 500$. We note, however, that there could be cases where the relevant sample size would be the number of studies k, which is typically much smaller than N. This would occur, for example, if a moderator variable is included in a meta-regression where it is a study level characteristic (e.g., organization size, national culture score) where the variance is only between studies. In such cases, to the degree k is small, the sample size concern with P_M would be serious (Schmidt, 2017).

[13] In a review of mediation analysis in epidemiology, "over one-third of the studies…reported the proportion mediated as a relative effect size measure for the mediated effect" (Rijnhart et al., 2021). In marketing, Pieters (2017, p. 706) emphasized that "Mediation analysis decomposes the total treatment effect in conditional direct and indirect effects. It is thus informative to report estimates of all indirect and conditional direct treatment effects and separate paths, rather than of the indirect effect only. Doing so makes it possible to compare the indirect to the total and direct effects, and to gauge how much of the total effect is transferred by the mediator." However, as in HRM, it is not clear that typical practice in marketing research follows this advice.

[14] As an example, in *the New England Journal of Medicine*, Hu et al. (2018) examine "potential mediation effects of weight change" (p. 625) in the relationship between smoking cessation and health outcomes. One finding was that "weight change within 6 years after cessation explained 68.4%… of the elevated risk of type 2 diabetes among those who reported quitting smoking" (p. 626). As another example, in *The Lancet*, Lu et al. (2014), "quantified how much of the effects of BMI [body mass index] on coronary heart disease and stroke are mediated through blood pressure, cholesterol, and glucose, and how much is independent of these factors" (p. 970). They found that "blood pressure was the most important mediator, accounting for 31% (28-35) of the excess risk of coronary heart disease and 65% (56-75) for stroke" (p. 970). Finally, another example, Wang et al. (2024) used large national surveys to study the effect of socioeconomic status (SES) on incident dementia, and the degree to which lifestyle (behavioral risk) factors mediated the effect. They reported that "compared with participants of high SES, those of low SES had higher risk of incident dementia [3.17 times as high in the United States, 1.43 times as high in the United Kingdom] and that the proportions mediated by overall lifestyle were 10.4%…and 2.7%."

[15] These include using the 'mediate' package or specifying model constraints in the 'lavaan' package in R; using 'estat proportion' after running the 'mediate' command in Stata; '%MEDIATE' macro in SAS; specifying model constraints in MPlus).

present (Fig. 1, Model 3), the computation of P_M depends on the researcher's goal. If one wishes to isolate the effect of a single mediator, then that mediator's indirect effect is used as the numerator (Table 7, Eq. 2). On the other hand, if one wishes to find out how much of X's total effect on Y a set of mediators account for, then all indirect effects are included in the numerator (Table 7, Eq. 3). A similar approach applies to serial mediation scenarios (Fig. 1, Model 4), otherwise known as the "three-path mediated effect" model (Taylor et al., 2008). For example, the P_M for M_2 is calculated using Eq. 4 while the overall P_M value is calculated using the sum of all indirect effect combinations as shown in Table 7, Eq. 5.

Multiple Mediation. When reporting and interpreting mediation effect size for multiple mediation scenarios, researchers should be guided by their theory-driven hypotheses on the mediation process. For instance, if the multiple parallel mediators were hypothesized to be equally weighted components of an aggregate intermediary index or construct (e.g., knowledge, skills, and abilities as components of an aggregate Human Capital construct which mediates the HRM-Job Performance relationship), interpreting the total P_M and *Absolute* P_M for all mediators combined (Table 7, Eq. 3) would be more theoretically informative. However, if the multiple mediators were hypothesized to be competing or substitutive pathways (e.g. intrinsic motivation and extrinsic motivation as mediators of HRM-Job Performance relationship), interpreting the P_M and *Absolute* P_M independently for each mediator (Table 7, Eq. 2) and then comparing the magnitude of these mediation effect sizes may be more theoretically informative. If one or more of the multiple parallel mediators hypothesized to be competing or alternate pathways also displays evidence of inconsistent mediation (i.e., mediator with opposite sign to other mediators and total effect), it will be critical to report P_M to flag its suppressive countervailing influence and to use *Absolute* P_M to compare the extent of mediation through each of the theorized competing intermediary pathways.

Serial Mediation. In serial mediation scenarios, typically researchers' theory-driven hypotheses will reference a cascading logic that ties a sequence of intermediary mechanisms from the predictor to the outcome (e.g., HRM➔absenteeism➔speed to market➔Firm Performance). Therefore, reporting and interpreting the P_M and *Absolute* P_M for the entire series of serial mediators (Table 7, Eq. 5) will often be most informative in making precise conclusions. However, some researchers may include separate hypotheses theorizing the role of each mediator in its relationship with the predictor and outcome in addition to hypothesizing the same mediator's function within a sequence of mediators that link the predictor and the outcome (e.g., HRM➔voluntary turnover➔Firm Performance, in addition to HRM➔job satisfaction➔voluntary turnover➔Firm Performance). In such cases, researchers may find it theoretically meaningful to report, interpret, and compare P_M and *Absolute* P_M for each of the mediating pathways (Table 7, Eq. 4). Here too, any evidence of inconsistent mediation in these mediating pathways should be flagged in the reporting of P_M along with the interpretation of *Absolute* P_M to infer the extent of mediation through theoretically competing mechanisms.

In both multiple and serial mediation scenarios, we suggest that authors compute P_M and *Absolute* P_M both for all mediators combined and for each mediator separately, interpreting them in line with theory. Mediator-specific values are necessary even when the combined value is the subject of theoretical interest because opposing indirect effects can offset one another so that the combined P_M falls within 0–1.00. Consider for example, if $a_1b_1 = 0.30$, $a_2b_2 = -0.20$, and $c' = 0.10$, the combined P_M is 0.50, whereas the respective mediator-specific P_M are 1.50 and − 1.00. A gap between P_M and *Absolute* P_M (in this case, 0.50 versus 0.83) likewise indicates that some effects in the model carry opposing signs.

More generally, both sets of values are conditional on the mediators included in the specified model and should therefore be interpreted and compared within the theoretical specification that generated them, rather than treated as model-free quantities. In linear models with the same covariates, the total effect of X on Y does not change when mediators are added or removed, but its partition into indirect and direct effects does. When mediators are correlated, adding a new mediator can change the specific indirect effect and PM of an existing mediator. Therefore, P_M and *Absolute* P_M values should be compared across models with comparable sets of mediators. Furthermore, theoretically relevant mediators should be estimated in tandem so that their unique contributions can be assessed (Podsakoff et al., 2026), and differences between specific indirect effects can be tested directly, for example with a bootstrap confidence interval for the difference between two specific indirect effects (Lau & Cheung, 2012). Ultimately, authors can P_M and *Absolute* P_M as a springboard for discussing implications and future research. A low P_M value calls for identifying additional mediators, while a gap between P_M and *Absolute* P_M points to countervailing mechanisms that an alternative theory may explain (Johns, 2021).

Beyond this, it is also important to report the confidence intervals for indirect, direct, and total effects. This issue is especially relevant to how researchers treat direct effects that are not statistically significant. In many published studies, a non-statistically significant direct effect is implicitly treated as a zero effect. As we have also noted (and bears repeating), there are two problems with that. First, statistical significance tests of direct effects have lower power than tests of indirect effects (Kenny & Judd, 2014). Second, the best estimate of the population direct effect is the *sample* estimate, not zero. The sampling variability of the direct (and other) effects is conveyed through confidence intervals rather than assuming a direct effect of 0.00, an incorrect estimate. Forcing the direct effect to be 0.00 has mechanical consequences: it makes the indirect effect identical to the total effect ($P_M = 1.00$), which implies that the theoretical mediating mechanisms completely explain the X–Y relationship—an implication unlikely to be confirmed in larger samples (For an example of this practice resulting in $P_M = 1.00$, see Endnote #6).

Thus, reporting confidence intervals for indirect, direct, and total effects is essential for conveying the uncertainty around each component and for preventing misinterpretation driven by dichotomous "significant / non-significant" reporting. Emphasizing effect estimates and their confidence intervals, rather than binary statistical significance tests alone, would help align mediation analysis with contemporary best practices in effect-size reporting and help ensure more complete and accurate interpretation of study results.

Finally, even though a brief mention does not do justice to the importance of this issue, we believe it is essential to echo the critically important previous calls (e.g., MacKinnon et al., 2007; Maxwell & Cole, 2007; Shrout & Bolger, 2002) to focus on the validity of causal inference in the study of mediation. This requires going beyond modeling observed covariation/correlation between X, Y, and M, by addressing threats to validity due to endogeneity (e.g., measurement error, omitted variables, simultaneity, selection bias) through the use of statistical modeling and/or stronger designs (e.g., Cook & Campbell, 1979; Hill et al., 2021; Pearl, 2014).

Table 6
Recommended Best Practices for Reporting and Interpreting Mediation.

1. Report indirect, direct, and total effect size estimates and signs (i.e., in our Fig. 1, Model 1, *ab*, *c'*, and (*ab* + *c'*)) and pay greater attention to inconsistent mediation where signs on the direct and indirect effects are opposed (either not hypothesized a priori or in conflict with the hypothesized mediation). This is especially critical where the sign of the total effect differs from the sign of the indirect effect. Report confidence intervals for all of the above effect size estimates.
2. Interpret the magnitude and signs of the indirect, direct, and total effects. In making policy/practice recommendations, the total effect is likely to be of primary importance.
3. Describe whether the confidence interval for the indirect, direct, and total effects include zero and whether the sign of each effect is as hypothesized.
4. Report both P_M and *Absolute* P_M. Note that even if the indirect effect is not statistically significant, the best estimate of the population indirect effect is the sample estimate, not zero. This sample estimate of the indirect effect is necessary to compute P_M and *Absolute* P_M. A lack of statistical significance will be reflected in wider confidence intervals for P_M and *Absolute* P_M.
5. Use P_M to determine whether mediation is consistent (P_M falls within 0 to 100%) or inconsistent (P_M falls outside the 0 to 100% interval). In models with multiple mediators, apply this check to each mediator-specific P_M, not only the combined value.
6. Use *Absolute* P_M in interpreting mediation effect size when mediation is inconsistent.
7. Include the following types of effect size interpretations: The *Absolute* P_M indicates that _ % of the absolute total effect of X on Y operates via the mediator M. Its 95% confidence interval is _ to _. The total effect of X on Y indicates that a one-unit (or one SD unit) increase in X is associated with a _ unit (or _ SD unit) increase/decrease in Y. [Do the same for the direct and indirect effects.] Give the 95% confidence interval for each effect.
8. In cases of multiple parallel mediators hypothesized as substitutive or competing intermediary mechanisms, report both P_M and Absolute P_M for each mediator independently and compare their magnitude. If multiple mediators were hypothesized as complementary intermediary mechanisms or components of a configuration/index, report P_M and Absolute P_M for all mediators in the model in combination. In cases of serial mediation, report and compare P_M and Absolute P_M for each mediator independently as well as for the entire series of serial mediators.
9. Use sample sizes of $N = 500$ or more when possible to reduce sampling variability of mediation effect size estimates.
10. Evaluate the ability of the research, including its design and statistical modeling to address endogeneity/rule out alternative models and draw valid inferences, including inferences about mediation.

Table 7
Calculations of Proportion of Total Effect Mediated (P_M) and Absolute P_M in Complex Mediation Models.

Research Goal	P_M Equation	*Absolute* P_M Equation
(1) Determine the mediator's effect as influenced by the moderator *z* (e.g., Model 2).	$\frac{(ab)z}{[(ab)z + c']}$	$\frac{\lvert(ab)z\rvert}{\lvert(ab)z\rvert + \lvert c'\rvert}$
(2) Isolate the effect of a single mediator (M_1) among multiple mediators (e.g., Model 3)	$\frac{(a_1b_1)}{(a_1b_1 + a_2b_2 + c')}$	$\frac{\lvert a_1b_1\rvert}{\lvert a_1b_1\rvert + \lvert a_2b_2\rvert + \lvert c'\rvert}$
(3) Determine the total mediated effect among multiple mediators ($M_1 + M_2$) (e.g., Model 3)	$\frac{(a_1b_1 + a_2b_2)}{(a_1b_1 + a_2b_2 + c')}$	$\frac{\lvert a_1b_1\rvert + \lvert a_2b_2\rvert}{\lvert a_1b_1\rvert + \lvert a_2b_2\rvert + \lvert c'\rvert}$
(4) Isolate the effect of a single mediator (M_2) in a serial mediation scenario (e.g., Model 4)	$\frac{(a_1a_3b_2 + a_2b_2)}{(a_1a_3b_2 + a_1b_1 + a_2b_2 + c')}$	$\frac{\lvert a_1a_3b_2\rvert + \lvert a_2b_2\rvert}{\lvert a_1a_3b_2\rvert + \lvert a_1b_1\rvert + \lvert a_2b_2\rvert + \lvert c'\rvert}$
(5) Determine the total mediated effect ($M_1 + M_2$) in a serial mediation scenario (e.g., Model 4)	$\frac{(a_1a_3b_2 + a_1b_1 + a_2b_2)}{(a_1a_3b_2 + a_1b_1 + a_2b_2 + c')}$	$\frac{\lvert a_1a_3b_2\rvert + \lvert a_1b_1\rvert + \lvert a_2b_2\rvert}{\lvert a_1a_3b_2\rvert + \lvert a_1b_1\rvert + \lvert a_2b_2\rvert + \lvert c'\rvert}$

Note. All path coefficients (e.g., *a*, *b*, a_1, b_1, etc.) correspond to the models in Fig. 1.

3.3. Theoretical implications for HRM research

Complete and valid mediation interpretation can help improve theory building, refinement, integration, correction, and advancement in HRM research. Because HRM theory is fundamentally mechanism-centered, mediation evidence is often used to explain how HRM practices and systems create value. Yet, as we have shown, the validity of these theoretical claims depends on mediation results being fully reported and interpreted precisely and completely. Explicitly and completely reporting and interpreting the indirect, direct, and total effects, together with P_M, helps inform HRM scholars (and practitioners) the degree to which a proposed mediator is central or peripheral; whether multiple mechanisms operate simultaneously; and whether countervailing pathways (inconsistent mediation) serve to weaken or even reverse the direction of the overall relationship implied by the hypothesized mechanism. These countervailing pathways are a potential source of what Johns (2021) calls opposite effects, which are scientifically valuable yet rarely identified and theorized. Our review suggests that many such candidates already sit unexamined in published mediation models. Thus, complete mediation interpretation does more than test existing theory; it refines theoretical claims, integrates competing explanations, corrects misleading conclusions, advances more fully developed process models, and initiates new questions about how HRM policies/practices and systems simultaneously create value, generate costs, and produce tradeoffs.

3.4. Practical implications for HRM

Beyond strengthening the interpretations researchers can draw, complete reporting of indirect, direct, and total effects, together with P_M and *Absolute* P_M, has direct implications for HRM practice and policy implementation. First, it enables more precise *diagnosis* of why HRM interventions succeed or fail. When an HRM initiative underperforms, the question of "what went wrong?" can be unpacked into mechanism-level investigations: did the HRM practice fail to influence the proposed mediator, did the mediator fail to produce the expected outcome, and/or is a countervailing pathway offsetting the gains? Each diagnosis points to a different remedy, respectively: redesigning the practice's content and delivery, addressing organizational conditions that decouple the mediator from the outcome, or

rebalancing the HRM system to manage the offsetting pathway. To illustrate, in Table 2 Example A, PFP has a negative indirect effect on intrinsic motivation via employees' sense of being controlled (lack of autonomy), as expected under self-determination theory (SDT). This pathway identifies a possible obstacle to the success of a PFP plan. However, SDT also recognizes that PFP can have a positive indirect effect on intrinsic motivation to the degree PFP improves employee sense of competence (Deci et al., 2017). This positive path via competence (and/or other mediators) is most likely among high performers, particularly when sorting effects can operate, with high performers drawn to stronger PFP systems and low performers gravitating toward weaker ones (Kim et al., 2022). In other words, our theoretical explanation may wish to incorporate moderated mediation. In Example A, however, the indirect effect of competence was not part of the model. Any unincluded indirect effect is captured by the direct effect and thus, the total effect. Thus, examining the total effect can better guide theory and practice in identifying how to strengthen positive pathways and mitigate negative pathways.

Second, comprehensive reporting supports more careful and better HRM investment decisions. Strategic HRM has long argued that finite resources should be allocated where they generate the largest marginal return (Becker & Gerhart, 1996; Becker & Huselid, 2006; Cascio et al., 2019; Delery & Gupta, 2016), and P_M and Absolute P_M provide exactly the kind of evidence such allocation requires: a dollar invested in a practice whose effect runs largely through a well-understood mediator is a more defensible/less risky allocation than the same dollar invested in a practice whose effect runs through comparatively less understood pathways.

Altogether, these recommendations speak to the broader research-practice gap in HRM. Paauwe and Van De Voorde (2025) characterize that gap in terms of two distinct challenges: knowledge transfer (i.e., translating rigorous findings into actionable form) and knowledge production (i.e., generating findings that are rigorous and contextually relevant). Comprehensive mediation reporting addresses both. Regarding knowledge transfer, it converts the abstract claim that "HRM practice X improves outcome Y through mediator M" into a quantitative statement about how much of the X–Y relationship M accounts for, in what direction, and with what degree of uncertainty. As for knowledge production, it disciplines theory testing: HRM scholars must no longer infer mechanism-level support from a statistically significant indirect effect alone. Instead, they must examine their theoretical assumptions based on the combined pattern of indirect, direct, and total effects and their relative magnitudes. Thus, our recommendations can help move the field closer to mediation analyses that are more rigorous in their methods and more valuable and informative in providing implications for both theory and practice.

4. Conclusion

We have demonstrated that focusing only on the indirect effect and its statistical significance is the current practice in HRM-related mediation research. We have also shown how this current practice results in an incomplete and/or invalid interpretation of findings, a major impediment to advancing both theory and practice. We have provided specific recommendations (Table 6) on how to improve the validity of conclusions in future mediation research.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the first author used Claude Opus 5.5 (Anthropic) to proofread the manuscript, check the accuracy of the coded study data and analysis R code, and prepare materials for an open science repository. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Data availability

I have shared the review data via a ResearchBox link in the manuscript.

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