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How Much Have We Learned about Consumer Research? A Meta-Meta-Analysis

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This meta-meta-analysis study quantifies the development of scientific knowledge in consumer research by summarizing the findings of 222 meta-analyses that together include 2481 meta-analytic effect sizes. The results provide an overview of *how much* we know and *how* knowledge has developed in consumer research over time. By explaining 7.8% variance ($r = 0.28$) in consumer-relevant dependent variables, the findings show that consumer research, a comparatively young discipline, is relatively effective at knowledge development compared to other disciplines. Furthermore, the accumulation of knowledge is significantly increasing, suggesting that our discipline is still in the growing phase of its life cycle and generating continuously improving explanations of consumer-related phenomena. The development of knowledge varies across consumer-relevant dependent variables, with strong explanations for *relationships* but significantly weaker ones for *memory*, *affect*, and *attitudes*. Moreover, the knowledge synthesized in meta-analyses is fairly—though not fully—representative of the content of primary research on consumers overall. The findings convey a future research agenda by identifying under-researched areas, advising on the selection of dependent variables, providing indicators for the expected contributions of future studies, suggesting implications for career strategies of consumer researchers, and discussing explanations for the observed knowledge growth effects.

Keywords: scientific knowledge, knowledge development, meta-analysis, meta-meta-analysis, effect size, consumer research

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The 50-year anniversary of the *Journal of Consumer Research* (*JCR*) is a sign of a matured field of inquiry that has accumulated substantial knowledge about consumers, as evidenced by the thousands of published consumer research studies. Several scholars have taken stock of the status of the discipline, painting a big picture of what we have learned about consumers, and how impactful existing research has been. Some scholars agree on a successful history of investigation (Cohen and Wilkie 2022). For instance, using text-mining and citation analysis of all articles published in *JCR*, Wang et al. (2015) show that social identity research has been flourishing and that consumer culture articles are heavily cited. A bibliometric analysis by Baumgartner (2010) identifies influential research articles and reveals that only few shooting stars exist, while many articles have a long and steady or even

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accelerating impact, providing little evidence of obsolescence of the field. Other scholars paint a more differentiated picture. Simonson et al. (2001) describe a growing emphasis on substantive phenomena, originality, and theory development over practical applications, while also identifying hot and cold topics and a fragmentation into subareas. MacInnis et al. (2020) highlight the relatively narrow impact of the field and the lack of research significance. These exemplars of big-picture approaches to consumer research all focus on *what is done and appreciated by scholars*. However, they do not address the crucial questions of *what* and *how much is known*.

We do not know how much empirical knowledge—in terms of the variance explained in consumer responses—we have accumulated, how this knowledge differs across consumer variables, and how it compares to knowledge accumulation in other fields. Moreover, as knowledge from primary research gets synthesized and further developed via secondary research studies, it is vital to verify whether such studies are representative of the content of primary research on consumers overall, and where disconnects between primary and secondary research may lie. Answering those questions is important, as they allow researchers to objectively assess the maturity level and knowledge growth trajectory of consumer research, benchmark it against that of related fields, and identify promising future research avenues.

The current study answers the questions of: (1) how much we know about consumers (that is, how well we have explained the variance observed in different consumer responses), (2) how this explained variance varies across (a) time and (b) key research constructs (i.e., dependent variables), (3) how this variance compares to that observed in other research fields, and (4) how well the knowledge synthesized in secondary research is aligned with primary research on consumers. We answer the first three questions by quantitatively measuring knowledge using the meta-analytic effect sizes extracted from all 222 meta-analyses published so far in consumer research. We focus on meta-analyses (and their derived product, meta-meta-analyses), as they represent the "highest level of evidence" in empirical research (Ioannidis 2017), whose benefits include: providing robust conclusions about the size of cause–effect relationships (Chan and Arvey 2012), helping to uncovering explanations for inconsistent findings (Grewal, Puccinelli, and Monroe 2018), and potentially contributing toward alleviating the replication crisis in science (Ones, Viswesvaran, and Schmidt 2017; Sharpe and Poets 2020). We answer the fourth question by comparing research trends in meta-analyses (i.e., changes in research topic volume before and after 2014, the year associated with *JCR*'s 40th anniversary) with recent research trends observed in primary research (Wang et al. 2015).

In recent years, the number of meta-analyses in marketing and consumer research has increased exponentially (Grewal et al. 2018)—a phenomenon consistent with the proliferation of meta-analyses in the behavioral and life sciences (Ioannidis 2017). In view of this expanding body of research, the present work complements the burgeoning practice of evaluating knowledge accumulation in a specific behavioral field via a meta-meta-analytical approach that summarizes all meta-analyses conducted in that field (Nuijten et al. 2020; Siegel et al. 2022). Our findings contribute to the consumer research field by quantitatively measuring its knowledge development, comparing it to that of neighboring fields, and investigating the alignment in trends between primary and meta-analytical research topics. The findings differ across dependent variables and research topics, which helps to identify under-researched yet promising topics for future research and funding initiatives. The findings also illustrate what effect sizes are considered normal and should be exceeded in future studies, for such studies to provide substantial research contributions. This knowledge in turn helps researchers, reviewers, and readers better evaluate the merits of future research. Ultimately, as effect sizes are linked to scientific contributions and recognition in the academic community, the findings provide insights for successful career strategies of consumer research scholars.

MEASURING KNOWLEDGE AMOUNT, PROGRESS, AND RESEARCH TRENDS

Knowledge Amount and Progress Measurement

Successful scientific knowledge development rests on the explanatory power of research statements (i.e., hypotheses and theories) that link constructs to one another (Lehmann 1996). Explanatory power is empirically assessed via the *effect size*, which provides evidence for how strongly two variables are related to or depend on each other—in other words, whether and how well a research question has been answered (Chan and Arvey 2012). Effect sizes indicate the value of scientific explanations and the usefulness of scientific hypotheses and theories: the more variance is explained, the more useful and relevant the underlying theory, and the more valuable the knowledge generated by that theory (Aguinis et al. 2011). Effect sizes also have practical relevance in applied behavioral research, as acting on theories supported by small effects produces results that are likely trivial (Combs 2010). The value of scientific knowledge further depends on the generalization potential of the corresponding effect—that is, being able to identify patterns that are likely to recur in future situations (Lehmann 1996). Because a meta-analysis relies on large samples and repeated tests, averages out sampling error deviations from correct values, and corrects mean values for biases caused by measurement error and other artifacts (Schmidt 1992), the meta-analytic effect size serves as a quantifiable and generalizable measure of the merit of scientific explanations and the value of scientific knowledge (Aguinis et al. 2011). Moreover, summarizing all meta-analytical effect sizes across a particular field—via a so-called *meta-meta-analysis* (Ioannidis 2017; Schmidt and Oh 2013)—provides a quantitative, big-picture overview of the amount of knowledge accumulation in that field. A meta-meta-analysis is a straightforward generalization of first-order meta-analytic methods which integrates mean effect sizes across multiple meta-analyses, while modeling the between-meta-analysis variance (Schmidt and Oh 2013).

Changes in observed effect sizes over time can be used to assess how scientific knowledge develops (Eisend 2015), whereby positive changes signal increases in the scope, depth, or precision of a scientific paradigm (Chan and Arvey 2012). Based on a discussion of different science philosophers' views on the trajectory of scientific progress, Eisend (2015) suggests three knowledge development models: *continuous growth*, where additional empirical research increases the scope of explanations; *discontinuous growth*, where strong research contributions occur especially in the beginning of a research program or certain topics exhibit patterns of exhaustion over time; and *stasis*, where researchers do not build on one another's work, as no research paradigm is widely accepted and the research environment is selecting problems unsystematically. The three models can be identified by effect size variations over time that follow a linear trend or an exponential growth curve (continuous growth model), a quadratic curve (discontinuous growth), or remain unchanged (stasis).

Measuring Alignment between Primary and Meta-Analytical Research Trends

A meta-analysis is typically conducted when a topic reaches maturity (i.e., research findings around that topic reach a volume and level of complexity or dispersion large enough that evidence synthesis is needed to shed light on the true strength or nature of the observed effects, Paul and Barari 2022). As such, the volume of meta-analyses on a topic should closely track the research volume for that topic (albeit with a time delay). We examine the extent to which recent research trends observed in primary studies on consumers line up with research trends observed in meta-analytical research, to identify how representative meta-analysis research is of the consumer research field as a whole, and where re-alignment opportunities lie.

METHOD

Meta-Analysis Dataset

To investigate the amount and progress of knowledge development in consumer research, we perform a meta-meta-analysis that follows the procedure employed in marketing research (Eisend 2015) and related fields (Richard, Bond, and Stokes-Zoota 2003; Siegel et al. 2022; Stanley, Carter, and Doucouliagos 2018). To locate all meta-analyses published in consumer research until the end of 2021, we performed the following steps: (1) retrieved all relevant meta-analyses from a prior meta-meta-analysis (Eisend 2015); (2) searched all relevant electronic databases (e.g., *ABI/INFORM*, *EBSCO*, *INFORMS PubsOnLine*) and *Google Scholar*, using the keywords "metaanaly*," "meta-analy*," "quantitative review," "synthesis," and "generalization," combined with "consumer;" and (3) systematically searched journals that were major outlets of meta-analyses. To be included, a paper had to (1) be a meta-analysis and (2) qualify as a consumer research study. All meta-analytic effect sizes that have as dependent variable a construct that measures a consumer response (i.e., a consumer-related state, evaluation, or behavior) were included. Web appendix A provides full details on the inclusion and exclusion criteria used, including the operationalization of *consumer research topic*. We chose to focus on dependent variables as the main unit of categorization because dependent variables are considered the central constructs in behavioral research studies (Larsen et al. 2021).

To achieve the broadest generalization, the most highly aggregated meta-analytic effect sizes were selected. If a meta-analysis combined findings from primary studies into several meta-analytic effect sizes rather than a single one, we coded all of those effect sizes. On average, a meta-analysis provides 11.13 effect sizes (median = 6, with 25% of the meta-analyses providing only one effect size). We observed that the number of meta-analytic effect sizes extracted from each meta-analysis is highly correlated with the number of studies included in a meta-analysis, indicating that the number of effect sizes that a meta-analysis contributes is not the effect of randomness or inconsistent dependent variable coding (see web appendix A for further details). We retrieved data from meta-analyses published until 2012 from the dataset reported in Eisend (2015), which we updated and recoded when necessary. Data from the meta-analyses published after 2012 were coded by a total of 5 coders, who also provided quality checks and oversight. The coding was done using the Cognetto (Hyperthesis) Meta-Extractor (https://cognetto.ai/meta), an artificial intelligence (AI)-enabled, interactive data extraction tool for meta-analyses and systematic reviews that allows data coding directly on top of PDF documents, automatically detects and extracts key elements of research papers, organizes the coded data, and links it back to its source location in the text, facilitating fast and accurate data extraction and rapid quality checks.

The correlation coefficient was chosen as the meta-analytic effect size that captures the explained variance in a relationship between two variables. The final dataset includes 2,481 meta-analytic effect sizes extracted from

222 meta-analyses published by the end of 2021 (see web appendix B for the full list). Of the 222 meta-analyses, 93 were included in Eisend (2015). The meta-analyses include around 14,000 primary studies (62.9 studies per meta-analysis)[1] and more than 100,000 primary effect sizes. Based on the 121 meta-analyses that reported the sample sizes of the included primary studies, we calculated that, on average, a meta-analysis includes data from 58,475 consumers. Assuming roughly the same sample size for the remaining meta-analyses, the full dataset of 222 meta-analyses covers an overall sample size of more than 20 million consumers. Absolute values of the correlation coefficient were coded because we are interested in the size of the effect rather than its direction.[2]

Effect Sizes and Dependent Variables

For each effect size, we assigned the dependent variable to a conceptual category. The categories were developed based on a review of the consumer research literature and inspection of the dependent variables in our set of collected meta-analyses. The assignment of each dependent variable to its corresponding category was done via a rule-based computer classification model, which produced a 90.6% agreement rate with a human coder (see table 1 and web appendix C for the categorization details).

Effect Sizes and Time

We assume that the *time* variable explains effect sizes as a function of consumer research progression over time. To this end, we used a variable that reflects the time when the knowledge included in a meta-analysis was generated. This variable was calculated from the average publication year of the studies included in a meta-analysis, where available. On average, the mean is located after 66% of the time has passed since the publication of the oldest study. If we could not retrieve the full list of studies, the mean value was computed based on the time difference between the publication year of the oldest and the most recently published study of the meta-analysis.[3] To explore the best-fitting model(s) of scientific progress, we estimated different functional forms: a linear function (for continuous, linear progress), a logistic or growth function (for continuous, non-linear progress), and a quadratic function (for discontinuous progress, see Eisend 2015). A non-significant effect denotes a static progress model. In cases where more than one model was significant, the additional explained variance of each model was tested against the explained variance of the significant linear model as the base model, to determine the model with the highest explanatory power.

Primary and Meta-Analytical Research Trends

To measure trends in primary research on consumers, we used Wang et al.'s (2015) historical analysis of the content of *JCR* articles. Published on the occasion of *JCR*'s 40th anniversary,[4] the analysis employs a Latent Dirichlet Allocation-based topic modeling procedure to group *JCR* article abstracts into 16 topics investigated in consumer research. Using these 16 topics, along with Wang et al.'s (2015) list of representative terms for each topic, we trained two coders to manually assign the abstracts of the 222 meta-analyses to each topic. Since each abstract can be represented by a mixture of topics (Wang et al. 2015), coders could categorize an abstract to up to three topics (see web appendix H for an overview of the topics and the categorization criteria used). Inter-rater reliability for each topic (Cohen's kappa) was sufficiently high (0.81), and differences were resolved through discussions. To determine how well trends in meta-analysis research line up with trends in primary research in consumer behavior, our analysis compares, for each topic, the change in meta-analysis research volume before and after 2014 (where 2014 represents the cutoff point for Wang et al.'s [2015] analysis). We then contrast the observed changes in meta-analysis research volume against the changes identified or predicted by Wang et al. (2015). Importantly, since the overall number of meta-analyses in consumer research has been exponentially increasing over the years, examining research volume in terms of number of published meta-analyses may not reveal true trends, as publication numbers would be trending up across all topics. Hence, a more informative metric for research volume is the proportion of all meta-

1 We checked for study overlap (i.e., studies that were included in more than one meta-analysis) in meta-analyses for which we could retrieve the study list. We found that 16% of the meta-analyses include only unique, non-overlapping studies and 50% show an overlap of less than 16%. The relationship between the percentage of overlapping studies and the mean effect size of a meta-analysis is not significant ($r = 0.12$, $p = .11$, $n = 188$). Because our analysis is largely descriptive, the overlap of studies should cause no problem, as the overlap affects only the standard errors and confidence intervals and causes no biases in averages or mean values (Stanley et al. 2018).

2 Around 10% of the meta-analytic effect sizes were negative and were converted into positive ones (see web appendix E for the exact figures of negative effect sizes). Similar to Eisend (2015), we found that attenuation-corrected estimates are larger than unattenuated ones (0.31 vs. 0.28, $F(1, 479) = 18.11$, $p < .001$), because the correction factor increases unattenuated effect sizes. The average ratio of unattenuated to attenuated effect sizes is 0.89, which was used to correct the estimates from meta-analyses that provide attenuation-corrected estimates (i.e., the estimates were multiplied by 0.89). We found no difference between unweighted and weighted mean values (0.28 vs. 0.27, $F(1, 479) = .31$, $p = .57$) and thus did not correct them.

3 For 24 meta-analyses, neither the study list nor information on the timeframe could be retrieved, and they were therefore excluded from the analysis of temporal developments.

4 While extrapolating the results from *JCR* articles to the entirety of the consumer research field is not without limitations, we nevertheless consider *JCR*, with its "big tent" approach to research, to be representative enough of consumer research developments and trends (Inman et al. 2018) to warrant such extrapolation.

TABLE 1

META-META-ANALYTIC EFFECT SIZES PER DV CATEGORY AND THE FUNCTIONAL FORMS OF THE RELATIONSHIP BETWEEN EFFECT SIZE AND TIME

Dependent variable category	Definition	# effect sizes	# meta-analyses	(Raw) mean *r*	Median *r*	% variance expl.	Aggreg. mean *r*	Multi-level mean *r*	Best fitting form
Affect	Valenced emotional state	51	23	0.200	0.161	4.0	0.228	0.235	Static
Attention	Amount of concentration, focus	37	11	0.322	0.340	10.4	0.228	0.226	Static
Attitudes	General evaluations of consumption-related objects	303	80	0.224	0.195	5.0	0.244	0.242	Linear (+)
Behaviors/intentions (general)	Likelihood of engaging in consumption-related behaviors, where the exact behavior is not specified	326	64	0.217	0.186	4.7	0.263	0.265	Linear (+)
Choice and decisions	Reaching a conclusion and selection from alternatives	32	15	0.341	0.337	11.6	0.281	0.311	Static
Cognitions	Perceptions and beliefs regarding specific features of consumption objects (e.g., quality, brand image)	580	99	0.269	0.244	7.2	0.278	0.282	Linear (−)
Involvement	Level of engagement, motivation, and invested efforts	27	7	0.344	0.369	11.8	0.328	0.322	Static
Memory	Ability and process of storing and remembering information	45	22	0.206	0.175	4.2	0.252	0.243	Static
Post-purchase behaviors	Consumer behavior after product purchase (e.g., use, return); excludes social behaviors	110	22	0.248	0.233	6.2	0.222	0.217	Static
Processing	Process of receiving, interpreting, storing, retrieving information	11	9	0.219	0.229	4.8	0.215	0.216	
Purchase behaviors	Actions taken when buying a product (e.g., acquisition)	314	68	0.257	0.229	6.6	0.283	0.280	Linear (+)
Relationship strength	Ties between relational partners and relationship quality	144	35	0.406	0.422	16.5	0.418	0.407	Growth (+)
Satisfaction	Evaluation of outcomes compared with expectations	264	42	0.364	0.362	13.2	0.356	0.355	Static
Social behaviors	Consumer behavior that influences or is influenced by others (e.g., reviewing, recommending, defending a product or brand)	129	30	0.364	0.365	13.2	0.360	0.364	Static
Trust	The extent to which an entity can be believed or trusted	95	33	0.343	0.350	11.8	0.336	0.340	Growth (+)
Willingness-to-pay	Maximum amount a consumer is willing to pay/invest	13	1	0.344	0.332	11.8	0.344	–	
All effect sizes	–	2,481	222	0.280	0.263	7.840	0.270	0.276	Linear (+)

Note: All mean *r*s are significant at $p < .01$.

analysis publications that is represented by each meta-analysis topic. We therefore examine changes in the proportional representation of each topic.

RESULTS

Overall Effect Sizes

The observed mean effect size (i.e., the meta-meta-analytic effect size, corresponding to the correlation coefficient Pearson's *r*) is 0.28. This effect size indicates 7.8% explained variance (0.28^2), leaves 92.2% variance unaccounted for, and counts as a medium-sized effect (Gignac and Szodorai 2016).

Effect Size Variations by Dependent Variable Category

The meta-meta-analytic effect sizes differ based on the dependent variable used, as indicated in table 1. These differences are substantial, with effect sizes ranging from large to medium to small. The effects for *relationship strength* (16.5% explained variance) and *satisfaction* and *social behaviors* (both 13.2%) stand out as being large in size. They are also significantly stronger ($p < .05$) than the effects for the remaining dependent variable categories (except for *trust*, *involvement*, *choice/decision*, *willingness-to-pay*, and *attention*; see web appendix D for all statistical difference tests). Small-sized effects include, among others, effects for *attitudes* and *processing*. Among those, the weakest effects are for *affect* and *memory* (4.0% and 4.2%). The differences between the largest and smallest effects are notable, as the largest effect (for *relationship strength*) explains more than four times the variance explained by the weakest one (for *affect*). Also notable is the finding that effect sizes related to *attitudes*, one of the most frequently used dependent variables in consumer research (second, in our list of effect frequencies, only to *cognitions* and *behaviors*), are substantially lower (r = 0.22) compared to effect sizes for conceptually related constructs such as *choice* or *satisfaction*. Table 1 reports not only the raw mean but also the median, the mean based on multiple effect sizes from a meta-analysis that were averaged before integration, and a multi-level mean value that accounts for dependencies of multiple effects. The analytical approach is described in more detail in web appendix E, alongside further robustness tests. The comparison of the different mean computation procedures shows that for all effect sizes and for all but two dependent variables the deviation from the raw mean r is less than 0.05. These findings suggest that the results are quite robust, even for variables that are based on sparse data (i.e., less than 10 meta-analyses).

Effect Size Variations over Time

Table 1 additionally provides the results of the curve estimation procedure, with *time* as the independent variable and *effect size* as the dependent variable (see detailed results in web appendix F). The overall relationship between *time* and all effect sizes is significant and described by a linear and positive trend, suggesting a pattern of continuous knowledge growth. Trend variations, nevertheless, occur across dependent variables. We notice a positive linear trend for *attitudes*, *behavior/intentions*, and *purchase-related behaviors*, a positive growth curve for *relationship strength* and *trust*, a negative linear trend for *cognitions*, and a static (non-significant) trend for all remaining dependent variables.[5] Web appendix G depicts the fitted values of the significant relationships ($p < .1$).

Primary and Meta-Analytical Research Trends

Web appendix I shows an overview of the distribution and trends of meta-analyses by research topic and indicates how well those trends align with primary research trends. We find that, for meta-analyses published before 2014, the most frequently researched topics include *Persuasion* (21%), *Advertising* (17%), *Satisfying Customers* (16%), *Methodological Issues*, *Buying Process*, and *Self-Control and Goals* (all at 9%). For meta-analyses published in or after 2014, the most frequently researched topics include *Satisfying Customers* (29%), *Advertising* (13%), *Persuasion* (14%), *Social Identity and Influence* (12%), and *Buying Process* (10%). When comparing the changes in meta-analysis research volume distribution before and after 2014 (using χ^2 tests) against the trends predicted by Wang et al. (2015), we observe a substantial overlap between primary and meta-analytical research trends. For example, consistent with Wang et al. (2015), there is a significant decline in the share of meta-analysis research on *Persuasion* and *Methodological Issues*, a significant increase in the share of *Emotional Decision-Making* research, and a static development for *Contextual Effects*. Discrepancies also exist. For *Advertising*, while primary research volume was on a clearly declining trajectory by 2014, the share of meta-analysis research shows no evidence of decline. For *Satisfying Customers*, despite speculations that primary research volume may have peaked by 2014, the share of meta-analysis research continued increasing, to the point where it represents the most frequently researched topic after 2014 (29%), with a research volume more than twice as large as the next most frequently researched topic (*Advertising*, with 13%). Additionally, while *Self-Control and Goals* and *Social Identity and Influence* were expected to deliver healthy streams of consumer research past 2014, the share of meta-analysis research for those topics shows a static development.

DISCUSSION

The findings show how much is known in consumer research, how this knowledge has progressed over time, and how well its synthesis aligns with the content of primary studies. They provide not only a big picture of the development and current status of a dynamic research field but also a research agenda with implications for knowledge progress.

Distinction from Eisend's (2015) Meta-Meta-Analysis of Marketing Research

Ninety-three out of the 222 meta-analyses in this article were also included in Eisend's (2015) meta-meta-analysis of marketing research. When compared to Eisend (2015), the present investigation offers additional contributions in both methodology and findings. First, our results show an overall effect size of 0.28, which is larger than the 0.24 effect size obtained by Eisend (2015), suggesting that consumer research is better able to explain its phenomena than the broader area of marketing. Second, while Eisend (2015)

5 We find a positive relationship between time and the number of studies in a meta-analysis ($r = 0.26$, $p < .01$), suggesting that the overall positive trend results could reflect learning as expressed by the progressively larger number of studies included in consumer research meta-analyses. Thus, we added the number of studies to the models in table 2 and found it to be a significant predictor in several cases. However, the significant effects of time remain unchanged, supporting the robustness of our results.

finds that marketing research up to 2012 displays knowledge growth but at a decreasing rate, the consumer research knowledge growth trajectory until 2021 is linear and steady, indicating that the field has not yet matured as much as marketing, hence still offering plenty of room for new contributions. The reasons for the observed distinction between consumer and marketing research results are both substantial and methodological. Substantially, consumer research benefits from a constant provision of more varied and innovative research topics that are inspired by a strong interdisciplinary approach, by interactions between different research areas and disciplines, and by fewer challenges brought on by increasing specialization (Eisend 2015; MacInnis and Folkes 2010). Compared to the broader area of marketing, consumer research gets published in several journal outlets, which—despite some specializations—still seem to reach the whole research community. As for methodological explanations of knowledge progress, it appears that the advancement of rigorous methods has strengthened the effects obtained in consumer research. This finding is in line with the improvements observed in behavioral research over the recent decades due to the implementation of stronger experimental controls (Cohen and Wilkie 2022). Consumer research hence appears more successful at knowledge development than marketing research overall, which suggests that consumer researchers can capitalize on some of the key characteristics of our field to further accelerate knowledge generation. For example, important knowledge contributions may arise from the exploration of interdisciplinary, boundary-breaking consumer research topics (MacInnis et al. 2020), such as timely investigations at the intersection of consumer and computer science—an area currently being transformed by the adoption of generative AI technologies into mass consumption practices. Finally, the present investigation further extends Eisend's (2015) approach methodologically, as it breaks findings down per dependent variables, thereby shedding light on individual constructs' contributions to knowledge development in consumer research and illustrating how the careful, strategic selection of study variables can be key to researchers successfully explaining consumer phenomena of interest.

Contributions

First, by explaining 7.8% variance in the dependent variables, the results offer an objective, standardized measure of how much we have learned in consumer research. While this variance may initially appear small, it allows us to determine how our field's knowledge development compares to that of other fields, as shown in table 2. In other behavioral fields—whether across a broad swath of the behavioral sciences (particularly psychology, 3.6%), in specific sub-disciplines such as memory, intelligence, or individual differences research (from 4% to 6.8%), or in applied fields such as organizational psychology (6.8%)—the explained variance is below the level observed in consumer research. The explained variance differences are small, but given the range from 3.6% to 7.8%, a 1% advantage in consumer research is relevant. This represents an encouraging finding, as it suggests that consumer research, a comparatively young discipline, is relatively effective at explaining its phenomena compared to neighboring disciplines. Consumer research also compares favorably to a more remote field such as medical (clinical) research, where effect sizes range from 0.13 (for dichotomous) to 0.15 (for continuous dependent variables).

Second, the findings show that knowledge accumulation in consumer research has been steadily growing and is improving the explanations of phenomena related to consumers, suggesting that the field has still not reached the peak of its knowledge life cycle. This result is notable, because other behavioral and psychological science research indicates either the absence of a time effect (Schäfer and Schwarz 2019) or a downright decline in effect sizes over time in well-established fields such as intelligence research (Gong and Jiao 2019; Pietschnig et al. 2019). This insight, combined with the favorable effect size comparison to other disciplines, paints consumer research as a field characterized by dynamism and relatively powerful findings. The effect size increase in consumer research—especially when compared to marketing—can be explained both substantially and methodologically, as discussed in the previous section comparing this investigation to Eisend (2015).

Third, knowledge development in consumer research varies across dependent variable categories. The field excels at explaining *relationship* building and maintaining, which is in line with a shift toward relationships in marketing research (Palmatier et al. 2006). The variation in effect sizes across dependent variables suggests that relationship strength is linked closest to behavior and furthest to processing. Less successful explanations refer to variables such as *affect*, *memory*, or *attitudes*. The finding that effect sizes for *choice* and *satisfaction* are larger than those for either *attitudes* or *behavior/intentions (in general)* suggests that classic hierarchical models (e.g., awareness to attitude to intention [purchase]) may not operate as strongly as previously thought in our field. The observed small effect sizes could also be due to the heterogeneity of measures used for assessing such constructs. For example, *affect*, *cognitions*, and *behavior/intentions (general)* represent combinations of different individual constructs and measures, which could explain their lower effect size estimates compared to more homogenous or standardized constructs like *satisfaction*, *choice*, or *willingness-to-pay*. Of course, the low effect sizes could indicate that those constructs are more difficult to capture by the current measures and manipulations. Finally, knowledge progress also varies across dependent variable categories: *relationship* variables show an increase in knowledge accumulation, while *cognitions*

TABLE 2

COMPARISON OF EFFECT SIZES WITH OTHER DISCIPLINES

Authors	Discipline	# meta-analyses included	Journals included	Mean effect size (*r*)	% var. expl.
Behavioral research					
Stanley et al. (2018)	General psychology	200	*Psych. Bulletin*	0.19	3.61
Gignac and Szodorai (2016)	Individual differences	87	Multiple journals	0.20	4.00
Richard et al. (2003)	Social psychology	322	Multiple journals	0.21	4.41
Rubio-Aparicio et al. (2018)	Clinical psychology	54	Multiple journals	0.23	5.29
Nuijten et al. (2020)	Intelligence research	131	Multiple journals	0.26	6.76
Siegel et al. (2022)	Org. psychology	128	*Applied Psych.*	0.26	6.76
Medical (clinical) research					
IntHout et al. (2015)	Medical research	3,263	Multiple journals	0.13–0.15	1.69–2.22
Current study	Consumer research	222	Multiple journals	0.28	7.84

even display a decrease. What stands out are *purchase* and *behavioral intentions*: although the effects are only medium-sized, their development over time shows an increase, which could be explained by a stronger focus on measuring and explaining managerially relevant variables.

FUTURE RESEARCH AGENDA

The insights from this meta-meta-analysis provide several substantive, theoretical, and methodological opportunities for future consumer research (points 1–4) and implications for meta-analysis research (point 5).

Mismatch and Its Implications

Assuming that meta-analytic research provides a representative picture of research in a field,[6] the current findings suggest areas of mismatch between research activities and explanatory power in primary research. The constructs that have been investigated the most (i.e., in the largest number of meta-analyses) as dependent variables (e.g., *cognitions*, *attitudes*, *purchase*) do not provide high explanatory power, while some with high explanatory power are investigated less frequently (e.g., *involvement*, *choice*). As larger effect sizes promise more reliable and replicable effects, the observed mismatch suggests that methodological shifts such as focusing more on *incentivized choice* rather than *attitudes* could be fruitful, provided that the theoretical insights are comparable and useful for the field.

Dependent Variable Selection and Career Considerations

Both small and large effect sizes present opportunities for researchers, particularly junior scholars who are starting out their careers. A large effect size means that an effect can more easily be uncovered or replicated. Hence, when the goal is to determine whether an initial research hypothesis should be rejected or not, researchers may want to supplement the dependent variables most frequently examined in consumer research (*attitudes*, *purchase intentions*) with variables associated with larger effect sizes (*choice*, *willingness-to-pay*, *satisfaction*). Alternatively, if a study calls for the use of a dependent variable associated with small effect sizes (e.g., *attitudes*), researchers may want to increase the sample size to ensure that the study is adequately powered. We recognize that the former suggestion is not without controversy, in light of the practice of "fishing" for significant effects being discouraged in scientific research. Yet, our results show that not all dependent variables are created equally, as some are significantly better than others at reflecting the impact of various predictors. Hence, we believe that the strategic inclusion of a battery of different dependent variables in a study is warranted, provided that the study authors report all the dependent variables and the effect size-based rationale for their inclusion in the results section.

At the same time, small effect sizes present an opportunity for further theoretical, methodological, or programmatic advances around a given topic. In the case of *post-purchase behaviors*, for example, the small effect sizes observed likely signal that the topic has not yet reached

6 We explored the assumption that the distribution of dependent variables examined across meta-analyses is representative of those variables' distribution across primary research studies. To do so, we first separated meta-analyses into two categories: (1) those that focused on a specific dependent variable (either alongside a specified predictor or alongside all predictors examined in relation to that dependent variable) and (2) those that focused on a specific predictor variable and hence captured all available dependent variables examined in the literature in relation to that predictor. We assume that, when taken as a whole, the latter category (which covers 33% of all meta-analyses) provides a representative coverage of the dependent variables examined across primary research. We then compared the latter category of meta-analyses against the full dataset of meta-analyses and observed that the dependent variables have comparable distributions across the two datasets, particularly when it comes to the most and least frequently researched variables. This implies that the distribution of dependent variables examined across all meta-analyses can be considered largely representative of those variables' distribution across primary research studies. The supporting data for this analysis are provided in web appendix J.

maturity and is a promising candidate for further research initiatives and funding programs. Small effect sizes suggest the need to develop more precise and nuanced theories of the consumption phenomenon being studied or to explore alternative or complementary methods for studying a phenomenon, for example, by combining different methods or using more sensitive measures. The field could particularly benefit from using consistent constructs and measures to avoid construct fragmentation (i.e., situations where several conceptualizations coexist with no clear shared understanding of the construct among consumer researchers), since such fragmentation hampers knowledge accumulation (as illustrated by the development of the involvement construct; Bergkvist and Eisend 2021; Bosco 2022).

The findings also provide insights for career considerations of scholars and their strategies in a competitive academic market, as academic career success strongly depends on the contribution one makes to the field. Given that high effect sizes increase a scientific paper's likelihood to be published in a leading academic journal and its subsequent citation volume (Eisend and Tarrahi 2014) and hence act as a predictor for both research contribution and recognition by the scientific community, the current findings illustrate how the choice of dependent variables can influence a study's contribution. The findings reveal varying knowledge life cycles and show which variables and thus topics still promise knowledge growth in the future (e.g., *relationship-related* variables). Junior researchers can use the present findings as a tool for guiding research topics and study design selections for primary research studies.

Minimum Amount of Knowledge Required for Future Research Contributions

The effect sizes observed for different dependent variables can serve as indicators for the amount of knowledge currently produced that is considered "normal" for primary research. They can provide guidance for reviewers and authors regarding the minimum amount of knowledge a future study should provide or exceed, so as to offer a substantial research contribution. For instance, the effect size of 0.32 for *attention* could serve as an approximation for the expected contribution of new attention-focused consumer studies. Similarly, knowing that the average effect size for *satisfaction* is about twice as large as for *affect* could help ensure a fairer evaluation of a study that may report a significant effect for satisfaction, but not for affect.

Need for Further Probing of the Mechanisms Underlying Effect Size Increases

Our findings require further explanations regarding knowledge development in consumer research. While they point toward higher effect sizes over time, the exact reasons for such increases can benefit from in-depth probing. In general, larger meta-analytical effect sizes can be achieved via (1) increasing the precision of a paradigm (using better construct operationalization and measurement), (2) broadening the scope of a paradigm (by extrapolating to other domains), or (3) building consensus in a field (by creating feedback loops between initial and subsequent results) (Chan and Arvey 2012). Hence, larger effect sizes may imply not only larger amounts of knowledge but also "better" knowledge—that is, more confidence in the documented knowledge. For the increases we observed, a plausible explanation involves methodological advances such as stronger manipulations in experiments, better controls of other variables, or the use of dependent variables that are more sensitive to manipulations (in response to journals' demand for stronger effects that are linked to small *p*-values). Effects might increase due to publication bias, though our analysis does not support this explanation.[7]

Further research can shed light on the exact factors driving the observed effect size increases. Moreover, the finding that effect sizes have been increasing for *attitudes*, *behavioral intentions*, and *purchase-related behaviors*, as well as for *trust and relationship strength*, but decreasing for *cognitions*, can also benefit from further examination. It is particularly noteworthy that cognitions—which cover the largest share (23%) of all effect sizes across consumer meta-analyses—are characterized by both low and decreasing effect sizes. Has our field reached maturity when it comes to explaining what drives consumers' cognitions? Alternatively, as the number and type of cognitions studied in our field keep increasing, the development and adoption of validated measures for such cognitions may not have kept up. If our community has difficulty reaching measurement consensus for the increasingly large number of consumer cognitions being assessed, this could explain why such cognitions show less knowledge accumulation

7 While we find that, as expected, the percentage of unpublished papers in a meta-analysis is negatively related to the magnitude of the effect sizes in a meta-analysis ($r = -0.15$, $p < .01$), this percentage is not related to the average publication year of studies in a meta-analysis ($r = 0.02$, $p = .51$). When controlling the relationship between effect size and *time* for the percentage of unpublished studies, the relationship becomes weaker compared to the finding in web appendix I but remains significant ($r = 0.05$, $p = .04$). At the same time, we find a highly encouraging change in the application of publication bias tools in consumer research over time, though the use of such tools is not related to effect sizes: We correlated the year variable with several dummy variables indicating whether publication bias tools were used in meta-analyses and found an increase in the general reporting of a publication bias analysis ($r = 0.41$, $p < .01$), the comparison of effect sizes by publication source ($r = 0.16$, $p = .03$), the use of publication source as a moderator in meta-regression ($r = 0.15$, $p = .03$), trim-and-fill analysis ($r = 0.13$, $p = .08$), reporting of funnel plots ($r = 0.29$, $p < .01$), fail safe N ($r = 0.20$, $p < .01$), and the application of other publication bias analysis methods ($r = 0.20$, $p < .01$), but we did not find any relationship between use of publication bias techniques and meta-analytical results.

progress compared to other, less heterogeneous constructs (Bergkvist and Eisend 2021). Future research can explore why the pattern for cognitions deviates from that of other major constructs, and which cognitive responses could benefit the most from additional consensus-building measure development efforts.

Opportunities for Future Meta-Analytical Research

Our findings indicate that the trends observed in meta-analysis research are relatively representative of those observed in primary research, suggesting that evidence synthesis in consumer research follows a fairly balanced and rigorous pattern. Nevertheless, an imbalance exists for certain topics, creating opportunities for further meta-analytical research. Notably, meta-analyses on *Satisfying Consumers* and *Advertising* appear over-represented compared to primary research on those topics, suggesting saturation on the meta-analytical front, while research on consumers' *Self-control and Goals* and *Social Identity and Influence* appears under-represented, suggesting promising opportunities for additional meta-analytical work. We would also like to point out the relative scarcity of meta-analytical research that measures *willingness-to-pay*, which was investigated in a single meta-analysis in our dataset, despite its managerial importance.

In summary, the present investigation paints an optimistic picture of the knowledge we have accumulated in consumer research. At the same time, it identifies important research gaps and helps ensure that the next wave of primary and meta-analytic research is well-equipped to provide significant contributions to the consumer research literature.

DATA COLLECTION STATEMENT

For meta-analyses published after 2012, the systematic retrieval round took place between April 2021 and September 2021 and was followed by cross-checks for the meta-analyses retrieved from Eisend (2015), that is, meta-analyses published by 2012. Another round of retrieval for meta-analyses published until December 2021 was performed in March 2022. The data were collected by the first, third, and fourth authors. The data were coded by the second, third, fourth, and fifth authors with the help of two student assistants, from June 2021 to March 2022 and from July to November 2022. The data were analyzed by the first and second authors from February to April 2022 and from September to November 2022. The data are currently stored at ResearchBox.

REFERENCES

Aguinis, Herman, Dan R. Dalton, Frank A. Bosco, Charles A. Pierce, and Catherine M. Dalton (2011), "Meta-Analytic Choices and Judgment Calls: Implications for Theory Building and Testing, Obtained Effect Sizes, and Scholarly Impact," *Journal of Management*, 37 (1), 5–38.

Baumgartner, Hans (2010), "Bibliometric Reflections on the History of Consumer Research," *Journal of Consumer Psychology*, 20 (3), 233–8.

Bergkvist, Lars and Martin Eisend (2021), "The Dynamic Nature of Marketing Constructs," *Journal of the Academy of Marketing Science*, 49 (3), 521–41.

Bosco, Frank A. (2022), "Accumulating Knowledge in the Organizational Sciences," *Annual Review of Organizational Psychology and Organizational Behavior*, 9 (1), 441–64.

Chan, Meow Lan Evelyn and Richard D. Arvey (2012), "Meta-Analysis and the Development of Knowledge," *Perspectives on Psychological Science*, 7 (1), 79–92.

Cohen, Joel B. and Willam L. Wilkie (2022), "Consumer Psychology: Evolving Goals and Research Orientations," in *APA Handbook of Consumer Psychology*, ed. Lynn R. Kahle, Tina M. Lowrey, and Joel Huber, Washington, DC: American Psychological Association, 3-45.

Combs, James G. (2010), "Big Samples and Small Effects: Let's Not Trade Relevance and Rigor for Power," *Academy of Management Journal*, 53 (1), 9–13.

Eisend, Martin (2015), "Have We Progressed Marketing Knowledge? A Meta-Meta-Analysis of Effect Sizes in Marketing Research," *Journal of Marketing*, 79 (3), 23–40.

Eisend, Martin and Farid Tarrahi (2014), "Meta-Analysis Selection Bias in Marketing Research," *International Journal of Research in Marketing*, 31 (3), 317–26.

Gignac, Gilles E. and Eva T. Szodorai (2016), "Effect Size Guidelines for Individual Differences Researchers," *Personality and Individual Differences*, 102, 74–8.

Gong, Zhun and Xinian Jiao (2019), "Are Effect Sizes in Emotional Intelligence Field Declining? A Meta-Meta Analysis," *Frontiers in Psychology*, 10, 1655.

Grewal, Dhruv, Nancy Puccinelli, and Kent Monroe (2018), "Meta-Analysis: Integrating Accumulated Knowledge," *Journal of the Academy of Marketing Science*, 46 (1), 9–30.

Inman, Jeffrey J., Margaret C. Campbell, Amna Kirmani, and Linda L. Price (2018), "Our Vision for the Journal of Consumer Research: It's All about the Consumer," *Journal of Consumer Research*, 44 (5), 955–9.

IntHout, Joanna, John P. A. Ioannidis, George F. Borm, and Jelle J. Goeman (2015), "Small Studies Are More Heterogeneous Than Large Ones: A Meta-Meta-Analysis," *Journal of Clinical Epidemiology*, 68 (8), 860–9.

Ioannidis, John (2017), "Next-Generation Systematic Reviews: Prospective Meta-Analysis, Individual-Level Data, Networks and Umbrella Reviews," *British Journal of Sports Medicine*, 51 (20), 1456–8.

Larsen, Kai R., Lauren J. Ramsay, Cristina A. Godinho, Victoria Gershuny, and Dirk S. Hovorka (2021), "IC-Behavior: An Interdisciplinary Taxonomy of Behaviors," *PloS One*, 16 (9), e0252003.

Lehmann, Donald R. (1996), "Knowledge Generalization and the Convention of Consumer Research: A Study in Inconsistency," in *Advances in Consumer Research*, ed. K. Corfman and

J. Lynch, Vol. 23. Provo, UT: Association for Consumer Research, 1–23.

MacInnis, Deborah J. and Valerie S. Folkes (2010), "The Disciplinary Status of Consumer Behavior: A Sociology of Science Perspective on Key Controversies," *Journal of Consumer Research*, 36 (6), 899–914.

MacInnis, Deborah J., Vicki G. Morwitz, Simona Botti, Donna L. Hoffman, Robert V. Kozinets, Donald R. Lehmann, John G. Lynch Jr., and Cornelia Pechmann (2020), "Creating Boundary-Breaking, Marketing-Relevant Consumer Research," *Journal of Marketing*, 84 (2), 1–23.

Nuijten, Michèle B., Marcel A. L. M. van Assen, Hilde E. M. Augusteijn, Elise A. V. Crompvoets, and Jelte M. Wicherts (2020), "Effect Sizes, Power, and Biases in Intelligence Research: A Meta-Meta-Analysis," *Journal of Intelligence*, 8 (4), 36.

Ones, Denis S., Chockalingam Viswesvaran, and Frank L. Schmidt (2017), "Realizing the Full Potential of Psychometric Meta-Analysis for a Cumulative Science and Practice of Human Resource Management," *Human Resource Management Review*, 27 (1), 201–15.

Palmatier, Robert W., Rajiv P. Dant, Dhruv Grewal, and Kenneth R. Evans (2006), "Factors Influencing the Effectiveness of Relationship Marketing: A Meta-Analysis," *Journal of Marketing*, 70 (4), 136–53.

Paul, Justin and Mojtaba Barari (2022), "Meta-Analysis and Traditional Systematic Reviews—What, Why, When, Where, and How?," *Psychology & Marketing*, 39 (6), 1099–115.

Pietschnig, Jacob, Magdalena Siegel, Junia Sophia Nur Eder, and Georg Gittler (2019), "Effect Declines Are Systematic, Strong, and Ubiquitous: A Meta-Meta-Analysis of the Decline Effect in Intelligence Research," *Frontiers in Psychology*, 10, 2874.

Richard, F. D., Charles F. Bond, and Juli J. Stokes-Zoota (2003), "One Hundred Years of Social Psychology Quantitatively Described," *Review of General Psychology*, 7 (4), 331–63.

Rubio-Aparicio, María, Fulgenico Marín-Martínez, Julio Sánchez-Meca, and José A. López-López (2018), "A Methodological Review of Meta-Analyses of the Effectiveness of Clinical Psychology Treatments," *Behavior Research Methods*, 50 (5), 2057–73.

Schäfer, Thomas and Marcus A. Schwarz (2019), "The Meaningfulness of Effect Sizes in Psychological Research: Differences between Sub-Disciplines and the Impact of Potential Biases," *Frontiers in Psychology*, 10, 813.

Schmidt, Frank L. (1992), "What Do Data Really Mean?" *American Psychologist*, 47 (10), 1173–81.

Schmidt, Frank L. and In-Sue Oh (2013), "Methods for Second Order Meta-Analysis and Illustrative Applications," *Organizational Behavior and Human Decision Processes*, 121 (2), 204–18.

Sharpe, Donald and Sarena Poets (2020), "Meta-Analysis as a Response to the Replication Crisis," *Canadian Psychology / Psychologie Canadienne*, 61 (4), 377–87.

Siegel, Magdalena, Junia Sophia Nur Eder, Jelte M. Wicherts, and Jakob Pietschnig (2022), "Times Are Changing, Bias Isn't: A Meta-Meta-Analysis on Publication Bias Detection Practices, Prevalence Rates, and Predictors," *The Journal of Applied Psychology*, 107 (11), 2013–39.

Simonson, Itamar, Ziv Carmon, Ravi Dhar, Aimee Drolet, and Stephen Nowlis (2001), "Consumer Research: Search of Identity," *Annual Review of Psychology*, 52, 249–75.

Stanley, T. D., Evan C. Carter, and Hristos Doucouliagos (2018), "What Meta-Analyses Reveal about the Replicability of Psychological Research," *Psychological Bulletin*, 144 (12), 1325–46.

Wang, Xin, Neil T. Bendle, Feng Mai, and June Cotte (2015), "The Journal of Consumer Research at 40: A Historical Analysis," *Journal of Consumer Research*, 42 (1), 5–18.