

From Insight to Impact: Closing the Marketing Science Value Chain with Interactive, Research-Driven Apps

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Abstract

Every year, several thousands of marketing articles are published in academic journals, often with the aim of disseminating new insights not only to the academic community but also to managerial practice. However, there is wide acknowledgment of gaps in the marketing science value chain, hindering the flow of marketing knowledge to other researchers and managers. The authors posit that interactive, research-driven (IRD) apps that provide a deeper understanding of the usability of the research contribution are a viable solution to improve the diffusion of marketing knowledge. They shed light on the motivations and barriers to develop IRD apps as well as the market potential and impact of IRD apps through a multimethod examination, which includes interviews, secondary data analyses, and experimental studies. The authors find an untapped potential of IRD apps among published articles and complementary evidence of their value to researchers and managers. They further provide a tutorial to guide the development of IRD apps that complement static research papers and close with a forward-looking section about the future of IRD apps.

Keywords

interactive research-driven apps, marketing science value chain, research–practice gap

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There is widespread agreement that a research–practice gap exists in marketing science (Kohli and Haenlein 2021; Moorman et al. 2019; Roberts, Kayande, and Stremersch 2014). According to the Web of Science, around 2,700 articles¹ are published in marketing journals every year. Most of them aim to create relevant and impactful research, but reaching a wider audience remains always challenging (Haenlein and Jack 2025; Stäbler and Haenlein 2025). One promising and up-to-date solution to bridge the research–practice gap is to create interactive, research-driven (IRD) apps, defined as “online interactive tools that provide a deeper understanding of the usability of the research contribution” (Chintagunta et al. 2022). That is because the interactivity of IRD apps not only triggers active learning (Moreno and Mayer 2007) but

also can increase the diffusion of research across scholars and practitioners (Mayer et al. 2020).

An example of an IRD app is the work from Dew, Ansari and Toubia (2022), who analyzed a large set of brand logos with a strong brand identity. They then decomposed the logos with the help of a deep learning algorithm into various visual elements such as colors, fonts, and number of corners and matched these insights with data on how brand personalities and industries are perceived. Their results are extremely rich but rather complex to convey in a traditional research paper format. To

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¹ Average number of publications per year for the time frame of 2014–2024 in the 47 marketing journals of the Social Sciences Citation Index.

make these more appealing and easier to understand, they developed an IRD app to convey their findings in an interactive way.

Despite recent calls for more research that includes IRD apps (Chintagunta et al. 2022), there is no clear theory, practical evidence, or guidelines for authors on how to develop such apps. We draw on the marketing science value chain (Roberts, Kayande, and Stremersch 2014), which posits that the diffusion of marketing knowledge to practice is driven by three consecutive steps: (1) the *knowledge generation* by marketing researchers, (2) the *knowledge conversion* by marketing intermediaries, and (3) the *knowledge application* by marketing practitioners. Previous research has mainly focused on the knowledge generation problem, examining what topics should be studied for real-world relevance (Kohli and Haenlein 2021; Lilien, Roberts, and Shankar 2013; Schauerte et al. 2023; Van Heerde et al. 2021) or how to get more media coverage (Stäbler and Haenlein 2025). Complementing these valuable insights, we focus on knowledge conversion and knowledge application problems.

As indicated in Figure 1, two potential gaps emerge from the marketing science value chain (Roberts, Kayande, and Stremersch 2014). First is the adaptation and integration gap, which hinders the conversion of marketing knowledge into practical tools. In fact, authors might face challenges when building a marketing tool such as an IRD app (e.g., costs, technology, incentives) that translates the insights of their work for other researchers, consultancies, or practitioners. Second is the adoption and implementation gap, which hinders the application of marketing knowledge by marketing managers via practical tools to make better marketing decisions. Many academic articles are written in a way that is difficult for practitioners to understand (Warren et al. 2021), making it unlikely that marketing insights are implemented by marketing managers. In addressing these gaps, and in line with recent calls for more IRD apps in marketing (Chintagunta et al. 2022), our article focuses on three broad research questions:

RQ₁: What are the motivations and barriers for developing IRD apps?

RQ₂: What is the market potential and impact for IRD apps?

RQ₃: How can authors develop IRD apps that complement published articles?

We address RQ₁ by reviewing the last five years of published marketing research in the field's leading journals and find that so far only 24 articles have an accompanying IRD app. To gain further insights into this low number, we interviewed 21 authors concerning the motivations and barriers of their app development process. We respond to RQ₂ by estimating how many papers in the last five years could have been complemented by an IRD app and by empirically testing whether adding an IRD app to a published article increases its impact among other scholars and marketing managers. We find that articles with an IRD app receive above-average citations and higher perceptions of how interesting, useful, and relevant the

research is. Finally, we address RQ₃ by providing a tutorial with insights into the target groups of IRD apps and the costs of such apps. We then offer concrete steps on how to develop interactive research-driven apps with little or no coding experience. We conclude with future considerations of IRD apps.

The Marketing Science Value Chain and Interactive Research-Driven Apps

We believe that IRD apps are novel and unique tools that enable the knowledge conversion and knowledge application of marketing insights, helping to close the two gaps in the marketing science value chain outlined in Figure 1. First, IRD apps close the *adaptation and integration gap* from articles because they enable a concise presentation of findings and contributions, increasing their ability to be understood and applied. Hence, generated marketing knowledge can be more seamlessly converted, and fellow researchers or marketing intermediaries can more efficiently use this knowledge. For example, when novel insights such as the automated identification of passive voice in text emerge in text analysis, researchers unfamiliar with the method may find it more accessible to engage with the IRD app from Sepehri, Mirshafiee, and Markowitz (2023) instead of relying on the paper alone. Second, IRD apps also help overcome the *adoption and implementation gap* because they make marketing knowledge more interesting and applicable, motivating marketing managers to apply the generated knowledge. For example, when crafting social media posts, managers might find it easier to apply the recommendations of the IRD app from Atalay, El Kihal, and Ellsaesser (2023) to improve their writing effectiveness than following the guidance outlined in the paper alone.

We argue that IRD apps are complementary to other research paper companions aiming to close the gaps in the marketing science value chain such as articles in business magazines, podcasts, videos, or sharing code and data. In this set of alternatives, we posit that the key property of IRD apps is that they enable knowledge conversion by means of making research more interactive and accessible to readers and users. IRD apps fulfill the task to provide “a deeper understanding of the usability of the research contribution” in the form of an interactive tool (Chintagunta et al. 2022). An app thus serves as a dynamic computational supplement to a published article, thereby adding interactivity to the otherwise static nature of a research publication. In this way, IRD apps are also considerably different from the practice of sharing code and data in the open science movement (Deer et al. 2025). Web Appendix A provides a comparison of these different paper companions.

The functionality and type of IRD apps depend intricately on the scope of the research article. In this context, Chintagunta et al. (2022) classified four types of apps for marketing research: predictors, optimizers and recommenders, explorers, and converters. We used Table 1 to describe the characteristics of each IRD app type, together with a theoretical link regarding how the specific app capabilities can overcome the two marketing science value chain gaps.

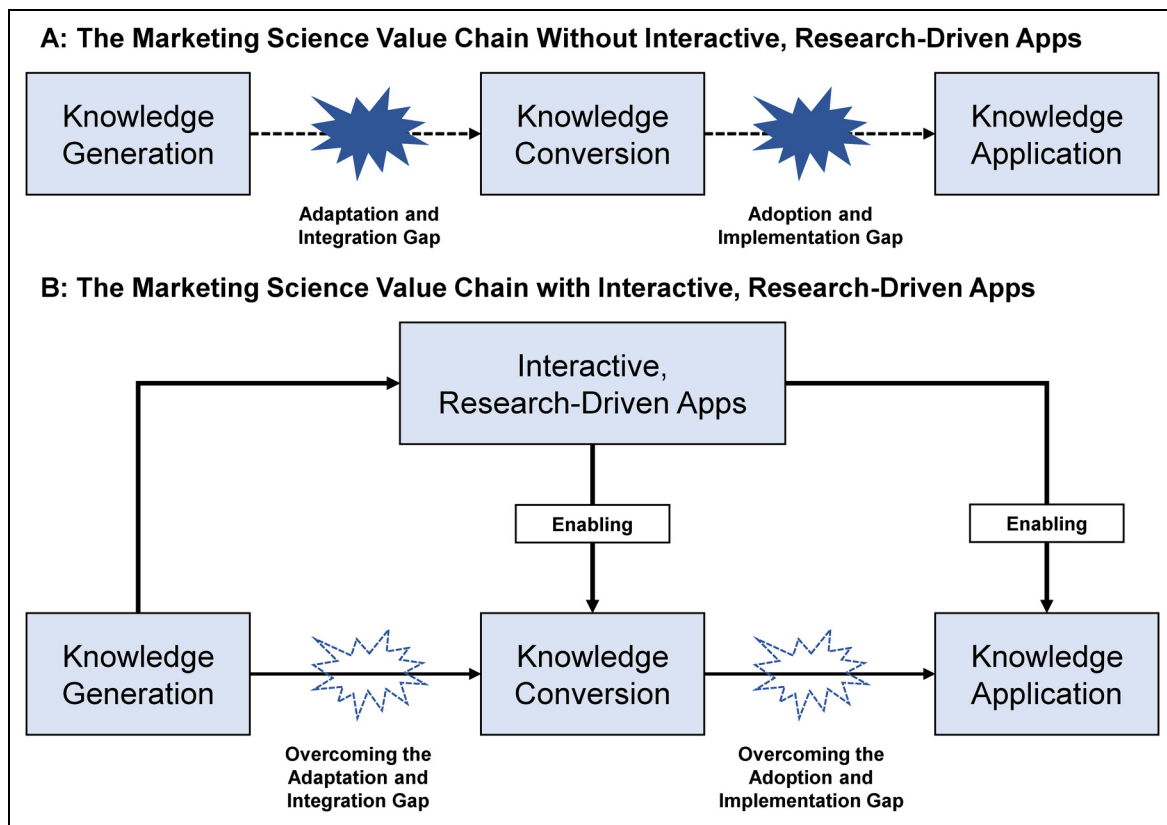


Figure 1. Interactive, Research-Driven Apps in the Marketing Science Value Chain.

Notes: The underlying diffusion process of the marketing science value chain is based on Roberts, Kayande, and Stremersch (2014).

To understand the status quo of IRD apps in marketing, we searched all articles published from 2020 to September 2025 in the leading marketing journals² and classify all existing IRD apps using the typology outlined in Table 1. We chose this time frame as the majority of IRD apps were published after 2020.³ In order to identify all existing apps, we screened the article abstract and the online supplementary material. Our search resulted in 24 IRD apps, summarized in Table 2. These apps span a wide range of topics, including branding (Dew, Ansari, and Toubia 2022), scientific writing (Warren et al. 2021), and linguistic phenomena (Packard, Li, and Berger 2024; Sepehri, Mirshafiee, and Markowitz 2023). We find that most apps are of type “converters” and “explorers.” It is noteworthy that most IRD apps (N=23) in our search target the adaptation and integration gap or both gaps, therefore strengthening the marketing science value chain by facilitating the application of marketing insights by other academics and

marketing students. Only half of the IRD apps (N=13) also consider the adoption and implementation gap, and only one existing IRD app has a clear managerial audience.

Motivations and Barriers to Develop Interactive, Research-Driven Apps

To address RQ₁ and obtain a better understanding of the motivations and barriers when developing IRD apps, we interviewed 21 authors that have developed or are currently developing IRD apps. We used five open questions in our written interviews:

1. Why did you decide to invest time and resources into the development of your IRD app?
2. How did you develop your IRD app?
3. What were the biggest challenges and barriers you encountered?
4. What is the primary target group(s) of your IRD app?
5. How many visitors/users does your IRD app approximately have?

Detailed summaries of all responses are provided in Web Appendix B. Authors described five key motivations for developing IRD apps. Many sought to make research more accessible and engaging and to increase the visibility and impact of their work beyond traditional papers. Others aimed to democratize

² Including *Journal of Marketing*, *Journal of Marketing Research*, *Marketing Science*, *Journal of Consumer Research*, *Journal of the Academy of Marketing Science*, *Journal of Consumer Psychology*, *International Journal of Research in Marketing*, and *Journal of Interactive Marketing*.

³ There are two notable exceptions: Blanchard, Aloise, and DeSarbo (2017) did have an IRD app that accompanied their article; however, this app is not hosted anymore. McShane and Böckenholt (2017) also accompanied their paper with an app, but this article was outside our targeted time frame.

Table 1. Different Types of Interactive, Research-Driven Apps.

	Predictor Apps	Optimizer and Recommender Apps	Explorer Apps	Converter Apps
Description	Predictor apps offer model-based predictions and thereby depict the interplay among various factors affecting a marketing input, process, or outcome.	Optimizer apps offer normative solutions to improve currently suboptimal marketing decisions made by agents, and recommender apps offer superior solutions to current problems marketing stakeholders face.	Explorer apps investigate sensitivity of research results to various research design assumptions.	Converter apps provide accessible marketing insights through the conversion of unstructured input (e.g., text, audio, videos) to structured data, and models developed in the research framework.
Examples for overcoming the adaptation and integration gap	Researchers can easily apply predictive models for their own data without the need of implementing the code (e.g., predicting the optimal sample size for an experiment; André and Reinholtz 2024).	Researchers can follow best practices involving general aspects of research (e.g., writing recommendations for a marketing paper; Warren et al. 2021).	Researchers can obtain additional insights from research articles that otherwise cannot provide all potential analyses due to space limitation (e.g., further exploration of a meta-analysis dataset; Li, Lai, and, Wang 2025).	Researchers can have simple access to tools that allow them to operationalize new marketing constructs (e.g., measuring the presence or absence of passive voice in brand communications; Sepehri, Mirshafiee, and Markowitz 2023).
Examples for overcoming the adoption and implementation gap	Managers can obtain an estimation of the effect of changing in marketing actions and outcomes (e.g., frontline language and customer satisfaction; Packard, Li, and Berger 2024).	Managers can utilize scientific suggestions on how to improve marketing actions relative to the marketing mix (e.g., recommending a greater level of syntactic surprise in ads; Atalay, El Kihal, and Ellsaesser 2023).	Managers can interactively explore and visualize insights about marketing actions related to areas such as branding, market structure, and sentiment (e.g., visualization of color properties of logos; Dew, Ansari, and Toubia 2022).	Managers can more easily implement communication tactics involving text, audio, images, and video (e.g., using more concrete messages for customers near to the end of the funnel; Humphreys, Isaac, and Wang 2021).

Notes: The typology and the potential use cases are based on Chintagunta et al. (2022). This taxonomy does not pretend to be exhaustive, but it fit our classification of IRD apps. Roggenkamp, Boegershausen, and Hildebrand's (2025) app is one notable exception; it enables researchers to improve their experimental methodologies to simulate a research environment. Once data is collected, researchers can explore the results (Table 2).

access to complex methods by creating user-friendly apps that reduce technical barriers. Several authors emphasized demonstrating the practical usability of their findings or advancing methodological innovation where existing tools fell short. A few authors also mentioned external drivers, such as reviewer requests or funding mandates. Collectively, these motivations reflect a shared goal to turn insights into usable tools.

The authors often opted to build their IRD app internally, either themselves or with the help of research assistants or students. Most of them reported using open-source tools and framework such as Shiny (based on R) or Streamlit (based on Python), but also tools like KNIME or even Excel. To facilitate development, some authors also used AI tools like ChatGPT to help with coding tasks. Some of the authors reported that they had fully or partially outsourced the development to freelancers of agencies.

Authors frequently described app development as challenging, primarily due to the specialized technical skills required. As one author noted, it was “exceptionally cumbersome before we had GenAI that could generate code for us,” underscoring the steep learning curve faced by researchers without formal software training.

Several authors emphasized that creating IRD apps demanded substantial personal time. Most apps required between 20 and 150 hours of development, though a few extended to several months of work. Despite the time commitment, the financial costs remained relatively low in most cases, apart from an exceptional case where expenditures exceeded \$200,000. Many authors noted that low monetary costs were achieved by self-developing their IRD apps rather than outsourcing. However, technical challenges persisted, particularly in maintaining the apps over time and refining the underlying models. One author explained that “without members of the core team, it would be difficult to maintain the code in the long run,” highlighting the sustainability issues that often arise postdevelopment. Finally, several authors observed that app development is less valued than traditional publications, making it difficult to justify the required effort within existing academic incentive structures.

Most authors named other researchers as their primary target group, often describing IRD apps as tools to “make research outputs more accessible” or “inspire others” to build similar tools. IRD apps were deemed helpful to

Table 2. Overview of Existing Interactive, Research-Driven Apps in Marketing.

Article	Type	Link	Targeted Gap	Description of Functionality
André and Reinholtz (2024)	Predictor	PRIApp	Adaption and Integration	Design, simulate and pre-register interim analysis design, helping to predict the appropriate study sizes in online experiments. Potentially reducing the costs of experiments, this app improves the integration of experiments into studies.
Atalay, Kihal, and Ellsaesser (2023) ^a	Optimizer	Syntactic Surprise Calculator	Both	Trained on 150k tokens from a publicly available corpus, the app calculates how syntactically surprising a marketing message is and then gives recommendations on how to optimize for optimal surprising syntax. Through the app, practitioners can adopt the findings easily to their context (e.g., by creating social media posts).
Blanchard et al. (2025) ^a	Converter	GPT-Coder	Adaption and Integration	Allows the user to upload a CSV file and code its contents using OpenAI's GPT models. This enables researchers to apply state-of-the-art research methods more easily.
Cascio Rizzo, Berger, and Zhou (2025) ^a	Converter	Hand Movement Classifier	Both	Trained on almost 200k video segments, this multimodal classifier can automatically detect and categorize hand gestures in video content. It facilitates research into multimodal communication, but can also help practitioners improve their non-verbal communication skills.
Dew, Ansari, and Toubia (2022) ^a	Explorer	Logo Explorer	Both	Based on a dataset of logos from 700 brands, the app explores the connections between logo features (e.g., color or font), industry, and brand personalities using interactive visualizations. Researchers can explore branding-related research questions while practitioners can use the logo explorer in their design process (e.g., rebranding).
Dyachenko and Allenby (2023)	Predictor	BAHM	Adaption and Integration	Bayesian analysis of heterogeneous mediation helps predicting how mediating effects vary among participants due to their heterogeneity. Easy usability through the app helps other researchers to improve their methodological approaches.
Farace et al. (2025) ^a	Predictor	Text Overlay App	Both	Predicts engagement on social media channels based on the position, size, and content of textual overlays on social media posts. Practitioners can use scientific evidence to improve their social media posts, while other researchers can use the app to advance studies on multimodality.
Hartmann, Bergner, and Hildebrand (2023) ^a	Predictor	Mindminer	Both	Uses a language model trained on customer reviews to predict mind perception of consumers in smart objects. This facilitates research into mind perception (e.g., for application in other contexts) and can be used by practitioners to track mind perception of their customers.
Hotz-Behofsits, Wlömert, and Abou Nabout (2025) ^a	Converter	NADE	Both	Converts text into emojis and then emotions on Plutchik's wheel of emotions. This facilitates the research process for academics (no-coding, free of charge) and enables practitioners to easily apply it (e.g. market research, content-creation).
Hovy, Melumad, and Inman (2021)	Converter	Wordify	Adaption and Integration	After uploading a series of documents, this app helps to find those n-grams that are most indicative among desired dependent variables. For example, it identifies the terms that differ between good and bad reviews. The app facilitates the usage of this methodology by other researchers.

(continued)

Table 2. (continued)

Article	Type	Link	Targeted Gap	Description of Functionality
Humphreys, Isaac, and Wang (2021) ^a	Converter	Construal Score Tool	Both	Converts text strings into concreteness scores based on two dictionaries, enabling easier analysis of this textual dimension by researchers and optimization of search keyword campaigns by practitioners.
Jaikumar, Chintagunta, and Sahay (2024)	Explorer	DPCO 2013	Adaption and Integration	Allows users to browse the content and interact with the findings of the research. This way, researchers can obtain a deeper understanding which helps the dissemination of findings.
Jedidi et al. (2021)	Explorer	R2M Index	Both	Scores an article on its relevance for marketing practice using text-mining methodology and gives the opportunity to explore other articles in the database that already have been scored. This way, researchers can assess the relevance of articles, while practitioners can find relevant articles.
Laghaie and Otter (2023) ^a	Predictor	BFMediate_APP	Adaption and Integration	Through simulation, this app improves the accuracy for the prediction of mediation in the case of measurement-of-mediation designs. Researchers can enhance their mediation studies through this app.
Li, Lai and, Wang (2025) ^a	Explorer	AI Meta Analysis	Adaption and Integration	Explores and synthesizes the existing literature on the key drivers of acceptance of AI. Additionally, it offers the possibility of contributing new data. This way, by exploring existing literature, researchers can position their (future) research more efficiently.
Matthe, Ringel, and Skiera (2023) ^a	Explorer	Evo Map	Both	Using visualization, this app helps to explore longitudinal spatial relationships, specifically product market competition among over 1,000 publicly listed firms from ten different industries. The app facilitates both academic and managerial research into industry dynamics.
McShane and Böckenholt (2022) ^a	Converter	MCSM	Adaption and Integration	Converts study results with multiple contrasts and measurements into a coherent meta-analysis. This app facilitates the creation of multiple contrast standardized meta-analysis for researchers.
Packard, Li, and Berger (2024) ^a	Predictor	When Language Matters	Both	Analyses text in multi-turn conversations (e.g., customer support) to predict the relationship between language features and outcome measures (e.g., affective language and perceived helpfulness). This app facilitates language research and can provide valuable customer service insights.
Ringel (2023) ^a	Explorer	mapXP	Both	Enables users to discover relationship between objects, such as firms or brands. The example map in this app explores manufacturer positioning and consumer perception in the digital camera market.
Roggenkamp, Boegershausen, and Hildebrand (2025) ^a	Explorer	DICE (Digital In-Context Experiments)	Adaption and Integration	Offers an interactive environment to test experimental manipulations in realistic social media settings, enabling researchers to improve their experimental methodology.
Schoenmueller, Netzer, and Stahl (2023) ^a	Explorer	Social Listening	Both	Based on two datasets on brands, this app allows to explore the political affiliation of social media brand followings in the US. Researchers can easily access data to test new hypotheses, while practitioners could use the database to improve marketing interventions (e.g., brand partnerships).
Sepehri, Mirshafiee, and Markowitz (2023) ^a	Converter	PassivePy	Adaption and Integration	Identifies passive voice in text and converts it into scores for further analysis by academics and practitioners. This enables academics to easily

(continued)

Table 2. (continued)

Article	Type	Link	Targeted Gap	Description of Functionality
Warren et al. (2021) ^a	Optimizer	Clarity Calculator	Adaption and Integration	integrate passive voice analysis in their research (e.g., as control variables). Analyses text on three main dimensions: The use of passive voice, its readability, and the use of examples. It then gives suggestions for improvement. Improving readability facilitates understanding and bridges the gap between marketing researchers and marketing intermediaries.
Yang, Zhang, and Kannan (2022)	Explorer	Market-Structure	Adoption and Implementation	Interactive visualization of market structure among brands. Similar brands are close to each other, while dissimilar ones are further away. This app enables managers to identify opportunities and threats beyond product-market boundaries.

^aAuthor participated in survey.

integrate novel methodological approaches, visualize relationships, or apply findings directly. Students are another key target group that benefits from IRD apps' dynamic environment, as the apps offer tangible educational experiences that make abstract theories more tangible. Importantly, many authors also identify practitioners; IRD apps can help demonstrate the practical relevance of findings, facilitating the translation of academic insights into applied outcomes. Some authors report target groups that extend beyond academics, students, and managers, including broader audiences such as consumers and journalists.

We also inquired about usage statistics, but not all authors had implemented tracking, citing reasons such as privacy concerns, technical limitations, or restrictions from hosting platforms. As one author explained, they “deliberately chose not to implement user tracking to respect researcher privacy,” keeping the development simple. Among those who did provide usage estimates, responses clustered into three groups. One group reported relatively high levels of activity, with “several thousand” to “nearly ten thousand” users or visits. A second group described more concentrated use within a limited audience, often on small-scale. However, several authors indicated that usage remained low because their “companion paper is still in press,” meaning the apps had not yet been publicly disseminated.

Taken together, the interviewed authors agreed that in line with our theorization, IRD apps have the potential to close the gaps in the marketing science value chain. One author connected the IRD app with the number of citations, stating that “the paper associated with the app has over 500 citations.” Other authors report that their IRD apps have sparked interest among managers. One author team even shared that a company had reached out to them about integrating their IRD app into their proprietary software. However, to go beyond these anecdotal evidence, we next systematically explore the market potential and impact of IRD apps.

The Market Potential and Impact of Interactive, Research-Driven Apps

Assessing the Market Potential for Interactive, Research-Driven Apps

We used articles that share the same keywords with the 24 articles that already have an IRD app to assess the potential for app development in marketing research, as detailed in Web Appendix C. Using the same time frame and the same journals as before, we retrieved a total of 1,096 articles with 106 keywords. After excluding those articles where an IRD app already existed ($N=21$)⁴ and articles that were categorized as editorial or commentaries ($N=25$), we further examined a total of 1,050 articles. The first author and a research assistant assessed the abstract of each article, judging whether the paper was a good fit for the development of an IRD app or not. We defined three requirements that an article must meet to have potential for an IRD app. First, we asked whether the research solved an important marketing science problem by addressing real-world issues that impact managers, researchers, or stakeholders, or by targeting a specific relevant issue (e.g., advertising attribution) (Van Heerde et al. 2021). Second, we inspected whether the article offered actionable solutions to solve this problem (i.e., predict, optimize and recommend, explore, or convert). Finally, we assessed whether the article sufficiently described the contribution that can be used as a base for the IRD app development process (e.g., describing the creation of a predictive machine learning model as one of the contributions). We followed a detailed flowchart to facilitate the coding process, which is displayed in Web Appendix C.

⁴ The difference from 24 total articles is because 3 articles were not yet added to the Web of Science database: Cascio Rizzo, Berger, and Zhou (2025), Roggenkamp, Boegershausen, and Hildebrand (2025), and Li, Lai, and Wang (2025).

We find that 25% of articles (i.e., 262 articles) have the potential to add an IRD app, including 8% (83) predictors, 5% (49) optimizers and recommenders, 9% (99) explorers, and 3% (31) converters.⁵ For example, Kronrod, Gordeliy, and Lee (2023), who develop a way to predict fake reviews using linguistic features via machine learning, have potential for a predictor app; Nguyen, Johnson, and Tsiros (2024), who use large-language models to optimize email headlines, have potential for an optimizer and recommender app; Dzyabura and Peres (2021), who develop a brand visual elicitation platform, have potential for an explorer app; and Pamuksuz, Yun, and Humphreys (2021), who develop an algorithm to identify brand personalities from social media data, have potential for a converter app. While the market potential appears impressive, our conclusion should nevertheless be taken as a rough estimation based on a subjective interpretation of the potential to develop an IRD app from a research article.

Assessing the Impact of Interactive, Research-Driven Apps

Having established the market potential of IRD apps, we next combined several complimentary approaches to assess the impact of interactive, research-driven apps, including (1) a citation analysis, (2) an online study with 146 marketing managers, and (3) an A/B test with 36 marketing students.

First, we assessed the impact of IRB apps in marketing papers in a citation analysis that is detailed in Web Appendix D. Of the 11 papers that contain an IRD app published in 2022 and 2023, 8 received more citations in 2024 than the average paper implied by their journals' impact factors, suggesting that 73% of these papers had an above-average impact with other scholars within the marketing field.

Second, we recruited 146 marketing managers on Prolific who passed an instruction check (60.3% female, 38.4% male, 1.4% nonbinary; $M_{\text{age}} = 38.77$ years) for a 4×2 within-subject experimental study (details are in Web Appendix E). We exposed all participants to a randomized sequence of four recent marketing articles that were published in top journals (i.e., Atalay, El Kihal, and Ellsaesser 2023; Dew, Ansari, and Toubia 2022; Farace et al. 2026; Humphreys, Isaac, and Wang 2021). For each article, the respective IRD app was randomly either provided or not, in addition to the abstract and an excerpt of the article. We checked whether this manipulation was successful after each article ("To what extent do you think the research paper is interactive?"). To measure interestingness and relevance, we used a three-item scale for interestingness ($\alpha = .88$) and a four-item scale for relevance ($\alpha = .90$), adapted from Schauerte et al. (2023). For our analysis, we average the interestingness and relevance items as dependent variables, with the experimental condition (exposure to an

IRD app or not) as the independent variable. We find that the presence of an IRD app increases both the perception of interestingness ($b = .255$, $p = .022$) and relevance ($b = .265$, $p = .028$) of the same research article for the managerial audience. These effects remain significant when controlling for work experience and education of participants.

Third, to extend our findings to future marketing managers, we run an A/B test with 36 graduated marketing students from a large public Dutch university in two existing tutorial groups from a larger marketing class. The same short lecture, focused on how logos influence brand perception, was delivered in both tutorials. After the lecture, the students in both tutorials were tasked to engage with the research article from Dew, Ansari and Toubia (2022). In the first tutorial, all students were given a summary of the paper and a link to the research article. In the second tutorial, all students were given a summary of the paper, a link to the research article, and a link to the IRD app.⁶ After working for 20 minutes on the task, we then asked three questions regarding the research's interestingness, usefulness, and relevance ("In your opinion, how interesting is it to implement the findings from this research?," "In your opinion, how useful is it to implement the findings from this research?," and "How relevant do you find this research paper?"). A one-way ANOVA reveals that students that were exposed to the IRD app perceived the research article as more interesting ($M_{\text{app}} = 5.32$, $SD = 1.42$; $M_{\text{control}} = 3.88$, $SD = 1.32$; $F(1, 35) = 9.814$, $p = .004$), useful ($M_{\text{app}} = 4.79$, $SD = 1.32$; $M_{\text{control}} = 3.76$, $SD = 1.09$; $F(1, 35) = 6.379$, $p = .016$), and relevant ($M_{\text{app}} = 4.58$, $SD = 1.43$; $M_{\text{control}} = 3.71$, $SD = 1.26$; $F(1, 35) = 3.741$, $p = .061$) compared with those that were not exposed to the IRD app.

Based on our combined findings, we conclude that IRD apps have a positive impact on other scholars, as evident in our citation analysis, and on marketing managers, given that participants find papers with an IRD app more interesting, useful, and relevant. However, while IRD apps are an emerging phenomenon that can potentially close the gaps in the marketing science value chain, to date IRD apps are also underused by marketing researchers. We believe this shortcoming can be overcome in two ways. First, researchers need a better understanding of the value and cost of IRD apps. Clearer insights about what the target audiences of apps want and the development costs could be important for researchers interested in developing and hosting IRD apps. Second, a basic understanding of app development should help demystify the app development process, so that unexperienced scholars can either build simple solutions themselves or collaborate effectively with external developers to integrate IRD apps into academic publications. We detail both aspects in the next section.

⁵ We also conducted an additional analysis of 100 randomly selected articles that did not match the keywords of the articles with existing IRD apps. We find IRD app potential in 23% (23) of these articles.

⁶ Students were randomly assigned to one of two tutorial groups for the length of the whole course. While a link to the app is available in the full text of the paper, none of the students in the first tutorial indicated that they used the app in the debriefing of the experiment. In any case, if some students in the first tutorial would have used the app, then the obtained effects would underestimate the true impact of adding the IRD app to the research paper.

Developing Interactive, Research-Driven Apps

Identifying the Core Audience for the Interactive, Research-Driven App

IRD apps can help overcome the adaptation and integration gap as well as the adoption and implementation gap. While the former focuses mostly on fellow researchers who value the possibility of integrating knowledge in their own research, the latter focuses on practitioners who value practical insights for their marketing objectives. By tackling these gaps, IRD apps can help researchers to make their research more valuable for their target audiences. Humphreys, Isaac, and Wang (2021) provides a good example of an IRD app targeting both gaps and audiences: Researchers have easier access to concreteness scores, while practitioners can use them to improve their marketing campaigns by getting quick insight about the fit of a campaign goal with its actual content. As Table 2 shows, most published IRD apps target both gaps. However, targeting both gaps can expose pitfalls. While enhancing their potential impact, researchers might “fall between two stools” (i.e., failing to address either gap). For example, researchers prefer rigor over usability, whereas practitioners tend to appreciate usability more. Therefore, researchers should carefully assess what contributions their article makes (e.g., does it have a more research or practical orientation?) and develop their IRD app accordingly.

Assessing the Cost of the Interactive, Research-Driven App Development

Assessing costs plays a crucial role in the decision of whether develop an app or not. While internal development is cheaper and sometimes can be supported by a university's resources (e.g., university IT departments), it requires significant time to acquire the skills necessary for development. Though app development might seem dauntingly expensive, most interviewed authors report costs ranging from \$1,000 to \$5,000 and a time investment of 7 to 20 hours. Those are rough estimates, and outliers exist. One author reported spending half a year developing their app. While most authors develop internally, some authors report external development through agencies or freelancers. We did not get cost estimates from these authors, but we expect these to be many times higher than the estimation above. We conclude that while cost is an important factor that should be taken into consideration, it does not appear to be an unsurmountable barrier to app development.

Motivated by these cost considerations, we present a seven-step tutorial to provide authors an actionable guide on how to optimize their development of research driven apps.

How to Develop an Interactive Research-Driven App

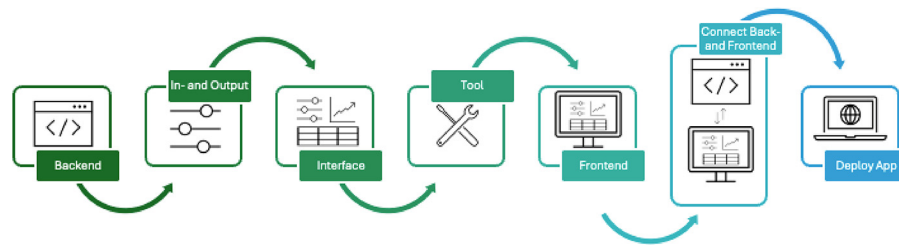
IRD apps can be used to (1) overcome the adaptation and integration gap, transforming marketing research into tools used by marketing intermediaries and to (2) overcome the adoption and implementation gap, enabling practitioners to apply the findings to drive their decision-making. To guide marketing researchers

in the development of IRD apps that are able to do both, we develop a practical guide featuring seven essential steps: (1) specifying the IRD app type and preparing the back end, (2) deciding on input and output parameters, (3) designing the graphical user interface and widgets, (4) choosing the implementation tool, (5) building the front end, (6) connecting back end and front end, and (7) deploying the IRD app, as summarized in Table 3. Next, we discuss the key considerations for each stage and a range of commonly used tools, with a specific focus on Streamlit (<https://streamlit.io/>) and KNIME (<https://www.knime.com/>).

We created the brand reputation app displayed in Figure 2 as a running example, developed based on the research from Rust et al. (2021), which applies text-mining on social media data to measure brand reputation. We selected this article for four reasons. First, it was in our list of articles with the potential to become an IRD app. Second, it involved the use of unstructured data, which poses some challenges due to its complexity and is increasingly common in marketing research (Balducci and Marinova 2018). Third, the brand reputation tracker offers an example of an IRD app that has the potential to bridge both the adaptation and integration gap as well as the adoption and implementation gap. Due to its multiple potential inputs (e.g., text upload) and outputs (e.g., scores, visualizations), it can be described as an explorer app. Fourth, Rust et al. provided all the information needed to develop the IRD app (available at <https://research-driven-app.streamlit.app/> for Streamlit and at <http://knime.com/research-driven-app> for KNIME). The workflow in KNIME is displayed in Web Appendix G, and the full code in Streamlit is available at <https://github.com/research-driven-app/br>.

Step 1: Specifying the IRD App Type and Preparing the Back End

Marketing researchers must first decide on the type of IRD app they want to develop: predictor, optimizer and recommender, explorer, or converter. This decision is linked to the key contributions of the paper, and the flowchart in Web Appendix C can guide in selecting the appropriate IRD app type. Importantly, the choice of app type shapes how researchers address the marketing science value chain gap. Converter apps are the least interactive because their typical focus is transforming an input into a score, and therefore they tend to be easiest to develop. Researchers targeting the adaptation and integration gap (e.g., through the automatization of text analysis routines) can benefit from these apps. Similarly, the simplicity of converters can help when targeting marketing managers. Predictor apps tend to be more complex and interactive than converter apps, as they often have multiple inputs (e.g., both image and text, multiple parameters) and a single output (i.e., the prediction). They are a good fit for researchers who implement methodological innovations that target academics (e.g., novel methodologies for meta-analysis; McShane and Böckenholt 2022) or want to offer predictive capabilities to managers. Optimizer

Table 3. Process to Develop Interactive, Research-Driven Apps.

Step	Description	Example: Brand Reputation App
1. Specify the IRD app type and prepare the back end	Choose among the four app types (predictors, optimizers and recommenders, explorers, and converters), depending on the contribution of the paper along with the desired degree of interactivity. Identify the back end from the empirical analysis.	The main contribution is the brand reputation score from social media data. The back end converts social media posts to brand reputation scores, using word lists for brand attributes. Results can be visualized, making it viable for an explorer app.
2. Decide on input and output parameters	Depending on app type, all desired input and output parameters are listed and described. Mandatory and optional settings are defined.	Social media data as input (e.g., .csv table for tweets on each brand), parameters for input selection (e.g., which field contains tweet date?), and output configuration (e.g., brand reputation scores to be aggregated daily/monthly/yearly).
3. Design the graphical user interface and widgets	The graphical user interface is designed based on widgets (i.e., interactive buttons and fields) that are chosen depending on the needed input and output parameters.	Widgets include, among others, a field to upload data, single selectors for data fields of social media data, multiple selectors for visualization settings and chart plot.
4. Choose the implementation tool	Tool depends on researcher capabilities and scope of the app. Decision is made on existing back end, researcher preferences, and budget.	KNIME and Streamlit because of existing codebase, free open-source frameworks, text-mining and visualization capabilities.
5. Build the front end	Using the widgets from the selected tool, the front end is built based on design heuristics (e.g., top-left organization of buttons based on importance).	Using the layout editor in KNIME and the column structures in Streamlit, the IRD app is structured from top left to bottom right.
6. Connect back end and front end	The back end analysis is triggered through interactive widgets in the front end. The logic of execution is clarified.	Computational heavy text-processing and mining is triggered only on demand and is designed to not be retrIGGERED when the user interacts with the interface.
7. Deploy the IRD app	Budget, expected usage, and accessibility are assessed in order to choose the best deployment option.	Streamlit and KNIME can publish apps publicly. They also offer sufficient computational power and contained costs (free for academic use).

and recommender apps are even more complex and interactive, as these tend to have multiple inputs and outputs (typically a prediction and a recommendation on how to improve the result). The integration of both prediction and recommendation makes them an appropriate choice when researchers want to target the adoption and implementation gap by reaching managers directly. Explorer apps can be the most complex and interactive, as they have multiple inputs and outputs that are visualized for the user. The exploration of large datasets can be interesting for both researchers and practitioners (e.g., Schoenmueller, Netzer, and Stahl 2023).

The choice of app type can determine not only the app's functionality but also how it tightens the gaps in the marketing science value chain. Once the type of the app—and, thus, its contribution—has been specified, the researcher needs to prepare the back end. The back end for an IRD app usually

corresponds to the steps in data processing and analysis that were taken to obtain the main results via programming code. For example, in Sepehri, Mirshafiee, and Markowitz (2023), the back end is composed of a set of grammatical rules that scores the level of passive voice in text, making it a converter app. The back end of the predictor app MindMiner consists of a machine-learning model that processes textual consumer-generated content, such as customer reviews, and predicts the extent of mind perception in smart objects (Hartmann, Bergner, and Hildebrand 2023). Similarly, in the optimizer and recommender app Syntactic Surprise Calculator, the back end processes marketing messages and analyzes their syntax (Atalay, El Kihal, and Ellsaesser 2023), scores how surprising the syntax is, and creates recommendations for the optimal range of syntactic surprise in a marketing message. Technical details are provided in Web Appendix G.

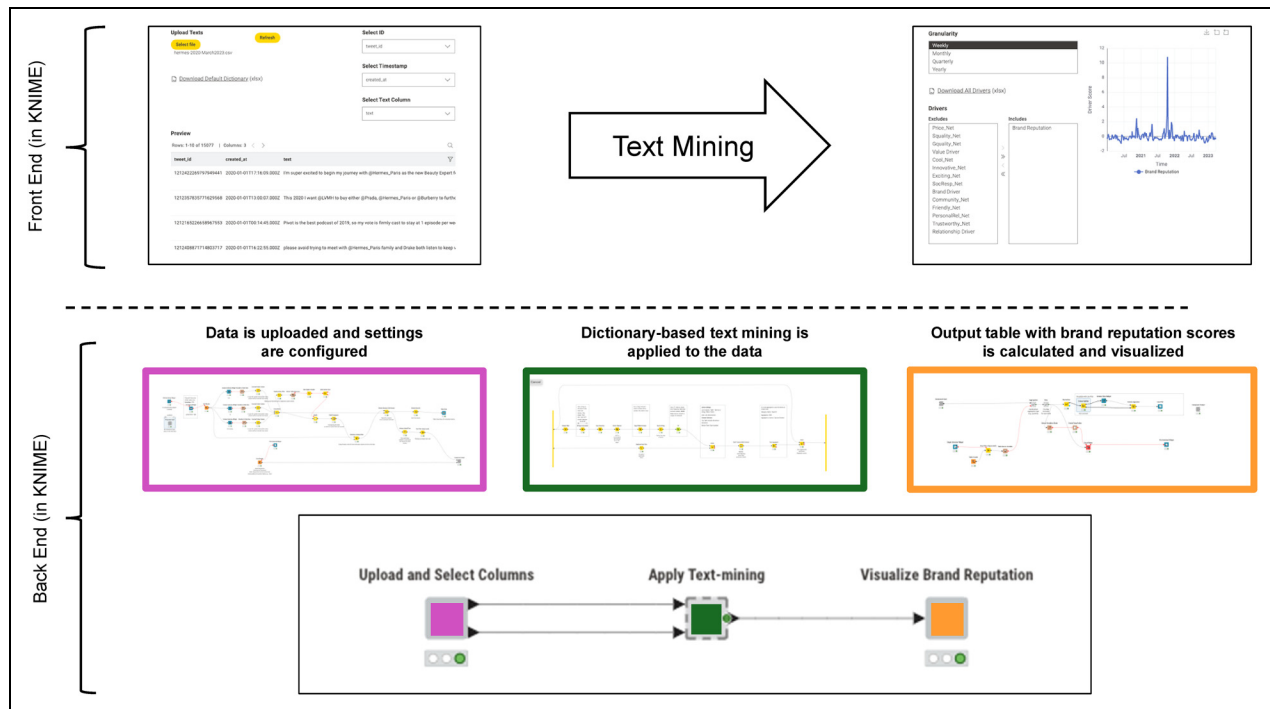


Figure 2. The Brand Reputation App.

Notes: The IRD app is available at <https://research-driven-app.streamlit.app/> for Streamlit and at <http://knime.com/research-driven-app> for KNIME.

Step 2: Deciding on Parameters for Input and Output

All IRD apps are based on an input, a model that is applied, and then an output. Parameters specify the way that the analysis is done. We provide examples for input, output, and parameters in Figure 3. To gain a comprehensive understanding of the app's desired components, both mandatory and optional input should be documented, along with the relevant input parameters, output parameters, and the intended output. The more input and output parameters that are added, the more interactive an app will become. However, it is advised to keep the number of inputs to an app relatively low (Krug 2014), as too many input possibilities might overwhelm the user. More technical details on input and output are provided in Web Appendix G.

Step 3: Designing the Graphical User Interface and Choosing the Widgets

When designing the graphical user interface, some common user experience heuristics should be followed (Blair-Early and Zender 2008; Nielsen and Molich 1990). First, the interface should have an obvious starting point. When users see the IRD app, they should immediately know what action to take, such as entering the text to be analyzed. Second, the interface should have a consistent logic and flow, meaning that the next action that needs to be taken is apparent to the user (Halvorsrud, Kvale, and Følstad 2016). Third, in the moment that an action is taken on the IRD app, feedback should be immediate. For example, when a model runs, a loading bar explains to users that they have to wait. Fourth, to further

facilitate usage, the proximity of interaction elements is crucial. Related settings (e.g., input parameters) should be visually grouped together. Fifth, IRD apps should be created in such a way that errors can be prevented as much as possible (e.g., through default settings, limited choice). We summarize these heuristics with examples in Web Appendix H and give additional technical details in Web Appendix G.

Step 4: Choosing the Implementation Tool

The appropriate implementation tool should be chosen based on what interactive elements are needed, the programming language of the existing back end, and the researcher's programming skills. Most tools are frameworks that are based on specific programming languages, like Python or R. All frameworks offer premade functions to simplifying the coding process. For example, the multiselect widget in Streamlit, which is based on Python. If the existing analysis of the back end has been done in Python and the researcher is skilled in Python, it is sensible to pick an implementation tool that is based on Python (such as Streamlit). If more variety and flexibility is needed for the choice and design of the widgets, more extensive tools such as Observable (<https://observablehq.com/>) can be a better fit. Researchers who are more skilled in R should use a framework that is based on R, like Shiny (<https://shiny.posit.co/>). We use two tools in our example, Python-based Streamlit and KNIME, which is a low-code solution (Villaruel Ordenes and Silipo 2021). Web Appendix J provides an overview of different implementation tool options.

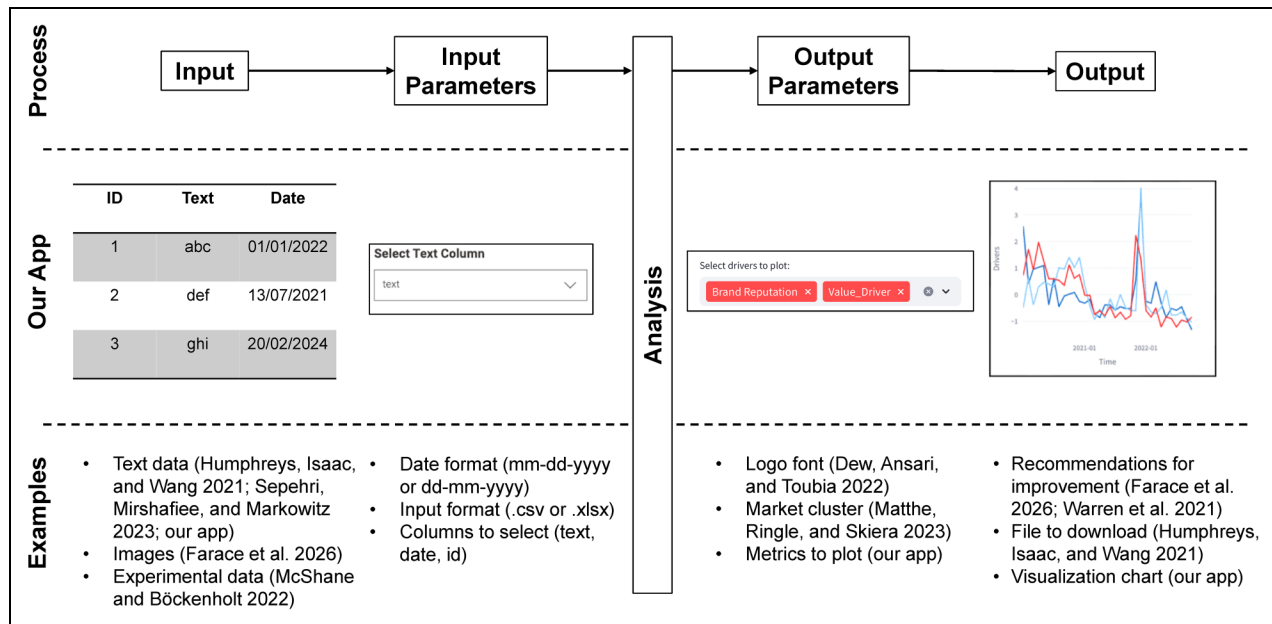


Figure 3. From Input to Output via Configuration Parameters.

Step 5: Building the Front End

The front end represents the graphical layer where the user interacts with the IRD app. It is composed of the widgets that have been defined and chosen in Step 3. Web apps are normally structured around a top-left-to-bottom-right orientation, where the most important elements are positioned on the top left and the least important elements are on the bottom right. The title of the app and instructions (in the form of widgets) are normally placed in the top-left quadrant, in line with mandatory settings (Krug 2014). The widgets for optional settings, such as the sample size taken, can be placed on the bottom left. Visualization widgets like graphs can be placed on the top-right corner of the app. Some tools offer “what you see is what you get” visual editors that facilitate design of the front end (see an example in Web Appendix K). When programming is strictly done via code (e.g., R, Python), large language models (LLMs) are starting to assist directly in the implementation and debugging of code. However, mainstream GenAI systems such as ChatGPT or Gemini are not yet fully capable of substituting integrated development environments, which limits the users’ ability to inspect and visualize the results of the code (OpenAI 2025b). However, LLMs can offer an easy way to adapt code to different frameworks and can be used to understand the code (Nam et al. 2024). When generating code (Chen et al. 2021), for example for back-end tasks, researchers should still proceed with caution and test the proposed solutions (Nejjar et al. 2025).

Step 6: Connecting Back End and Front End

To render the IRD app interactive, back and front ends need to be connected. Technically, the connection between front and back ends is based on variables and data frames. In the case

of an input parameter, to connect the front and back ends, a widget converts the input into a variable that is then used in a subsequent function, as indicated in Figure 2. In most cases, the following conceptual logic is applied: Data is uploaded, if there is no default dataset (such as in Dew, Ansari, and Toubia’s [2022] logo app) and the settings are chosen (both mandatory and optional). The analysis is then triggered, for example, through a button widget. The back end now analyses the data. Meanwhile, the user might see a loading bar. After the analysis has finished, the results are either visualized in a graph or table widget or provided for download (or both).

How exactly the execution is handled depends on the framework used. For example, Streamlit, as a Python-based framework, executes code from top to bottom, page by page. In the case of computationally heavy calculations (e.g., topic model algorithms), it makes sense to split Python code into multiple pages to ensure that the code is sequentially executed. If not, any interaction will trigger the user interface to be updated and reexecuted. Researchers with computation-intensive code should additionally cache (temporally save) results for multiple outcomes. In our brand reputation app, the user is allowed to change the brand metrics that are visualized, along with the aggregation. Using built-in capabilities in the framework, this can then be done without reexecuting the text-mining code, reducing waiting time for a better user experience.

Step 7: Deploying the IRD App

When deploying the IRD app, the researcher needs to define its scope by deciding how to share the IRD app and how much computational resources it will need. This will then determine the budget needed and help in choosing the platform on which the IRD app should be deployed. For this, the researcher should

consider whether the IRD app should be published privately or publicly. Public apps can reach a wider audience and therefore can have higher impact. Next, the researcher should think about computation power. Complex IRD apps need more computational resources (e.g., applying AI models on cloud hardware), which will drive the cost for hosting the app. Cost structure normally varies by deployment provider, with some options being free (but slow) and others being costly (but fast). For the brand reputation app, the deployment via Streamlit is free and has almost no limitations in usage, while the deployment via KNIME is also free for academic use.⁷ Web Appendix L compares different options for deploying IRD apps.

Conclusion: Interactive, Research-Driven Apps in Marketing

Summary and Contributions

In this article, we offer insights into the impact of IRD apps and practical recommendations on their development. Theoretically grounded in the marketing science value chain, we identified two gaps that can be addressed through IRD apps: the adaptation and integration gap and the adoption and implementation gap. We argued that these gaps might be addressed in different ways by different IRD apps (Chintagunta et al. 2022): predictors, optimizers and recommenders, explorers, and converters. We then addressed three research questions that guided our work: the motivations and barriers that authors of IRD apps are facing, the market potential and impact of IRD apps, and the development of an actionable guide for IRD apps. In doing so, we make theoretical, substantive, and methodological contributions.

Theoretically, drawing on the marketing science value chain, we introduce IRD apps as new tools that can address the gaps in the conversion and application of marketing knowledge. Specifically, we show how IRD apps address the adaptation and integration gap (mainly targeting other researchers) and the adoption and implementation gap (mainly targeting managers). We show that these two gaps can be addressed differently by each of the IRD app types described by Chintagunta et al. (2022): predictors, optimizers and recommenders, explorers, and converters. However, some IRD apps target both gaps at the same time. Overcoming both gaps solidifies the marketing science value chain, improving both speed and volume of knowledge dissemination.

Substantively, we demonstrate the potential of IRD apps by (1) offering a better understanding of authors' motivation and barriers to develop such apps, (2) comparing IRD apps with other possible companions of research papers, (3) estimating the potential number of articles to be complemented by an IRD app, (4) showing that articles with an IRD app have an

above-average citation impact, and (5) by demonstrating that papers with an IRD app create higher value for managers. In demonstrating the potential of IRD apps, we identify their three main benefits. First, they facilitate adaptation and integration of findings by other researchers, stimulating knowledge transfer to other academics and increasing citation potential. Second, IRD apps facilitate adoption and implementation of findings by practitioners by rendering research articles more interesting and relevant. Third, IRD apps help improve students' appreciation of scientific research; as many interviewed authors report, students often use their IRD apps to engage with findings.

Methodologically, we provide guidance on the specifics of developing IRD apps that can complement published articles. To do so, we developed a seven-step hands-on tutorial that covers the development process of an IRD app using a recent marketing article as an example (Rust et al. 2021), using both code and low-code frameworks to make this process accessible to a broad range of marketing researchers. Our code repositories and live versions for Streamlit (repository; online version) and KNIME (repository; online version) are publicly available. We hope that our seven-step tutorial complements other tutorials for marketing researchers on topics such as statistical reporting (McShane et al. 2024), web scraping (Boegershausen et al. 2022; Guyt, Datta, and Boegershausen 2024), and implementing open science standards (Deer et al. 2025).

The Future of Interactive, Research-Driven Apps

We believe that the future of IRD apps in the marketing domain is bright. Although technical requirements for researchers are still considerably high, advances in GenAI may help address some of the challenges outlined in our article, as illustrated in a recent methodological guide on how to build GenAI-driven apps for marketing research (Joerling 2025). Another emerging trend is vibe coding (Karpathy 2025), where developers use natural language to collaborate with AI agents. Anecdotal evidence suggests that vibe coding can significantly reduce the amount of time needed to develop an app. However, there is always the risk of hallucinations, diminished explainability, and, ultimately, a decline in code quality. Consequently, even though GenAI can assist in the development of apps (Ratnayake and Wang 2024), researchers still need guidelines supporting this development.

Driven by the democratization of programming through GenAI, we also expect to see a larger variety in IRD apps that go beyond our current classification. For example, IRD apps could use scientific insights from language research to not only optimize but directly generate better content (e.g., creating more concrete search ads toward the end of the customer funnel; Humphreys, Isaac, and Wang 2021). So far, we have yet to see IRD apps based on purely conceptual articles. We believe that even conceptual research might benefit from the visualization and simplification of findings through apps. As an example, the article on customer experience by Lemon and Verhoef (2016) could be the base for an explorer app, with which

⁷ Our brand reputation app is built with the purpose of showcasing the app development process, but it does not necessarily fulfill the requirements for high-traffic, high-processing usage.

researchers could inspect less-researched links in its framework to stimulate new research ideas.

Although the future seems bright, we also acknowledge that there are reasons that might discourage researchers from developing IRD apps. Privacy considerations or limited access to data (e.g., through nondisclosure agreements signed when cooperating with a company) can prevent researchers to use field data as an input for app creation (e.g., back-end training). Similarly, researchers' incentive systems are geared toward publications, and not IRD apps (Haenlein and Jack 2025). Researchers who must concentrate their scarce time resources might be inclined to decide against developing an app. Furthermore, if researchers developing an IRD app lack rigor in their findings or app development, the increase in diffusion through easier access might backfire. One can imagine the reputational damage that a popular IRD app based on wrong or sloppily implemented findings could have for the scientific community.

Finally, while we provide some theoretical insights into how IRD apps can increase the impact of marketing science, future research might explore the mechanisms that are behind this observed effect. With a hopefully growing number of IRD apps in the future, researchers can design large-scale studies to empirically identify the unique contributions of apps' interactivity. Similarly, we see comparing IRD apps against other companion options as a fruitful avenue for further research. We would also be glad to see further initiatives that stimulate the development of IRD apps. For example, more special issues in marketing journals, such as the special issue on IRD apps in the *Journal of Marketing* (Chintagunta et al. 2022) and the special issue on methodological advances in the *Journal of Marketing Research* (Hamilton et al. 2024), or initiatives that include industry grants (OpenAI 2025a) or university grants (AI & Wharton Analytics Initiative, <https://ai-analytics.wharton.upenn.edu/>) could encourage IRD app development. Collaborations within universities, for example with the IT or computer science department, could be similarly helpful. We hope our insights and guidelines stimulate other marketing researchers to complement their articles with apps. By doing so, we believe that IRD apps can have meaningful impact on managerial decision-making, ultimately helping narrow the research–practice gap.

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Data Availability

The data that support the findings of this article are available at <https://osf.io/uxr42/overview>.

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