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Best-Practice Recommendations for Defining, Identifying, and Handling Outliers

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Abstract

The presence of outliers, which are data points that deviate markedly from others, is one of the most enduring and pervasive methodological challenges in organizational science research. We provide evidence that different ways of defining, identifying, and handling outliers alter substantive research conclusions. Then, we report results of a literature review of 46 methodological sources (i.e., journal articles, book chapters, and books) addressing the topic of outliers, as well as 232 organizational science journal articles mentioning issues about outliers. Our literature review uncovered (a) 14 unique and mutually exclusive outlier definitions, 39 outlier identification techniques, and 20 different ways of handling outliers; (b) inconsistencies in how outliers are defined, identified, and handled in various methodological sources; and (c) confusion and lack of transparency in how outliers are addressed by substantive researchers. We offer guidelines, including decision-making trees, that researchers can follow to define, identify, and handle error, interesting, and influential (i.e., model fit and prediction) outliers. Although our emphasis is on regression, structural equation modeling, and multilevel modeling, our general framework forms the basis for a research agenda regarding outliers in the context of other data-analytic approaches. Our recommendations can be used by authors as well as journal editors and reviewers to improve the consistency and transparency of practices regarding the treatment of outliers in organizational science research.

Keywords

quantitative research, ethics in research, outliers

The presence of outliers, which are data points that deviate markedly from others, is one of the most enduring and pervasive methodological challenges in organizational science research (Bollen &

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Jackman, 1990; Grubbs, 1969; Hunter & Schmidt, 2004; Rousseeuw & Leroy, 2003). Outliers, by virtue of being different from other cases—be it other individuals, teams, or firms—usually exert disproportionate influence on substantive conclusions regarding relationships among variables. Accordingly, the issue of outliers is of concern to organizational science research spanning all levels of analysis and ranging from organizational behavior and human resource management (e.g., Orr, Sackett, & DuBois, 1991) to strategy (e.g., Hitt, Harrison, Ireland, & Best, 1998). Moreover, the topic of outliers has also caught the popular attention, as indicated by Gladwell's (2008) book *Outliers*, which occupied the number one position on the best-seller list for the *New York Times* for 11 consecutive weeks. The fact that outliers are of concern to micro- and macro-level organizational science researchers, as well as the public in general, indicates that, indeed, this is an important methodological topic.

Despite the importance of outliers, researchers do not have clear guidelines about how to deal with them properly. Furthermore, although in many cases outliers are seen as ''data problems'' that must be ''fixed,'' outliers can also be of substantive interest and studied as unique phenomena that may lead to novel theoretical insights (e.g., Hitt et al., 1998). Thus, there is a need for a better understanding and clear guidelines regarding the following three issues: (a) how to define them (i.e., ''What exactly is an outlier?''), (b) how to identify them (i.e., ''How do I know whether a particular case is an outlier?''), and (c) how to handle them (i.e., ''What do I do with a case that has been identified as an outlier?''). At present, researchers are faced with multiple and often conflicting definitions of outliers, techniques to identify outliers, and suggestions on what to do with outliers once they are found. Moreover, the methodological literature on outliers seems fragmented and, for the most part, addresses outliers in specific contexts only; for example, most methodological sources discuss outliers only within the context of a single data-analytic approach such as ordinary least squares (OLS) regression (e.g., Cohen, Cohen, West, & Aiken, 2003). In addition to the conflicting and fragmented methodological literature on outliers, there is little transparency surrounding how substantive researchers define, identify, and handle outliers in published journal articles.

The main goal of our article is to offer best-practice recommendations for defining, identifying, and handling outliers within the context of the three most popular data-analytic techniques in management and related fields as identified by Aguinis, Pierce, Bosco, and Muslin (2009): regression, structural equation modeling (SEM), and multilevel modeling. Note that because the general linear model serves as a common mathematical foundation for both regression and ANOVA, our discussion of outliers in the context of regression also applies to the ANOVA context. As such, our article serves as a useful guide for the majority of organizational science researchers who engage in empirical research using these data-analytic techniques. In addition, we report results of a literature review on the topic of outliers that will serve as a foundational step toward a research agenda addressing outliers within the context of other data-analytic approaches such as cluster analysis, meta-analysis, and time-series analysis, among others.

The remainder of our article is organized around four sections. In the first section, we provide evidence that different ways in which outliers are defined, identified, and handled change substantive conclusions. In the second section, we describe a literature review leading to the creation of a comprehensive taxonomy including 14 outlier definitions, 39 outlier identification techniques, and 20 different ways of handling outliers. In addition, results of our literature review reveal challenges and problems encountered by organizational science researchers when addressing outliers in substantive domains. The third section includes best-practice recommendations, including decision-making trees, that researchers can follow when defining, identifying, and handling outliers within the context of regression, SEM, and multilevel modeling. Finally, we offer suggestions that rely on our literature review regarding a research agenda on the topic of outliers.

Choices About Defining, Identifying, and Handling Outliers Change Substantive Conclusions

Outliers can lead to important changes in parameter estimates when researchers use statistical methods that rely on maximum likelihood estimators (Cohen et al., 2003; Hunter & Schmidt, 2004; Kutner, Nachtsheim, Neter, & Li, 2004). Accordingly, Bollen and Jackman (1990) concluded that how we deal with outliers "can lead us to false acceptance or rejection of hypotheses" (p. 286). There is an additional important consideration regarding the treatment of outliers, which was described by Cortina (2002) as follows:

> Caution also must be used because, in most cases, deletion [of outliers] helps us to support our hypotheses. Given the importance of inter-subjectivity and the separation of theoretical and empirical evidence in the testing of hypotheses, choosing a course of action *post hoc* that is certain to increase our chances of finding what we want to find is a dangerous practice. (p. 359)

The impact of outliers on substantive conclusions is perhaps most evident in situations where an article is first published, and then a subsequent rebuttal is published by a different team of researchers demonstrating that the original findings should be put into question specifically because of the way outliers were dealt with in the original study. For example, Hollenbeck, DeRue, and Mannor (2006) demonstrated the influence that one data point can have on substantive conclusions. To do so, they reexamined data collected by Peterson, Smith, Martorana, and Owens (2003), who investigated the relationships among CEO personality, team dynamics, and firm performance. Peterson et al. tested 48 different correlations for statistical significance based on a sample of 17 CEOs, and 17 of these 48 relationships were found to be statistically significant. To assess the influence that single data points had on Peterson et al.'s results, Hollenbeck et al. removed each of the 17 data points (i.e., 17 CEOs) one at a time, thereby conducting 17 different outlier analyses, and they calculated how many times each of Peterson et al.'s 17 correlations remained statistically significant. Hollenbeck et al.'s results showed that, of the 17 statistically significant results, only 1 correlation was significant for all 17 analyses. Of the remaining 16 statistically significant correlations, 7 were not significant once, 5 were not significant between 2 and 6 times, and 4 were not significant between 10 and 17 times. In short, substantive conclusions regarding relationships among CEO personality, team dynamics, and firm performance changed almost completely depending on the treatment of outliers. Several additional examples of results and substantive conclusions that have been challenged based on how authors dealt with outliers exist in other research domains including social psychology (e.g., see exchanges in Blanton et al., 2009a, 2009b; McConnell & Leibold, 2001, 2009; Ziegert & Hanges, 2009) and sociology (e.g., see exchanges in Jasso, 1985; Kahn & Udry, 1986), among others.

In summary, the decisions that researchers make about how to define, identify, and handle outliers have important implications. Specifically, such decisions change substantive conclusions including the presence or absence, direction, and size of an effect or relationship. Next, we describe a literature review that allows us to understand the current state of science regarding outliers in a comprehensive and systematic fashion.

Outliers: Literature Review

We conducted a literature review with the goal of producing a comprehensive taxonomy of the various ways in which outliers are defined, identified, and handled. As a result of our review, we found that there is a great deal of confusion and contradictory information regarding how researchers are

supposed to address issues about outliers. On a more positive note, however, our review allowed us to distill best-practice recommendations within the context of regression, SEM, and multilevel modeling, as well as identify fruitful directions for future work regarding outliers in other data-analytic contexts such as cluster analysis, meta-analysis, and time series analysis, among others.

Literature Search Procedures

Our review focused on two distinct bodies of literature. First, we conducted a search involving methodological sources that addressed issues about outliers. Second, we conducted a search involving articles published in organizational science journals that addressed substantive issues and mentioned the topic of outliers—typically because the study included some type of outlier analysis. In short, our review consisted of a review of the methodological literature and also of the substantive literature.

Review of the methodological literature. We conducted the methodological review in two parts. The first part involved a broad review of the methodological literature on outliers. The second part involved a specific review of the outlier literature, focused within three contexts: regression, SEM, and multilevel modeling.

Our broad review of the methodological literature involved four steps. In the first step, we conducted a full-text search using the Advanced Scholar Search function in Google Scholar with the following terms: *outlier*, *influential case*, *influential cases*, *influential observation*, *influential observations*, *influential data*, *extreme influence*, and *outlying*. Because our purpose in this first step was to identify influential journal articles, we constrained our search to articles with at least 100 citations (as indicated by Google Scholar). In the second step, we conducted the same search but did not use the 100-citation cutoff. The purpose was to identify articles that may not have been cited more than 100 times because they were published more recently, yet may be relevant to the topic of outliers. Third, we manually examined each of the sources identified through the two previously mentioned searches. Among these manually examined sources, we kept those that addressed a definition of a specific type of outlier, an identification technique, or a handling technique. As a result of Steps 1 through 3, we were able to identify 18 articles. Fourth, we manually examined the references section of each of the 18 articles to identify sources other than journal articles that may also provide suggestions on how to address outliers. This final step led to 59 non-journal article sources. Out of these 59 sources, 10 sources (i.e., three book chapters and seven books) were cited more than 100 times. Adding the 18 articles, which were compiled in the first three steps, to the 10 sources we selected in the fourth step, resulted in a total of 28 sources (the list of 28 sources is available from the authors on request). Taken together, these sources included a total of 13 outlier definitions, 34 identification techniques, and 16 handling techniques.

Next, we conducted a more focused review of the methodological literature with the purpose of distilling best-practice recommendations on how to deal with outliers when using regression, SEM, and multilevel modeling. We used Google Scholar to identify articles dealing specifically with how to define, identify, and handle outliers in these three data-analytic contexts. We used the same search terms we used in the broad literature review, and we also added the three focal data-analytic approaches as search terms. We also checked the references section of each article for additional relevant sources. It was not uncommon for an article published more recently to offer a revised and improved recommendation on how to define, identify, and/or handle outliers initially offered by a previously published source. In these instances, we kept only the improved recommendation. This review allowed us to identify 18 sources specifically addressing outliers in the context of regression, SEM, and multilevel modeling, which added 1 outlier definition, 5 identification techniques, and 4 handling techniques to our previous lists (the list of 18 sources is available from the authors on request).

Review of the substantive literature. The main goal of our review of the substantive literature was to understand current practices on how organizational science researchers define, identify, and handle outliers in their substantive research. To do so, we conducted a full-text search using the Advanced Scholar Search function in Google Scholar with the same search terms used in our review of the methodological literature described earlier. In addition, we constrained our search to the following journals covering the years 1991 through 2010: *Academy of Management Journal*, *Journal of Applied Psychology*, *Personnel Psychology*, *Strategic Management Journal*, *Journal of Management*, and *Administrative Science Quarterly*. Our search resulted in 232 journal articles (the list of articles is available from the authors on request).

Results and Discussion

R.K.G. and H.J. examined 5 of the 46 sources from the methodological review in detail and independently extracted any paragraphs including information on any of these three issues. After the process was completed, the two coders met and compared results. More than 90% of their selected paragraphs matched. Given the high level of agreement, we divided the remaining 41 sources between the two coders. Our review of the 232 substantive organizational science journal articles did not lead us to identify any additional and appropriate outlier definitions, identification techniques, and handling techniques, although we found instances of improper outlier definitions, identification techniques, and handling techniques (e.g., outliers were identified through a subjective process as being deemed either ''too big'' or ''too small'' compared to the rest of the data). We did not include these improper techniques in our tables so as to not perpetuate their use.

Our review of the 46 methodological sources led to a comprehensive and mutually exclusive list of 14 outlier definitions (see Table 1), 39 identification techniques (see Table 2), and 20 handling techniques (see Table 3). Given the large number of definitions, identification techniques, and handling techniques identified in our review, it is no surprise that prominent methodological sources such as Kutner et al. (2004) and Tabachnick and Fidell (2007), which are textbooks widely used in doctoral seminars in the organizational sciences, provide inconsistent recommendations as to how to define, identify, and handle outliers.

In addition to inconsistent recommendations in the methodological literature, our review of the 232 substantive articles dealing with outliers uncovered three specific shortcomings in the current state of how outliers are addressed in the organizational sciences. These shortcomings highlight the need for clear guidelines and best-practice recommendations.

First, it is common for organizational science researchers to be either vague or not transparent in how outliers are defined and in how a particular outlier identification technique was chosen and used. For example, Reuer and Ariño (2002) studied strategic alliances and noted that ''After accounting for missing data and outliers, 71 alliances (37.6%) involving 63 companies were available for analysis'' (p. 54). Unfortunately, this statement fails to explain the type of outlier the authors were trying to identify, describe the method used to do so, or provide a clear rationale for why the removal of such data points was the most appropriate handling technique.

Second, many authors define outliers in one way but then use an outlier identification technique that is not congruent with their adopted outlier definition. As an illustration of this issue, Kulich, Trojanowski, Ryan, Haslam, and Renneboog (2011) examined gender differences in executive compensation to identify ''a small number of influential observations'' (p. 312) that could have driven the results (i.e., model fit and/or parameter estimates). However, Kulich et al. identified as outliers those data points that were three standard deviations away from the mean. As we describe in more detail later in our article, extreme observations may or may not influence parameter estimates (Cohen et al., 2003). In other words, the way in which outliers are identified is often inconsistent with how outliers are defined.

Table 1. Outlier Definitions Based on a Review of Methodological and Substantive Organizational Science Sources.

1. Single construct outliers	Data values that are unusually large or small compared to the other values of the same construct. These points typically fall in the tails of a data distribution.
2. Error outliers	Data points that lie at a distance from other data points because they are the result of inaccuracies. More specifically, error outliers include outlying observations that are caused by not being part of the population of interest (i.e., an error in the sampling procedure), lying outside the possible range of values, errors in observation, errors in recording, errors in preparing data, errors in computation, errors in coding, or errors in data manipulation.
3. Interesting outliers	Accurate (i.e., nonerror) data points that lie at a distance from other data points and may contain valuable or unexpected knowledge.
4. Discrepancy outliers	Data points with large residual values, with possibly (but not necessarily) large influence on model fit and/or parameter estimates.
5. Model fit outlier	An influential outlier whose presence influences the fit of the model.
6. Prediction outlier	An influential outlier whose presence affects the parameter estimates of the model.
7. Influential meta-analysis effect size outlier	A data point that is unusually large or small compared to others in a meta-analytic database, specifically regarding the size of the effect or relationship.
8. Influential meta-analysis sample size outliers	In the context of a meta-analysis, these are single construct outliers in terms of their sample size compared to the other studies' sample sizes.
9. Influential meta-analysis effect and sample size outliers	Primary-level studies that, via a combination of unusually large or small effect sizes and unusually large sample sizes, exert a large influence on the meta-analytic results.
10. Cluster analysis outliers	Outliers that exist as a result of conducting cluster analysis.
11. Influential time series additive outlier	An observation that markedly deviates from surrounding others in a time series analysis. A time series additive outlier may exist in isolation, such that connecting the surrounding data points and the outlier with a continuous line would yield a spike shape at the time point where the outlier exists. Alternatively, a group of time series additive outliers may exist as a patch within a range of time points.
12. Influential time series innovation outlier	An observation that not only has a large absolute value compared to surrounding others in a time series analysis, but also affects the values of subsequent observations in unequal amounts.
13. Influential level shift outliers	A data point causing an abrupt and permanent step change (i.e., jump) in the values of subsequent observations in a series.
14. Influential temporary changes outliers	A data point causing an abrupt step change (i.e., jump) in the values of subsequent observations in a series, but this differs from a level shift outlier in that this change eventually dies out with time. That is, the step change is not permanent.

Table 2. Outlier Identification Techniques Based on a Review of Methodological and Substantive Organizational Science Sources.

Single-construct techniques	
1. Box plot	A plot that depicts a summary of the smallest value of a construct (excluding outliers), lower quartile (Q1), median (Q2), upper quartile (Q3), and largest value (excluding outliers). Outliers can be identified as those points that lie beyond the plot's whiskers (i.e., the smallest and largest values, excluding outliers).
2. Stem and leaf plot	A plot that simultaneously rank-orders quantitative data and provides insight about the shape of a distribution. Stem-and-leaf pairs that are substantially far away from the rest of the pairs signal the presence of outliers.
3. Schematic plot analysis	Similar to a box plot, but used specifically for effect sizes in the context of a meta-analysis.
4. Standard deviation analysis	Distance of a data point from the mean in standard deviation units.
5. Percentage analysis	Relative standing of a data point in a distribution of scores as indexed by its percentile.
Multiple-construct (i.e., "distance") techniques	
6. Scatter plot	A plot of the values of two variables, with one variable on the x-axis (usually the independent variable) and the other variable on the y-axis (usually the dependent variable). A potential outlier can be identified by a data point lying far away from the centroid of data.
7. q-q plot	A plot (q stands for quantile) that compares two probability distributions by charting their quantiles against each other. A nonlinear trend indicates the possible presence of outlier(s).
8. p-p plot	A plot (p stands for probability) that assesses the degree of similarity of two data sets (usually the observed and expected) by plotting their two cumulative distribution functions against each other. A nonlinear trend indicates the possible presence of outlier(s).
9. Standardized residual	A residual value that is calculated by dividing the *i*th observation's residual value by a standard deviation term. Observations with high standardized residual values are likely to be outliers. However, an observation's standardized residual value does not measure an observation's outlyingness on the predictor variables.
10. Studentized residual	A residual value that measures *both* the outlyingness of the observation in terms of its standardized residual value (i.e., one type of distance) and the outlyingness of the observation on the predictor variables (i.e., another type of distance), such that a data point that is outlying in terms of both types of distance would have a studentized residual value that is greater than its standardized residual value. Observations with high studentized residual values are likely to be outliers.
11. Standardized deleted residual	A residual value that is identical to a standardized residual, except that the predicted value for the focal observation is calculated without the observation itself. This exclusion prevents the focal observation from deflating the residual value and inflating the standard deviation term, where such deflation and inflation mask the existence of any outlyingness of the observation. Observations with high standardized deleted residual values are likely to be outliers.
12. Studentized deleted residual (i.e., externally studentized residual, jackknife residual)	A residual value that is identical to a studentized residual, except that the predicted value for the focal observation is calculated without the observation itself. This exclusion prevents the focal observation from deflating the residual value and inflating the standard deviation term, where such deflation and inflation mask the existence of any outlyingness of the observation. Observations with high studentized deleted residual values are likely to be outliers.

(continued)

Table 2. (continued)

13. Euclidean distance	Length of the line segment between two specified points in a one-, two-, or *n*-dimensional space. A large Euclidean distance between two data points may mean that one of the two data points is an outlier.
14. Mahalanobis distance	Similar to Euclidean distance, but different in that Mahalanobis distance is the length of the line segment between a data point and the centroid (instead of another observation) of the remaining cases, where the centroid is the point created at the intersection of the means of all the predictor variables. A large Mahalanobis distance may mean that the corresponding observation is an outlier.
15. K-clustering (with or without modified hat matrix) or other similar cluster analysis techniques	Yields different candidate subsets that then have to be evaluated by one or more multiple-case diagnostics.
16. 2- or 3-dimensional plots of the original and the principal component variables	A two- or three-dimensional plot of variables produced as a result of a principal component analysis. An isolated data point denotes a potential outlier.
17. Autocorrelation function plot	A plot created by computing autocorrelations for data values at varying time lags. Potential outliers can be identified by data points that lie at a distance from other data points.
18. Time plot	A plot of the relationship between a certain variable and time. Potential outliers can be identified by data points that lie at a distance from other data points.
19. Extreme studentized deviate (i.e., Grubbs method)	Difference between a variable's mean and query value, divided by a standard deviation value.
20. Hosmer and Lemeshow goodness-of-fit test	A Pearson chi-square statistic from a table of observed and expected (i.e., implied) frequencies.
21. Leverage values	Also known as the diagonal elements of the hat matrix, leverage values measure the extent to which observations are outliers in the space of predictors.
22. Centered leverage values	A centered index of leverage values. Certain statistical packages (e.g., SPSS) report centered leverage values instead of regular leverage values.
23. Deletion standardized multivariate residual	A standardized residual term in the context of multilevel modeling. This allows for an assessment of the effect that a higher level outlier has on model fit. If an outlier is found at the higher level, lower level units should be investigated.
Influence techniques	
24. Cook's D_i	Assesses the influence that a data point *i* has on all regression coefficients as a whole.
25. Modified Cook's D_i	Similar to Cook's D_i, but it uses standardized deleted residuals rather than standardized residuals.
26. Generalized Cook's D_i	Similar to Cook's D_i, but applied to structural equation modeling to assess the influence that a data point has on the parameter estimates.
27. Difference in fits, standardized ($DFFITS_i$)	Just like Cook's D_i, this technique also assesses the influence that a data point *i* has on all regression coefficients as a whole. A large difference between the two techniques is that they produce information that exists on different scales.
28. Difference in beta, standardized ($DFBETAS_{ij}$)	Indicates whether the inclusion of a case *i* leads to an increase or decrease in a single regression coefficient *j* (i.e., a slope or intercept).
29. Chi-squared difference test	This method allows a researcher conducting SEM to assess the difference in the model fit between two models, one with the outlier included and the other without the outlier.
30. Single parameter influence	Similar to $DFBETAS_{ij}$, this identification technique is used in SEM to assess the effect of an outlier on a specific parameter estimate, as opposed to the overall influence of an outlier on all parameter estimates in the model.

(continued)

Table 2. (continued)

31. Average squared deviation technique	When conducting multilevel modeling, this method, a direct analog of Cook's D_i, investigates the effect that each group has on the fixed and/or random parameters, allowing for the identification of higher level prediction outliers. If an outlier is found at the higher level, lower level units should be investigated.
32. Sample-adjusted meta-analytic deviancy (SAMD)	In meta-analysis, this test statistic takes the difference between the value of each primary-level effect size estimate and the mean sample-weighted coefficient computed without that effect size in the analysis, and then adjusts the difference value based on the sample size of the primary-level study. Outliers are identified by their extreme SAMD values.
33. Conduct analysis with and without outliers	This technique refers to conducting the statistical analysis with and without a particular data point. If results differ across the two analyses, the data point is identified as an outlier.
34. Nearest neighbor techniques	Calculation of the closest value to the query value using various types of distance metrics such as Euclidean or Mahalanobis distance. Techniques include K-nearest neighbor, optimized nearest neighbor, efficient Type 1 nearest neighbor, Type 2 nearest neighbor, nearest neighbor with reduced features, dragon method, PAM (partitioning around medoids), CLARANS (clustering large applications based on randomized search), and graph connectivity method.
35. Nonparametric methods	Consist of fitting a smoothed curve without making any constraining assumptions about the data. A lack of a linear trend in the relationship signals the presence of outliers.
36. Parametric methods	Unlike nonparametric methods, parametric methods make certain assumptions about the nature of the data. One such assumption is that the data come from a particular type of probability distribution (e.g., normal distribution). Outliers are identified by these techniques as data points that fall outside the expectations about the nature of the data. Parametric methods include convex peeling, ellipsoidal peeling, iterative deletion, iterative trimming, depth trimming, least median of squares, least trimmed squares, and M-estimation.
37. Semiparametric methods	These methods combine the speed and complexity of parametric methods with the flexibility of nonparametric methods to investigate local clusters or kernels rather than a single global distribution model. Outliers are identified as lying in regions of low density.
38. Iterative outlier identification procedure	In a sequence of steps, this procedure allows for the estimation of the residual standard deviation to identify data points that are sensitive to the estimation procedure that is used when conducting a time series analysis. Such data points are subsequently identified as outliers.
39. Independent component analysis	A computation method used to separate independent components by maximizing the statistical independence among them. The separate independent components, when found in a time series analysis, are identified as outliers.

We emphasize that our review of the substantive literature revealed that lack of transparency and incongruence in how outliers are defined, identified, and handled are quite pervasive in articles published in some of the most prestigious and influential journals in the organizational sciences. As suggested by anonymous reviewers, we offer the aforementioned illustrations as concrete examples of these issues, but we emphasize that we do not wish to convey the impression that there is anything particularly unique about these specific studies.

Table 3. Outlier Handling Techniques Based on a Review of Methodological and Substantive Organizational Science Sources.

1. Correct value	Correcting a data point to its proper value.
2. Remove outlier	Elimination of the data point from the analysis.
3. Study the outlier in detail	Conducting follow-up work to study the case as a unique phenomenon of interest.
4. Keep	Acknowledging the presence of an outlier, but doing nothing to the outlier value prior to the analysis.
5. Report findings with and without outliers	Reporting substantive results with and without the outliers—which also includes providing an explanation for any difference in the results.
6. Winsorization	Transforming extreme values to a specified percentile of the data. For example, a 90th percentile Winsorization would transform all the data below the 5th percentile to the 5th percentile, and all the data above the 95th percentile would be set at the 95th percentile.
7. Truncation	Setting observed values within a believable range and eliminating other values from the data set.
8. Transformation	Applying a deterministic mathematical function (e.g., log function, ln function) to each value to not only keep the outlying data point in the analysis and the relative ranking among data points, but also reduce the error variance and skew of the data points in the construct.
9. Modification	Manually changing an outlier value to another, less extreme value.
10. Least absolute deviation	Similar to ordinary least squares, this method chooses values of the regression coefficients that limit the residuals by producing a function that closely approximates a set of data.
11. Least trimmed squares	This technique orders the squared residual for each case from the highest to the lowest, and then trims or removes the highest value.
12. M-estimation	A class of robust techniques that reduce the effect of influential outliers by replacing the squared residuals by another function of the residuals. In particular, in a time series analysis, this method is used when influential time series innovation outliers are identified.
13. Bayesian statistics	Bayesian statistics derive parameter estimates by weighing prior information and the observed data at hand. The use of such prior information helps "shrink" or pull the outlying data points closer to the center or centroid of the data.
14. Two-stage robust procedure	This method uses Mahalanobis distance to assign weights to each data point, so that cases that are extreme in the predictor variables are downweighted. This assignment of weights is completed through a two-stage process.
15. Direct robust method using iteratively reweighted least squares	Similar to two-stage robust procedures, this method uses Mahalanobis distance to assign weights to each data point. However, the assignment of weights is completed through the use of an iteratively reweighted least squares algorithm.
16. Generalized estimating equations (GEE) methods	These methods estimate the variances and covariances in the random part of the multilevel model directly from the residuals. The emphasis of this approach is on estimating average population effects, rather than on modeling individual and group differences. Though GEE estimates are less efficient than maximum likelihood estimates, GEE estimates make weaker assumptions about the structure of the random part of the multilevel model, thereby limiting the effect of influential outliers.
17. Bootstrapping methods	These methods estimate the parameters of a model and their standard errors from the sample, without reference to a theoretical sampling distribution. As a result, the researcher can calculate the estimates of the expected value and the variability of the statistics as taken from an empirical sampling distribution.

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Table 3. (continued)

18. Nonparametric methods	A nonparametric analysis does not assume that the data are distributed in any particular way. This flexibility helps researchers derive results that are robust in the presence of outliers. For example, to derive parameter estimates from data, one type of nonparametric method uses the rank of observations, as opposed to the raw values of the observations, some of which may be so extreme that they cause the corresponding observations to be influential outliers. As a result, a nonparametric analysis based on rank reduces (i.e., downweights) the influence of outliers.
19. Unweighted meta-analysis	Obtaining meta-analytic statistics (e.g., mean, standard deviation) that do not give more weight to primary-level studies with larger sample sizes.
20. Generalized M-estimation	A class of robust techniques that reduce the effect of outliers by replacing the squared residuals by another function of the residuals. In particular, in a time series analysis, this method is used when influential time series additive outliers are identified.

The third shortcoming we uncovered in our review of the substantive literature is that we found little discussion, let alone recommendations, on the subject of studying outliers that are found to be interesting and worthy of further examination. A pervasive view of outliers among substantive researchers is that outliers are "problems" that must be "fixed," usually by removing particular cases from the analyses. However, there are research domains in which outliers should more frequently be the focus of substantive research. For example, O'Boyle and Aguinis (2012) conducted five separate studies including 198 samples and 632,500 individual performers including researchers, politicians, entertainers, and athletes. O'Boyle and Aguinis found that the distribution of individual performance based on untransformed scores (i.e., scores expressed in their original metric) is not normal, but instead follows a Pareto (i.e., power law) distribution. The percentage of individual scores that deviate markedly from the sample mean is larger under a Pareto compared to a normal distribution, and therefore, outliers are more pervasive than previously thought. In short, there are some particular research domains in which studying outliers, rather than treating them as a nuisance that must be eliminated prior to conducting "cleaner" data analyses, may lead to important theoretical advancements.

In conclusion, as shown in Tables 1 through 3, our review of the methodological literature uncovered a staggering list of 14 outlier definitions, 39 identification techniques, and 20 handling techniques. Our review of the substantive literature revealed lack of transparency as well as incongruence in how substantive researchers define, identify, and handle outliers. Moreover, the pervasive view of outliers is that they are problematic observations that somehow must be "fixed"—which is not necessarily appropriate in many research contexts. Overall, our literature review provided evidence regarding the need for guidelines on how to define, identify, and handle outliers. We address this need next.

Making Decisions on How to Define, Identify, and Handle Outliers

Our recommendations on how to define, identify, and handle outliers are based on two overarching principles. The first principle is that choices and procedures regarding the treatment (i.e., definition, identification, and handling) of outliers should be described in detail to ensure transparency—including a rationale for the particular procedures that have been implemented. The second principle

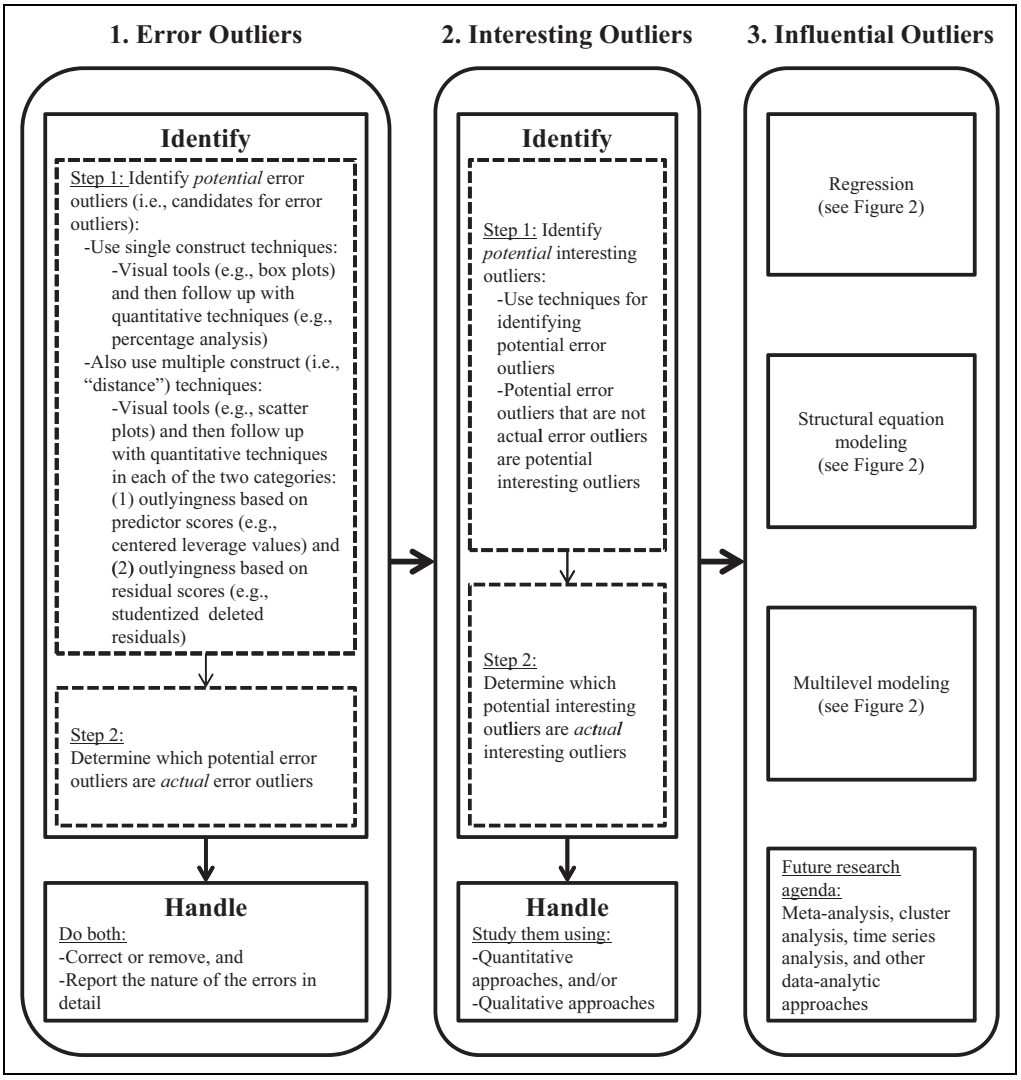


Figure 1. Decision-making tree summarizing sequential steps in the process of understanding the possible presence of outliers.

is that researchers should clearly and explicitly acknowledge the type of outlier in which they are interested, and then use an identification technique that is congruent with the outlier definition. Although the focus of our article is on regression, SEM, and multilevel modeling, these principles apply to outliers in all data-analytic contexts because their adoption will improve the replicability of substantive results—which is required for the advancement of science in general (Aytug, Rothstein, Zhou, & Kern, 2012; Brutus, Aguinis, & Wassmer, 2013). Moreover, the application of these two overarching principles will improve the interpretability of substantive conclusions.

Our more specific best-practice recommendations described next are built around a sequence of steps involving three categories of outliers, as shown in Figure 1. The first category consists of *error outliers*, or data points that lie at a distance from other data points because they are the result of inaccuracies. The second category represents *interesting outliers*, which are accurate data points that

lie at a distance from other data points and may contain valuable or unexpected knowledge. The third category refers to *influential outliers*, which are accurate data points that lie at a distance from other data points, are not error or interesting outliers, and also affect substantive conclusions. The approaches to identifying and handling error and interesting outliers are similar across data-analytic techniques. However, the way influential outliers are identified and handled depends on the particular technique—for example, regression versus SEM. Thus, we first provide a discussion regarding error and interesting outliers and then offer a separate treatment of influential outliers within each of the specific contexts of regression, SEM, and multilevel modeling. As seen in Figure 1, our recommendation is that all empirical studies follow the same sequence of steps. In addition, an anonymous reviewer suggested that all empirical research reports should include a short section on "Outlier Detection and Management," including a description of how each of the three types of outliers has been addressed.

Error Outliers

As shown in Figure 1, the first step in the process of understanding the possible presence of outliers is to check for error outliers. For this particular type of outlier, no a priori theory is needed. The rationale for checking for the possible presence of error outliers first is that this type of outlier is always undesirable (Huffman, Cohen, & Pearlman, 2010).

Defining Error Outliers

Error outliers are data points that lie at a distance from other data points because they are the result of inaccuracies. More specifically, error outliers include outlying observations that are caused by not being part of the targeted population of interest (i.e., an error in the sampling procedure), lying outside the possible range of values, errors in observation, errors in recording, errors in preparing data, errors in computation, errors in coding, or errors in data manipulation (Kutner et al., 2004; Orr et al., 1991; Tabachnick & Fidell, 2007). In short, error outliers are nonlegitimate observations.

Identifying Error Outliers

Identifying error outliers involves the first step of locating outlying observations (i.e., identification of *potential* error outliers—candidates for error outliers), and then the second step of separately investigating whether the outlyingness of such data points was caused by errors (i.e., identification of *actual* error outliers). Identifying potential error outliers involves using a variety of visual and quantitative techniques, which compensates for the relative weakness of each (Belsley, Kuh, & Welsh, 1980; Edwards & Cable, 2009). In other words, using more than one technique is necessary to identify as many potential error outliers as possible, even if some of these observations eventually do not turn out to be actual error outliers.

Results of our literature review summarized in Table 2 show that there are several techniques available for identifying potential error outliers, which can be grouped into two categories: single construct techniques and multiple construct (also labeled "distance") techniques. Single construct techniques examine extreme values within each individual construct, whereas multiple construct techniques assess how far an observation is from a centroid of data points computed from two or more constructs. We recommend that both single and multiple construct techniques be used.

For single construct techniques, the recommendation is to use visual tools first and then follow up with quantitative approaches, which include standard deviation analysis or percentage analysis. The recommended cutoff for the quantitative techniques is that potential error outliers be identified as observations in the top and bottom 2.5% (two-tailed, $\alpha = .05$) in a percentage analysis, or observations

above or below ± 2.24 standard deviation (*SD*) units in a standard deviation analysis, if the underlying population distribution is assumed to be approximately normal (M. Martin & Roberts, 2010). The reason for this cutoff rule is that cases above or below the top and bottom 2.5% are considered sufficiently unlikely to be caused by substantive reasons assuming a "*t*-like" distribution (M. Martin & Roberts, 2010, p. 258). Furthermore, the cutoff rule accounts for a study's particular research design by identifying a greater number of potential error outliers for studies with larger sample sizes.

For multiple construct techniques, the recommendation is to also begin with visual tools and then follow up with at least one quantitative approach in each of the following two categories: (a) outlyingness based on scores of predictors (i.e., leverage, centered leverage, and Mahalanobis distance values) and (b) outlyingness based on residual scores (i.e., studentized deleted residuals, deletion standardized multivariate residuals). Regarding outlyingness based on scores of predictors, researchers can use leverage, centered leverage, or Mahalanobis distance values because they produce the same type of information but on different scales (Fidell & Tabachnick, 2003). Regarding outlyingness based on residuals scores, studentized deleted residuals can be used for regression (Cohen et al., 2003) and SEM (Tabachnick & Fidell, 2007), and deletion standardized multivariate residuals can be used for multilevel modeling (Snijders & Bosker, 2012). Also, for the particular case of multilevel modeling, identification techniques are first applied at the highest level of analysis. For example, in a two-level model consisting of individuals nested in groups, single construct techniques are applied to the groups (in a later section on influential outliers in multilevel modeling, we discuss when and how to then check for error outliers in lower level[s] of analysis). We recommend this top-down approach based on a practical consideration given that it allows the researcher to pinpoint a smaller number of groups whose lower level data points are worth examining.

Recommended cutoffs for leverage values are $2(k + 1)/n$ for large sample sizes and $3(k + 1)/n$ for small sample sizes, where $k =$ number of predictors and $n =$ sample size (Cohen et al., 2003). For centered leverage values, recommended cutoffs are $2k/n$ for large sample sizes and $3k/n$ for small sample sizes (Cohen et al., 2003). For Mahalanobis distance, recommended cutoffs are $\chi^2_{df = p;\ \text{alpha level} = \alpha/n}$ for large sample sizes (Becker & Gather, 1999), and $\frac{p(n-1)^2\left(F_{df=p,n-p-1;\text{alphalevel}=\frac{\alpha}{n}}\right)}{n\left(n-p-1+pF_{df=p,n-p-1;\text{alphalevel}=\frac{\alpha}{n}}\right)}$ for small sample sizes (Barnett & Lewis, 1994), where $p =$ number of variables, $\chi^2 =$ critical value in a chi-square distribution, $F =$ critical value in an F distribution, and $\alpha = .05$ or .01. Recommended cutoffs for studentized deleted residuals are $t_{df = n-k-1;\ \text{alphalevel} = \alpha/n}$, where $t =$ critical value in a t distribution, and $\alpha = .05$ or .01. Finally, cutoffs for deletion standardized multivariate residuals for multilevel modeling are based on $\chi^2_{df = n \text{ of highest level unit } j;\ \text{alphalevel} = \alpha/n}$, where $\alpha = .05$ or .01 (Snijders & Bosker, 2012, p. 169).

The rationale for the aforementioned recommendations is that they take into account research design considerations by adjusting the cutoff value based on the sample size and number of predictors in the model (M. Martin & Roberts, 2010). From a practical standpoint, our recommendations are also based on the availability of these techniques in widely used software packages for regression (Cohen et al., 2003), SEM (Byrne, 2001; Tomarken & Waller, 2005; Zhang & Yuan, 2012), and multilevel modeling (Raudenbush, Bryk, Cheong, Congdon, & Du Toit, 2004). Moreover, code that derives deletion standardized multivariate residuals is also available in MLwiN, R, and Stata (see www.stats.ox.ac.uk/~snijders/mlbook.htm).

Once potential error outliers have been identified, it is premature to subsequently conclude that the outlying data points are error outliers—at this point, they are only candidates for error outliers. Instead, it is necessary to determine the cause of the identified outlying observations by, for example, checking whether original data entries (e.g., questionnaire responses) match the entries in the electronic data files. If caused by an error in recording, coding, or data collection (e.g., not part of population of interest), then an outlying observation is an error outlier (Huffman et al., 2010). All

remaining outlying data points whose cause is unclear are treated as interesting outliers (as discussed later in our article).

Handling Error Outliers

Once error outliers have been identified, the correct procedure is to either adjust the data points to their correct values or remove such observations from the data set (Kutner et al., 2004). In addition, it is necessary to explain in detail the reasoning behind the classification of the outlier as an error outlier. For example, was it a coding error? A data entry error? A case that was inadvertently and incorrectly included in the database? As noted earlier, transparency is an important overarching principle that is particularly critical in the case of error outliers. The reason is that an error outlier must be handled by changing the value of the data point or removing it—either of which can lead to important changes in substantive conclusions.

Table 4 includes information resulting from our substantive literature review. Specifically, it includes examples of common situations faced by researchers in terms of how they have defined, identified, and handled various types of outliers. We will continue to refer to Table 4 throughout our article. Regarding error outliers, this table illustrates the common situation researchers face when dealing with such outliers. A positive example of handling error outliers is a study by Worren, Moore, and Cardona (2002). First, Worren et al. identified an outlying data point (i.e., a potential error outlier). Then, to determine whether this was an error outlier, they placed a phone call to the respondent and found that this individual had misunderstood some of the questions. Subsequently, corrections were made to the error outlier based on the conversation. Table 4 also describes an incorrect, yet frequently used, way of addressing possible error outliers. This involves automatically deleting data points that deviate markedly from the rest without clearly understanding the reasons for such deviation. Deleting outlying data points prior to determining if they are indeed errors or not is an incorrect procedure. Each row in Table 4 includes illustrations of correct and incorrect ways of dealing with outliers—including error, interesting, and influential outliers—and how these different procedures result in changes in substantive conclusions.

We readily acknowledge that Institutional Review Boards (IRBs) vary with respect to how they would view the practice of contacting participants to clarify outlying responses. Moreover, many IRBs may require that data files be made anonymous as quickly as possible by stripping out identifying information, which may make it very difficult to identify individual respondents. Thus, it is important for researchers to keep diaries, logs, or journals during data collection that can be used retrospectively to determine if something unusual happened with some particular case that can no longer be traced after the fact.

Interesting Outliers

As shown in Figure 1, the second step in the process of understanding the possible presence of outliers is to examine *interesting outliers*. As noted in the previous section, we recommend against the practice of automatically treating any outlying data point as harmful (Hawawini, Subramanian, & Verdin, 2003). We make this recommendation for two reasons. First, defining outliers in a negative way most often leads to simply removing these cases, a practice that may result in artificial range restriction (McNamara, Aime, & Vaaler, 2005). Second, whether these outliers are eventually excluded from the analysis or not, simple removal and thus failure to study these outliers separately in detail can mean forgoing discovery of valuable, future-oriented knowledge (Mohrman & Lawler, 2012).

Table 4. Common Research Situations Illustrating Correct and Incorrect Procedures for Defining, Identifying, and Handling Different Types of Outliers.

	Correct Procedures	Rationale for Correct Procedures	Incorrect Procedures	Difference in Substantive Conclusions
Error outlier	Worren et al. (2002) identified a potential error outlier. They investigated further and found that, after a phone call, the respondent had misunderstood some of the questions. Corrections were made to the data based on the telephone conversation. Also, Huffman et al. (2010) eliminated some outliers, which they found were caused by coding errors.	The amount of deviation of a data point from others does not necessarily mean that the data point was caused by error. A potential error outlier is an actual error outlier when its deviation is caused by inaccuracies—and evidence must be provided regarding this issue.	Huffman et al. (2010) removed outlying data points that were caused by "some unidentifiable change in the [firm] structure" (p. 263), suggesting that these cases were outside the population of interest. Yet, neither the hypotheses nor the theoretical rationale for the hypotheses explained why these outlying firms, which underwent unidentifiable changes in firm structure, fell outside the focal population, thereby putting into question whether such cases were actually error outliers. Thus, Huffman et al. essentially deleted some outliers that were assumed to be error outliers, but without determining beforehand whether they were indeed error outliers.	Huffman et al. (2010) noted that some of the data points they incorrectly removed had "corrupting effects" on the results (p. 263), indicating that the removal of these data points changed substantive conclusions. Had the authors instead treated these data points as interesting or influential outliers, and then reported the results with and without the influential outliers, they would have been able to provide multiple versions of the analytical results, thereby enriching the substantive conclusions and potential for replicability of their study.
Interesting outlier	Treating unusually successful or unsuccessful acquisitions as potential sources of valuable knowledge, Hitt et al. (1998) identified the 12 most successful and the 12 least successful acquisitions as interesting outliers. Then, they applied a case study method on the 24 pairs of firms identified as interesting outliers.	A study of interesting outliers may result in a generation of future-oriented knowledge that also informs practice (Mohrman & Lawler, 2012).	Although Hawawini et al. (2003) defined exceptionally high-performing (i.e., outlying) but rare firms as "interesting" outliers (p. 2), the authors did not separately study these cases as sources of knowledge. Instead, Hawawini et al. investigated the influence that outliers have on firm-specific and industry effects by simply reporting the results with and without the outliers.	By applying the correct procedures, Hitt et al. (1998) were able to derive potential predictors of outliers in the research domain of acquisitions. That is, they found that certain attribute configurations (e.g., resource complementarities, friendly negotiations, low to moderate debt, and change experience) facilitated unusual acquisition success, whereas other distinct attribute configurations (e.g., large to extraordinary debt, inadequate target evaluation, ethical concerns, and top management team changes) led to unusual acquisition failure.

(continued)

Table 4. (continued)

	Correct Procedures	Rationale for Correct Procedures	Incorrect Procedures	Difference in Substantive Conclusions
Influential outliers when conducting regression	Multiple authorship teams clearly stated the identification techniques that they used, and these identification techniques were appropriate (although authors did not use $DFBETAS_{ij}$; Colbert et al., 2008; Edwards et al., 2006).	Correct identification techniques, and their description, are necessary to maximize transparency and to ensure that influence outliers are properly detected.	Godfrey, Merrill, and Hansen (2009) did not explicitly state how outliers were identified. Instead, they made the vague statement that they "ran regression diagnostics to look for outliers" (p. 435).	Failure to explicitly state how outliers were identified or failure to use any outlier identification technique harms the credibility of substantive conclusions in the eyes of a skeptical scientific readership. Had Godfrey et al. (2009) used correct procedures (i.e., use appropriate identification techniques, and clearly state that they were used), the authors would be better able to prevent readers from raising doubts about the conclusions of their studies.
Influential outliers when conducting structural equation modeling	Goerzen and Beamish (2005) used a handling technique (i.e., deletion) and reported findings with and without the handling technique to ensure transparency.	Reporting results with and without the handling technique ensures transparency and prevents readers from questioning whether the data were "manipulated" to confirm support for the hypotheses.	Multiple authorship teams used a handling technique (i.e., deletion) on higher level units, but did not report the findings both with and without the deleted outliers (Amiot, Terry, Jimmieson, & Callan, 2006; Brown, Cober, Kane, Levy, & Shalhoop, 2006).	In studies conducted by Amiot et al. (2006), as well as Brown et al. (2006), results were not reported with and without the outlier handling technique used, thus providing readers with only one version of the results. In contrast, by reporting the results both with and without influential outliers, Goerzen and Beamish (2005) not only ensured transparency but also gave readers both versions of their analytical results, thereby enriching the substantive conclusions of their studies.
Influential outliers when conducting multilevel modeling	Smillie et al. (2006) used a short footnote to clearly state that the removal of three influential outliers changed the statistical significance of two parameter estimates but ultimately failed to change the substantive conclusions.	Even if influential outliers ultimately fail to change the substantive conclusions, the practice of reporting the results with and without the handling technique (e.g., deletion) prevents skeptical readers from suspecting that the researchers of a study manipulated data to maximize the chance of finding support for their hypotheses and then deliberately refrained from mentioning such a manipulation.	Wanberg, Glomb, Song, and Sorenson (2005) used a handling technique (i.e., replacing outlier values at the 99th percentile of the responses) but did not report the findings both with and without the handling technique.	In Wanberg et al. (2005), the authors did not report their findings with and without the handling technique. Thus, readers were presented with only one version of the results, possibly raising suspicion in the eyes of a skeptical scientific readership. Had Wanberg et al. reported their results with and without the handling technique, such a suspicion would be minimized or even eliminated.

Defining Interesting Outliers

Interesting outliers are outlying data points that are accurate—that is, data points that have been identified as outlying observations (i.e., potential error outliers), but not confirmed as actual error outliers. Also, these cases may contain potentially valuable or unexpected knowledge (Cohen et al., 2003; Mohrman & Lawler, 2012). Consider the following three examples from different organizational science domains. First, Wiggins and Ruefli (2005) identified firms that were interesting outliers because they lost their superior economic performance. Second, the positive psychology movement has focused on studying and analyzing individuals who are interesting outliers in terms of their feelings of happiness (Diener, 2000; Seligman & Csikszentmihalyi, 2000). Finally, as mentioned earlier, O'Boyle and Aguinis (2012) encouraged the study of interesting outliers defined as top performers. In fact, Gladwell's (2008) best-selling book is based on the premise of interesting outliers: unique individuals whose lives and career trajectories can be used in support of the contention that success in any field is largely the result of practicing a specific task for a minimum of about 10,000 hours.

Identifying Interesting Outliers

Identifying interesting outliers involves two steps. The first step is to identify potential interesting outliers, and the second step is to identify which outliers are actually interesting outliers. The first step will have been already completed by the researcher following our decision-making tree in Figure 1. The reason is that this step also involves the use of techniques that are the same as the techniques used to identify potential error outliers, and then any potential error outlier that is not an actual error outlier automatically becomes a potential interesting outlier. In the second step, the particular research domain influences how interesting outliers are identified from potential interesting outliers identified in the previous step. For example, if there is an interest in identifying certain individuals who are on more than 10 corporate boards, then potential interesting outliers identified through single construct techniques would be considered interesting outliers. If there is an interest in studying the relationship between two constructs, such as firms that are outliers in annual profit and annual cost in research and development, then potential interesting outliers would be identified through multiple construct identification techniques. Note that interesting outliers can either be the focus of a study prior to data collection (i.e., a priori interesting outliers) or be identified after the data are collected (i.e., post hoc interesting outliers).

It is possible that a case is an error outlier, but the source of the error is not detected. In such situations, this case is likely to be treated as a potential interesting outlier incorrectly. As noted by an anonymous reviewer, pursuing potential interesting outliers is likely to include the examination of a great many error outliers that simply went undetected as errors. Such a situation is addressed by referring back to the first of the two overarching principles we mentioned earlier: Choices and procedures regarding the treatment of outliers should be described in detail to ensure transparency—including a rationale for the particular procedures that have been implemented. In the particular situation involving possible undetected error outliers, because procedures were open and transparent, future research would be able to attempt to replicate results (i.e., the presence of a large number of potentially interesting outliers). As noted by an anonymous reviewer, "The chances of an error outlier occurring twice are calculably infinitesimal. If it does occur twice, however, then the evidence of its uniqueness is almost beyond reproach."

Handling Interesting Outliers

Our recommendation on how to handle interesting outliers is to study them. This can be done by using a quantitative approach similar to that used by St. John and Harrison (1999), who empirically

analyzed differences between the manufacturing synergies of high and low outlier performers. In addition, interesting outliers can be examined by adopting a qualitative approach similar to the one used by Gladwell (2008), who investigated the factors that contribute to high levels of individual success.

A positive example of how to handle interesting outliers is a study by Hitt et al. (1998), which examined firm acquisitions that were either highly successful or highly unsuccessful. These authors identified highly successful acquisitions as 12 pairs of firms that showed increases in both industry-adjusted performance (i.e., return on assets) and industry-adjusted research and development intensity after the acquisition, whereas highly unsuccessful acquisitions were identified as 12 pairs of firms exhibiting the greatest reduction in both of the previously mentioned firm characteristics after the acquisition. They then applied a case study method on the 24 pairs of firms identified as interesting outliers. Doing so resulted in substantial theoretical implications in which Hitt et al. were able to derive potential predictors of outliers in the research domain of acquisitions. In contrast, failing to study numerous observations identified as interesting outliers constitutes an incorrect way of handling interesting outliers (see Table 4). The alternative of studying such outliers could have resulted in novel theoretical insights.

Influential Outliers

In contrast to the procedures for defining, identifying, and handling error and interesting outliers, which are fairly invariant across data-analytic approaches, *influential outliers* are addressed differently depending on particular statistical techniques. There are two types of influential outliers: (a) *model fit outliers* and (b) *prediction outliers*. Model fit outliers are data points whose presence alters the fit of a model, and prediction outliers are data points whose presence alters parameter estimates. Next, we discuss influential outliers within the particular contexts of (a) regression, (b) SEM, and (c) multilevel modeling. Please refer to Figure 2 for decision-making charts showing the sequence of steps involved in defining, identifying, and handling model fit and prediction outliers within the context of each of these three popular data-analytic approaches.

Regression

Defining and identifying model fit outliers. Model fit outliers are defined as cases that affect model fit (e.g., R^2). Depending on their location, they can either increase or decrease model fit. In practice, a model fit outlier often affects both model fit and parameter estimates (i.e., slope and/or intercept coefficients).

Figure 3 includes a simplified graphic illustration of a regression analysis on a hypothetical data set involving one predictor and one criterion. Please note that we use an unusually small sample size for this illustration for pedagogical purposes. The R^2 for the data included in Figure 3 is .73 when Cases 1, 2, and 3 are excluded from the analysis. When Case 1, Case 2, or Case 3 is included, model fit changes to .11, .95, or .17, respectively. Furthermore, the inclusion of Case 1 or Case 3 reduces model fit and also affects the parameter estimates (i.e., the intercept and/or slope). In contrast, Case 2 affects (i.e., improves) only model fit because of its location along the regression line.

To identify model fit outliers, we recommend a two-step process. The first step involves identifying data points that are most likely to have influence on the fit of the model because they deviate markedly from other cases in the data set. The second step involves investigating such cases to understand if they actually have influence on model fit. The rationale for the first step is a practical one because the first step reduces the number of cases to which the more time-consuming and effortful second step must be applied.

The first step is automatically completed once the researcher has implemented our recommendations regarding error and interesting outliers earlier (see Figure 1). More specifically, cases that have

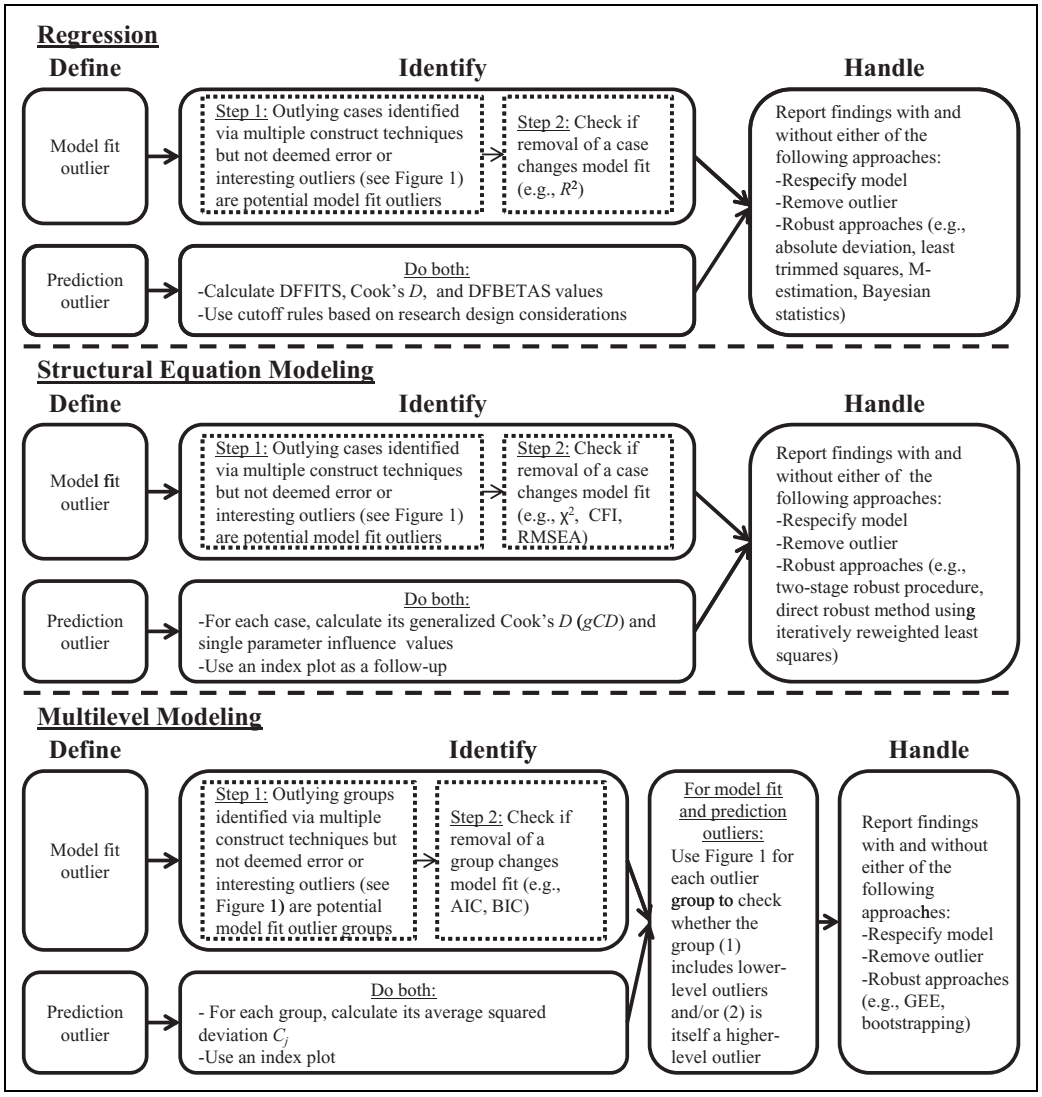
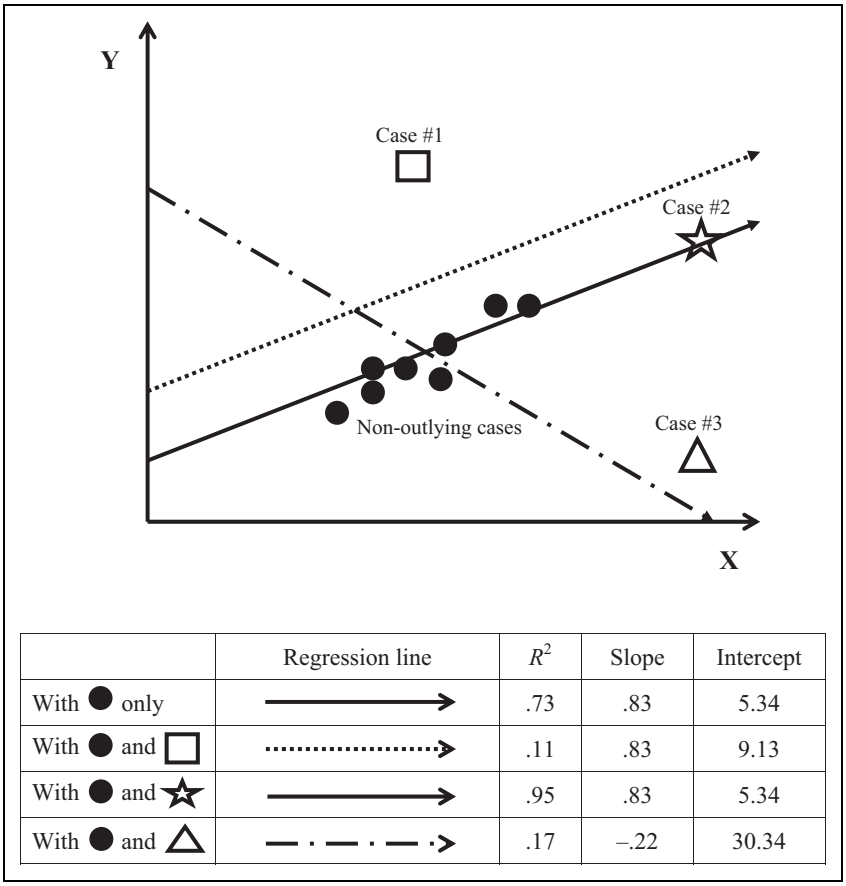


Figure 2. Decision-making tree summarizing sequential steps in the process of defining, identifying, and handling influential outliers in the context of regression, structural equation modeling (SEM), and multilevel modeling.

been identified with multiple construct techniques and subsequently determined not to be error or interesting outliers constitute candidates for model fit outliers.

The second step in the identification of model fit outliers is to determine whether cases that differ markedly from the rest actually influence model fit (e.g., R^2). This involves checking whether the removal of an observation changes the statistical significance of a model fit index either from statistically significant to statistically nonsignificant, or vice versa (Yuan & Bentler, 1998).

Defining and identifying prediction outliers. Prediction outliers are defined as cases that affect parameter estimates (i.e., slope and/or intercept coefficients). As illustrated in Figure 3, a data point can



	Regression line	R^2	Slope	Intercept
With ● only	———	.73	.83	5.34
With ● and □	·····	.11	.83	9.13
With ● and ☆	———	.95	.83	5.34
With ● and △	— · — · —	.17	–.22	30.34

Figure 3. Graphic illustration of influential outliers (i.e., model fit and prediction outliers) in the context of regression.

be a prediction outlier by either (a) having a large residual value (e.g., Case 1) or (b) having both a large residual value and extreme value(s) on the predictor(s) (e.g., Case 3). Note that having extreme values on the predictors but a small residual value will not make a data point a prediction outlier (see Case 2), although, as noted earlier, this case is likely to be a model fit outlier.

There are three techniques that are specifically designed to assess the presence of prediction outliers in the context of regression: $DFFITS_i$ (DIFFerence in FIT, Standardized—note that this is an index of prediction and not model fit outliers in spite of its label), Cook's D_i, and $DFBETAS_{ij}$ (DIFFerence in BETA, Standardized). Subscript *i* refers to an observation, and *j* denotes a regression coefficient (Cohen et al., 2003). These prediction outlier identification techniques are available in most software packages, and they share two common characteristics. First, each is calculated for every observation. Second, each of them is a ratio, where the numerator quantifies the amount of change in the parameter estimate(s) when the observation *i* is excluded from the sample. The denominator is a standard error term that is also calculated without observation *i* in the sample.

In spite of their similarities, these three techniques also have an important difference. $DFFITS_i$ and Cook's D_i are global indicators that assess the influence that a data point has on all regression coefficients as a whole, whereas $DFBETAS_{ij}$ is a more specific index that quantifies the influence that an observation has on a particular regression coefficient *j*. Given this difference, $DFFITS_i$ or

Cook's D_i and DFBETAS$_{ij}$ do not always converge. That is, a case may have a strong influence on just one regression coefficient but very small influence on others. As a result, the observation's strong influence on the single regression coefficient may be masked in a global measure of influence. Referring back to Figure 3, DFFITS$_i$ and Cook's D_i could easily detect prediction outliers such as Case 3 because it exerts a disproportionate influence on both the slope and the intercept. However, these two global measures of influence are less likely to detect Case 1 because this prediction outlier exerts a disproportionate influence only on the intercept. Using DFBETAS$_{ij}$ would increase the likelihood that Case 1 is identified as a prediction outlier. Therefore, it is important to also investigate specific prediction outliers in addition to global prediction outliers.

We suggest the following cutoffs (Belsley et al., 1980). For DFFITS$_i$, the recommended cutoff is $\pm 2\sqrt{\frac{k+1}{n}}$ for observation i to be considered a prediction outlier, where k represents the number of predictors, and n represents the number of observations. For Cook's D_i, the recommendation is to use the F distribution, with $df = (k + 1, n - k - 1)$ and $\alpha = .50$, to determine the statistical significance of the values at hand (Cohen et al., 2003). For DFBETAS$_{ij}$, the recommended cutoff is $\pm 2/\sqrt{n}$ for the observation i to be considered a prediction outlier regarding regression coefficient j. The rationale for these recommendations is that they were intentionally designed to adjust cutoff values depending on characteristics of the particular research context such as sample size and number of predictors (Cohen et al., 2003).

Handling model fit and prediction outliers. The options for handling model fit and prediction outliers are the same. Cohen et al. (2003) offered a framework that consists of three courses of action: (a) respecification, (b) deletion, and (c) robust approaches. These approaches also coincide with the handling techniques that we identified in our review of the methodological literature.

Respecification refers to adding additional terms to the regression equation. For example, these additional terms may carry information about nonlinear effects (i.e., squared terms; Pierce & Aguinis, 2013) or moderating effects (i.e., product terms; Aguinis, 2004; Cohen et al., 2003). If the added variable adds incremental variance, there is a chance that the outlier may no longer be such. If the respecified model is supported (i.e., if the terms added post hoc significantly improve model fit or prediction), then the researcher can also build new theoretical models that can be tested, confirmed, or disconfirmed in future research. In other words, respecifying models post hoc is beneficial in terms of helping researchers engage in theory building (Locke, 2007), which is a type of contribution that is underutilized in many domains in the organizational sciences (Aguinis, Forcum, & Joo, in press; Shepherd & Sutcliffe, 2011). Note that respecification capitalizes on chance—an element that should not be used for theory testing because of generalizability and ethical concerns (Leung, 2011). So if the researcher decides to report respecified model(s), along with a discussion about their implications for theory building, we recommend that the discussion be elaborated in the ''future research directions'' section of the manuscript (Brutus et al., 2013).

Regardless of whether respecification is used, other ways of handling influential outliers are to delete them or use robust approaches (which involves a non-OLS standard such as least absolute deviation, least trimmed squares, M-estimation, and Bayesian statistics; Kruschke, Aguinis, & Joo, 2012). We emphasize the importance of reporting the results with and without the chosen handling technique, which includes providing an explanation for any differences in the results, because the mere presence of influential outliers causes a dilemma in determining proper inference about a population based on a sample. In other words, deletion or robust techniques remove or limit the information provided by an actual data point, perhaps making the sample a biased representation of the population. Because the absence or presence of a handling technique may lead to improper inferences about a population, both results should be reported to (a) place the burden of determination for the most ''accurate conclusions'' on the reader and (b) ensure complete transparency so that

the handling technique does not appear to have been chosen because it supported one's hypotheses. This recommendation is consistent with a customer-centric approach to reporting scientific results (Aguinis et al., 2010).

On a positive note, our review of the substantive literature yielded examples of authorship teams that clearly stated the identification techniques used, and these identification techniques were appropriate (although authors did not use $DFBETAS_{ij}$; e.g., Colbert, Kristof-Brown, Bradley, & Barrick, 2008; Edwards, Cable, Williamson, Lambert, & Shipp, 2006). However, on a less positive note, other authors did not clearly state the techniques used to identify influential outliers (see Table 4). Without a description of the identification techniques used, a skeptical scientific audience might raise doubts about a study's substantive conclusions.

Structural Equation Modeling

In this section, we discuss influential outliers in the context of SEM by addressing model fit and prediction outliers. Please refer to Figure 2 for a summary of the decision points involved.

Defining and identifying model fit outliers. Similar to regression, the identification of model fit outliers in SEM is a two-step process. The first involves identifying model fit outlier candidates. The second involves investigating which of the candidates have influence on the model's fit. As explained in our earlier section on regression, the first step helps researchers save time and effort, especially if the sample size is large.

As was the case with regression, the first step should already be completed after the implementation of our recommendations regarding error and interesting outliers (see Figure 1). In other words, outliers that have been identified with multiple construct techniques and subsequently determined not to be error or interesting outliers constitute candidates for model fit outliers. The second step in identifying model fit outliers in SEM is to check whether the removal of a candidate changes the fit of the model (Yuan & Bentler, 1998). That is, excluding an observation may cause a change in the statistical significance of the overall model fit based on χ^2 or other fit indexes such as the comparative fit index (CFI) or root mean square error of approximation (RMSEA).

Defining and identifying prediction outliers. As is the case in the context of regression, there are two types of prediction outliers: global prediction outliers and specific prediction outliers. A global prediction outlier influences all parameter estimates in a particular model. On the other hand, a specific prediction outlier is defined as a data point that exerts influence on a single parameter estimate. Thus, global prediction outlier methods in SEM are analogous to Cook's D_i and $DFFITS_i$ in regression, whereas specific prediction outlier techniques in SEM are analogous to $DFBETAS_{ij}$.

Our recommendation is to use the generalized Cook's distance (gCD_i) statistic to identify global prediction outliers, where i refers to a data point (Pek & MacCallum, 2011). We suggest calculating a gCD_i value for every observation for the following reasons. First, gCD_i values are calculated using a software package, and, consequently, there is no additional effort required in investigating all cases compared to just a few. Second, it is usually the case that there are no specific a priori predictions about which cases may be prediction outliers. Accordingly, it is beneficial to examine gCD_i values for all observations.

A gCD_i value is interpreted as a ratio, where the numerator quantifies the amount of change in a group of parameter estimates when an observation i is excluded from the sample. The denominator of this ratio is a standard error term that is also calculated without observation i in the sample. Note that gCD_i will always be positive, such that it indicates the absolute magnitude of change but not the direction of change. The reason for this is that gCD_i represents the change in multiple parameter estimates (not a single estimate), and it is not logically possible to show through a single value how

multiple parameter estimates change in possibly different directions. Nonetheless, the absolute magnitude of change is summarized in a single value of gCD_i: The greater the value of gCD_i, the greater the global influence of the corresponding data point on the parameter estimates (Pek & MacCallum, 2011). There are no clear cutoffs regarding what gCD_i value indicates a global prediction outlier. Thus, we recommend the use of an index plot, which includes case numbers on the *x*-axis and gCD_i values on the *y*-axis, to gain a better understanding of which gCD_i values, and thus corresponding cases, markedly deviate from others. For example, N. Martin and Pardo (2009) used index plots for a variety of test statistics.

Note that a case may have a strong influence on just one parameter estimate but very small influence on others. As a result, the observation's strong influence on the single parameter estimate may be masked in a global measure of influence. Therefore, it is important to also examine specific prediction outliers. Specific prediction outliers are identified by $\Delta\hat{\theta}_{ji}$, or the single parameter influence, which is the standardized change in the *j*th parameter resulting from the deletion of observation *i* (Pek & MacCallum, 2011). Please note that positive values of $\Delta\hat{\theta}_{ji}$ indicate that excluding case *i* causes a smaller value of $\hat{\theta}_j$ (i.e., estimate of the *j*th parameter), whereas negative values of $\Delta\hat{\theta}_{ji}$ indicate that excluding case *i* causes a larger value of $\hat{\theta}_j$. Thus, unlike a global prediction outlier represented by gCD_i, which expresses the absolute magnitude of change but not the direction of change, a specific prediction outlier identified by $\Delta\hat{\theta}_{ji}$ captures both the magnitude and the direction of change. In addition, for $\Delta\hat{\theta}_{ji}$ values to be identified as being influential, we recommend that $\Delta\hat{\theta}_{ji}$ values also be graphed in an index plot because there are no clear cutoffs. Observations with $\Delta\hat{\theta}_{ji}$ values that markedly deviate from other $\Delta\hat{\theta}_{ji}$ values are deemed specific prediction outliers (Pek & MacCallum, 2011). Finally, $\Delta\hat{\theta}_{ji}$ can be calculated by using a combination of R code, Mplus batch runs, and SAS code. More generally useful R code is currently being developed by Pek and MacCallum (Jolynn Pek, personal communication, July 6, 2012).

Handling influential outliers. Our recommendations for handling influential outliers in SEM are, overall, similar to those for regression. That is, regardless of whether researchers decide to respecify the model for theory-building purposes, we recommend the use of deletion or robust approaches. Regarding robust approaches, we recommend a two-stage robust procedure (Yuan & Bentler, 1998) or a direct robust method using iteratively reweighted least squares (Yuan & Zhong, 2008; Zhong & Yuan, 2011). Both of these methods use Mahalanobis distance to identify extreme cases and limit their influence in the analysis. Using either of these robust methods will lead to estimators that are not as heavily affected by influential outliers (Zhong & Yuan, 2011). Whether deletion or robust regression is used, we again emphasize the need to report the results obtained with and without the technique—a practice that also includes providing an explanation for any difference in substantive results. Implementing this recommendation will improve transparency in the eyes of a skeptical scientific audience.

Based on our review of the substantive literature, fewer than 5% of the 232 studies relied on SEM. One likely reason for this low frequency, compared to approximately 40% of the 232 studies that used regression, is that there are not many studies or textbooks discussing the role of outliers when conducting SEM as is the case for regression. Therefore, it is likely that if more clear guidelines for SEM exist, as we are hoping to provide with our article, researchers will be able to routinely address outliers, and also will report their choices for doing so, in future studies relying on SEM. At the same time, a common situation that we found across the studies that dealt with outliers when using SEM was the choice of how to handle influential outliers. In a study by Goerzen and Beamish (2005), the authorship team addressed outliers correctly by reporting their findings with and without a specific handling technique (i.e., deletion). On the other hand, there were multiple other authorship teams

that engaged in a specific handling technique (i.e., deletion) yet did not report their findings with and without the handling technique (see Table 4).

Multilevel Modeling

Multilevel modeling incorporates data at multiple levels of analysis and estimates parameters that reflect fixed and random effects. Given the complexity of the issues involved, it is not surprising that there are few resources that discuss outliers in multilevel modeling, and many of those are highly technical (e.g., Shi & Chen, 2008). In the multilevel modeling context, the task of defining, identifying, and handling outliers becomes more complex compared to regression and SEM. When using multilevel modeling, assuming a research design involving individuals nested within groups, the relationship between a lower level predictor and a lower level criterion can be plotted for each group, representing as many lines of relations as there are groups. So, for each of these groups, there could be model fit and/or prediction outliers. Also, there could be groups that are vastly different from other groups in terms of their mean value, variance, intercept, and/or slope. Finally, there can be variation in sample sizes across groups, such that one group has many lower level units and another group has few lower level units. Specifically, Mathieu, Aguinis, Culpepper, and Chen (2012) reviewed 79 multilevel investigations published in the *Journal of Applied Psychology* between 2000 and 2010 and found that Level 2 sample size ranged from 12 to 708 ($Mdn = 51$).

Regardless of whether a multilevel study includes hypotheses about same-level direct effects (e.g., effect of individual job satisfaction on individual job performance), cross-level direct effects (e.g., effect of team-level cohesion on individual job performance), or cross-level interaction effects (e.g., moderating effect of team-level cohesion on the relationship between individual job satisfaction and individual job performance), the main goal of any analysis is to assess the size of the variance components and the sources of such variances. Consider the case where there is a data point in one group that causes the intercept and/or slope of that group to be vastly different from other groups. Such a point could lead one to believe that there are between-group differences when in fact such differences may not actually exist across most groups. Figure 2 includes a summary of the decision points involved in the process of defining, identifying, and handling influential outliers in multilevel modeling, which we discuss next.

Defining and identifying model fit outliers. From a practical standpoint, it is beneficial to adopt a top-down approach to identifying model fit outliers in multilevel modeling (Langford & Lewis, 1998). Thus, the implementation of outlier identification procedures begins at the highest level of analysis (i.e., Level 3 in a three-level model, Level 2 in a two-level model). As a result of these identification procedures, the researcher then determines whether a group of observations affects the model fit because of (a) the group itself and/or (b) a particular data point(s) in the group. If the former situation is correct, then the focal group is identified as a higher level outlier (i.e., outlier group). If the latter situation is correct, then the individual observation(s) is identified as a lower level outlier. Again, the rationale for this top-down approach is practical in nature because doing so is less time-consuming compared to using a bottom-up approach (i.e., examining lower level outliers within each group first). Next, we elaborate on the details of this top-down approach applied to model fit outliers. In doing so, we base our discussion on a two-level model, but our discussion can be extrapolated to situations involving more than two levels.

The identification of model fit outliers takes place through three steps: first, identifying model fit outlier group candidates; second, assessing whether the candidate groups truly affect model fit; and third, checking whether an actual model fit outlier group's outlyingness is driven by (a) an outlying data point(s) in the group and/or (b) the entire group. The first step is automatically completed once the researcher has implemented our recommendations regarding error and interesting outliers

discussed earlier (see Figure 1). In short, outlier groups that have been identified with multiple construct techniques and subsequently determined not to be error or interesting outliers constitute candidates for model fit outlier groups. The second step involves checking whether the removal of a candidate group changes model fit either from statistically significant to statistically nonsignificant, or vice versa (Yuan & Bentler, 1998). More specifically, the exclusion of a candidate group may cause a change in the statistical significance of the overall model fit (e.g., Akaike information criterion [AIC] or Bayesian information criterion [BIC]) or incremental variance explained (see Van Dick, Van Knippenberg, Kerschreiter, Hertel, & Wieseke, 2008). If the exclusion of a candidate group changes the statistical significance of a model fit index, then the group constitutes a model fit outlier group. The third step is to check whether the outlier group's effect on model fit is driven by (a) an outlying data point(s) in the group (hence, an individual observation identified as a lower level model fit outlier) and/or (b) the entire group (hence, a group identified as a higher level model fit outlier). To determine exactly which one of the two situations is at hand for a model fit outlier group, we recommend that researchers follow our recommendations in Figure 1—those regarding error outliers, then interesting outliers, and finally influential outliers in the context of regression—for the lower level cases in each model fit outlier group. The reason is that each group in a multilevel analysis constitutes a separate regression analysis. If one or more nonerror, model fit outliers exist within the focal group, and if the exclusion of the model fit outliers within the group, in turn, makes the exclusion of the *group* to no longer cause a statistically significant change in a model fit, then the model fit outliers within the focal group are lower level model fit outliers. In contrast, if no model fit outliers exist within the focal group, or if the focal group's exclusion still causes a statistically significant change in a model fit index even after removing the model fit outlier(s), then the focal group itself is (also) considered a higher level model fit outlier.

Defining and identifying prediction outliers. As was the case with model fit outliers, prediction outliers are identified by using a top-down approach (Langford & Lewis, 1998). First, the recommendation is to calculate the average squared deviation, or C_j, for each group of cases, where the focal group is denoted by j (Snijders & Berkhof, 2008; Snijders & Bosker, 2012). That is, C_j assesses the combined influence of a group j on both the fixed and random parameter estimates. A statistical test for determining the significance of C_j has not yet been formally developed. Nevertheless, researchers can compare C_j values against one another using an index plot. Snijders and Bosker have made statistical code available for this procedure in MLwiN, R, and Stata (see www.stats.ox.ac.uk/~snijders/mlbook.htm).

Next, for each group whose C_j is found to be markedly deviant, the researcher should check exactly what is driving the group's particularly large value. As was with the previous situation involving model fit outliers, a markedly large C_j may be driven by (a) a prediction outlier(s) within the group and/or (b) the entire group as a prediction outlier. To determine which one of the two situations is at hand for a group with a markedly large C_j (i.e., prediction outlier group), we once again recommend an examination of any prediction outliers within each prediction outlier group by using procedures described in our discussion of prediction outliers in the context of regression. If one or more prediction outliers within the focal group are identified, and if the exclusion of the prediction outlier(s) within the group makes the group's C_j value no longer notably different from those of other groups, then the prediction outlier(s) within the focal group are lower level prediction outliers. In contrast, if the prediction outlier identification procedure reveals no prediction outliers within the focal group, or if the focal group's C_j value remains notably different from other groups even after removing the prediction outlier(s) in the group, then the focal group itself is (also) considered a higher level prediction outlier.

Handling influential outliers. Approaches for handling influential outliers in multilevel modeling are, overall, similar to those used in regression and SEM. One option is to try to respecify the

model for theory-building purposes. Regardless of whether respecification is used, the recommendation is to use either deletion or robust techniques. Furthermore, regardless of whether deletion or robust regression is used, results should be reported based on all of the approaches used—a practice that also includes providing an explanation for any differences in the results. This ensures transparency and also empowers the reader to be more fully informed of the study's results.

The technique of respecification, as in the situation involving regression, can take the form of including another term in the model (e.g., cross-level interaction term). Once again, this inductive practice of respecifying models post hoc is beneficial in terms of helping researchers engage in theory building. However, unlike in regression, the multilevel modeling context requires the researcher to first decide on the level where any additional predictor(s) are to be added. In a two-level model, if the identified outliers (by following the procedures previously explained) mainly consist of higher-level outliers (i.e., outlier groups), then we may consider adding additional Level 2 predictors. If the identified outliers mainly consist of lower level outliers, then we may consider adding additional Level 1 predictors. In either case, if the added variable is one that significantly adds incremental variance explained, a data point previously identified as an outlier may no longer be such after the model is respecified.

Options regarding robust techniques in the multilevel context include generalized estimating equations (GEE) methods and bootstrapping methods. GEE methods estimate the variances and covariances in the random part of the multilevel model directly from the residuals (Hox, 2010). This approach estimates average population effects rather than modeling individual and group differences. The result of using GEE estimates is that they are less efficient than maximum likelihood estimates, but they make weaker assumptions about the structure of the random part of the multilevel model, which limits the effect of influential outliers. One drawback to this approach is that it only approximates the random effects, so that these effects cannot be analyzed in detail. Bootstrapping methods is another type of robust technique that could be used (Hox, 2010). These methods estimate the parameters of a model and their standard errors from the sample, without reference to a theoretical sampling distribution. One drawback of this approach is that it is accurate only for large sample sizes ($n > 150$; Hox, 2010).

An example of a study that used a correct handling procedure in the multilevel modeling context is Smillie, Yeo, Furnham, and Jackson (2006; see Table 4). In this study, the authors used deletion as a handling technique. In doing so, they reported their results with and without the handling technique. On the other hand, Table 4 includes an example of a study that used an incorrect handling procedure because researchers deleted outliers, which is not necessarily incorrect per se, but they did not report results with the outliers included in the analysis.

A Framework for Future Research on Outliers

Our article provides specific guidelines regarding how to define, identify, and handle outliers within the context of the three most popular data-analytic techniques in organizational science research. In addition, our article offers a general framework that can be used in future research for creating guidelines that are specific to other data-analytic contexts.

First, Figure 1 shows that the process of addressing error and interesting outliers is virtually the same regardless of which data-analytic technique is used. Therefore, these first two steps in the process remain very similar if a researcher uses any of the three data-analytic approaches we discussed (i.e., regression, SEM, and multilevel analysis), meta-analysis, cluster analysis, or any other data-analytic technique.

Second, regarding influential outliers, Tables 1 to 3 include information that forms the basis for a future research agenda. Specifically, we foresee future research on outliers focusing on

other data-analytic approaches that would rely on the results of our literature review summarized in these tables. For example, Table 1 includes definitions of outliers in the context of additional data-analytic approaches such as meta-analysis (e.g., influential meta-analysis effect size outlier), time series analysis (e.g., influential time series innovation outlier), and cluster analysis (e.g., cluster analysis outlier). Similarly, Table 2 includes various options in terms of how to identify outliers in contexts other than regression, SEM, and multilevel modeling. As examples, these identification techniques include schematic plot analysis (for meta-analysis), 2- or 3-dimensional plots of the original and the principal component variables (for principal component analysis), and autocorrelation function plot (for time series analysis). Finally, Table 3 includes a list of outlier handling techniques, some of which can be used across various data-analytic contexts.

In short, we see our article as the first within a broader research agenda on outliers that will eventually include specific guidelines that researchers can use in their substantive work regardless of the particular data-analytic approach used. The general framework offered in Figure 1, combined with the information included in Tables 1 to 3, form the basis for future work that can produce decision-making charts similar to those summarized in Figure 2 and would address other data-analytic approaches such as meta-analysis, cluster analysis, principal component analysis, and time-series analysis, among others.

Concluding Remarks

Outliers, or observations that deviate markedly from the rest, often cause important changes in substantive conclusions. Outliers, although typically not acknowledged or discussed openly in published journal articles, are pervasive in all empirical research, ranging from the micro to the macro level of analysis and spanning all types of methodological and statistical approaches. The way in which researchers define, identify, and handle outliers has important implications for substantive conclusions. Yet, our review of influential methodological sources regarding outliers revealed that there is inconsistent information regarding how researchers should define, identify, and handle them. It is not surprising that our literature review of substantive articles published in organizational science journals revealed that researchers often implement idiosyncratic, nontransparent, and difficult-to-replicate practices regarding outliers. Moreover, a cynical view is that outliers are treated in such a way that their inclusion or exclusion from a data set is not based on sound and standardized practices, but on whether results favor one's preferred hypotheses.

Our article offers specific recommendations that researchers can follow in a sequential manner to deal with outliers. We believe that our guidelines will not only be helpful for researchers, but also serve as a useful tool for journal editors and reviewers in the evaluation of manuscripts. For example, much like editors and reviewers should demand that authors be clear and specific about a study's limitations (Brutus et al., 2013), we suggest that they should also request that authors include a few sentences in every empirically based manuscript describing how error, interesting, and influential outliers were defined, identified, and handled. Moreover, an anonymous reviewer suggested that guidelines for publication such as those produced by the Academy of Management and the American Psychological Association should force authors to include a short section on "Outlier Detection and Management" within the results section. In other words, this description should include how each of the three types of outliers has been addressed in all empirical studies. Our decision-making charts can serve as a checklist in this regard. Overall, we hope that our guidelines will result in more consistent and transparent practices regarding the treatment of outliers in organizational science research.

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