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MetaBUS as a vehicle for facilitating meta-analysis☆,☆☆

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ABSTRACT

To address new research questions and get a clearer picture of research, scientists and practitioners in human resource management have come to rely heavily on meta-analyses. However, meta-analyses may take months or years to produce and are becoming increasingly difficult to produce as the corpus of available research grows exponentially. We describe how the metaBUS platform can assist in tackling two central challenges to conducting meta-analyses. In addition, we provide a detailed description of the platform, with information on all fields included in the database. Next, we provide recommendations for three use cases: generating literature search terms by using the metaBUS taxonomy, conducting metaBUS queries to locate findings and generate first-pass meta-analyses, and identifying relevant findings that might have gone overlooked during traditional literature searches. We demonstrate a new software and a cloud-based interface that allow users to leverage the platform. We conclude with implications, limitations, and future directions.

Meta-analyses are often highly cited scientific works, with many viewing them as authoritative summaries of a field (Cooper & Hedges, 2009). They can provide building blocks for knowledge development and theory building (Chan & Arvey, 2012), benchmarks and baselines for future studies, correlation matrices for use as input to structural equation modeling, estimates of generalizability, identification of moderators and outliers, and prior distributions for Bayesian analyses (Steel, Kammeyer-Mueller, & Paterson, 2015). Meta-analytic summaries can also assist in settling long-lasting debates as they allow us to see effect sizes largely clear of the haze from sampling error. Also, many consider meta-analyses the basis for evidence-based practice, bridging the research-practitioner gap (Bosco, Steel et al., 2015; Rynes, Giluk, & Brown, 2007). As Marler and Fisher (2013) described, the "evidence-based management (EBM) movement is intended to motivate research syntheses that will permit more effective use of research data" (p. 19). Pfeffer (2007) expressed a similar sentiment, "The huge body of knowledge created by management science in the past 50 years, however, is more than capable of being transformed into real world applications of benefit to business and society" (p. 1334). Despite these potential advantages, there are many fundamental and serious challenges to the timely creation of quality meta-analytic reviews. In this paper, we focus on two particular challenges that may begin to be addressed by leveraging the metaBUS platform.

The first challenge, following the specification of topic scope and inclusion-exclusion criteria (Cooper, 2010), lies in generating a list of relevant search terms (Rothstein, 2012), often submitted to electronic search engines. The process is often highly

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cumbersome, owing to the "vocabulary problem…variability in word usage" (Furnas, Landauer, Gomez, & Dumais, 1987, p. 964). The problem's severity is reduced to some degree by the availability of optical character recognition (OCR) technology and full-text document search. Indeed, the presence of multiple phrasings of a given concept is likely to appear within an article's body of text. However, for non-OCR documents, only a very limited body of text is available for searches (e.g., titles; abstracts; keywords). This text often follows suggestions set forth in the Publication Manual of the American Psychological Association (2010), to "include in the abstract only the four or five most important concepts…you think your audience will use in their electronic searches" (p. 26).

The use of full-text searches is also problematic due to the high prevalence of false positives returned. As an example, the letter string 'age' occurs in 956 distinct words in the English language according to the MRC psycholinguistic database (Wilson, 1988) including "management," "percentage," and "language." Results of full-text queries must then be laboriously hand-culled to remove studies without pertinent data. Unfortunately, sorting through false positives is, at the present time, a necessity for a "full-blown systematic review and meta-analysis" (Rothstein, 2012, p. 137), yet also reminiscent of "archaeology: academic teams searching for buried artifacts and working tirelessly to reveal their true meaning" (Ip et al., 2012, p. 4). As summarized by Spellman (2015), "Our keyword system has become worthless, and we now rely too much on literal word searches that do not find similar (or analogous) research if the same terms are not used to describe it" (p. 894). Still, however, comprehensive literature searches rely on the specification of an exhaustive list of search terms.

A second challenge for meta-analysts, following the specification of search terms, is the sheer amount of resources required to conduct a literature search. As described by Rothstein (2012), the resources required will vary as a function of project purpose. Indeed, conducting a thorough systematic review is one of many reasons to conduct a literature search, and typical search procedures can last anywhere from a few days to six months or more. Literature reviews serving research methods projects (e.g., a review of questionnaire response rates), for which tens of thousands of observations are readily available, might purposely target only a few outlets and be less threatened by a lack of search comprehensiveness. Some substantive topics might be so frequently studied and appear in literatures so vast as to make the task of a "full-blown" review unfeasible given even plentiful resources. Additionally, the project scale for some topics may escalate to the point where forecasts of return on investment make the undertaking unattractive for even relatively large teams. In such cases, it may be advantageous to have estimates available, even if derived from a limited sampling frame.

Ultimately, comprehensive literature searches require significant resource investment because there exists no large-scale search engines that operate at the level of individual research findings (to our knowledge, this is currently the case for all social sciences). Indeed, as described in existing guidelines for conducting searches (e.g., Cooper, 2010; Rothstein, 2012), databases are often used to locate relevant sources (e.g., journal articles), which must be filtered for mundane characteristics such as whether the article is empirical and, if empirical, whether it contains data pertaining to the concepts of interest or simply referred to concepts by name as justification for the importance of an ancillary research question, as a distal implication, and the like.

After a research team has overcome these challenges, the meta-analysis provides only a snapshot in time on a particular topic, one that is rarely updated more frequently than every five to ten years. What is worse, when updates are conducted to include the newly accumulated findings, the starting point for the update is often a blank slate. Around the world, groups of researchers may also be duplicating each other's efforts, making the entire process highly redundant and wasteful. This sad state of affairs is at odds with the modern research climate of data sharing, which has many clear benefits (e.g., Borgman, 2012). Despite all these obstacles, evermore of our journal space is being dedicated to systematic reviews, with an exponential increase in their publishing (Tebala, 2015), attesting to their usefulness. We appear to be spending an increasing amount of our efforts and resources reiteratively summarizing slices of our field rather than conducting core research. As described by Ferris, Hochwarter, and Buckley (2012), "Where we are now is an uncomfortable spot – we have broadened the base of theory in the organizational sciences without a commensurate increase in explanatory power, or what we know about how people behave in organizations" (p. 103). Concomitantly, criticisms of our field's inability to bridge science and practice abound (Rynes et al., 2007), an unimpressive situation for an applied discipline.

The purpose of the present manuscript is to describe how users may leverage the metaBUS platform to at least partially overcome two central challenges in conducting meta-analyses: the specification of search criteria for comprehensive literature search and facilitated location of research findings for rapid summary. The remainder of our manuscript is organized as follows. First, we provide rationale for the need of platforms like metaBUS. Next, in order to familiarize the user with this resource for human resource management (HRM) research, we provide an anatomy of metaBUS by describing processes involved in the semi-automated extraction of findings, database content, manual coding processes, and a new cloud-based software. Next, we provide recommendations for using metaBUS to address three use cases. We conclude with a discussion of data sharing and science-practice gap implications, limitations, and future directions for the metaBUS platform.

1. Improving and facilitating meta-analyses

As described by Schmidt and Hunter (2015), our field stands to realize great benefit from more efficiently summarizing and curating research findings. As they write, "We need a new type of journal…that systematically archives all studies that will be needed for later meta-analyses.... failure to have such a journal system in place is retarding our efforts to reach our full potential in creating cumulative knowledge" (p. 30). This is being sporadically recognized, with research curation efforts being built or at least discussed in several other research disciplines (Elliott et al., 2014; Ip et al., 2012; Lefebvre, Glanville, Wieland, Coles, & Weightman, 2013; Tsuji, Bergmann, & Cristia, 2014). However, there has not previously existed a system for curating the findings within the HRM field for future meta-analytic use. And none in the social sciences, to our knowledge, have accomplished curation on a large scale. This issue is nearing a boiling point, however, with the volume of reported scientific findings presently doubling every nine years (Bornmann & Mutz, 2015). Producing meta-analyses using current processes may soon become an even more challenging – if not impossible – process.

The genesis of the metaBUS project (a portmanteau of "meta-analysis" and "omnibus") was to address challenges associated with producing meta-analyses. Rather than a top-down approach that starts at a research question of interest and then identifies all relevant research, we considered a bottom-up alternative: over time, collect and code a large corpus of findings into a searchable database thereby enabling much more rapid and up-to-date summaries. With a vast corpus of data curated and shared for broad use, the amount of time required for the completion of a systematic review would be vastly reduced. Our vision was to curate researchers' collective findings, generate a protocol for researchers to collaboratively build upon each other's efforts, and speed the progress of science in our discipline to facilitate eventual EBM. Consequently, the metaBUS project aims to extract, curate, and classify virtually all HRM-related research findings in order to provide facilitated access to the HRM community through large-scale, "living" meta-analyses (cf. Elliott et al., 2014, p. 1).

The metaBUS platform relies on three central features: (1) A taxonomy (i.e., ontology) that arranges approximately 4900 concepts into a flexible hierarchy (Bosco, Aguinis, Singh, Field and Pierce, 2015; Bosco, Singh, & Field, 2014); (2) procedures for the semi-automated extraction of findings from sources; (3) a standards-based manual coding protocol to enhance the extracted findings with additional information (e.g., response rates; sample type; taxonomic location); and (4) cloud-based software to allow rapid, flexible queries and empirical summaries of the query results. As of the authoring of this manuscript, the metaBUS corpus contains more than 800,000 correlation coefficients from more than 9000 articles from 23 HRM-related journals. All journals are focused in management (but not those focusing exclusively on strategic management), applied psychology, human resources, or organizational behavior. Thus, each journal has high relevance to HRM and the database contains virtually all major topics found in such journals. We turn next to providing detail on the platform's protocols.

2. An anatomy of metaBUS

2.1. Semi-automated extraction of findings

Human resource management scholars are fortunate to operate in a research environment where relatively efficient effect size reporting practices are prevalent. Indeed, the correlation matrix is an impressive repository of research findings, and each effect size is an inclusion candidate for later research syntheses. The metaBUS extraction protocol leverages this relatively standardized format to extract large quantities of information accurately and efficiently. The protocol takes as input raw correlation matrices which, through a series of algorithms and optical character recognition processes, are transposed into rows and columns representing variable information (i.e., variable name; mean; standard deviation; reliability value reported on the diagonal), and effect size information (i.e., a list of each variable name pair with its corresponding correlation).

The semi-automated extraction process unfolds as follows. First, a journal article PDF file is opened in a PDF extraction software (there exist several proprietary and open-source software options) and the to-be-extracted portion of the matrix is selected (see Fig. 1, left panel). Next, the selected area is exported, via optical character recognition (OCR), to a spreadsheet format (see Fig. 1, right panel). At this stage, the extraction will contain a variety of non-numeric entries (e.g., correlation values appended with an asterisk). All non-numeric entries are automatically highlighted after being pasted into the metaBUS coding platform (Fig. 2, left panel) and, after running a Visual Basic for Applications (VBA) script, most or all invalid entries are automatically repaired (see Fig. 2, right panel). Any unusual instances not handled by the script remain highlighted for manual review. Thus, each matrix is cleaned by removing irrelevant characters (e.g., *, ‡), letters used as subscripts in the original article and, for non-OCR articles, common extraction errors (e.g., O vs. 0; l vs. 1). All cleaning is done with a simple series of find-and-replace commands (e.g., replace "*" with ""). As will be described further, the cleaned matrix is automatically transposed into a standardized format that allows one to build collections from matrices of any size.

From start to finish, the semi-automated extraction process is the least time-consuming aspect of the metaBUS coding process. Indeed, applying the process, experienced coders extract and clean "typically-formatted" matrices in 30 s or less. However, importantly, there exists some degree of variation in matrix format. For example, some matrices contain values for M and SD in rows at the bottom of the matrix rather than in the second and third column of the matrix (i.e., following the variable names). Some matrices provide reliability values (e.g., alpha) in a column alongside M and SD rather than along the diagonal, and some

Variable	*M*	*SD*	1	2	3	4
1. Content knowledge	77.21	5.49	—			
2. Task conflict	1.93	0.44	−.04	(.76)		
3. Openness	3.80	0.27	.09	.08	(.79)	
4. Emotional stability	3.51	0.35	−.10	−.06	.35**	(.89)
5. Team performance	56.09	3.78	.09	−.04	.01	.01

→

	A	B	C	D	E	F	G
1	Content knowledge	77.21	5.49				
2	Task conflict	1.93	0.44	—.04	(0.76)		
3	Openness	3.80	0.27	0.09	0.08	(0.79)	
4	Emotional stability	3.51	0.35	—.10	—.06	.35**	(0.89)
5	Team performance	56.09	3.78	0.09	—.04	0.01	0.01

Fig. 1. Selection of to-be-extracted correlation matrix area from PDF file (left panel) and resulting Microsoft Excel extraction output (right panel). Matrix source: Bradley, Klotz, Postlethwaite, and Brown (2013).

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VARIABLE NAME	M	SD	1	2	3	4	5
Content knowledge	77.21	5.49					
Task conflict	1.93	0.44	—.04	-0.76			
Openness	3.80	0.27	0.09	0.08	-0.79		
Emotional stability	3.51	0.35	—.10	—.06	.35**	-0.89	
Team performance	56.09	3.78	0.09	—.04	0.01	0.01	

→

VARIABLE NAME	M	SD	1	2	3	4	5
Content knowledge	77.21	5.49					
Task conflict	1.93	0.44	-0.04	-0.76			
Openness	3.80	0.27	0.09	0.08	-0.79		
Emotional stability	3.51	0.35	-0.1	-0.06	0.35	-0.89	
Team performance	56.09	3.78	0.09	-0.04	0.01	0.01	

Fig. 2. Imported matrix contents in metaBUS coding platform with automated red shading for non-numeric values (left panel) and output matrix after running automated cleaning macro (right panel). In this instance, the diagonal contains negative values because the original values were flanked by parentheses (our software takes the absolute value during ingestion). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

articles do not provide reliability values at all, necessitating Method section perusal. Some matrices contain effect size information above *and* below the diagonal (e.g., for two separate samples, time points, or units of analysis), with two reliability values for each variable. Still other matrices are not matrices at all, but rather rectangular arrays that often lack all possible intercorrelations.

Although the metaBUS platform automatically handles most correlation table formats, we continue to encounter -and there will likely always arise- exceptions and unexpected formats. Given the sheer variety, the development of input filters to accurately recognize and handle every possible format might be, in the aggregate, not much of a time saver. Further, in most cases, coders familiar with basic data manipulation commands in Microsoft Excel (e.g., copy, paste, transpose, concatenate, find and replace) can easily handle atypical and complicated arrays in approximately 60 s. Thus, although a fully-automated "machine learning" approach to matrix extraction could be possible, we have yet to determine whether it will provide substantial return on investment because (1) extracted output would still require manual error-checking, and (2) most of the coding time is expended elsewhere (e.g., manual coding of moderator information, which we turn to next). Unfortunately, at this time, even semi-accurate curation of research findings, at any reasonable level of comprehensiveness, requires time and human intelligence.

2.2. Manual coding and database contents

The manual coding process is conducted by graduate student coders in management (i.e., organizational behavior; human resources) or I-O psychology who are selected following a résumé screen and two- or three-person panel structured interview with a knowledge test. All coders undergo a paid, intensive three-day training and practice seminar. Following practice, approximately 10% of each coder's entries are checked on a weekly basis by a coding team supervisor, who also serves to respond to coders' regular queries on difficult or questionable items. Since May 2014, the metaBUS team has worked with about 25 graduate students and the team of 12 active high-inference coders are all current doctoral students in research-intensive programs who contribute primarily during the summer months.

Following the semi-automated extraction described in Step 1, database contents are augmented with manual coding at the article- and variable-level. During the project planning phase, several difficult breadth-versus-depth decisions were made regarding what data to collect and what data *not* to collect. Our goal in amassing this database was to extract as much information as possible to facilitate later meta-analyses without requiring excessive and time-consuming research to locate information; our thinking was that one could use metaBUS to locate relevant findings of interest (i.e., as a search engine), and then augment the search results with any additional information desired. To this end, we elected to collect information that is *usually* readily available and clearly presented in *most* articles. As examples of information that we could have elected to collect, consider scale length. Pilot testing revealed that scale length is often presented ambiguously, with many authors citing only the scale's original author. Furthermore, authors often exclude items, making the number of items used in analyses often difficult to ascertain without fine-toothed combing through articles.

One benefit of our protocols is that no manual coding is required at the effect size-level. Indeed, if we had relied on such an approach, it would have taken an army of doctoral students decades to amass such a large database. Rather, information pertaining to each of two variables involved in a given bivariate relation is automatically migrated downward to the effect size-level. As an example, imagine a complete correlation matrix containing 18 variables (and, thus, 153 correlations). Once the matrix is extracted (Step 1), and the variable-level codes are applied to the 18 variables (Step 2), software is used to assign variable-level information, for each of two variables, to each of the 153 rows of correlation information. The result is a data structure that is easily searchable and readily scalable. An early, simplified version of the database is freely available for download at the following link: http://frankbosco.com/data. The database currently contains more than 800,000 effect sizes extracted from more than 9000 articles from 23 journals.

As described earlier, following extraction, a cleaned correlation matrix is loaded into the metaBUS coding platform (see Fig. 3) and coders augment each variable row with information pertaining to a variety of codes. All categorical codes (e.g., journal name) are input using in-cell dropdown menus in Microsoft Excel. We turn next to detailing each code contained in the metaBUS database, with levels for each categorical variable, following the layout of the array shown in Fig. 3. Sample data for each field are shown in Table 1. Note that the metaBUS team is in the process of error-checking, indexing, and releasing many of these data fields, a process to unfold over time.

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ARTICLE-LEVEL INFORMATION		VARIABLE NAME	Var_code name	VARCODE	ALPHA?	REVERSE?	TIME	RESP RT	N	MEAN N?	SAMPLE #	CODING CONFIDENCE
Journal	JAP	Content knowledge	Exam performance	20223		N	1	1	117	N	1	Normal
Year	2013	Task conflict	Task conflict	10189	Y	N	1	1	117	N	1	Normal
Volume #	98	Openness	Openess	20437	Y	N	1	1	117	N	1	Normal
Issue #	2	Emotional stability	Emotional stability	20442	Y	N	1	1	117	N	1	Normal
Start page	385	Team performance	Role performance	40067	Y	N	1	1	117	N	1	Normal
End page	392											
Grant-funded?	N											
Coder notes	[NONE]											

PERTAIN	SOURCE	UNIT OF A	LOCATE	VARIABLE NAME	M	SD	1	2	3	4	5	6	7	8
Self (ratings of source BY same source)	Students	Teams/Families/Groups/etc.	United States	Content knowledge	77.21	5.49								
Self (ratings of source BY same source)	Students	Teams/Families/Groups/etc.	United States	Task conflict	1.93	0.44	-0.04	-0.76						
Self (ratings of source BY same source)	Students	Teams/Families/Groups/etc.	United States	Openness	3.80	0.27	0.09	0.08	-0.79					
Self (ratings of source BY same source)	Students	Teams/Families/Groups/etc.	United States	Emotional stability	3.51	0.35	-0.1	-0.06	0.35	-0.89				
Students	Managers/Supervisors/Mentor	Teams/Families/Groups/etc.	United States	Team performance	56.09	3.78	0.09	-0.04	0.01	0.01	0.62			

Fig. 3. metaBUS coding platform populated with augmented codes for a sample matrix (Bradley et al., 2013). The figure is split at the column titled *coding confidence*.

2.2.1. Article-level information

For each article, the metaBUS database contains (1) journal name (selected with in-cell dropdown menu), (2) volume number, (3) issue number, (4) start and end page, (5) publication year, and (6) whether financial support was acknowledged (e.g., grant funding; yes or no). To code for the latter, the acknowledgements section of each article was inspected.

2.2.2. Variable-level information

For each variable appearing in a given matrix, the following information was extracted:

1. Reported variable name. We extracted the variable name appearing in the original journal article. Ambiguous abbreviations were replaced with their full-string unabbreviated forms.
2. Sample size. Coders recorded the sample size associated with each variable. In some cases (e.g., following listwise deletion), the sample size was equal for all variables in a given matrix and, thus, presented only once (e.g., "for all correlations, N = 200"). In other cases, a separate column of sample size information was presented, with N varying across variables.
3. Exact sample size?. Often, the exact sample size associated with a given variable was not possible to extract. As an example, it was not uncommon to encounter a matrix whose table note indicated a range (e.g., "due to missing data, N ranged from 150 to 200"). Upon encountering such instances, coders took the mean of the two values (in this case, 175), and indicated that the sample size was not exact (i.e., Exact sample size = No).
4. Taxonomic node. Using the metaBUS taxonomy containing nearly 5000 terms, coders assigned a unique identifier (i.e., 5-digit code) to each variable. The exact value of the unique identifier (e.g., 20,072 = job satisfaction) is meaningless, and the value serves only as a unique identifier. Bosco, Aguinis et al. (2015) provide several tables and figures displaying frequently occurring nodes in the taxonomy.
5. Taxonomic node name. During the coding process, once a coder inputs a taxonomic code, the platform echoes back the full text of the taxonomic entry in an adjacent column. This code is automatically populated based on vertical lookup formula in Microsoft Excel. Specifically, a named range containing two columns (taxonomic node code and taxonomic node name) is placed on a separate sheet in the workbook. The vertical lookup formula (in the adjacent cell described above) refers to the 5-digit code provided by the coder and conducts a lookup on the named range. This is done to reduce typing errors.
6. Conceptual reversal. If the variable in question did not have an exact entry in the taxonomy, yet the taxonomy contained the variable's antipode, then coders assigned a value of "yes" to this field. As an example, the reported variable "perceived lack of autonomy" would have been coded as "autonomy" along with conceptual reversal = Yes. This code is essential for streamlining rapid meta-analyses, as meta-analysts often reverse-code correlation values to achieve construct consistency.
7. Variable M, SD, and reliability value. In most cases, M, SD, and reliability information is conveniently presented in correlation matrices. However, in cases where this information was not included, coders were instructed to scan Methods sections for their manual extraction.
8. Alpha?. For variable rows containing reliability information, coders indicated whether the reliability value was coefficient alpha (yes/no). Given that the overwhelming majority of reliability coefficients were of the alpha type, it made little sense to offer coders additional options and extend training procedures to handle them.
9. Time point. For each variable, coders assigned a positive integer representing the time point of observation. Thus, if a given matrix included the reported variables "Job satisfaction-time 1" and "job satisfaction-time 2," the time point fields for each variable would have been coded as 1 and 2, respectively. Time points were coded only when explicitly identified as such within correlation tables. The purpose of this coded information is to assist researchers in locating findings for which multiple time points had been recorded. Users interested in more specific temporal analyses may first use metaBUS to locate the findings of interest, and then extract more detailed time point information from the original articles.

Table 1
Fields contained in the metaBUS database with descriptions and sample entries.

	Description	Sample entry
Article-level codes		
metaBUS source identifier	A concatenation of abbreviated journal name, year, volume number, issue number, and start page	JAP-2016-101-6-815
DOI	Digital object identifier (if available)	10.1037/apl0000098
Reference	Full APA-formatted reference	Lin, S. H. J., Ma, J., & Johnson, R. E. (2016). When ethical leader behavior breaks bad: How ethical leader behavior can turn abusive via ego depletion and moral licensing. Journal of Applied Psychology, 101, 815–830. http://dx.doi.org/10.1037/apl0000098
Funding/support	Indicator for whether financial support was acknowledged (e.g., grant funding) Yes; No	Y
Variable-level codes		
Verbatim (reported) variable name		Abusive leader behavior
Sample size	[positive integer]	151
Exact sample size?	Yes; No	Y
Taxonomic node classification	[5-digit code from taxonomy]	10,046
Taxonomic node name	[Taxonomic node name]	Abusive supervision
Conceptual reversal?	Yes; No	N
Descriptives: M	[numeric]	1.81
Descriptives: SD	[positive numeric]	0.61
Reliability value	[positive numeric]	0.85
Reliability type: alpha?	Yes; No	Y
Time point	[positive integer]	1
Response rate	[positive numeric]	0.68
Sample number identifier	[positive integer]	1
Data source|data pertains to	Students; General employees/Subordinates/Protégés; Managers/Supervisors/Mentors; Upper managers; Armed forces; Job applicants; TMT; CEO; SMEs; Teams/Families/Groups/etc.; External stakeholders/Customers; Org records/Archives; Gov't records/Public; Mixed; Not specified; Other/Don't know; and Self ("self" is an option only for the "pertains to" category)	Managers/supervisors|Self
Unit of analysis	Individuals; Dyads; Teams/Families/Groups/etc.; Business Units/Departments/Stores/Plants/etc.; Organizations; Mixed; Not specified; Other/Don't know	Individuals
Data collection country	One of listed independent states, or: "Mixed" "Not specified" "Taiwan"	Not specified
Coding confidence	Normal; Low	Normal
r	Uncorrected, zero-order correlation [numeric]	Abusive leader behavior: Depletion = 0.19 Abusive leader behavior: Moral credits = 0.11 Abusive leader behavior: Moral credentials = −0.05 …(for all variable pairs)
Codes not included but ideal for meta-analysis		
Occupation	Occupation identifier from O*Net	N/A
Specific scale	Full reference(s) of scale used	Tepper, B. J. (2000). Consequences of abusive supervision. *Academy of Management Journal*, *43*,178–190.
Scale length: Original	Number of items in original scale [positive integer]	10
Scale length: Analyzed	Number of items analyzed in study [positive integer]	8
Scale type	Likert: Agreement Likert: Representativeness Likert: Occurrence frequency …. (other types)	Likert: Occurrence frequency
Scale granularity	Number of response options [positive integer]	5
Scale directionality	For ascending scales, higher values indicate higher levels of the scale type's substance. [Ascending; descending]	Ascending

10. Response rate. Coders calculated response rate as the number of respondents divided by the number solicitations (i.e., invites). Our definition of a "respondent" was any case containing valid or invalid data. Thus, if 100 individuals were solicited, 50 responded, and 40 presented with analyzable data, then response rate = 0.50. If desired, platform users may derive other rates using the reported N values.

11. Sample number. This field represents an identifier for data collection sample. Coders recorded a positive integer, with default = 1, and were instructed to increment the value by 1 for each new sample in an article. We chose to identify sample at the variable level because it is not uncommon for journal articles to contain two separate matrices containing data pertaining to the same sample. In addition, an identifier for sample facilitates later meta-analyses, whose unit of analysis is the sample effect size.
12. Data source and data pertains to. Originally, we sought to code for sample type (e.g., student; employee) with a single variable. However, after piloting our procedures, we decided to code for sample type with two variables: "source" and "pertains to." The former refers to the entity providing the information, and latter refers to the target of the information. As examples, in the typical case of employees' self-reported job satisfaction, source = employees and pertains to = self. In the case of the modal employee performance evaluation, source = supervisors and pertains to = general employees. The complete set of response options is shown in Table 1.
13. Unit of analysis. Coders were instructed to record the unit of analysis for each variable, having been instructed to consider: *If N = 200, then ask yourself: 200 what*? Response options were: Individuals, Dyads, Teams/Families/Groups/etc., Business Units/Departments/Stores/Plants/etc., Organizations, Mixed, Not specified, and Other/Don't know. For samples with data pertaining to more than one level of analysis (e.g., below diagonal = individual-level; above diagonal = team-level), all effect sizes were extracted represented as two separate matrices belonging to the same sample. Filters allow users to limit search results to particular levels of analysis.
14. Location. Coders recorded the country of data collection. A list containing all countries (available at the U.S. Department of State website) was embedded in the coding sheet. In rare cases where a country of origin was not specified, coders recorded the country of the first author's affiliation.
15. Coding confidence. For each variable row, coders indicated "normal" to indicate a normal level of confidence or "low" to indicate that at least one decision made in the row is associated with uncertainty. Currently, this code exists for future uses (e.g., recoding; use as a moderator in analyses).

2.3. Taxonomy development

HRM, like many social sciences, appears to suffer from the so-called vocabulary problem (Furnas et al., 1987). Put differently, many HRM constructs (e.g., employee performance) can take on literally dozens of names (e.g., in-role behavior; supervisor assessment; number of errors; accidents). Thus, to search for the letter string "performance" would exclude a great deal of relevant findings. As one approach to remedying this concern, the metaBUS platform includes a hierarchical taxonomy containing nearly 4900 variables branching from major classifications (e.g., intentions; behaviors) to finer-level classifications (e.g., behavior: performance; behavior: counterproductive behavior) (see Bosco, Aguinis et al. 2015; Bosco, Steel et al., 2015). By selecting *parent* nodes, one may alleviate concerns brought by the varied terminology. Perhaps the greatest challenge to taxonomy development lies in establishing consensus classifications. Indeed, as described by Levi (2013), such classifications can reflect "more the biases of the classifying entity rather than our reality" (p. 34). However, we add that this challenge is also an opportunity to answer questions related to the layout of the HRM field and potentially combat construct proliferation (see also Chan & Arvey, 2012) and the jingle-jangle problem (e.g., Shuck, Ghosh, Zigarmi, & Nimon, 2013). We revisit this topic in the Discussion section.

To address the above concerns, Bosco, Aguinis et al. (2015) set out to develop a "map" of the field – a generic taxonomy that arranges constructs by group membership and follows standards for the construction of controlled vocabularies by the National Information Standards Organization (NISO;, 2005). Typical to generic taxonomies are "IsA" links. For example, turnover "IsA" behavior; conscientiousness "IsA" personality trait, and so forth. The development of the taxonomy unfolded over many hours of discussions involving three subject matter experts, and development continues today. Indeed, to develop a consensus classification of *all* topics in a given scientific discipline is a daunting task. However, as a first step towards achieving this goal, the metaBUS platform includes the Bosco, Aguinis et al. (2015) taxonomy and recognizes that researchers will have different views on components that should be included or excluded in their construct conceptualizations. Further, the taxonomy is currently undergoing expansion to accommodate different link types described in the NISO (2005) standards (e.g., synonyms; related terms). Such enablements allow the metaBUS platform to deliver on flexibility. Users may add components from various branches of the taxonomy and choose to include or not include children nodes (i.e., more specific classifications) and exclude specific terms or branches, and apply a variety of other options.

2.4. Analysis specifications

By employing linkages between the research finding database and text- or taxonomy-based searches, users are able to generate instant summaries between any two concepts using meta-analysis methods contained in the R package metafor (Viechtbauer, 2010). At this time, the metaBUS platform employs a single statistical approach: multilevel meta-analysis with effects nested by sample and then article, and with random-effects estimation using the restricted maximum likelihood (REML) algorithm. Of course, the platform is expandable to accommodate virtually any meta-analytic estimation procedure available in R. However, some analyses (e.g., REML estimation on more than 1000 effects) become resource and time consuming, making it relatively unpalatable for cloud-based use. Users are welcome to request the complete source code and modify it to suit their needs.

As mentioned above, the query logic is also very flexible, allowing search criteria as combinations of taxonomy nodes, originally reported letter strings, union sets, exclusions, and the like for each concept. For example, a user could conduct a meta-analysis between satisfaction (excluding pay satisfaction) and performance (excluding contextual performance). The meta-analytic inputs could then be filtered by any variable included in the database (e.g., limit by level of analysis; limit by publication year), although, due to technical constraints, not all filters are in place at this time. As additional analytic flexibility, researchers may opt to exclude rows of data or reverse correlations (i.e., $r \times -1$) on a case-by-case basis as needed.

With the platform described, we turn next to illustrating several use cases of the metaBUS platform.

3. Use Case #1: generating search terms for use in a literature search

Rothstein (2012) described the challenge of identifying keywords of interest prior to conducting a meta-analysis: a balance between achieving high recall (i.e., capturing all relevant sources) and coping with low precision (i.e., filtering false positives). Essential to the former is the specification of an exhaustive set of search strings. Rothstein (2012) suggested that meta-analysts consult existing controlled vocabularies, such as the Thesaurus of Psychological Index Terms (TPIT; Tuleya, 2007) and other sources to locate terms. However, the TPIT is relatively coarse and does not contain many of the terms in which HRM researchers are interested (e.g., TPIT contains "turnover" but not "quit," "leave," or "exit"). The TPIT also does not contain "turnover intention," making the thesaurus relatively ineffective at generating the terms needed to inform a more thorough literature search on this topic. Given the lack of existing, extensive controlled vocabulary, without a comprehensive search of the literature in advance, how does one arrive at an exhaustive set? In this use case, we demonstrate how metaBUS can assist in achieving exactly that goal.

Following the turnover example, imagine that you were searching for all literature related to turnover intention (but not turnover behavior). To ascertain the variety of reported variable names, we used the following approach. First, we explored the "quit intentions" node of the metaBUS taxonomy. By examining the finer-level nodes nested under "quit intentions," we observed the use of four key terms: turnover, quit, leave, and exit (typically coupled with intent, intentions, anticipated, or similar). Next, we used the located key terms (e.g., "turnover") to search for other related terms. To this end, we entered the first term ("turnover") into the box labeled Concept 1 Text Include. Once entered, the platform displays all reported variable names that contain the string "turnover." At this point, the user may simply select each variable name of interest. This process was repeated for the terms "leave," "exit," and "quit," and resulted in a list of 194 unique variable names that appeared to refer to our intended construct (i.e., turnover intention). For the purposes of this manuscript, we conducted additional analyses on the set of 194 unique variable names to address the question: How many exact letter string combinations and Boolean-based letter string combinations would be required to capture all records in the metaBUS database? As shown in Table 2, 24 search terms are required using an exact-match letter string search strategy. Table 3 shows the 13 search terms required using a Boolean search string approach.

Table 2
Letter strings needed to capture verbatim variable names pertaining to turnover intention with exact letter string query.

Text string used for search	Number of unique reported variable names captured
Containing string *turnover*	
Turnover intent*	71
Intent to turnover	2
Intention to turnover	2
Turnover motivation	2
Turnover propen*	1
Containing string *quit*	
Intentions to quit	22
Intention to quit	20
Intent to quit	13
Quit intent*	7
Desire to quit	1
Conviction of decision to quit	1
Propensity to quit	1
Quitting intent*	1
Containing string *leave*	
Intention to leave	13
Intent to leave	13
Intentions to leave	12
Propensity to leave	4
Desire to leave	1
Leave intent*	1
Prop. to leave	1
Containing string *exit*	
Intention to exit	2
Considering exit	1
Exit intent*	1
Intentions of exit	1

Asterisks indicate wildcards (i.e., any characters).

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Table 3
Letter strings needed to capture verbatim variable names pertaining to turnover intention with Boolean operator-based letter string query.

Text string used for search	Number of unique reported variable names captured
Containing string *turnover*	
Turnover + intent	75
Turnover + motivation	2
Turnover + propen*	1
Containing string *quit*	
Quit + intent	63
Quit + desire	1
Quit + conviction	1
Quit + propensity	1
Containing string *leave*	
Leave + intent	39
Leave + propen*	4
Leave + desire	1
Leave + prop	1
Containing string *exit*	
Exit + intent	4
Exit + consider	1

Asterisks indicate wildcards (i.e., any characters).

Thus, we recommend that users interested in leveraging metaBUS to generate search terms follow these steps: (1) explore the variable taxonomy to locate key terms; and (2) use the taxonomic key terms (or letter string fragments of them) to search for additional terms using the reported variable name search feature.

4. Use Case #2: conducting metaBUS queries for location and first-pass meta-analyses.

The authors of this manuscript recently attended a workshop to demonstrate the functionality of the metaBUS platform. One of the attendees of the workshop requested a first-pass meta-analysis on the relation between employee age and career satisfaction. We demonstrate the new metaBUS portal functionality using this bivariate relation, guiding the reader through the stages of concept specification, row removal, correlation value reversal, filter application, and result comprehension. Importantly, this intended use case of metaBUS is not to function as an instant systematic review machine. Rather, it is intended to demonstrate the use of a search engine that provides ease of location and rudimentary meta-analytic estimates of query results. It is entirely possible that the query results contain coding errors and, thus, our estimate in this manuscript is not intended as a thorough estimate from a systematic review – only a first-pass estimate.

The metaBUS portal graphical user interface contains query and filter specifications, a body displaying meta-analytic results, plots, and a table of meta-analytic inputs (i.e., effect size rows). When searching for findings using the metaBUS platform, the user must first specify two "concepts" (i.e., variables or constructs) using either exact letter string match, taxonomy match, or both. Specifically, the portal provides four input boxes for each concept (i.e., text include; text exclude; taxon include; taxon exclude). The text include and exclude functions are relatively straightforward. One may, for example, specify "satisfaction" as an include object and, after having viewed the query results, decide to exclude "family" and "life" (i.e., to exclude "family satisfaction" and "life satisfaction," depending on the query of interest). The taxonomy include and exclude input boxes allow the user to specify a taxonomic branch of interest based on a search of the entire taxonomic path. For example, the full taxonomic path of career satisfaction, in the metaBUS taxonomy, is "Attitudes ➔ Object = Career/Occupation/Employment ➔ Career satisfaction". The corresponding taxonomic codes for each taxon in the path are 20015 ➔ 30024 ➔ 11181, respectively. Thus, one interested in all career attitudes *other than* career satisfaction may choose to include 30,024 and exclude 11,181. Importantly, the taxon codes function hierarchically, meaning that a taxon also includes that taxon's children nodes unless otherwise specified through taxon exclusions.

To return to our example, we specified career satisfaction using both text string (i.e., "career satisfaction") and taxonomy code (i.e., 11181) parameters (see Fig. 4). The specification is interpreted by the database as an OR query (i.e., match *either* the text string *or* the taxonomy code). Next, we specified age using only its taxonomic code (i.e., 20457), given that the letter string 'age' appears in many words and even an exact letter string match (i.e., "age") would exclude other relevant terms (e.g., "employee age"). Upon entering the inclusion criteria for both concepts, we ran our query by pressing the button "Run query." The platform returned a meta-analytic estimate with $r = 0.014$ based on 60 effect sizes. A portion of the initial, unfiltered results are shown in Fig. 5.

Next, we inspected each row of data returned by the query. Upon examining the query results, we observed some apparently irrelevant concepts (e.g., protégé age; mentor age; age at first international experience), as well as some extraction errors (e.g., "Career satisfactionc), which is likely due to superscripts added to variables in the original correlation matrices. Indeed, it is possible that protégé age or mentor age, in this example, could be relevant and future versions of the metaBUS interface will include the "source" and "pertains to" codes (described earlier) to allow one to filter these results easily. However, to continue the example, we excluded

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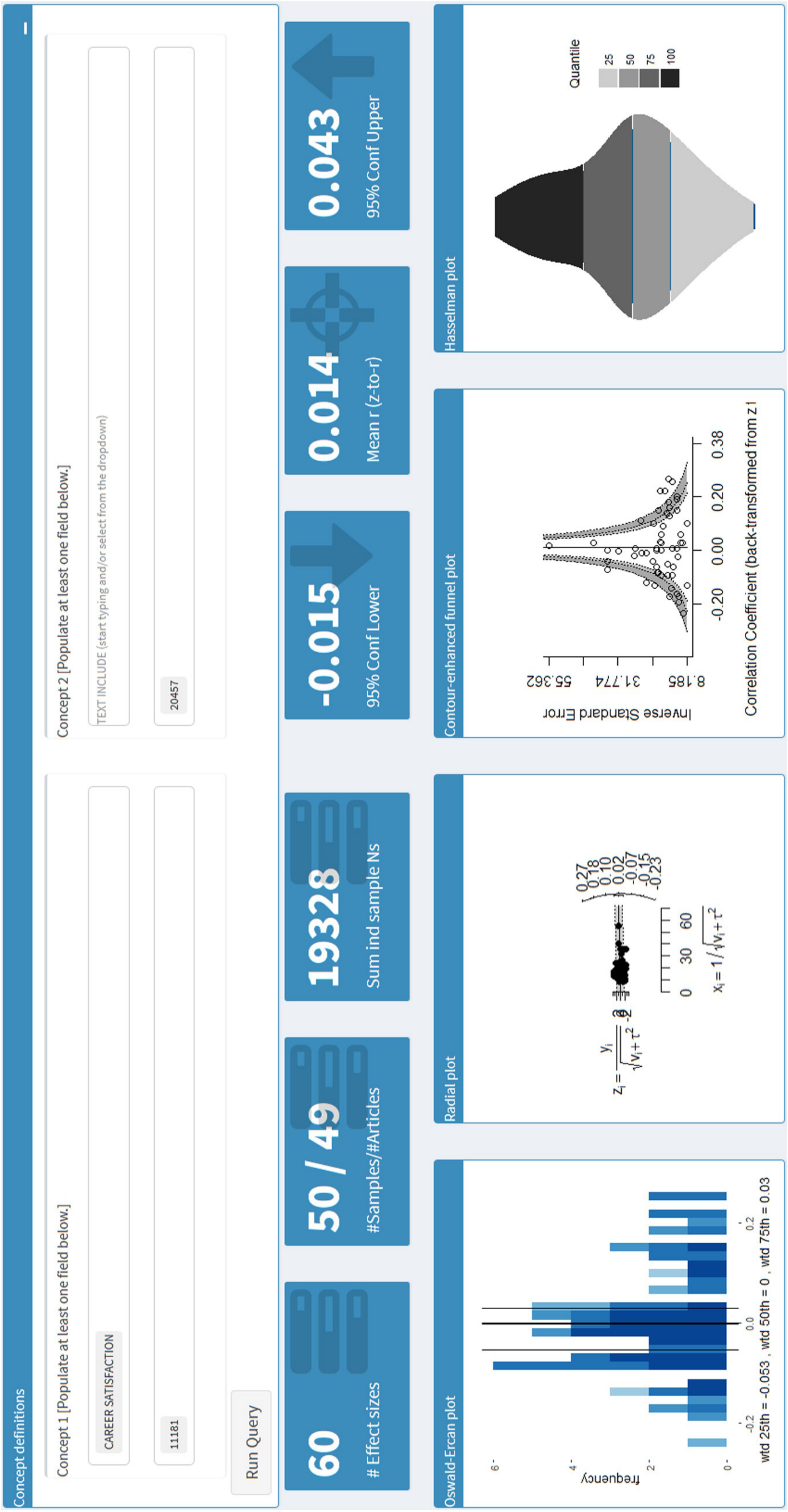

Fig. 4. metaBUS platform showing initial query specification and initial meta-analytic summary for 60 effect sizes. *Career satisfaction* is defined as Concept 1 (using text string and taxonomy-based search) and *age* is defined as Concept 2 (using taxonomy-based search).

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RowID	remove	reverse	ArticleID	PubYear	Var1	Var2	r	MinN	Var1M	Var2M	Var1SD	Var2SD	Var1Unit	Var2Unit
102905			JOB-34-1-24|1	2013	Objective career success	Age	0.030	1612.0	10.77	46.29	1.15	8.71	Individual	Individual
107223			JVB-73-2-242|1	2008	CarSatl	Age	0.000	1269.0			0.85	10.80	Individual	Individual
107258			JVB-73-2-242|1	2008	CarSat4	Age	-0.070	1269.0			1.07	10.80	Individual	Individual
107294			JVB-73-2-242|1	2008	CarSat3	Age	-0.040	1269.0			0.68	10.80	Individual	Individual
107331			JVB-73-2-242|1	2008	CarSat2	Age	-0.070	1269.0			0.67	10.80	Individual	Individual
131379			GOM-29-4-442|1	2004	Career satisfaction	Protégé age	-0.090	217.0	3.58	30.96	0.75	6.70	Individual	Individual
131382			GOM-29-4-442|1	2004	Career satisfaction	Mentor age	-0.050	217.0	3.58	39.06	0.75	9.70	Individual	Individual
154720			HR-64-1-59|1	2011	Career satisfaction	Age	-0.130	376.0	4.44	42.96	1.32	8.49	Individual	Individual
196542			AMJ-36-4-830|1	1993	Career Satisfaction	Age	-0.020	695.0	3.64	37.70	0.74	5.96	Individual	Individual
314180			JVB-63-3-417|1	2003	Career satisfaction	Protégé age	-0.090	217.0	3.58	30.96	0.37	6.77	Individual	Individual
314185			JVB-63-3-417|1	2003	Career satisfaction	Mentor age	-0.050	217.0	3.58	39.06	0.37	9.66	Individual	Individual
384407			IJHRM-23-6-1074|1	2012	Career satisfaction	Age	-0.120	489.5	3.47	44.00	0.75	10.09	Individual	Individual
444097			JVB-79-2-438|1	2011	Career satisfaction	Age	-0.010	561.0	3.50	41.17	0.79	9.10	Individual	Individual
457982			GOM-26-3-369|1	2001	Career satisfactionc	Age (at survey date)	-0.023	129.0	5.43	32.96	1.19	2.39	Individual	Individual
557133			JVB-69-2-315|1	2006	Career satisfaction (Ti)	Age	0.180	214.0	3.82	53.33	1.64	8.43	Individual	Individual
557136			JVB-69-2-315|1	2006	Career satisfaction (T2)	Age	0.260	214.0	4.22	53.33	1.82	8.43	Individual	Individual
589774			HR-63-7-1007|1	2010	Career satisfaction	Age	0.090	274.0	3.28	2.68	0.91	1.23	Individual	Individual
670243			PP-58-4-859|1	2005	Career satisfaction	Age	0.000	295.0	5.00	34.58	1.00	9.21	Individual	Individual
675087			PP-57-2-305|1	2004	Career satisfaction	Age	0.220	253.0	4.69	44.32	1.52	10.86	individual	individual
715475			JAP-82-3-359|1	1997	Satisfaction with career opportunities (Survey Variables)	Age (years) (Survey Variables)	-0.130	70.5	12.63	45.17	3.56	4.36	Individual	Individual

Fig. 5. Sample metaBUS query output for the career satisfaction-age relation (records 1–15 of 60 shown).

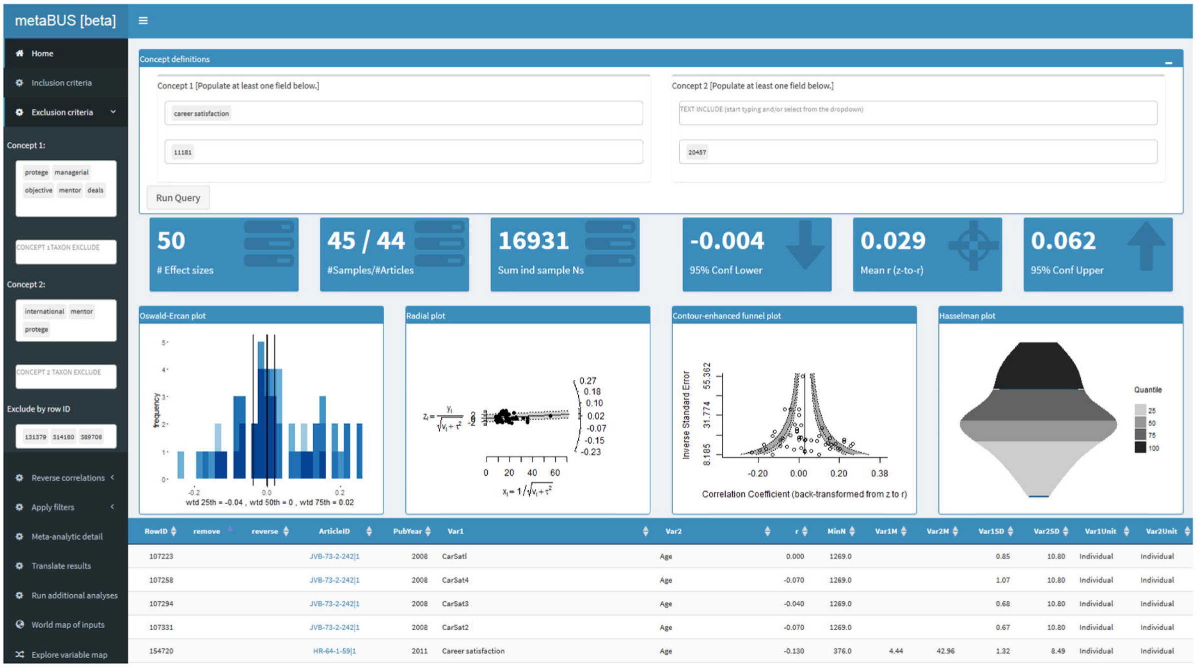

Fig. 6. Full view of metaBUS platform showing query specification (inclusion and exclusion criteria) and refined meta-analytic results.

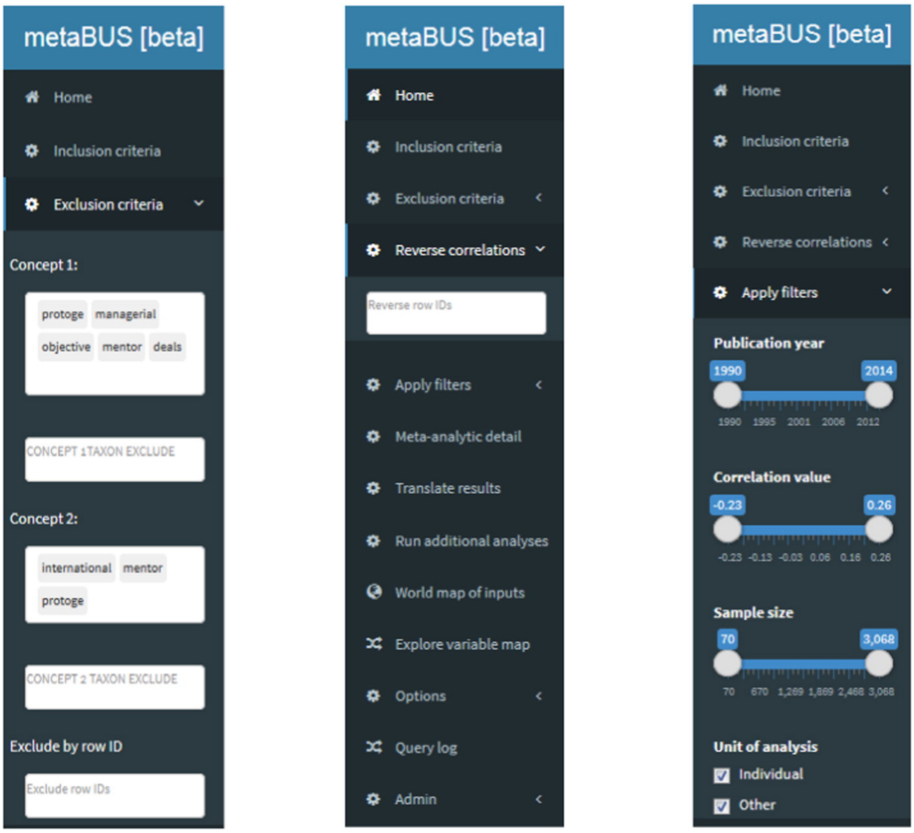

Fig. 7. Fields for specification of exclusion criteria (left panel), row reversals (i.e., rows whose correlations should be multiplied by −1; center panel), and filter options for query results (right panel).

some letter strings (e.g., "protégé," "mentor," and "international") thought to be irrelevant. We performed a similar exclusion criteria specification procedure for Concept 2 (i.e., age) (see Fig. 7, left panel). The resulting meta-analytic estimate after applying the exclusions, $r = 0.029$ based on 50 effect sizes, is 0.015 off from the initial, unfiltered estimate (see Fig. 6).

The platform also offers the ability to filter by various entry attributes, such as publication year, correlation size, and sample size (see Fig. 7, right panel). Further, to facilitate rapid, first-pass meta-analytic estimates, the platform offers the ability to exclude rows, or to reverse their correlation value (i.e., $r * -1$) on a case-by-case basis, by inputting the row identifier (see Fig. 7, center panel). In each case, recalculations are done on-the-fly, and revised estimates are provided instantly without having to re-run the query.

The metaBUS graphical user interface (GUI) is currently – and will hopefully always be – in a state of refinement and enhancement. Indeed, our project team regularly receives requests to add various features (e.g., assessment of publication bias). Importantly, the platform described here provides the community a solid foundation that facilitates the location of research findings and the derivation of initial meta-analytic estimates.

5. Use Case #3: locating findings overlooked during a traditional literature search

As a third use case, meta-analysts conducting a traditional or "full-blown" systematic review may wish to search the metaBUS database for findings after completing a traditional literature search. Although the previous use cases each come with limitations, we cannot imagine a drawback to searching one more resource for meta-analytic inclusion candidates (other than increased time expenditure, which is minimal in the case of metaBUS). We suggest the following steps. First, we recommend that the meta-analyst follow the steps outlined in Use Case 1, using as search terms items from the traditional search as well as any newly discovered taxonomic node names discovered by exploring the taxonomy. Next, we suggest that a metaBUS query be conducted according to Use Case 2, with each concept defined using *both* the taxonomic nodes of interest (if any) and all exact letter strings. Finally, the meta-analyst may choose to export and download the results to a spreadsheet and, using a unique identifier or article information, examine the output for overlooked articles. Finally, each of the records unique to the metaBUS output should be checked against the original article.

To illustrate the efficacy of Use Case 3, we attempted to locate findings that were overlooked in an existing meta-analysis on the relation between job satisfaction and employee performance (Judge, Thoresen, Bono, & Patton, 2001). We chose this meta-analysis because it represents one of the largest and most comprehensive meta-analyses to date on any topic in HRM and is often praised for its adherence to best practices. Our purpose here is not to challenge the results of Judge et al. and, in fact, we doubt that their omnibus estimates would be affected by including what we have located. Rather, our purpose is to arrive at a conservative estimate of the percentage of findings that one might overlook with a typical electronic search, yet recover using metaBUS's effect size-level search. Indeed, we can't expect meta-analysts to hand-check every article in the field each time a meta-analysis is conducted. In addition, as described earlier, our field and others are at a disadvantage owing to their large backlog of non-OCR documents whose correlation matrices might contain relevant findings not alluded to in the salient electronic search text. This will likely be the case until OCR technology is perfected.

To arrive at our estimate, we examined the sampling frame and inclusion criteria specified by Judge et al. (2001). We then conducted a search as recommended above, with the exception that we only used the strings "satisfaction" and "performance" and the taxonomic codes for general job affect: satisfaction ("20072") and in-role performance ("30031"). Given that we did not conduct a comprehensive search of terms, if our search is biased, is it biased *against* high recall (i.e., we are likely to have overlooked findings in the metaBUS database). We chose this approach because we wanted to arrive at a conservative estimate relying on relatively low effort. Finally, we examined each returned metaBUS record against the original journal articles, removing findings that failed to meet Judge et al.'s inclusion criteria (e.g., those relying on only one facet of satisfaction; those relying on self-ratings of performance; those relying on student samples; those not at the individual level of analysis).

From the information presented in their Appendix, Judge et al. (2001) located 312 samples dated between 1945 and 1999. Of these, 220 (71%) were extracted from published sources. Given that we sought to compare the metaBUS search results to the Judge et al. database, we created matched sampling frames. The metaBUS database contains findings published 1990–2015 (with *Journal of Applied Psychology* and *Personnel Psychology* from 1980 to 2015). We were thus able to create two comparisons. The first comparison involved all Judge et al.'s published samples dated between 1990 and 1998 and all metaBUS sources published in the same years (note that the metaBUS sample contained data from only 23 journals). The second comparison, designed to control for the variety of journal outlets, involved all Judge et al. or metaBUS sources published in *JAP* or *PPsych* between 1980 and 1998. Note that we chose to end both comparisons at 1998, as Judge et al. reported 1999 as the end year of the literature search but included only one published sample from 1999, indicating a truncated year.

Relevant sources located in metaBUS but not present in Judge et al. (2001) are presented in Appendix A (all journal sources from 1990 to 1998) and Appendix B (*JAP* and *PPsych* from 1980 to 1998). The former comparison revealed an additional nine samples beyond Judge et al.'s 66 samples, a 14% increase in located samples. The latter, more controlled comparison revealed an additional six samples beyond Judge et al.'s 27 samples, a 22% increase in located samples. Thus, the metaBUS platform was successful in locating relevant findings that went overlooked in a very well-executed meta-analysis. We concede that, upon closer inspection, it is possible that a few of our located samples might not meet Judge et al.'s inclusion criteria. However, increases at half the rate we have detected likely warrant a search of an effect size-level search engine such as metaBUS; the traditional search process is simply too cumbersome to expect perfect recall.

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6. Discussion

In the present manuscript, we have described how metaBUS can assist in addressing two central challenges to conducting meta-analyses, both linked to the ease of locating research findings. We have also detailed three potential use cases of the metaBUS platform to facilitate the generation of search terms, to conduct rapid, first-pass meta-analyses, and as a final check for overlooked findings when conducting a meta-analysis. As the database grows, technological developments emerge, and additional functionality is built in, we look forward to evaluating the extent to which the platform will serve the goals of open science (see Baker, Bosco, Uggerslev, & Steel, 2016) and EBM (see Bosco, Steel et al., 2015).

Regarding implications for science, we look forward to how others will leverage the platform to answer a variety of "science-of-science" research questions. As an example, given a large corpus of data and a taxonomic classification of entries narrowed down to the particular construct name, investigations of the jingle-jangle problem become increasingly feasible. As one possible approach, researchers might apply network- or factor-analytic approaches to examine overlap in construct spaces and constructs' relative positions in a large-scale nomological network. In this way, metaBUS allows a "Big Data" approach to scientific evidence (cf. George, Haas, & Pentland, 2014), allowing answers to long-standing and pressing questions.

There are several limitations to metaBUS that are imperative to list. Although metaBUS can provide first-pass meta-analytic estimates and facilitate the location of research findings (provided there is primary data available), its results are not to be interpreted as on-par with systematic reviews. A full systematic review requires the researcher to obtain all data regardless of its publication status, language, the journal it is published in, year, and so on. At this time, the metaBUS corpus of data is limited to data from 23 journals, which is a major limitation. Additionally, the metaBUS dataset has been single-coded, making the high-inference classification (e.g., taxonomic location) useful but not entirely trustworthy. Although this latter limitation is addressed somewhat by offering users the ability to search by verbatim reported variable text, it is certainly not perfect. Still, to the extent that metaBUS is primarily a search engine, many users will likely be comfortable with its size-accuracy tradeoff characteristics. Baker et al. (2016) suggest that future embodiments of the platform leverage user behavior (e.g., exclusion frequency; error flagging) as a mechanism to improve the reliability of the database contents.

Regarding future directions, to code and ingest all the scientific research that has and will continue to be done – not just in HRM, but in all of science – is an epic undertaking. Estimates of the number of articles and journals range. To limit ourselves to "serious scientific journals" (Larsen & Von Ins, 2010, p. 602), there were approximately 24,000 journals in 2010, but given a conservative annual growth rate of 3%, it is closer to 29,000 at the time of this writing. If we consider conference archives and nonrefereed journals, this figure could easily quadruple. The number of articles these sources contain is also debatable. In 2009, it was estimated to be 50 million (Jinha, 2010), but with a double rate estimated every nine years (Bornmann & Mutz, 2015); we are quickly closing in on the 100 million mark. Although many of these papers will not have data suitable for meta-analytic coding, it roughly defines the extent of the work ahead.

To code entire scientific fields outside of HRM, the coding platform will have to be expanded. Indeed, many findings tend to be reported in a form other than the correlation coefficient, such as those often found in experimental research. In addition, approaches have been developed to cumulate regression weights (i.e., elasticities), particularly useful in cases where zero-order correlations are not reported by default (e.g., economics; Leonard, Stanley, & Doucouliagos, 2014). At the current stage, however, we will focus on the relatively more straightforward bivariate and univariate findings. This choice was driven by a desire to curate as much as possible with our resources, with correlation matrices being our densest source of effect sizes. As resources expand, these harder to code effect sizes become feasible once again.

Regarding descriptive statistics, we do record them but not always in sufficient depth to maximize their usefulness. Means and standard deviations are often reported on different scales, from narrow (e.g., dichotomous) to broad (e.g., 1 to 100). Furthermore, some authors sum across all items in the measure and others average across all items. If they can be put on a common metric, which we have yet to do, there are several advantages. To begin with, new databases can emerge based on mean differences, such as Taras, Steel, and Kirkman (2012) update of the seminal Hofstede indices of national culture. We could track how various constructs are changing across time, group, and geography. Also, with a database of means, baseline or comparison groups could be referenced at will. And, to the extent that we have identified moderators that affect the mean (e.g., sex, age, employment status), we can synthesize custom control groups for most experiments that are far more accurate than could be locally developed. Local studies are often underpowered, with estimates rife with sampling error. However, if we swap or supplement the locally derived control group with one synthetically provided that is order of magnitude larger, power is vastly increased. We could even start making comparisons among groups that have yet to be formally examined, creating new findings that simply emerge from the literature.

We would also like to expand the contextual or moderator variables coded. For the most part, scientific fields are in a deplorable state when describing the setting in which their study occurs. Ideally, any description should target what moderates or affects the generalizability of the results. Context does matter (e.g., Morgeson, Dierdorff, & Hmurovic, 2010); consequently, it is important to know whether the study was conducted with the young versus the old, students versus employees, and men versus women. Unfortunately, often those very three characteristics (i.e., age, employment status, and sex) are the only three variables that are reported, at least in the area of applied psychology. Not only is their impact uneven – only sometimes do they make a difference – other potential moderators are overlooked. To the extent alternative moderators are reported, even sporadically, we should try to capture them. The coding platform can play its part in this. For example, we could have dropdown menus that give precise Diagnostic and Statistical Manual of Mental Disorders categories, team characteristics, O*NET occupational groups, or Standard Industrial Classification (SIC) categories. The potential moderators, as they should, will differ across topics of study, so any single study, depending on its focus, will cue a specific array of coding fields. Standardized reporting within primary studies would complement these efforts.

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Finally, future embodiments of the metaBUS system may change the approaches to science that have reigned since early origins. One can envision a future system enabling meta-analysts to save their decision points around variables and studies to include versus to exclude in particular analyses. They could then share their conceptualizations of concepts (such as distinctions between extra-role behavior and citizenship behaviors) with their collaborators for further refinement, and eventually, make their concepts and analyses public. Through contributions from other scholars, perhaps we can move in the direction of consensus on some topics, setting direction for future research. We envision that metaBUS will also offer a uniform resource locator (URL) for each meta-analytic correlation matrix published, enabling other researchers and the public to recreate the concepts and transparently see the analytic, filtering, and conceptual decisions made by the authors. Such an enablement would take the guesswork out of reproducibility of meta-analytic findings, but requires significant work towards implementing data and taxonomic versioning (such as incorporation of error corrections and article retractions, and additional data ingestion). In addition, the system could implement an "update" feature, highlighting how effects might have changed with the latest corpus of data and any changes to the dataset at the time of the publication following corrections. Moreover, through linkages using Digital Object Identifiers (DOIs), future enablements could include links to the primary studies in either exploratory or targeted searches. A natural follow-on will be to automatically generate reference lists. Indeed, one can imagine that as our meta-analyses grow in size with more and more available and curated data, journals publishing meta-analyses will no longer seek to publish reference lists, but rather will include electronic links to the information. Our goal is to develop these features into metaBUS in the short term.

As can be seen, coding a single study can be an extensive job and we have perhaps millions of them to tackle. How can this be done? Certainly it is beyond the scope of any single research team, no matter how well funded. There are three overlapping options. The first is simply computerized or machine coding. Some patterns of publications will fit a recognizable template or established rules. To the extent that the type and placement of data is predictable, we can scan the article and use computer algorithms to extract the data. So far, despite efforts from across the globe, results indicate this strategy is premature. The diversity of ways that researchers have presented data, at times transparent and others flawed or deceptive, does not indicate this can be implemented reliably in the near term. However, there are aspects that could be made at least more efficient with judicious use of programming. In particular, if we could record at the level of a particular measure (e.g., the NEO, the HEXACO), a practice we sporadically now employ, entries could be automatically associated with the correct node within the taxonomy.

Others have dealt with the problem of exabytes of information by enlisting citizen scientists, with Zooniverse being the largest and most successful consortium of crowdsourced scientific research (Cox et al., 2015). With over a million volunteers, formerly insurmountable informational problems become tractable when subjected to massive amounts of organized efforts. Fields that have drawn upon these efforts range from astronomy (e.g., the Galaxy Zoo) to conservation (e.g., Snapshot Serengeti). These efforts are particularly good at exactly what we are looking for: classification and coding. Still, not everyone is going to be able to properly read and discern scientific articles. Some might excel but only in fields they are familiar with and some articles will prove too obtuse for all but the most expert coder.

As a third approach to growing the database, journals could offer manuscript authors the opportunity to curate their own findings using metaBUS protocols and upload to the platform. The metaBUS team is actively developing cloud-based data entry forms to allow users to add their own data. A number of challenges come with this data sharing or open science approach, however. Indeed, additional protocols for ensuring reliability of untrained coders would be required.

To handle our backlog of millions (and growing!) of articles, as much automation of the process is desirable. If computer algorithms cannot yet code an article, they might do better at estimating the level of difficulty of the coding task or whether there is relevant information (e.g., an absence of any numbers is likely pertinent here). This will enable matching the appropriate article to the right volunteer. These volunteers will need to be vetted, trained, and periodically assessed, which can be done also automatically. Vetting or selection can occur through an online test of basic statistical knowledge and some sample, basic articles chosen from fields that the volunteer is comfortable with. Once they show a threshold of expertise, online video based instruction and discussion boards would walk them through the nuances of the coding platform. A set series of articles can be used during training and development, where the volunteer becomes familiar with the range of articles they encounter. Then articles appropriate to their expertise can be sent along with the coding platform, like metaBUS, available online. Being volunteers, every article should be successfully double coded. This also will identify any errant coder, whose error rates exceed acceptable limits. If a coder clearly is not reliable, their past coding efforts can be excised from the system along with a recommendation that they put their skills perhaps towards other projects.

Potentially, we would need approximately 100,000 volunteers each considering a 1000 articles each to code (i.e., 100,000 $\times$ 1000 = 100 million). However, the computerized winnowing will shrink this figure considerably. Like other Zooniverse projects, citizen coders do not make academic, doctoral students, postdoctoral, or professional coders obsolete. Taxonomic maps as well as coding characteristics will have unique features for each field. Development and refinement of coding options will need to rely on those who have dedicated their career to the topic. Translations of the coding platform into multiple languages will have to be done with exquisite care. Also, there should be a process of elevation, where particular difficult to code articles are addressed by an elite group. Questions regarding the coding process should be overseen by experts. And there should be a core that evaluates, recognizes, and celebrates the contributions of the citizen coders.

So far, this strategy is all tractable, with one caveat. Despite tax-paying citizens being the origin of funds that paid for the bulk of this research, these articles are often sequestered behind considerably expensive paywalls, where the price to see a single article can be greater than entire hardcover books on the topic. For the meanwhile, with the exception of those with journal access (e.g., university students or employees), open journals will have to be targeted first. Unless a solution for access is found, we will have to rely on those with academic credentials to expand further.

Appendix A. Characteristics of nine samples published between 1990 and 1998 not present in Judge et al. (2001).

Source	Article title	Employee satisfaction	Employee performance
Steel, Shane, & Kennedy (1990) r = 0.04 N = 69 "full-time civilian employees of an Air National Guard station" (p. 424)	Effects of social-system factors on absenteeism, turnover, and job performance	"Job satisfaction was measured by a five-item instrument developed by Andrews and Withey (1976)" (p. 426).	"…appraisals contained ratings on the following five performance dimensions: quantity, quality, efficiency, problem solving capacity, and adaptability… Supervisory appraisals were obtained from each employee's immediate supervisor" (p. 427).
Graen, Wakabayashi, Graen, & Graen (1990) r = 0.18 N = 71 employees of a "large Japanese, international marketing and distribution corporation" (p. 6)	International generalizability of American hypotheses about Japanese management progress: A strong inference investigation	"In the 13th year of tenure, *Job Satisfaction* was measured by the Hoppock Job Satisfaction Blank (Hoppock, 1935)" (p. 10)	"Performance appraisal was constructed based on data collected at six different times during the first three years… for validation on this instrument, see Graen, Novak and Sommerkamp (1982)" (p. 9).
Yammarino, Spangler, & Dubinsky (1998) r = 0.10 N = 111 "salespersons" (p. 34)	Transformational leadership and contingent reward leadership: Individual, dyad, and group levels of analysis	"subordinate job satisfaction was measured using three items from the Job Diagnostic Survey (Hackman & Oldham, 1980)" (p. 36).	"Three subjective (judgmental) measures of subordinate job performance were obtained from the reports of both superiors and subordinates using matched items. First, using a measure from Dansereau, Alutto, and Yammarino (1984) superiors and subordinates were asked how satisfied the superior was with the performance of the specific subordinate of interest- satisfaction with subordinate. Potential responses ranged on a five-point format from 0 = "very dissatisfied" to 4 = "very satisfied." Second, using another measure adapted from Dansereau et al. (1984), superiors and subordinates identified the degree to which the specific subordinate performed his/her job in line with the superior's preferences-job congruence. Potential responses ranged on a five-point format from 0 = "not at all" to 4 = "frequently, if not always." Third, subordinate effectiveness was assessed using two new items patterned after the MLQ effectiveness items (see Bass & Avolio, 1990)" (p. 36).
Podsakoff & MacKenzie (1995) r = 0.25 N = 1235 [various occupations]	An examination of substitutes for leadership within a levels-of-analysis framework	"General satisfaction was measured with the 20-item short form of the Minnesota Satisfaction Questionnaire (MSQ; Weiss, Dawis, England, & Lofquist, 1967)" (p. 298).	"Subordinates' in-role performance was measured with a 4-item scale developed by Williams (1989). This scale asks supervisors to rate the degree to which a subordinate performs all essential job duties, and fulfills the formal requirements of his or her job" (p. 298).
Kidwell & Bennett (1994) r = 0.02 N = 151 "data entry operators and first-line supervisors"	Employee reactions to electronic control systems: The role of procedural fairness	"...job satisfaction (seven items, a = 0.81) [was] gauged with measures taken from Chalykoff and Kochan (1989)" (p. 209)	"Two measures of job performance were obtained. First, supervisors were asked to provide the most recent performance appraisal rating for each employee… second, actual ECS data on job performance (i.e., keystrokes minus errors) was also obtained from several of the work groups" (p. 209).
Hackett, Bycio, & Hausdorf (1991) r = −0.03 N = 80 "bus operators" (p. 16).	Further assessments of Meyer and Allen's (1991) three-component model of organizational commitment	"Satisfaction was measured in both samples with the Job in General (JIG) Scale" (p. 17).	"We developed in-service rating checklists (ISRCs) from a job analysis of the bus operator position. The 43-item ISRC scire was the total number of performance standards the operator passed while under observation by a trained (incognito) rater on a single occasion" (p. 17).
Beauvais (1992) r = 0.15 N = 186 "scientists and engineers…employed by an energy R&D organization" (p. 336).	The effects of perceived pressures on managerial and nonmanagerial scientists and engineers	"Fourteen items from Hackman and Oldham's Job diagnostic survey (1974) measured satisfaction with pay, social relationships, job security, growth, and supervision" (p. 337).	Three items completed by immediate supervisors measured evaluations of a respondent's performance: (1) Contributions of the scientist to the technical field; (2) Contributions of the scientist to the organization; and (3) Overall performance. Each item was measured on a scale from 1 (Poor) to 5 (Excellent)" (p. 338).

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Appendix A (*continued*)

Source	Article title	Employee satisfaction	Employee performance
Taber (1991) r = 0.19 N = 126 "long distance or directory assistance telephone operators" (p. 582).	Triangulating job attitudes with interpretive and positivist measurement methods	"All operators filled out the five scales of the Job Descriptive Index (Smith, Kendall, & Hulin, 1969)" (p. 583).	"From company records, data were gathered for three key job behaviors for one year immediately prior to the questionnaire administration. Data were available for…the average speed with which each operator handled calls (referred to as Work Speed)" (p. 585).
Giles & Mossholder (1990) r = 0.03 N = 102 "employees from a national textile company" (p. 373).	Employee reactions to contextual and session components of performance appraisal	"The job satisfaction measure contained three items (e.g., "I am quite satisfied with my job")" (p. 374).	"Performance appraisal data from each employee's last review were gathered from personnel files…A global performance rating was derived for each employee by computing the mean of the supervisor's performance ratings" (p. 374).

Appendix B. Characteristics of six samples published between 1980 and 1998 in *JAP* and *PPsych* not present in Judge et al. (2001).

Source	Article title	Employee satisfaction	Employee performance
Campion, Papper, and Medsker (1996) r = −0.04 N = 395 "exempt professional (knowledge worker) jobs" (p. 434).	Relations between work team characteristics and effectiveness: A replication and extension	"The [employee satisfaction] survey included 40 items on a wide range of topics. A 5-point response format was used, with higher numbers indicating higher satisfaction" (p. 440).	"The organization's performance appraisal records were collected for 395 (95%) of the participating employees and managers… The appraisal was a management-by-objectives system with a single 4-point summary rating (ranging from 4 = exceeds requirements to 1 = needs improvement)" (pp. 441–442).
Giles and Mossholder (1990) r = 0.03 N = 102 "employees from a national textile company" (p. 373).	Employee reactions to contextual and session components of performance appraisal	"The job satisfaction measure contained three items (e.g., "I am quite satisfied with my job")" (p. 374).	"Performance appraisal data from each employee's last review were gathered from personnel files…A global performance rating was derived for each employee by computing the mean of the supervisor's performance ratings" (p. 374).
Green, Blank, and Liden (1983) r = 0.03 N = 100 "employees located at 23 branch offices of a large midwestern bank" (p. 300).	Market and organizational influences on bank employees' work attitudes and behaviors	"[*M*]anagers and staff responded to the Work… and Co-workers… scales of the Job Descriptive Index (JDI, Smith et al., 1969) Satisfaction with supervision was measured with the JDI Supervision scale for managerial respondents (a = 88)" (p. 301).	"Branch manager performance was based on an evaluation of each manager by his or her regional managers [e.g., "technical competence in banking matters;" "effectiveness in handling employees who are poor performers"] (1 = very poor, 5 = very good). These four ratings were summed to form a composite (a = 0.96). For the teller sample of the staff (n = 80), performance was measured by the sum of the absolute value of dollars over and under (r = 0.97)…These measures were standardized before being used in analysis" (p.302).
Hollenbeck and Williams (1986) r = 0.13 N = 112 "salespersons" (p. 607)	Turnover functionality versus turnover frequency: A note on work attitudes and organizational effectiveness	"Job satisfaction. A shortened version of the Job Descriptive Index (JDI; Smith et al., 1969) was used to measure satisfaction with pay, co-workers, supervision, and the work itself" (p.608).	"Performance was the individual's sales volume standardized within departments" (p.608).
Tharenou & Harker (1982) r = 0.11 N = 166 "electrical apprentices… full-time employment" (p. 799)	Organizational correlates of employee self-esteem	"The Job Diagnostic Survey (Hackman & Oldham, Note 1) was used to measure the apprentices' general job satisfaction. The score is obtained by averaging the ratings of five items with 7-point Likert scale formats" (p. 799).	"Each supervisor evaluated his subordinate's current job performance, using 5-point scales, with respect to the following seven aspects: speed of performance, quality of performance, attitude to the job, initiative, cooperation, punctuality, and ability to learn" (p. 799).
Wakabayashi et al. (1988) r = 0.13 N = 77 "newcomers…at the same hierarchical level" (p. 218)	Japanese management progress: Mobility into middle management	"[*J*]ob satisfaction was measured by the Hoppock Job Satisfaction Blank (Hoppock, 1935) and satisfaction with supervisor was assessed by a version of the Job Descriptive Index (Smith et al., 1969)" (p. 220).	"The job performance instrument used nine items: accountability, alertness, interpersonal skills, planning, technical skills, know-how, level of contribution, interpersonal attraction, and willingness to contribute to the company. The supervisor was asked to rate the job behavior of his subordinate on each dimension, using a 5-point scale" (p. 219).

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References

American Psychological Association (2010). *Publication manual of the American Psychological Association* (6th ed.). Washington, DC: American Psychological Association.
Andrews, F. M., & Withey, S. B. (1976). *Social indicators of well-being: American's perceptions of life quality.* New York: Plenum Press.
Baker, C. A., Bosco, F. A., Uggerslev, K. L., & Steel, P. (2016, July). metaBUS: An open search engine of I-O research findings. *The Industrial-Organizational Psychologist*.
Bass, B. M., & Avolio, B. J. (1990). *Transformational leadership development: Manual for the multifactor leadership questionnaire.* Palo Alto, CA: Consulting Psychologists Press.
Borgman, C. L. (2012). The conundrum of sharing research data. *Journal of the American Society for Information Science and Technology*, *63*, 1059–1078.
Bornmann, L., & Mutz, R. (2015). Growth rates of modern science: A bibliometric analysis. *Journal of the Association for Information Science and Technology*. http://dx.doi.org/10.1002/asi.23329.
Bosco, F. A., Aguinis, H., Singh, K., Field, J. G., & Pierce, C. A. (2015a). Correlational effect size benchmarks. *Journal of Applied Psychology*, *100*, 431–449.
Bosco, F. A., Singh, K., & Field, J. G. (2014, May). *Mapping I-O psychology: Content and trends from 1980 to 2010. Paper presented at the meeting of the Society for Industrial and Organizational Psychology, Honolulu, HI.*
Bosco, F. A., Steel, P., Oswald, F. L., Uggerslev, K. L., & Field, J. G. (2015b). Cloud-based meta-analysis to bridge science and practice: Welcome to metaBUS. *Personnel Assessment and Decisions*, *1*, 3–17.
Bradley, B. H., Klotz, A. C., Postlethwaite, B. E., & Brown, K. G. (2013). Ready to rumble: How team personality composition and task conflict interact to improve performance. *Journal of Applied Psychology*, *98*, 385–392.
Chalykoff, J., & Kochan, T. A. (1989). Computer-aided monitoring: Its influence on employee job satisfaction and turnover. *Personnel Psychology*, *42*, 807–834.
Chan, M. E., & Arvey, R. D. (2012). Meta-analysis and the development of knowledge. *Perspectives on Psychological Science*, *7*(1), 79–92. http://dx.doi.org/10.1177/1745691611429355.
Cooper, H. (2010). *Research synthesis and meta-analysis: A step-by-step approach* (4th ed.). Thousand Oaks, CA: Sage.
Cooper, H., & Hedges, L. V. (2009). Research synthesis as a scientific process. In F. Cooper, & L. Hedges (Eds.), *The handbook of research synthesis* (pp. 3–17). New York: Russell Sage Foundation.
Cox, J., Oh, E. Y., Simmons, B., Lintott, C., Masters, K., Greenhill, A., ... Holmes, K. (2015). Defining and measuring success in online citizen science: A case study of Zooniverse projects. *Computing in Science & Engineering*, *17*(4), 28–41. http://dx.doi.org/10.1109/MCSE.2015.65.
Dansereau, F., Alutto, J. A., & Yammarino, F. J. (1984). *Theory testing in organizational behavior: The varient approach.* Englewood Cliffs, NJ: Prentice Hall.
Elliott, J. H., Turner, T., Clavisi, O., Thomas, J., Higgins, J. P., Mavergames, C., & Gruen, R. L. (2014). Living systematic reviews: An emerging opportunity to narrow the evidence-practice gap. *PLoS Medicine*, *11*, e1001603.
Ferris, G. R., Hochwarter, W. A., & Buckley, M. R. (2012). Theory in the organizational sciences: How will we know it when we see it? *Organizational Psychology Review*, *2*, 94–106.
Furnas, G. W., Landauer, T. K., Gomez, L. M., & Dumais, S. T. (1987). The vocabulary problem in human-system communication. *Communications of the ACM*, *30*(11), 964–971.
Graen, G., Novak, M., & Sommerkamp, P. (1982). The effects of leader-member exchange and job design on productivity and job satisfaction: Testing a dual attachment model. *Organizational Behavior and Human Performance*, *30*, 109–131.
George, G., Haas, M. R., & Pentland, A. (2014). Big data and management. *Academy of Management Journal*, *57*(2), 321–326.
Hackman, J. R., & Oldham, G. R. (1980). *Work redesign. Reading.* MA: Addison-Wesley.
Hoppock, R. (1935). *Job satisfaction.* New York: Harper and Brothers.
Ip, S., Hadar, N., Keefe, S., Parkin, C., Iovin, R., Balk, E. M., & Lau, J. (2012). A web-based archive of systematic review data. *Systematic Review*, *1*, 15.
Jinha, A. E. (2010). Article 50 million: An estimate of the number of scholarly articles in existence. *Learned Publishing*, *23*, 258–263.
Judge, T. A., Thoresen, C. J., Bono, J. E., & Patton, G. K. (2001). The job satisfaction–job performance relationship: A qualitative and quantitative review. *Psychological Bulletin*, *127*(3), 376.
Larsen, P. O., & Von Ins, M. (2010). The rate of growth in scientific publication and the decline in coverage provided by Science Citation Index. *Scientometrics*, *84*, 575–603.
Lefebvre, C., Glanville, J., Wieland, L. S., Coles, B., & Weightman, A. L. (2013). Methodological developments in searching for studies for systematic reviews: Past, present and future. *Systematic Review*, *2*, 10–1186.
Leonard, M. D., Stanley, T. D., & Doucouliagos, H. (2014). Does the UK minimum wage reduce employment? A meta-regression analysis. *British Journal of Industrial Relations*, *52*(3), 499–520.
Levi, A. S. (2013, October). Humanities big data: Myths, challenges, and lessons. *IEEE International Conference on Big Data* (pp. 33–36).
Marler, J. H., & Fisher, S. L. (2013). An evidence-based review of e-HRM and strategic human resource management. *Human Resource Management Review*, *23*(1), 18–36.
Meyer, J. P., & Allen, N. J. (1991). A three-component conceptualization of organizational commitment. *Human Resource Management Review*, *1*, 61–89.
Morgeson, F. P., Dierdorff, E. C., & Hmurovic, J. L. (2010). Work design in situ: Understanding the role of occupational and organizational context. *Journal of Organizational Behavior*, *31*, 351–360.
National Information Standards Organization (US) (2005). *Guidelines for the construction, format, and management of monolingual controlled vocabularies.* Bethesda, MD: NISO Press.
Pfeffer, J. (2007). A modest proposal: How we might change the process and product of managerial research. *Academy of Management Journal*, *50*(6), 1334–1345.
Rothstein, H. R. (2012). Accessing relevant literature. In H. Cooper, P. Camic, D. Long, A. Panter, D. Rindskopf, & K. Sher (Eds.), *APA handbook of research methods in psychology, Vol 1: Foundations, planning, measures, and psychometrics* (pp. 133–144). Washington, DC: American Psychological Association.
Rynes, S. L., Giluk, T. L., & Brown, K. G. (2007). The very separate worlds of academic and practitioner periodicals in human resource management: Implications for evidence-based management. *Academy of Management Journal*, *50*(5), 987–1008.
Schmidt, F. L., & Hunter, J. E. (2015). *Methods of meta-analysis: Correcting error and bias in research findings* (3rd ed.). Washington, DC: Sage.
Shuck, B., Ghosh, R., Zigarmi, D., & Nimon, K. (2013). The jingle jangle of employee engagement further exploration of the emerging construct and implications for workplace learning and performance. *Human Resource Development Review*, *12*, 11–35.
Smith, P. C., Kendall, L. M., & Hulin, C. L. (1969). *Measurement of satisfaction in work and retirement.* Chicago, IL: Rand McNally.
Spellman, B. A. (2015). A short (personal) future history of revolution 2.0. *Perspectives on Psychological Science*, *10*(6), 886–899.
Steel, P., Kammeyer-Mueller, J., & Paterson, T. A. (2015). Improving the meta-analytic assessment of effect size variance with an informed Bayesian prior. *Journal of Management*, *41*(2), 718–743.
Taras, V., Steel, P., & Kirkman, B. L. (2012). Improving national cultural indices using a longitudinal meta-analysis of Hofstede's dimensions. *Journal of World Business*, *47*, 329–341.
Tebala, G. D. (2015). What is the future of biomedical research? *Medical Hypotheses*, *85*(4), 488–490.
Tsuji, S., Bergmann, C., & Cristia, A. (2014). Community-augmented meta-analyses: Toward cumulative data assessment. *Perspectives on Psychological Science*, *9*, 661–665.
Tuleya, L. G. (2007). *Thesaurus of psychological index terms.* Washington, DC: American Psychological Association.
Viechtbauer, W. (2010). Conducting meta-analyses in R with the metafor package. *Journal of Statistical Software*, *36*, 1–48.
Weiss, D. J., Dawis, R. V., England, G. W., & Lofquist, L. H. (1967). Manual for the Minnesota satisfaction questionnaire. *Minnesota studies in vocational rehabilitation no. XXII.* Minneapolis: University of Minnesota: Industrial Relations Center Work Adjustment Project.
Williams, L. J. (1989). Affective and non-affective components of job satisfaction and organizational commitment as determinants as organizational citizenship and in-role behaviors. *Unpublished Ph.D. dissertation, Indiana University*.
Wilson, M. D. (1988). The MRC psycholinguistic database: Machine readable dictionary, version 2. *Behavioural Research Methods, Instruments and Computers*, *20*, 6–11.

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