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R2M Index 1.0: Assessing the Practical Relevance of Academic Marketing Articles

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Abstract

Using text-mining, the authors develop version 1.0 of the Relevance to Marketing (R2M) Index, a dynamic index that measures the topical and timely relevance of academic marketing articles to marketing practice. The index assesses topical relevance drawing on a dictionary of marketing terms derived from 50,000 marketing articles published in practitioner outlets from 1982 to 2019. Timely relevance is based on the prevalence of academic marketing topics in practitioner publications at a given time. The authors classify topics into four quadrants based on their low/high popularity in academia and practice —"Desert," "Academic Island," "Executive Fields," and "Highlands"—and score academic articles and journals: *Journal of Marketing* has the highest R2M score, followed by *Marketing Science*, *Journal of Marketing Research*, and *Journal of Consumer Research*. The index correlates with practitioner judgments of practical relevance and other relevance measures. Because the index is a work in progress, the authors discuss how to overcome current limitations and suggest correlating the index with citation counts, altmetrics, and readability measures. Marketing practitioners, authors, and journal editors can use the index to assess article relevance, and academic administrators can use it for promotion and tenure decisions (see www.R2Mindex.com). The R2M Index is thus not only a measurement instrument but also a tool for change.

Keywords

information retrieval, marketing, marketing theory, marketing practice, relevance, topic modeling

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Given that marketing is an applied discipline, articles published in academic journals should fulfill marketing practitioners' informational needs and be relevant to marketing practice. However, many articles do not seem to present relevant and important insights and findings that impact business practice (Jaworski 2011; Kohli and Haenlein 2021; Kumar 2017; Stremersch, Winer, and Camacho 2021; Van Heerde et al. 2021). Prominent marketing scholars, including the founders of the annual Theory and Practice in Marketing (TPM) conference, have noted that "many observers complain that academia is far removed from addressing substantive problems of industry. This perception threatens to make our field irrelevant and undermine the legitimacy of research at business schools" (Gupta et al. 2014, p. 1).

For years, academic researchers have proposed changing the status quo. For example, they have proposed providing incentives and rewards for scholars to engage in relevant research, focusing less on technical sophistication and more on substantive issues, and improving communications and interactions between academics and practitioners (Kohli and Haenlein 2021; Lehmann, McAlister, and Staelin 2011; Lilien 2011; Reibstein, Day, and Wind 2009; Schmitt 2012; Winer 1999). The editors of the *Journal of Marketing* (*JM*) recently highlighted specific actions to help infuse real-world perspectives into academic research (Van Heerde et al. 2021). Scholars have also discussed how business schools can improve the practical importance of faculty research (Stremersch, Winer, and Camacho 2021). A similar discussion has taken place among business school faculty in other fields (e.g., management, information systems, accounting), leading to analogous conclusions and proposals (Benbasat and Zmud 1999; Gulati 2007; Kaplan 2011; Shapiro, Kirkman, and Courtney 2007; Vermeulen 2005). However, an objective and easy-to-use measure of the practical

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relevance of articles has been missing from this debate. We believe that a simple and automated measure of relevance is likely the most effective way to change the status quo. In this article, we present version 1.0 of the Relevance to Marketing (R2M) Index, which measures the relevance of an academic article to marketing practice.

We define marketing relevance as the degree of the topical relation between the topics contained in an academic article and topics of marketing practice at a given time. Following this definition, an academic article is relevant if it is topically related to marketing practice and is timely (i.e., the information in the article satisfies marketing practitioners' current informational needs). The R2M Index is a dynamic index based on text-mining methodology. It uses a carefully constructed dictionary of more than 1,000 marketing terms derived from approximately 50,000 marketing articles published in important practitioner outlets such as *Bloomberg Business Week*, *Financial Times*, *Forbes*, *Fortune*, *Harvard Business Review*, *McKinsey Quarterly*, *Marketing News*, and *The Wall Street Journal* from 1982 to 2019, supplemented by other sources such as a Google search and Kotler and Keller's (2011) *Marketing Management* textbook. We validate the dictionary and the index with more than 350 executives enrolled in an Executive Master of Business Administration (EMBA) program as well as other marketing practitioners. The index allows us to measure which academic papers and topics are most relevant to marketing practice, whether academic marketing has become more or less relevant over time, and which academic marketing journals are most relevant. The index can help marketing practitioners (managers, consultants, and researchers in agencies) as well as the media and social influencers quickly identify whether an academic article is practically relevant to their own context and thus speaks to their informational needs. The index is also useful for academic scholars, journal editors, and administrators reviewing the relevance of academic publications. Finally, it contributes to the broader debate about the relevance of academic marketing. For R2M implementation, we developed a web application (www.R2Mindex.com) for scoring articles and searching for practically relevant research.

We first conceptualize relevance and show how text mining can be used to measure relevance to marketing. We then present the empirical study, including the construction of the marketing dictionary and the R2M Index. We show which topics are most popular over time in academia and marketing practice and use quadrant analysis to classify the topics into four quadrants based on their (low/high) popularity in academia and practice —"Desert," "Academic Island," "Executive Fields," and "Highlands." We also assess the overall relevance of marketing journals. We find that *JM* has the highest R2M score, followed by *Marketing Science* (*MSC*), *Journal of Marketing Research* (*JMR*), and *Journal of Consumer Research* (*JCR*). Next, we present validity and robustness checks. Finally, we discuss how limitations of this first version of the index can be addressed and how various stakeholders (e.g., managers, consultants, marketing researchers, authors, editors, administrators) can use the index, based on focus groups that we conducted with former organizers of the annual TPM conference.

The Case for Measuring Relevance to Marketing

What Is Relevance?

Merriam-Webster's Dictionary defines "relevant" as (1) "a relation to the matter at hand," and (2) as "practical and especially social applicability" (https://www.merriam-webster.com/dictionary/relevance). Similarly, Lexico characterizes relevance as "the quality or state of being closely connected or appropriate" (https://www.lexico.com/en/definition/relevance), and Wikipedia states that the term refers to "the concept of one topic being connected to another topic in a way that makes it useful to consider the second topic when considering the first" (https://en.wikipedia.org/wiki/Relevance). The idea of a topical connection (or relation), which may lead to practical applicability, is central to the relevance concept in information science, and specifically information retrieval (IR) (Huang and Soergel 2013; Saracevic 2007a). Merriam-Webster also provides a third definition of relevance as it relates to IR, "the ability (as of an information retrieval system) to retrieve material that satisfies the needs of the user."

These definitions guided the development of the R2M Index, which is based specifically on the conceptualization of relevance in IR. In several comprehensive reviews of the relevance literature, Saracevic (1975, 2007a, b), a leading scholar in IR, conceptualizes relevance as "a property along which parts are related and may also be considered as a measure of the strength of the related connection" (Saracevic 2007a, p. 10) and stresses that relevance is information that meets a target's needs. Other IR scholars have also emphasized the notion of relations and the importance of connecting content with users' needs (Berlund 2003; Mizzaro 1998; Schamber, Eisenberg, and Nilan 1990). This view is consistent with a definition by the American Marketing Association's (AMA) Board of Directors, which states that marketing research "links the consumer, customer, and public to the marketer through information" (https://www.ama.org/the-definition-of-marketing-what-is-marketing/). Finally, in addition to topical relevance that serves informational needs, relevance is also conceptualized as being time and context dependent. Mizzaro (1998) includes time as well as task (or context) as key dimensions in the interaction of the user and the IR system.

Some IR scholars and researchers in other fields have defined the concept of relevance more broadly in terms of impact and change. For example, Harter (1992, p. 603) states that "a phenomenon that is relevant changes the matter in some way; it adds information, or decreases information, offers a new perspective, or causes other kinds of cognitive change." In discourse theory, relevance refers to a linguistic discourse that produces change in knowledge and assumptions (Wilson and Sperber 2004). The impact (or change) view of relevance is also central to Jaworski's (2011, p. 212) definition of managerial relevance as "the degree to which a specific manager in an organization perceives academic knowledge to aid his or her job-related thoughts or actions in the pursuit of organizational goals." Relatedly, some authors distinguish relevance from importance (Kohli and Haenlein 2021; Stremersch 2021). They suggest operationalizing importance by the number and status of stakeholders who are likely to change their behavior as well as the magnitude of the expected change (Kohli and Haenlein 2021).

The topic modeling approach we use in this article does not allow us to assess the broader meaning of relevance in terms of practical impact and change such as aiding or supporting decisions and actions related to organizational goals. However, topical relevance that provides timely information for marketing practitioners seems to be a necessary condition for practical impact and change. The index is also based on information that is important to practitioners. Outlets such as *Financial Times*, *Harvard Business Review*, *McKinsey Quarterly*, and *The Wall Street Journal* are read by numerous stakeholders, including high-status senior managers, to gain insight that they could use as part of their jobs. We therefore posit that marketers' need for topical and timely information can be captured by sourcing text (i.e., marketing terms from practitioner outlets such as practitioner-oriented journals, newspapers, and trade magazines) because the content in these outlets is written and published specifically for practitioners and reflects current topics of relevance to marketing practitioners.

How Can We Measure Relevance to Marketing?

Some scholars have measured the relevance of specific methodologies such as scanner data and conjoint analysis (Bucklin and Gupta 1999; Wittink and Cattin 1989). Roberts, Kayande, and Stremersch (2014) have used a measurement approach to address practical relevance more generally by asking practitioners (marketing managers and intermediaries) to rate academic articles. While the practitioners could identify practically relevant articles, the process of asking them to rate each article seemed tedious and time intensive. Only 20% of the managers and 37% of the intermediaries (e.g., consultants, agency researchers) in their study provided usable data. Because this process cannot be automated, constant practitioner input would be required to assess the relevance of new articles. In addition, the small sample of practitioners that might be recruited is unlikely to be representative and may be biased.

We build on these prior measurement approaches by pursuing an alternative, more efficient, and more contemporary approach based on text-mining and topic modeling (Berger et al. 2020), which allows for a continuous measurement of relevance. While there have been several prior text-mining analyses of article keywords or abstracts in marketing journals including *MSC* (Mela, Roos, and Deng 2013), *JMR* (Huber, Kamakura, and Mela 2014), and *JCR* (Wang et al. 2015), none of these analyses has focused on relevance. In this article, we use text mining to analyze full articles in *MSC*, *JMR*, *JCR*, and *JM* to assess the relevance of academic articles to marketing practice.

We measure practical relevance on the basis of the degree to which an academic article features relevant and current content to marketing practice. This measurement uses two components to capture relevance. The first, topical relevance, measures the degree to which concepts and ideas featured in the article are employed by marketing practitioners as part of their activities. The second, timely relevance, measures the degree to which the topics addressed in an article are current (or timely) to marketing practitioners within a given time period.

To assess topical relevance, the R2M Index uses a dictionary of more than 1,000 marketing terms derived from business and academic sources and validated by practitioners. The dictionary includes a wide variety of terms, ranging from words related to the "Three Cs" (company, competition, and customers) and strategy (segmentation, targeting, and positioning) to the "Four Ps" (product, pricing, place, and promotion) and other pertinent marketing concepts related to value, brand, innovation, choice, goals, culture, and measurement. To measure timely relevance, the index tracks the popularity of marketing topics in publications in practitioner outlets, assuming that these publications reflect topics of interest to practitioners within a given time period. From this input, the R2M Index is constructed to assess how relevant an academic article is to current marketing practice. This is done in two steps. First, we use topic modeling to identify topics in the marketing literature and assess topical relevance based on the dictionary of marketing terms. Second, the index assesses the articles on timely relevance based on the content published in practitioner outlets each year since the publication of the article. Thus, for each year, the R2M Index measures the degree to which an academic article includes marketing terms related to topics that are relevant and timely.

In summary, the R2M Index is an easy-to-use instrument to measure the practical relevance of an academic article. The index can be used to perform comparative analyses on the relevance of topics and entire journals and to conduct analyses over time. Next, we provide an overview of the empirical study, followed by the methodology, results, and validation and robustness checks.

Overview of the Empirical Study

As described in our conceptualization, we consider topical relevance (whether the content of an academic article covers topics that are associated with marketing practice) and timely relevance (whether the content relates to marketing practitioners' current interests). Regarding topical relevance, we constructed a dictionary of marketing words based on keywords extracted from marketing articles in practitioner outlets such as *Bloomberg Business Week*, *Financial Times*, *Forbes*, *Fortune*, *Harvard Business Review*, *McKinsey Quarterly*, *Marketing News*, and *The Wall Street Journal*. The database consisted of more than 50,000 marketing articles published in 15 practitioner outlets from 1982 to 2019. The final dictionary also included words from other sources (a Google search, an industry marketing dictionary, a textbook, and keywords from academic articles). The dictionary was validated with practitioners. Regarding timely relevance, we tracked the popularity of marketing topics published in practitioner outlets over time.

We text-mined the entire text of over 4,000 academic articles randomly sampled from four journals —*JM*, *MSC*, *JMR*, and

JCR. We then scored these articles on their relevance to marketing practice. *JM*, *MSC*, and *JMR* are certainly marketing journals (the word "marketing" is in their titles); *JCR* focuses on consumer research, which is considered a subdiscipline of marketing (MacInnis and Folkes 2010). Hereinafter, we refer to the journals collectively as "marketing journals."

Using topic modeling, we derive a total of 40 marketing topics, which we capitalize in this article to identify them clearly as topics. Articles related to these topics vary in terms of their relevance to marketing (as measured by the R2M Index) and in topical and timely relevance (the components of the index). There are topics for which practitioner outlets are ahead of academic journals (e.g., Online Marketing) and others for which we observe the opposite effect (e.g., Conjoint Analysis). There are also topics with similar dynamics for practitioner outlets and academic journals (e.g., Market Entry, Branding). Across academic journals, we find that *JM* has the highest R2M score, followed by *MSC*, *JMR*, and *JCR*, in this order. Except for *JCR*, the marketing journals have progressed toward publishing more relevant topics.

Regarding validation, the R2M Index correlates well with observable measures of relevance, such as practice prize awards, Roberts, Kayande, and Stremersch 's (2014) list of 100 impactful papers, TPM conference submissions, and Marketing Science Institute (MSI) working papers and reports. Using a holdout set of articles from *American Psychologist*, *American Economic Review*, *Psychological Review*, and *Quarterly Journal of Economics*, we find, as expected, that these psychology and economics journals score lower than marketing journals. We also used executives to validate both the dictionary and the index. We surveyed executives in an EMBA program to confirm the practical relevance to marketing practice for each of the terms in our dictionary. In addition, we asked MSI corporate members and another group of EMBA individuals to judge the relevance of articles and observed a significant relationship between practitioners' judgments and the R2M Index.

Methodology

The measurement methodology included four steps. First, we developed a dictionary of marketing terms based on 51,646 marketing articles, published in 15 practitioner outlets from 1982 to 2019, as well as other practice-related and academic sources, which were validated with marketing practitioners. Second, we employed text-mining techniques to extract key noun phrases ("words") from published articles and used latent Dirichlet allocation (LDA; Blei, Ng, and Jordan 2003) to identify marketing topics. Each topic is defined by the set of words characterizing it, and each article has a probability of addressing each topic. Third, we scored the topics on their topical relevance by assessing the prevalence of practical marketing words in the topic. Fourth, we used the LDA estimates to predict the topic probabilities of each of the 51,646 practitioner articles. The average topic probability of all practitioner articles published in a particular year corresponds to its timely relevance score. The R2M Index for an article in a particular year is the product of the probability of the article to be associated with a topic and the topical and timely relevance scores of the topic, summed over all topics.

Data

The data used to calibrate the LDA analysis included 4,229 articles, randomly sampled from a total of 5,495 (i.e., 77%), published in *JM*, *MSC*, *JMR*, and *JCR* over 34 years (from 1982 to 2015), employing JSTOR (dfr.jstor.org). This digital library provided the following information for each article: title, abstract, author(s), volume, issue, publication date, and full text. Our sample of articles was balanced over the years and journals with approximately 1,060 articles per journal and 125 articles per year. The cross-section and time-series nature of our data enabled us to compare journals and examine the evolution of the R2M Index over time.

We included the full text of each article for our textual analysis; the title, abstract, author(s), and references were removed. We preprocessed the PDF text of each paper by removing stop words, PDF markers, punctuation, plurals, author names, and references. We also fixed errors from converting the PDF files to text (e.g., the letter "h" in PDFs sometimes converts to "b" in text form). Following common practice in topic modeling, we also removed uncommon words that appeared in fewer than 20 (out of 4,229) papers or had a raw frequency across all papers (i.e., by counting duplicates) lower than 40. Note that if the infrequent word was related to a marketing concept, we looked for a marketing synonym and combined the two terms into one term without dropping the word. For example, "buzz marketing" was combined with "word of mouth marketing." The resulting tokenized text of each article was a bag of $W = 16{,}080$ key terms/words that occur at different frequencies across papers. This information was compiled in a spreadsheet of word counts with $D = 4{,}229$ rows (articles/documents) and $W = 16{,}080$ columns (words, key terms) where each element n_{dw} represents the number of times word w ($w = 1, \ldots, W$) appears in document d ($d = 1, \ldots, D$). We utilized this spreadsheet, which we denote by $\mathbf{X} = ((n_{dw}))$, as input to the LDA analysis that we perform to identify the topics in the marketing field.

Constructing the Marketing Dictionary

We employed a systematic process to construct and validate the marketing dictionary. Specifically, the dictionary was constructed based on term selections from practitioner-oriented articles and other business and academic sources that we describe next.

Practitioner-oriented articles. We used university library databases (e.g., ProQuest) to search for marketing articles published for practitioners. These archives contain subject indexing, keywords from articles, abstracts, and full texts of all published articles for each of the outlets. We searched for articles published in newspapers, magazines, and trade publications including *Ad Age*, *Bloomberg Business Week*, *California Management Review*, *Entrepreneur*, *Fast Company*, *Financial Times*, *Forbes*, *Fortune*, *Harvard*

Business Review, *Harvard Business School Publishing* (for marketing cases), *Inc.*, *McKinsey Quarterly*, *Marketing News*, *MIT Sloan Management Review*, and *The Wall Street Journal.* Our search retrieved 51,646 marketing-related articles that were published by these 15 outlets from January 1982 to April 2019. Using the subject terms and the keywords listed in the articles, we compiled a list of 18,200 terms.

Google search. We performed a Google search for definitions of marketing and selected the first ten documents that appeared. We used natural language processing to extract the most common words in these documents based on the frequency of occurrence (after removing stop words such as "and" and "the"), retaining the top 80 marketing words. These core marketing terms are shown as a word cloud in Figure A1 in the Web Appendix.

Marketing dictionary, textbook, and article keywords. We included the 500 terms of the Common Language Marketing Dictionary (https://marketing-dictionary.org/), created as part of a partnership of the AMA, Marketing Accountability Standards Board, MSI, and the Association of National Advertisers. We also included 1,200 index terms from Kotler and Keller's (2011) *Marketing Management*, a standard textbook in marketing education, and 2,900 keywords from the articles in our corpus.

The combined list from all sources contained 22,880 (= 18,200 + 80 + 500 + 1,200 + 2,900) marketing terms, with a large degree of overlap. We used an elaborate process to reduce the number of terms by removing obvious nonmarketing words (e.g., "Congress," "women poets," "European Union") and words appearing fewer than 20 times in our corpus of 4,229 articles. We also checked whether words were properly used as marketing terms. For example, the word "distribution" connotes not only channel of distribution but also statistical distribution, and the word "chain" connotes not only retail chain but also Markov chain. We do not consider the statistical meanings as marketing terms. To resolve ambiguous instances, we created bigrams and trigrams to qualify the marketing use of the word. For example, we replaced "distribution" with "channel of distribution" whenever it was used in a channel context. Similarly, we dropped the word "relationship" because it is often used in a statistical or a psychological sense and replaced it with terms such as "customer relationship" and "firm relationship," depending on the context. Finally, synonymous terms were combined into one term (e.g., "ad," "advertisement," and "commercial"; "brand equity" and "equity of the brand").

Each of the authors evaluated the resulting list of marketing terms to ensure that it contained only relevant marketing words. Disagreements were resolved in a group setting using the Delphi approach.[1] The final dictionary contains 1,154 nonoverlapping marketing terms. Figure A2 in the Web Appendix shows the top 30 unigrams (e.g., "brand") and the top 30 bigrams and trigrams (e.g., "brand equity," "customer relationship management") in our marketing dictionary, ordered by how many times they appeared in our corpus.

To assess the evolution of the marketing terms in the dictionary, we tracked their word frequency in practitioner publications over time. Figure A3 in the Web Appendix displays this evolution from 1982 to 2019 in percentage terms. The dictionary of marketing terms stabilized between 2000 and 2010 (arguably due to the maturity of the field), with very few new marketing terms emerging after that.

Dictionary Validation

We further validated our dictionary by surveying 247 executives enrolled in four sections of an EMBA course in a U.S. business school in the summer and fall semesters of 2019. This survey had two purposes: (1) to measure the extent to which each of the terms in our dictionary are related to marketing practice as perceived by business practitioners and (2) to use these measures to weigh the dictionary terms differently when we construct the R2M Index. The survey was administered in class using Qualtrics. We received 12,350 (= 247 × 50) observations, with each term in our marketing dictionary being evaluated by about 11 respondents. We did not offer compensation but randomly selected two students using a lottery to have a free dinner with the course professor, who is not an author of this article.

In the survey, we presented respondents with 50 marketing terms randomly drawn from our dictionary of 1,154 words and asked them to indicate whether the term (and, importantly, "the idea behind it") is relevant for the work of a marketing practitioner. Order of presentation of the terms was randomized for each respondent. The respondents had, on average, more than 9.59 years of business experience (2.17 years in a marketing-related job). They were asked how much their current job related to marketing; their average response was 3.94 on a 7-point scale (1 = "not all," and 7 = "very much"). The respondents had taken an average of 2.59 marketing courses in the past.

Each of the 1,154 marketing terms was judged to be relevant to marketing practice, on average, by 78% of the practitioners. For example, the term "brand equity" was judged to be relevant by 100% of the respondents who evaluated this term, "firm valuation" by 40%, and "accrual" by 0% (and thus was deemed irrelevant). Let $0 \leq r_w \leq 1$ be the marketing-term relevance score of word w (e.g., $r_w = .4$ for "firm valuation"). Then we can use this information to weigh dictionary terms differently when we construct our R2M measure.

Topic Modeling

We use LDA to uncover the latent topic structure of publications in marketing journals. In LDA, each article can be viewed as a mixture of T latent topics. A topic is characterized

[1] As part of this process, ten senior marketing executives from various industries also reviewed a preliminary version of our dictionary and crossed out any terms that they did not consider to be marketing terms. As a result, we eliminated 32 terms (e.g., "EBA," "valence," "volitional," "choice heuristic," "referent power") from the dictionary. In the survey, we also asked practitioners to suggest other terms they thought were missing from the dictionary. No additional terms were proposed.

by a set of words that is associated with it. A word or a term can be a single word (unigram) or a phrase (ngram). We use “word” and “term” interchangeably. For example, words most associated with the topic Customer Satisfaction/ Customer Relationship Management (CRM) include “customer,” “satisfaction,” and “loyalty.” An article can be associated with more than one topic (e.g., an article on channel coordination could be associated with Channel Management and with Analytical Models).

LDA uses the word count matrix $\mathbf{X} = ((n_{dw}))$, where n_{dw} is the frequency of word w in article d, as input to generate two output matrices of probabilities. The first is a word-by-topic matrix $\mathbf{P}_W = ((p_{wt}))$ where each element p_{wt} ($\sum_{w} p_{wt} = 1$) indicates the probability that word w (w = 1, …, W) is associated with topic t (t = 1, …, T). Similar to factor loadings, this matrix characterizes the set of words associated with each topic and is generally used to interpret the derived topics. The second is a document-by-topic matrix $\mathbf{Q}_D = ((q_{dt}))$, where each element q_{dt} ($\sum_{t} q_{dt} = 1$) indicates the probability that document d is associated with topic t. The Q_D matrix indicates the likely topic(s) to which an article can be assigned. It is akin to a factor score matrix.

LDA estimates $\mathbf{Q}_D = ((q_{dt}))$ and $\mathbf{P}_W = ((p_{wt}))$ by assuming that the data are generated from a Dirichlet process. Each document has a probability q_{dt} to be associated with topic t. The vector of topic probabilities for document d, $\mathbf{Q}_d = (q_{d1}, q_{d2}, \ldots, q_{dT})$ is assumed to be distributed Dirichlet ($\alpha_1, \alpha_2, \ldots, \alpha_T$), where the αs are hyperparameters. For topic t, each word has a multinomial probability p_{wt} to be associated with the topic. That is, the set of W words follows a multinomial distribution with parameters $\mathbf{P}_t = (p_{1t}, p_{2t}, \ldots, p_{Wt})$ conditioned on topic t. We use the Gensim Python package (radimrehurek.com/gensim/) to estimate $\mathbf{P}_W$ and $\mathbf{Q}_D$ for varying values of T. We pick the proper number of topics T* using a mix of criteria: minimum perplexity (Wallach et al. 2009), variance of $\mathbf{P}_t$ across topics, and topic interpretability. Perplexity measures the degree of “uncertainty” an LDA model has in predicting a holdout text. Next, we discuss how to use the LDA estimates to construct the R2M Index.

Topical Relevance

Our bag of W = 16,080 words consists of marketing and nonmarketing terms. A topic is a distribution over a set of words that is differentiated from others. We measure topical relevance (M_t) by the preponderance of the marketing terms in topic t weighted by their marketing-term relevance score (r_w) obtained from business practitioners. Let M denote the subset of marketing terms in our dictionary (M⊂W). Then the topical relevance of topic t (t = 1, …, T) is defined as

$$M_t = \sum_{w \in M} p_{wt} \times r_w.$$

Thus, a topic that is associated with a larger set of practical marketing terms from our dictionary would have a higher topical relevance to marketing. (Note that $0 \leq M_t \leq 1$.)

Timely Relevance

Timely relevance reflects how current a particular topic is for marketing practitioners in a given year. Articles that cover timely topics are judged to be more relevant to marketing practice than articles that treat nontimely topics. For example, the topic of Online Marketing is of more interest these days to marketing practitioners than the topic of Sales Promotions. In this regard, timely relevance captures which topics matter to practice in a given period and rewards academic articles at the forefront of these topics. Thus, we assess the timely relevance of a topic in a given year by assessing its prevalence in practitioner-oriented publications that year. We use the LDA estimates to predict the topic probabilities of each of the 51,646 marketing articles published in 15 business outlets from 1982 to 2019 based on the article’s title, abstract and keywords. Let $\hat{q}_{dty}$ indicate the predicted probability that practitioner article d published in year y covers topic t. Let D_y denote the number of practitioner articles published in year y. Then, we measure the timely relevance of a particular topic in a given year by its average topic probability across all practitioner articles published that year. That is,

$$C_{ty} = \frac{1}{D_y} \sum_{d=1}^{D_y} \hat{q}_{dty}.$$

Thus, topics that are more popular in a given year are considered to have higher timely relevance in that year than less popular topics. (Note that $0 \leq C_{ty} \leq 1$ and $\sum_{t=1}^{T} C_{ty} = 1$.)

Whereas topical relevance ensures that an article covers marketing topics, timely relevance ensures that the content of the article is current. The two measures are thus conceptually different. Indeed, the sample correlation between the average timely relevance, $\bar{C}_t = \frac{1}{D_y} \sum_{y} C_{ty}$, and M_t is only .16 ($p > .32$), suggesting discriminant validity between the two measures. To illustrate, in our study Analytical Models scores relatively high on topical relevance (M_t = .31) because it employs marketing terms that are highly relevant to practitioners (e.g., profit, channel, sales, price, margin, competition). However, it scores relatively low on timely relevance ($\bar{C}_t = .013$), suggesting low interest from practitioners in this topic.

The R2M Index

An article is a probability mixture over the set of T topics. Each topic t is associated with two measures of relevance: topical relevance (M_t) and timely relevance in year y (C_{ty}). Thus, to be practically relevant, an article needs to cover timely topics that are associated with marketing practice. Therefore, our R2M Index for article d in year y is given by

$$\mathrm{R2M}_{\mathrm{dy}} = 100 \sum_{\mathrm{t} \in \mathrm{T}} \mathrm{q}_{\mathrm{dt}} \mathrm{C}_{\mathrm{ty}} \mathrm{M}_{\mathrm{t}},$$

where q_{dt} is the probability that article d is associated with topic t. We multiply by 100 because the elements in the sum are products of three probabilities, resulting into low numbers. Thus, articles that are timely and are associated with more substantive marketing topics are expected to have higher R2M scores.

The R2M measure of an article is not static but, rather, evolves over time from the year when the article is published to the present. For example, an article on Multiattribute Models/Conjoint would score low on R2M if published in the early 1980s but higher in the late 1990s and afterward, when this topic became popular among marketing practitioners. Conversely, an article on Marketing Theory and Policy published in early 1980s would score high on R2M given the buzz about marketing as a discipline at that time, but relatively lower in mid-1990s and afterwards as new marketing topics of interest to practitioners emerged. Although trending lower over time, the popularity of Marketing Theory and Policy is still relatively high in 2015 compared with other marketing topics. Thus, for our R2M measurement, ideally one should report the complete evolution of the R2M score of an article from its inception to the present as well as related summary statistics (i.e., minimum, mean, maximum, and standard deviation). However, for a point estimate, we use the mean R2M score throughout to assess the relevance of an article to practice.

Does our R2M measurement disadvantage leading-edge research relative to older, more seasoned research? This is unlikely. First, our dictionary is cumulative; it includes all the marketing terms until 2019, and the dictionary stabilized between 2000 and 2010 (see Figure A3 in the Web Appendix). Second, the timely relevance component of the R2M Index should benefit leading-edge papers especially if they address emerging marketing topics that are of current interest to practitioners. Third, as an empirical illustration, we compared the mean R2M scores for the top 100 papers in Online Marketing (currently a leading-edge topic) with those from Sales Promotions (an older topic). We find that the Online Marketing papers have a significantly higher mean R2M score than the Sales Promotion articles (.86 vs. .75; $p < .001$).

Another question concerns the use of an indirect LDA approach rather than a straightforward measure based on the frequency of marketing words in a published article. A measure at the topic (vs. article) level is likely to create a more robust index because authors cannot easily inflate the relevance of an article by arbitrarily adding marketing terms. In other words, if the marketing jargon used in an article is not coherent with the topic, the work is less likely to be rewarded for it. Conversely, because a topic embodies a set of articles using similar language, the marketing terms used in the topic are more varied and are overall more exhaustive than those used in a single article. Thus, an article associated with the topic is less likely to be penalized if it misses some of the marketing jargon used in the topic because words that are synonymous are likely to appear in the same topic. In addition, a measure at the topic level (vs. article level) provides diagnostic information for why the R2M score for a journal (or article) is low or high, or why it is increasing or declining over time for a journal. Importantly, using LDA enables us to quantify the timeliness of the topics addressed in an article. Without LDA, it would be difficult to measure practitioners' interest in a topic in a particular time period.

Research Topics Results

What Are the Main Research Topics Published in Marketing Journals?

We implemented LDA on our data to determine the topics that best characterize the articles published in marketing journals. Because the number of topics is unknown a priori, we performed the LDA analysis in two stages. First, we conducted a series of fivefold cross-validations to determine the perplexity per word for 5, 10, 15, 20, 25, …, and 75, 80 topics. The perplexity plot in Figure A4 in the Web Appendix shows a U-shaped pattern with a plateau between 15 and 40 topics. Next, we examined the downward pattern of the variance of the posterior word-topic probabilities ($\widehat{P}_t,\ t = 1,\ \ldots, T$), as we varied the number of Topics T from 1 to 100. Such variance moves closer to 0 after 40 topics (not shown). As such, using our judgment (interpretability of topics), the variance declining pattern, and the minimum perplexity criterion, we decided to retain $T^* = 40$ topics.

In naming the 40 topics, we relied on (1) the top 30 words associated with the topic; (2) the top 30 papers that have the highest probability of loading on the topic; and (3) a comparative analysis with the topics generated in previous text analyses for *MSC* (Mela, Roos, and Deng 2013), *JMR* (Huber, Kamakura, and Mela 2014), and *JCR* (Wang et al. 2015). The 40 topics are meaningful and relatively easy to interpret. Importantly, these topics are consistent with the taxonomy by Grewal, Gupta, and Hamilton (2019) using articles published in *JMR* from 2013 to 2019 (Grewal, Gupta, and Hamilton 2019, Table 1, p. 987). Note that they found only 21 topics partly because they grouped consumer research topics under Consumer Psychology and empirical analysis topics under Research Methods. In addition, Roberts, Kayande, and Stremersch (2014, pp. 128–29) listed 12 key marketing decision areas in firm management. All of these areas are included in our list of topics, and 11 of them rank among our 20 most relevant topics.

Table A1 in the Web Appendix shows the labels for the 40 topic and reports selected frequent words associated with each topic. For example, the top words associated with Marketing Strategy are "firm," "competition," "strategy," "resource," "industry," "market," "target," and "business." Words associated with Branding are "branding," "category," "brand name," "private label," "extension," and "brand equity." The top words associated with Construct Measurement include "variable," "measure," "testing," "data," "factor," "correlation," "model," and "analysis."

Table 1 lists the 40 topics in descending order on the basis of their degree of relevance to practical marketing ($100\mathrm{M}_t\bar{\mathrm{C}}_t$). For example, Advertising, Marketing Strategy, and Market

Table 1. Topics Relevance Overall and Over Decades.

Overall Rank	Topic	$100M_t\bar{C}_t$	R2M Components[a] M_t	$\bar{C}_t$	Topic Rank by Decade 1980s	1990s	2000s	2010s
1	Advertising	2.74	.46	.06	3	1	1	3
2	Marketing Strategy	2.56	.52	.05	2	2	2	1
3	Market Orientation	2.31	.31	.07	1	3	3	2
4	Market Segmentation	1.31	.40	.03	5	4	6	5
5	Branding	1.19	.51	.02	11	5	5	4
6	Marketing Theory/Policy	1.13	.13	.09	4	8	8	11
7	Online Marketing	1.09	.37	.03	17	7	4	6
8	Sales Promotions	1.03	.41	.03	7	6	7	9
9	Market Entry	.88	.38	.02	8	9	10	17
10	Product Management	.88	.46	.02	6	11	13	13
11	Household Expenditure	.87	.26	.03	10	10	11	12
12	New Products	.82	.26	.03	9	12	16	8
13	Financial Impact	.81	.27	.03	13	13	9	10
14	Pricing	.74	.44	.02	12	15	14	15
15	Entertainment Marketing	.71	.22	.03	18	14	12	19
16	Innovation	.68	.37	.02	14	18	17	14
17	Customer Satisfaction/CRM	.68	.36	.02	15	16	18	16
18	Consumer Culture	.65	.12	.05	19	17	15	18
19	Sales Force Motivation	.56	.24	.02	16	19	20	21
20	WOM and Social Media	.55	.27	.02	26	23	21	7
21	Multiattribute Models/Conjoint	.51	.26	.02	23	20	19	20
22	Household Purchase Behavior	.48	.33	.01	21	21	22	23
23	Channel Management	.47	.29	.02	20	22	23	22
24	Influence and Persuasion	.41	.28	.01	25	24	25	24
25	Analytical Models	.41	.31	.01	22	26	26	26
26	Bargaining and Negotiation	.40	.24	.02	27	25	24	25
27	Sales Force Management	.36	.25	.01	24	27	27	27
28	Consumer Choice	.31	.25	.01	28	28	28	28
29	Behavioral Decision Theory	.29	.21	.01	31	29	29	30
30	Affect and Emotions	.29	.22	.01	30	30	30	29
31	Consumer Judgment	.28	.20	.01	29	31	31	31
32	Family and Socialization	.24	.12	.02	34	32	32	33
33	Information Processing	.24	.19	.01	32	33	33	32
34	Measurement Scales	.21	.13	.02	33	36	36	37
35	Cue Perception	.21	.12	.02	35	34	35	34
36	Self	.21	.15	.01	36	35	34	35
37	Dynamic Models	.18	.11	.02	37	37	38	38
38	Consumer Goals and Motives	.18	.13	.01	38	38	37	36
39	Empirical Estimation	.07	.06	.01	39	39	39	39
40	Construct Measurement	.06	.05	.01	40	40	40	40

[a]These are the topical and average timely relevance scores for topic t. Their product (× 100) in column 3 gives the overall relevance of the topic to marketing practice.

Orientation have the highest relevance-to-marketing scores ($100M_t\bar{C}_t$= 2.74, 2.56, and 2.31, respectively). Construct Measurement has the lowest score ($100M_t\bar{C}_t = .06$), likely because it involves methodological issues (e.g., structural equation modeling may be of little interest to practitioners). As a closer examination of academic research revealed, this does not mean that practitioners do not care about having methodological tools. For example, Bagozzi and Yi's (1991) seminal article proposing how to use structural equation modeling to test multitrait-multimethod matrices to assess convergent and discriminant validities had an R2M score of .08, whereas a similar paper by Rust and Cooil (1994, p. 7) addressing "practicing marketing researchers" had a score of .25.

Table 1 also reports the rank order of relevance to marketing topics per decade. Over the last decade, Marketing Strategy has become the most important topic; other topics, for example, Marketing Theory and Policy, have declined over time. Table 1 also reports the topical and timely components separately. Over

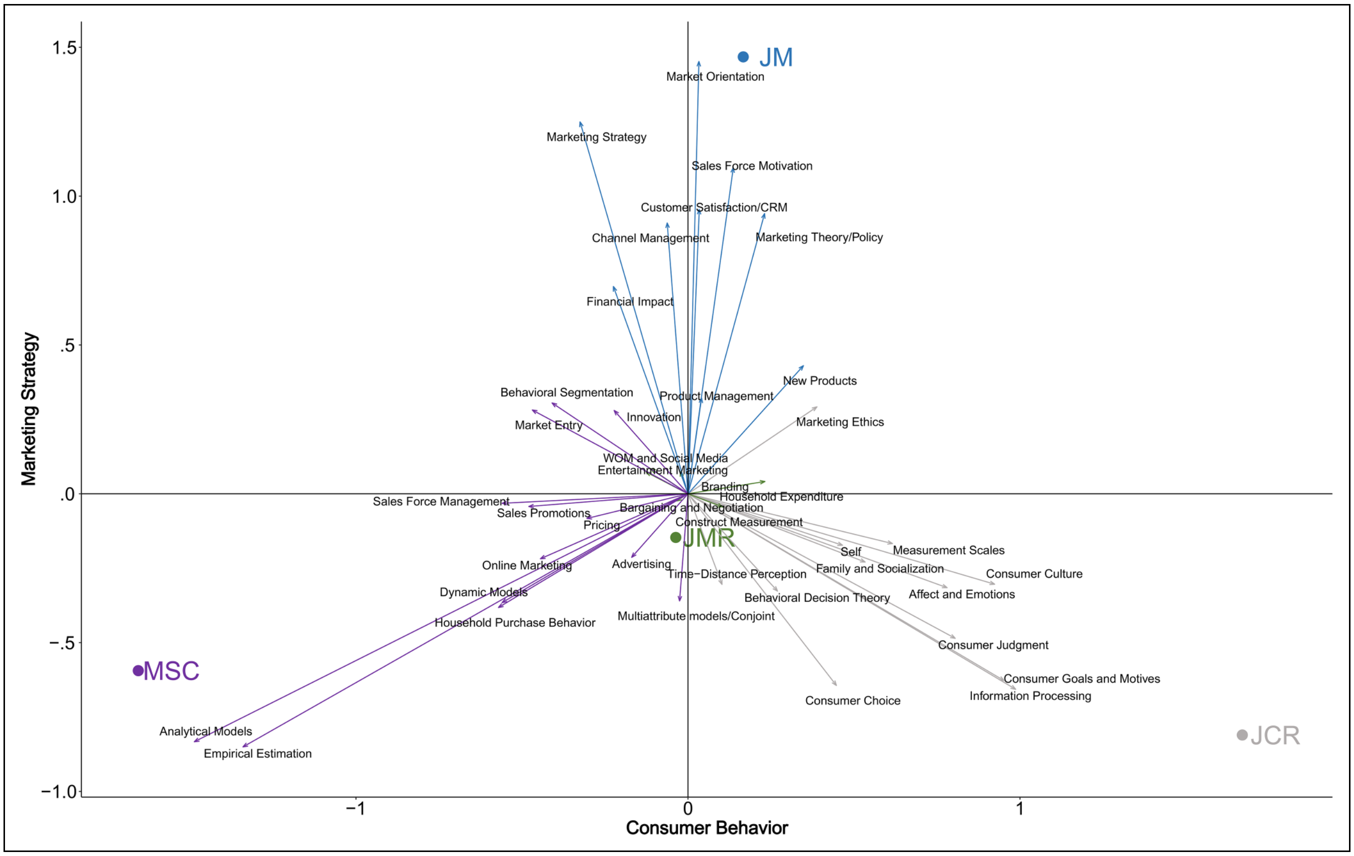


Figure 1. Multiple discriminant analysis map of marketing journals.
Notes: Figure depicts the topics as vectors and the journals as points. Topics with longer vectors better discriminate between the journals than those with shorter ones. The orthogonal projection of a journal on a topic vector indicates the degree to which the journal is associated with the topic. Figure highlights the journal with the highest projection on each topic using different colors. *JM*, *JCR*, and *MSC* are most associated with the topics highlighted in blue, gray, and purple, respectively. *JMR* does not seem to have the highest projection on any topic. Topic vectors and journal centroids are scaled to improve the readability of the figure.

the last four decades, Marketing Theory and Policy ($\bar{C}_t = .09$) had the highest mean timely relevance score. Interestingly, Analytical Models also has relatively high topical marketing relevance but low timely relevance. Conversely, Consumer Culture is a topic of timely interest to practitioners, arguably because of its high specificity in exploring contemporary phenomena, but scores low on topical relevance.

Are Marketing Journals Differentiated Across the 40 Topics?

We used multiple discriminant analysis to determine the topics that best differentiate the journals. The grouping variable is the journal where the article is published (*JM*, *MSC*, *JCR*, or *JMR*) and the independent variables are the probabilities of each article to be associated with each of the 40 topics, $\mathbf{Q}_d = (q_{d1}, q_{d2}, \ldots, q_{dT})$. The results indicate that all three discriminant functions are significant ($\chi^2 = 6{,}709.5$, $p < .0001$). For simplicity, we only retain the first two dimensions, which capture 93.7% of the variation in the data.

Figure 1 displays the journal centroids on the two dimensions as points and the topics as vectors. The vector coordinates are the "factor loadings" of the topics on each of the discriminant functions (i.e., structure matrix). Thus, topics with longer vectors better differentiate the journals than those with shorter ones. The orthogonal projection of a journal on a topic vector indicates the degree to which the journal is associated with the topic. For example, *JM* is most associated with Marketing Strategy, followed by *MSC*, *JMR*, and *JCR*. The figure highlights the topics with which each journal is mostly associated using different colors. Thus, almost all the topics in the lower-right quadrant of the figure are associated with *JCR*. Most of the topics in the lower-left quadrant are associated with *MSC*, and most of the topics in the upper half of the figure are associated with *JM*. Topics close to the center do not discriminate among topics. *JMR* seems to be central, with very few topics that clearly distinguish it.

The horizontal dimension, which explains 58.9% of the variability, contrasts consumer behavior (e.g., Information Processing, Consumer Goals and Motives) and analytical marketing topics (e.g., Analytical Models, Empirical Estimation). The vertical dimension, which explains 35% of the variability, contrasts managerial (e.g., Market Orientation) and nonmanagerial (e.g., Information Processing) topics. The marketing journals are well differentiated on the map. The triangular shape of the journal locations (with *JMR* at the center) is consistent with the standard classification of marketing scholarship into

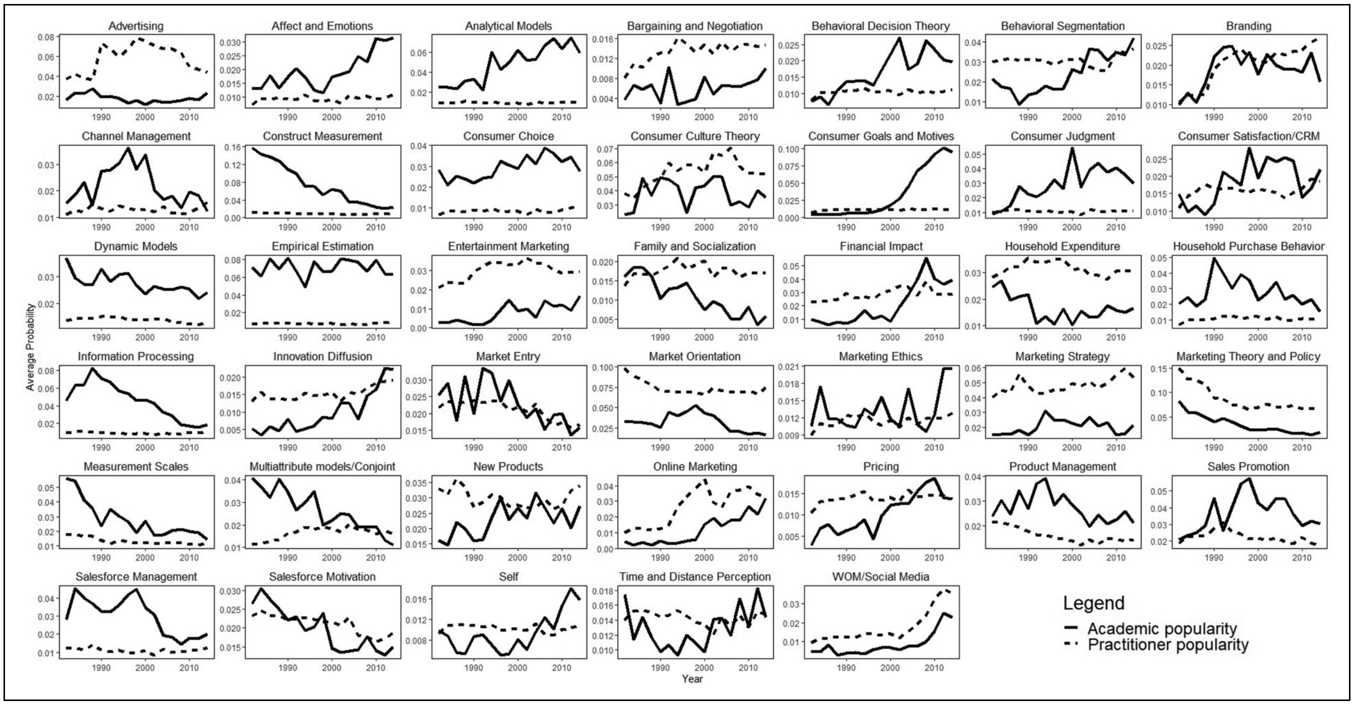


Figure 2. Popularity of topics in academic and practitioner publications over time.
Notes: For a given year, topic popularity in academic (practitioner) publications is measured by the average topic probability of all the articles published in academic (practitioner) outlets that year.

behavioral, quantitative, and managerial categories. *JCR* is mostly associated with behavioral topics, *MSC* with quantitative topics, and *JM* with managerial topics.

Which Marketing Research Topics Are Most Popular?

We next examine the popularity of each topic over the measurement period 1982–2015. Consider all the articles published in a given year, then the popularity of a topic in that year is given by the average probability ($\bar{q}_{ty}$) of each of these articles to be associated with this topic. Figure 2 traces the popularity of the 40 topics over time in academic and practitioner publications.

In the academic literature, research topics such as Behavioral Decision Theory, Innovations, Self, Online Marketing, Customer Satisfaction/CRM, and Word of Mouth (WOM) and Social Media have gained importance over time, whereas Advertising, Marketing Theory and Policy, Construct Measurement, and Information Processing have declined in popularity. Other topics, such as Market Orientation, Market Entry, and Channel Management, peaked around the early 2000s and then declined. By 2015, there was also a greater variety of topics, the most prominent ones being Self, WOM and Social Media, Online Marketing, Innovations, and Affect.

Topics that have been of relatively low interest to practitioners include Dynamic Models, Information Processing, Construct Measurement, and Analytical Models. Topics of relatively higher interest to practitioners include Household Expenditure, Marketing Theory and Policy, Advertising, Entertainment Marketing, Marketing Strategy, and Bargaining and Negotiations. Finally, there are similar evolution patterns in academic and practitioner publications for topics such as Market Entry, Salesforce Motivation, and Branding. In addition, there are topics where practitioners were ahead of the curve (e.g., Financial Impact, Innovations, Entertainment Marketing, Online Marketing, Pricing, WOM and Social Media). Conversely, academics were ahead of the curve with their articles related to topics such as Multiattribute Models/Conjoint and Sales Promotions.

To examine the topical relation between academic and practice topics, we suggest performing a quadrant analysis to create a map that displays topic popularity in academia and marketing practice. The four quadrants may be defined based on median splits along the two axes of topic popularity in academic journals and practitioner outlets. The quadrants may be labeled as follows: “Desert” (topics with low popularity in both academia and practice), “Academic Island” (topics with high popularity in academia but low popularity in practice), “Executive Fields” (topics with high popularity in practice but low popularity in academia), and “Highlands” (topics with high popularity in both academia and practice). From a theory-to-practice perspective, Highlands is the most desirable quadrant because the topical interests of scholars meet those of practitioners. To illustrate this approach and also depict the evolution of the topical relation over time, Figure 3 shows such a quadrant analysis for the recent time periods of 2000–2009 versus 2010–2015. The vectors in the figure indicate changes from the first to the second time period, and the colors of the vectors indicate the nature of the change.

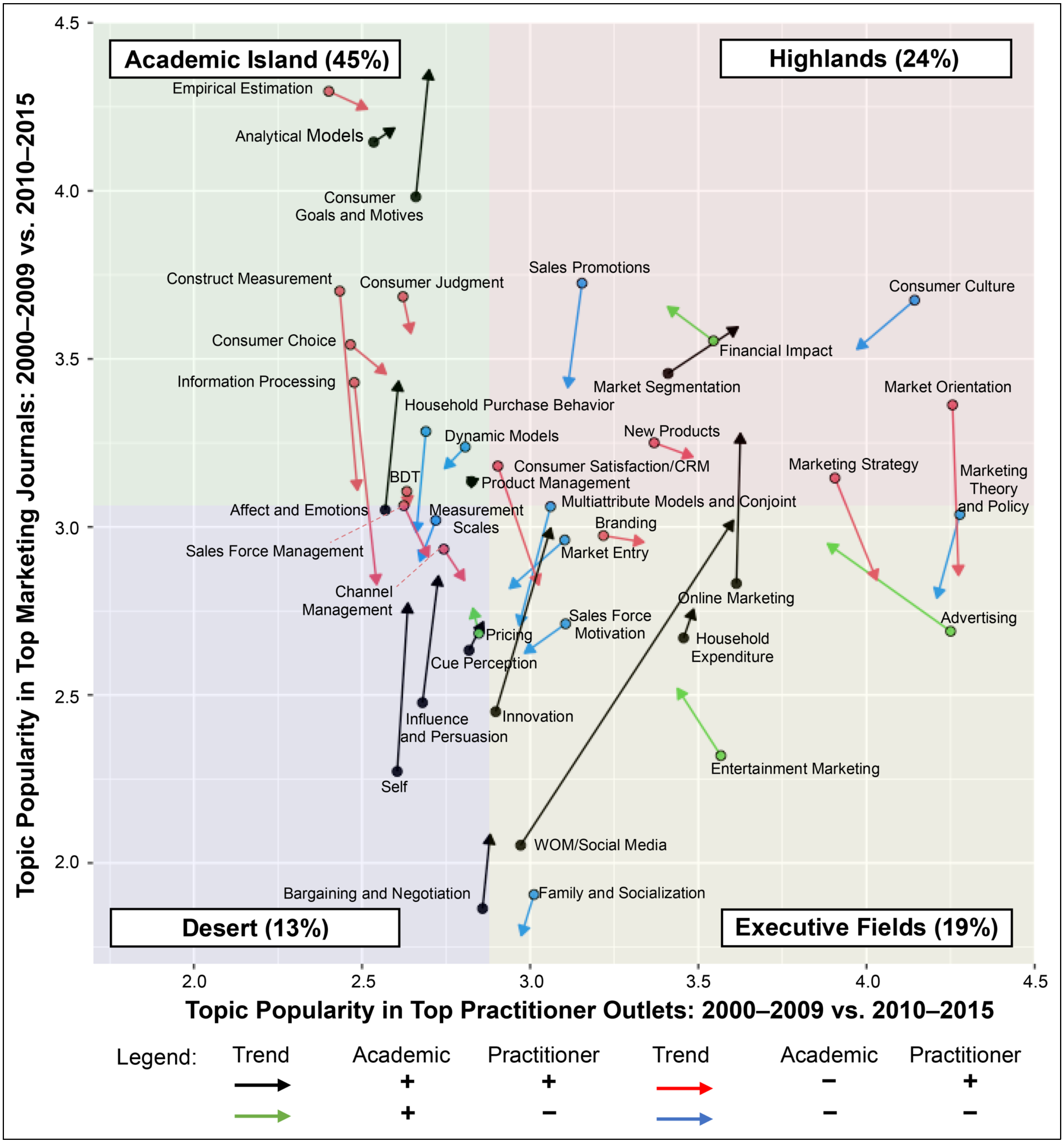


Figure 3. Quadrant analysis of topic popularities.

Notes: BDT = Behavioral Decision Theory. Figure contrasts the popularity of the LDA topics in practitioner outlets to that in academic journals. The axes are shown on a logarithmic scale (i.e., ln(1,000 $\bar{q}_t$). The arrows indicate the change in topic popularity between the periods 2000–2009 and 2010–2015. The quadrants are constructed based on a median split along the two axes. Numbers within parentheses indicate the sum of the topic popularities in a quadrant.

We choose two topics for illustration. The first topic, Information Processing, was still popular in the early 2000s in academia but moved toward the Desert quadrant by becoming less popular in academia and barely changing its below-average popularity in practice during the second time period. The second topic, Online Marketing, moved from Executive Fields to the Highlands quadrant by becoming more popular in academia while maintaining its popularity in practice.

We also calculated the aggregate popularity of each quadrant (i.e., sum of the popularity scores of the topics in each quadrant for the whole period 2000–2015). As Figure 3 shows, the most popular quadrant for topics published in all academic journals is the Academic Island quadrant (45%), whereas 24% are in Highlands, 19% are in Executive Fields, and 13% are in the Desert quadrant. A closer analysis of topics published in each journal revealed that relatively few of the topics published in *JM* are in the Academic Island quadrant (28%) compared with *MSC*, *JMR*, and *JCR* (50%, 50%, and 51%, respectively). Conversely, 39% of the topics in *JM* are in Highlands, which is more than double the percentage of topics in Highlands in any other journal: 19%, 19%, and 18% for *MSC*, *JMR*, and *JCR*, respectively.

Results of the R2M Index

In this section, we illustrate what information can be obtained by scoring an academic marketing article on the R2M Index. We then examine the R2M distribution across marketing journals and over time. Finally, we provide validity and robustness checks for the R2M Index.

What Information Do We Obtain by Scoring Articles on the R2M Index?

As Table 2 shows, for each article one can calculate its association with the topics (shown in the table for the top five topics), the mean R2M score, and the R2M evolution over time (here from 1982 to 2019). For illustration, we show two articles each from our four marketing journals that are associated with topics in different degrees, have different R2M scores, and, importantly, have opposite patterns over time. For example, consider the two selected *JM* articles. Hunt's (1983) article is primarily associated with Marketing Theory and Policy (probability = .59), has a mean R2M score of 1.03, and has a declining R2M score over time. In contrast, Keller's (1993) paper is associated with branding (.35), has a mean score of 1.0, but displays an increasing R2M score.

R2M Index Comparison across Marketing Journals

The mean R2M score of all articles across journals and years is .63 (SD = .29, min = .08, and max = 1.91). Mean R2M scores vary significantly across journals ($F = 432.33$, $p < .001$). Articles in *JM* have the highest mean R2M score (.85), followed by articles in *MSC* (.63), *JMR* (.56), and *JCR* (.48) (see Figure 4, Panel A); all pairwise journal comparisons are significant (all Bonferroni *p*s < .001). Table A2 in the Web Appendix shows the ten most relevant articles, nine of which have been published in *JM*.

R2M Index over Time

Has the relevance of academic marketing articles deteriorated or improved over time? A regression analysis that controls for journal effects indicates a modest annual increase of R2M scores ($\beta = .001$, $p < .001$). By journal, there is a positive trend toward more relevance for *MSC* and *JMR* (*MSC*: $\beta = .006$, $p < .001$; *JMR*: $\beta = .004$, $p < .001$), a relatively stable, barely significant trend for *JM* ($\beta = -.002$, $p = .056$), and a slightly significant declining trend for *JCR* ($\beta = -.003$, $p < .001$) (see Figure A5 in the Web Appendix for the R2M trend by journal and overall). As Figure A5 shows, while *JCR* was comparable in relevance to *MSC* and *JMR* in the early 1980s, it has widened the gap since 2000 and now is less relevant than *MSC* and *JMR*.

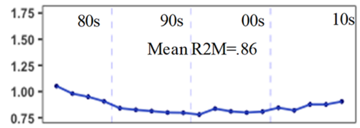
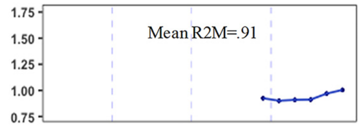
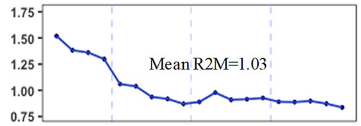
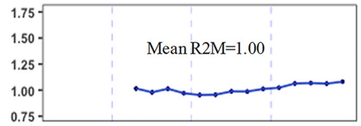
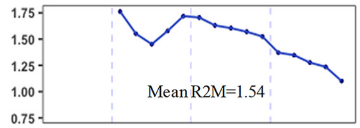
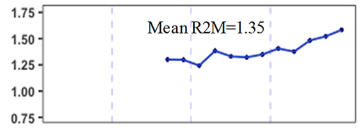
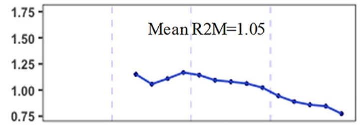
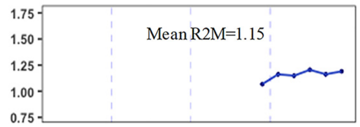
To examine the drivers behind the evolution of marketing relevance across journals over time, we generated positioning maps using correspondence analysis of the averaged topic probabilities for each of the four journals and each year. For each journal and year, we computed the average topic probability of all the articles published during that year. Given the large number of topics, we focused the analysis on the topics that are most associated with the journal (these topics capture about 80% of the topic probabilities for each journal). For readability, Figure 5 portrays only the ten topics that are most associated with each of the four journals over the years. In this two-dimensional map, years are depicted at the centroid of the topics they covered, and topics are depicted at the centroid of the years in which they were published. The size of the circles highlights the prevalence of the topic in the journal in which it is published. As in a heat map, the degree of relevance to marketing (computed as the product of $\bar{C}_t$ and M_t in Table 1) for a topic is reflected by the shade darkness of the color within the circle.

Across journals, Figure 5 shows that the horizontal dimension (Dimension 1) captures most of the variability of the input data. This dimension aligns well with the temporal sequence of the topics. For *JM*, for example, there is a U-shaped ("horseshoe") pattern starting in the early and mid-1980s in the top left corner of the figure, moving toward the 1990s and early 2000s in the bottom half of the figure, and toward the end moving back to more recent periods in the top right corner. We see similar horseshoe patterns for *JCR*, *JMR*, and *MSC*. As indicated by Huber, Kamakura, and Mela (2014, p. 88), the reason for the "wraparound" patterns in the figure is that the topics in the center of the horseshoe (e.g., Market Orientation and Marketing Strategy for *JM*) can be thought of as forming a gravitational field that captures the topics regularly published by the journal, and the topics at the periphery reflect specialized topics in the years near them (e.g., Financial Impact for 2013–2015 for *JM*).

Judging by the size of the topic circles, the three most prevalent topics published in *JCR* over the last 34 years are Construct Measurement and Measurement Scales (in the 1980s), Information Processing (in the 1990s), Consumer Culture and Consumer Judgment (in the 2000s), and Consumer Goals and Motives (in the 2010s). Judging by the shade darkness of the circles, most of the topics published in *JCR* have relatively low relevance to marketing. This explains why the average marketing relevance for *JCR* has slightly declined from 1982 to 2015.

For *JM*, the most studied topics are Marketing Theory and Policy (in the 1980s); Market Orientation and Marketing Strategy (in the 1990s and early 2000s); and, more recently, Customer Satisfaction/CRM and Financial Impact (metrics).

Table 2. Illustrative R2M Measurement for Academic Articles in the Marketing Journals.

Article (Authors, Title, and Journal)	Top Five Topics[a]	R2M Score over Time (1982–2019)[b]
Thomas (1982): Correlates of Interpersonal Purchase Influence in Organizations. *JCR*.	Market Orientation (.22) Sales Force Management (.18) Marketing Ethics (.15) Consumer Judgment (.11) Measurement Scales (.07)	
Cayla and Eckhardt (2008): Asian Brands and the Shaping of a Transnational Imagined Community. *JCR*.	Consumer Culture (.52) Household Expenditure (.17) Branding (.09) New Products (.06) Market Orientation (.06)	
Hunt (1983): General Theories and the Fundamental Explananda of Marketing. *JM*.	Marketing Theory/Policy (.59) Market Orientation (.07) Consumer Culture (.06) Channel Management(.05) Empirical Estimation (.04)	
Keller (1993): Conceptualizing, Measuring, and Managing Customer-Based Brand Equity. *JM*.	Branding (.35) Information Processing (.13) Product Management (.08) Marketing Theory/Policy (.07) Consumer Judgment (.05)	
Park and Hahn (1991): Pulsing in a Discrete Model of Advertising Competition. *JMR*.	Advertising (.32) Analytical Models (.18) Marketing Strategy (.13) Empirical Estimation (.10) Market Entry (.06)	
Maltz and Kohli (1996): Market Intelligence Dissemination Across Functional Boundaries. *JMR*.	Market Orientation (.51) WOM/Social Media (.14) Sales Force Management (.09) Dynamic Models (.05) Product Management (.04)	
Kanetkar, Weinberg, and Weiss (1992): Price Sensitivity and Television Advertising Exposures: Some Empirical Findings. *MSC*.	Sales Promotion (.18) Advertising (.18) H. Purchase Behavior (.16) Construct Measurement (.13) Branding (.09)	
Natter et al. (2008): Practice Prize Report—Planning New Tariffs at tele.ring: The Application and Impact of an Integrated Segmentation, Targeting, and Positioning Tool. *MSC*.	Behavioral Segmentation (.22) Market Orientation (.20) New Products (.11) Marketing Theory/Policy (.09) Analytical Models (.07)	

[a]The number in parentheses is the probability that the article is associated with the topic.
[b]The graph depicts the evolution of the R2M score of an article since its publication.

Judging by the shade darkness of the circles, most of the topics published in *JM* have relatively high relevance to marketing throughout the period of our study. This explains why the average marketing relevance for *JM* has remained high throughout the period. For *JMR*, the most studied topics are Construct Measurement (in the 1980s), Empirical Estimation (in the late 1990s), Sales Promotions (in the 2000s), and Consumer Goals and Motives (in the 2010s). Judging by the darkness of the topic circles, the Construct Measurement and Empirical Estimation topics explain why *JMR* had a low R2M score early on. However, most of the topics published later have relatively higher relevance to marketing scores, explaining the improved R2M score over time. A similar pattern for *MSC* topics has emerged: Construct Measurement (in the 1980s); Sales Promotions and Empirical Estimation (in the 1990s and early 2000s); and, more recently, Analytical Models. The low relevance of Construct Measurement and Empirical Estimation compared with recent topics explains why *MSC* (like *JMR*) had a low R2M score early on but a higher relevance score over time.

Validity and Robustness Checks

To check the validity of the index, we tested whether articles with practical impact (based on various measures) would have higher R2M scores, whether articles in nonmarketing journals would

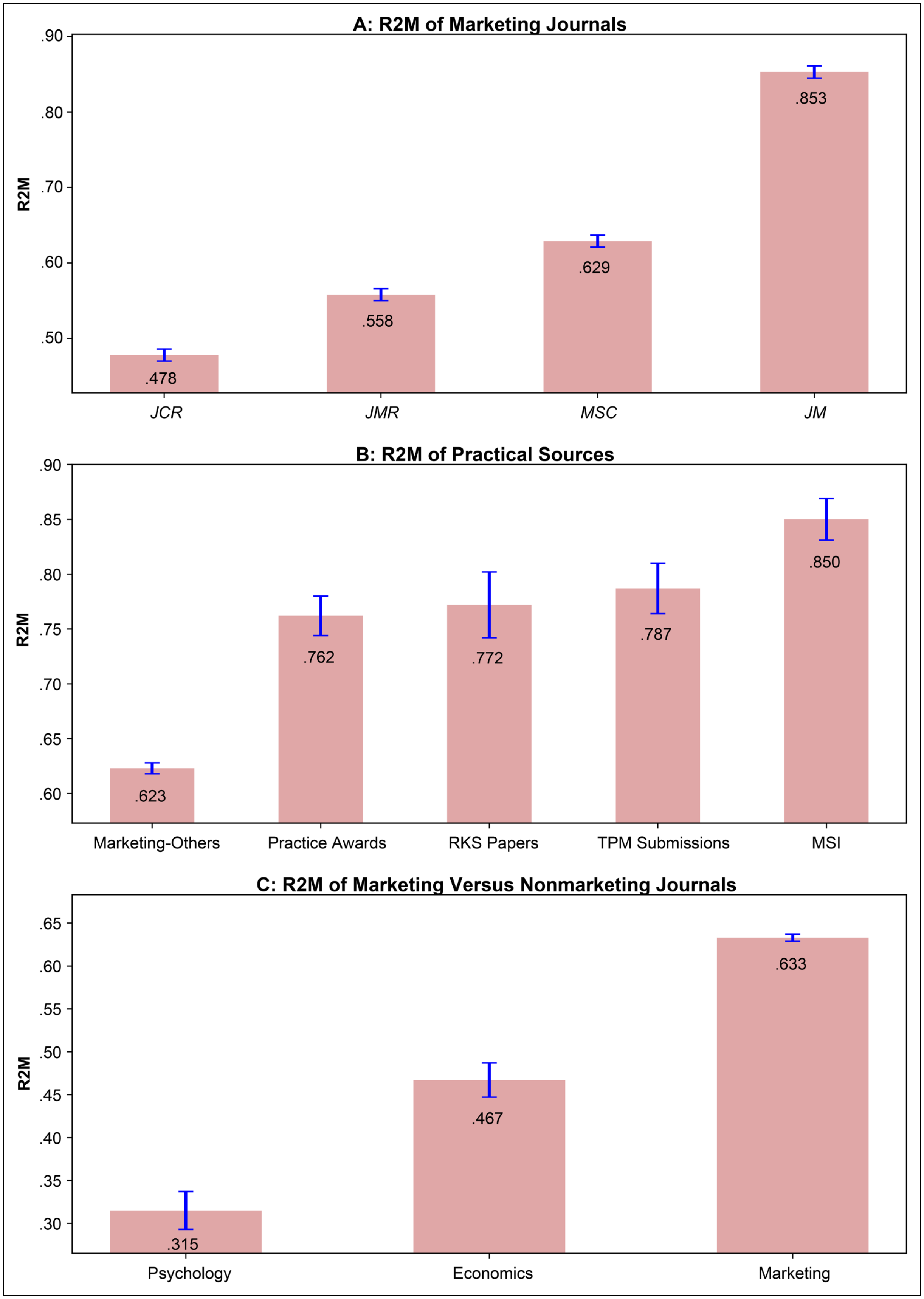


Figure 4. R2M findings and validity checks.
Notes: Error bars = ±2 SEs. RKS = Roberts, Kayande, and Stremersch (2014).

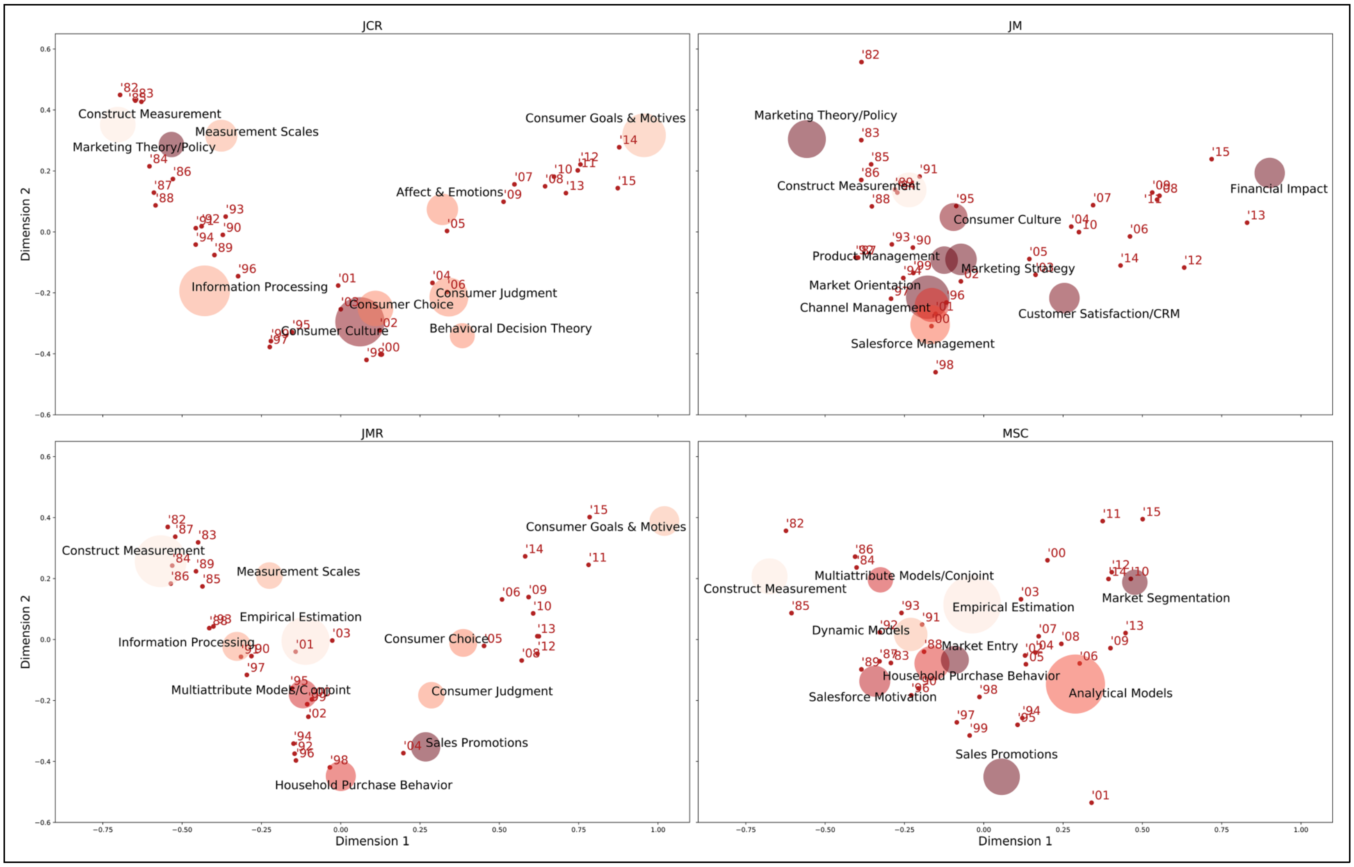


Figure 5. Correspondence analysis showing evolution of topics over time across journals.
Notes: Figure shows the top ten topics associated with each journal from 1982 (left) to 2015 (right). Topics in the center of the horseshoe represent topics regularly published by the journal, and topics at the periphery reflect specialized topics for the years near them. The size of the circle represents the prevalence of the topic in the journal. Topics with darker shades are more relevant to marketing practice than those with lighter shades.

have lower scores, and whether the index correlates with marketing practitioners' judgments. For robustness checks, we tested whether the index could be easily "gamed."

R2M Index Scores of Papers with Practical Impact

To examine the extent to which the R2M Index is predictive of practically relevant articles, we compared the mean R2M scores for practice-award papers, Roberts, Kayande, and Stremersch's (2014) list of 100 impactful papers, TPM conference submissions, and MSI working papers and reports with the R2M score of all other marketing articles in our corpus. We expect that the four sets of practically relevant articles (hereinafter, the validation papers) to have higher R2M scores than the others.

Practice-award papers. We identified 250 practice award-winning papers from 1982 to 2015 using multiple sources, including the MSI Long Term Impact Award, ISMS-MSI Practice Prize, John D.C. Little Award, Frank M. Bass Dissertation Paper Award, AMA Paul E. Green Award, Harold H. Maynard Award, Annual William F. O'Dell Award, and Sheth Foundation/ *Journal of Marketing* Award. While some of these awards are specifically focused on relevance to practice, others use multiple criteria including practical relevance.

Roberts, Kayande, and Stremersch's (2014) list of 100 impactful papers. Roberts, Kayande, and Stremersch (2014, p. 131) selected 100 "marketing science" papers published in *JM*, *JMR*, *MSC*, *Management Science*, and *International Journal of Research in Marketing* from 1982 to 2003 based on their high academic (citations) and practice impact (as judged by practitioners).

TPM conference submissions. We analyzed the submissions (175 in total) to the 2019 TPM conference hosted by Columbia Business School in collaboration with *JM*. Each submission includes about ten PowerPoint slides in which authors describe their research problem, method, findings, and how the research links theory and practice. In the call for conference submissions, TPM stresses the importance of addressing substantive business problems with broad relevance and sound methodology.

MSI working papers and reports. We used a set of 218 MSI working papers and reports published from 1997 to 2017.

These papers are screened by MSI for their practical relevance and are targeted to practitioners.

An analysis of variance with publication year as covariate shows that there is a significant difference in the R2M scores of the five sets of papers (the validation papers and other marketing papers in our corpus) ($F = 57.23$, $p < .001$). We control for year of publication because Roberts, Kayande, and Stremersch's (2014) list of 100 impactful papers was published much earlier (1982–2003) than the MSI working papers and reports (1997–2017) and TPM conference submissions (2019). Figure 4, Panel B, depicts the mean R2M scores (adjusted for time). The mean R2M scores of the validation papers are significantly higher than the mean R2M score of all other marketing articles (all Bonferroni ps $< .001$). Among the validation papers, the only significant difference is between the mean R2M score of award-winning papers and that of MSI working papers and reports.

R2M Index Comparison Across Marketing and Nonmarketing Journals

To assess the discriminant validity of the R2M Index, we calculated R2M scores on a holdout set of 700 articles randomly drawn from *American Psychologist* (132 articles), *American Economic Review* (131 articles), *Psychological Review* (99 articles), and *Quarterly Journal of Economics* (120 articles). These basic discipline journals were selected as relevant because marketing often draws from psychology and economics. If the R2M Index is valid, then marketing journals should have higher scores than nonmarketing journals. A one-way analysis of variance with year of publication as covariate shows that this is the case ($F = 126.3$, $p < .0001$; all pairwise Bonferroni ps $< .01$). Figure 4, Panel C, reports the time-adjusted R2M mean scores: marketing has a significantly higher R2M score than both economics and psychology ($p < .001$), and psychology has a significantly lower R2M score than economics ($p < .001$).

Validating the R2M Index with Marketing Practitioners

To examine the extent to which our R2M score correlates with practitioners' judgment, we sought MSI's help to survey trustees during the March 2018 Trustees Meeting as well as executives enrolled in an EMBA program.

MSI survey. We presented practitioners with five pairs of article abstracts (including the article title) and asked them to indicate the article in each pair they thought was more relevant to the practice of marketing. One abstract in each pair was drawn randomly from the set of articles ranked in the top third by our R2M Index while the other was drawn from the bottom third. The order of presentation of the pair of articles was randomized across the five choice tasks and across practitioners. We also asked them to indicate their occupation and marketing expertise.

The survey was sent to 70 MSI corporate members; only 14 respondents completed it (a 20% response rate). The practitioners were senior marketing managers (e.g., Marketing Director, Chief Marketing Officer, Vice President of Marketing) with expertise in various positions (e.g., brand management, new product development, marketing strategy) and working in different industries (e.g., pharmaceuticals, online media, consumer package goods, telecommunications, financial services, technology). On average, they had 18.5 years of marketing experience. Three of them did not disclose their background information, and one respondent indicated being a marketing professor and was excluded from the sample. In total, our statistical analysis was based on a sample of 65 observations (13 practitioners, each performing five choice tasks).

We conducted a logistic regression where the dependent variable indicates which article in a pair the practitioner judged to be more relevant, and the independent variable is the difference between the R2M scores of the two articles in the pair. The regression coefficient was positive and significant ($\beta = 2.1$, $p < .001$). In addition, the likelihood ratio test shows that the model fit difference between an intercept-only model and the R2M model is significant ($\chi^2 = 82.3$, $p < .001$). The hit rate is 71%, which is higher than the 50% chance criterion. In summary, while the sample is small, the statistical results provide evidence for the validity of the R2M measurement.

EMBA survey. We also validated the index with 101 EMBA executives in a course in spring 2020. On average, the respondents had more than 9 years of business experience (3.5 years in a marketing-related job). We asked how much their job related to marketing; the mean was 3.4 on a 7-point scale. They had taken 2.3 marketing courses, on average. Because MSI trustees had reported that it was cumbersome for them to read five pairs of abstracts, we used a different procedure with the EMBA participants. We presented them with 20 triplets of article titles (no abstracts) and asked them to identify the title of the article in each triplet that they deemed most relevant and the one that was the least relevant to the practice of marketing. The first title in each triplet was drawn randomly from the set of articles ranked in the top third by our R2M Index; the second title was drawn from middle third; and the third title was drawn from the bottom third. The order of presentation of each triplet of articles was randomized across the 20 choice tasks and across EMBA participants.

To assess the validity of the R2M Index, we estimated an ordinal logit model where article rank in the triplet is the dependent variable and the R2M score of the article is the independent variable. In a choice set, there are $3! = (3 \times 2)$ possible ways to order the three articles. Thus, there is a 16.67% (= 1/6) chance to randomly predict the correct ordering. We obtain a hit rate of 40.2% and a positive and significant R2M coefficient ($\beta = 1.15$, $p < .001$). This hit rate is significantly higher than chance. The likelihood ratio test shows that the model fit difference between an intercept-only model and the R2M model is significant ($\chi^2 = 153.4$, $p < .001$). Though modest, the results provide further evidence for the validity of the R2M Index.

Gaming the R2M Index

Can the R2M Index be "gamed"? That is, similar to companies trying to affect Google PageRank outcomes, can authors increase the relevance of a research paper by simply adding words from our dictionary? To examine this possibility, we randomly sampled 200 journal articles from our corpus of 4,229 articles (about 5% of the articles). To "game the index," we first augmented the text of each of the 200 articles by adding 10% of the terms in our marketing dictionary. For each article, these additional marketing terms were randomly drawn from the 512 most relevant terms in our dictionary (i.e., those with marketing-term relevance weight $r_w = 1$). We then used our LDA estimates to predict the topic probabilities for each article and calculate the new R2M score. If the index can be "gamed," we would expect the R2M scores for these 200 articles to be higher with "gaming" than without. Without "gaming" the mean R2M score is .64 and with "gaming" the mean R2M score across these 200 articles is .67. This score is only slightly higher and not significant ($t = 1.35$, $p > .18$). The robustness of the index stems from measuring the relevance to marketing at the topic rather than the article level because it is much more difficult to "game" the relevance to marketing of a collection of articles (which are subsumed under a topic) than that of a single article.

Final Discussion

Using a text-mining methodology, we developed the R2M 1.0 Index to measure the relevance of academic marketing articles to marketing practice. This dynamic measure fulfills the desiderata for an ideal measure compiled by Ailawadi, Lehmann, and Neslin (2003). The index can be summarized by a single number: the mean R2M score of an article. The index and its key components (topical and timely relevance) are grounded in theory, in particular, in the field of information science. The index is also diagnostic and predictive and captures the potential of an article such as the likelihood of winning practice-related awards and being seen as relevant by practitioners. In addition, it is an easy-to-use, objective measure rather than a subjective judgment, and is based on readily available data (i.e., publicly available articles and information). Finally, the index is reliable and robust against "gaming" and has been validated against several other measures of relevance.

We found that the relevance of academic articles has slightly increased over time. We also found that articles published in *JM* have higher R2M scores than *MSC* and *JMR*, with *JCR* being the least relevant. In addition, of all journals *JM* has the highest percentage of topics covered in its articles in the Highlands quadrant, and the lowest percentage of topics in the Academic Island. The leadership role of *JM* in terms of practical relevance seems to be due to *JM*'s long-standing commitment to serve not only academics but also practitioners. To continue this legacy, the current editor in chief has decided to focus on publishing marketing research that has important implications for firms, policy makers, and other societal stakeholders (see https://www.ama.org/editorial-guidelines-journal-of-marketing). In addition, the scores revealed that *MSC* and *JMR* have become more relevant over time, and *JCR* has become slightly less relevant. The positive trend for *MSC* and *JMR* is consistent with research indicating that quantitative marketing has responded well to the emergence of new industries and the availability of new data by introducing new relevant topics (Huber, Kamakura, and Mela 2014; Mela, Roos, and Deng 2013). The lower practical relevance of *JCR* and its slight decline in relevance over time may indicate that, during our time period, the journal deliberately chose to position itself as a purely academic publication. Our analysis also indicated that publications in *JCR* heavily focused on less relevant topics such as Information Processing, Consumer Judgment, and Consumer Goals and Motives and did not include more relevant marketing-related topics such as Branding, Online Marketing, New Products, and Innovation.

Limitations and Next Steps

This first version of the R2M Index has limitations that call for future refinement. First, we only analyzed articles in four marketing journals from 1982 to 2015. Future research should include a broader set of marketing journals and longer periods. Second, because it was our goal to cover all marketing content, our dictionary of relevant terms is rather exhaustive but also quite long. Future research should create a shorter dictionary and customize the index to the needs of particular journals and audiences (e.g., focusing on technology relevance, marketing strategy relevance, public policy relevance, or consumer relevance). Third, we empirically observed that the dictionary entries became quite stable between 2000 and 2010; however, new terms will emerge, and the dictionary needs to be updated. We recommend frequent updating of publications in practitioners' outlets and a periodic major overhaul of the dictionary. As new academic articles are published, they should also be included and scored. Fourth, further efforts should be expanded to validate the index with more managers and increase the robustness against "gaming." Fifth, in the long term, the index could be made more sophisticated using machine learning and artificial intelligence by using an algorithm to decipher the meaning of marketing terms by learning interrelations among terms and topics. In summary, the R2M Index version 1.0 is a starting point, but also a work in progress that requires further refinement.

In addition, relevance is only one indicator of the merit of an academic marketing article. Other important indicators may include how often an article is cited, whether it is widely shared (e.g., because it provides a critical theoretical, substantive, or methodological contribution), and whether it is intellectually stimulating and inspiring to read. We therefore propose that scholars assess the relationship of the R2M Index to other article measures such as citation counts, altmetrics, and writing-clarity measures (Warren et al. 2021). Most importantly, topical and timely relevance are distinct from business impact. While relevance is a necessary condition for impact in business, impact is a broader concept (Jaworski 2011; Schmitt 2012). A measure of impact may require the creation of a system that includes marketing practitioners as judges, employs measurement scales centered on behavioral and organizational change, and objectively assesses impact as part of a theory-to-practice chain. We urge researchers to develop such an "impact-on-marketing" measurement system to assess which academic ideas and knowledge have significantly changed marketing practice.

A Relevant Tool for Both Practitioners and Academics

We view the R2M Index as a useful and relevant tool for multiple stakeholders. We conducted two focus groups with senior marketing scholars, asking them to brainstorm about how the index could be used by various stakeholders.[2]

Important stakeholder groups include marketing managers in for-profit firms as well as marketing decision makers in nonprofit firms and public policy organizations. These groups can use the index to identify articles that satisfy their informational needs. In addition, market intermediaries such as market research firms and consultants can use the measure to identify relevant articles and compile curated relevant readings to satisfy their clients' needs for relevant information. Similarly, the media and social influencers who play an important role in bringing relevant academic work to the attention of decision makers can employ the index and the topics derived from it to screen academic articles and identify new trends in business and academic literature. Rating and accreditation agencies may also find the index useful for ranking business school research in marketing. For example, regulators in the United Kingdom, Australia, and the Netherlands have introduced systems that require universities to demonstrate relevance and impact (Jack 2020).

Inside academia, authors who are concerned about the practical relevance of their research could use the R2M index to assess the topical and timely relevance of their research as they market their research among the scholarly community and pitch it to business and media outlets. Editors of academic journals could use the index as a tracking device to assess the status quo of their journals and to position or reposition them based on the results. Editors could also employ the index to evaluate papers and make suggestions during the review process to identify topics of relevance, and as a screening device for awards. Finally, department heads and business school deans could utilize the index for fundraising and as part of promotion and tenure decisions.

In summary, the index is valuable for a wide range of marketing stakeholders. Following the dictum ascribed to Peter Drucker, "What gets measured, gets done," we view the index not only as a measurement and assessment instrument but also as a tool for change. In this vein, we hope that the index will be broadly embraced so marketing can fulfill its mission as an applied discipline and publish articles in academic journals that serve marketing practitioners' needs. We encourage scholars in other fields of business that have examined and debated the relevance of their own academic research (such as management, information systems, and accounting) to develop similar indices to show which scholarly work in their field is relevant to business and has the potential to change business practice. Toward this endeavor, we created a web application (www.R2Mindex.com) where users can score articles on R2M and search for practically relevant research.

[2] The second author moderated the focus groups; the first author was present for technical clarification about the index. We thank Professors Randolph Bucklin, Sunil Gupta, V. Kumar, Don Lehmann, David Reibstein, Venkatesh Shankar, Nader Tavassoli, Rajkumar Venkatesan, Kim White, and Raghu Iyengar for their participation. All these scholars were organizers of prior TPM conferences.

Postscript

The reader may wonder how the present article scores on the R2M Index. The answer is: .89, which is slightly above average in relevance to marketing and high for a measurement article. (And we promise we have not "gamed" the score.)

Associate Editor

Stefan Stremersch

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