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. We 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. We shed light on the motivations and barriers to develop IRD apps as well as the market potential and impact of IRD apps through a multi-method examination, which includes interviews, secondary data analyses, and experimental studies. We find an untapped potential of IRD apps among published articles and complementary evidence of their value to researchers and managers. We 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. We hope that our examination stimulates other researchers to complement their articles with IRD apps that enable the diffusion of research findings to other researchers and managers.

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

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

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. We 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. We shed light on the motivations and barriers to develop IRD apps as well as the market potential and impact of IRD apps through a multi-method examination, which includes interviews, secondary data analyses, and experimental studies. We find an untapped potential of IRD apps among published articles and complementary evidence of their value to researchers and managers. We 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. We hope that our examination stimulates other researchers to complement their articles with IRD apps that enable the diffusion of research findings to other researchers and managers.

Keywords: Interactive research-driven apps, marketing science value chain, research-practice gap

There is widespread agreement that a research–practice gap exists in marketing science (Kohli and Haenlein 2021; Moorman et al. 2019; Roberts et al. 2014). According to the Web of Science, around 2,700 articles[1] 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 (Stäbler and Haenlein 2025; Haenlein and Jack 2025). One promising and up-to-date solution to bridge the research–practice gap are 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 trigger active learning (Moreno and Mayer 2007) but can also increases 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 complex to convey in a traditional research paper format. To 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, nor guidelines for authors on how to develop such apps. We draw on the marketing science value chain (Roberts et al. 2014), which posits that the diffusion of marketing knowledge to practice is driven by three consecutive steps: the *knowledge generation* by marketing researchers, the *knowledge conversion* by marketing intermediaries, and

[1] Average number of publications per year for the timeframe of 2014-2024 in the 47 marketing journals of the Social Sciences Citation index.

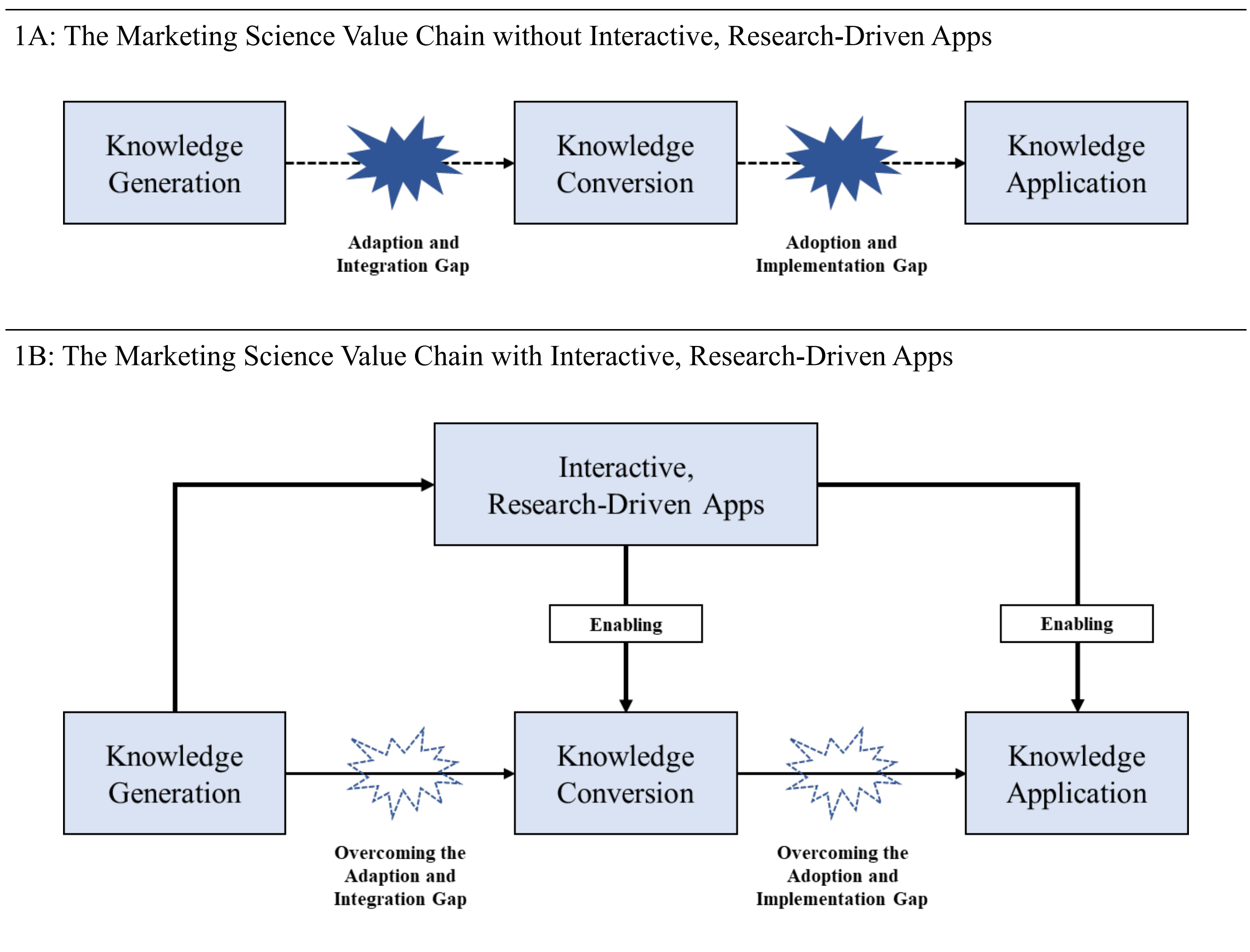
the *knowledge application* by marketing practitioners. Previous research has mainly focused on the knowledge generation problem, examining what topics should be studied to have real-world relevance (Kohli and Haenlein 2021; Lilien et al. 2013; Schauerte et al. 2023; van Heerde et al. 2021) or how to have 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 et al. 2014). First, the adaption and integration gap, hindering 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, the adoption and implementation gap, hindering 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 to understand for practitioners (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:

RQ_1: What are the motivations and barriers for developing IRD apps?
RQ_2: What is the market potential and impact for IRD apps?
RQ_3: How to develop IRD apps that complement published articles?

We address RQ_1 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 developed an 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 RQ_2 by estimating how many papers in the last 5 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 RQ_3 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.

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



Note. The underlying diffusion process of the Marketing Science Value Chain is based on Roberts et al. (2014).

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 *adaption and integration gap* from articles because they enable a concise presentation of findings and contributions, increasing their understanding and easing their application. 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 to 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 on Atalay, Kihal, and Ellsaesser (2023) to improve their writing effectiveness than following the guidance outlined in the paper alone.

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 Adaption 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, 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).

Note. The typology and the potential use cases are based on Chintagunta et al. (2022). This taxonomy does not pretend to be exhaustive, but it fitted our classification of IRD apps. Roggenkamp et al. (2025) is one notable exception. It enables researchers to improve their experimental methodologies to simulate a research environment. Afterwards, researchers can explore the results (Table 2).

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(s) 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 to 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 how the specific app capabilities can overcome the two marketing science value chain gaps.

To understand the status quo of IRD apps in marketing, we searched all articles published from 2020 to September 2025 in the leading marketing journals[2] and classify all existing IRD apps using the typology outlined in Table 1. We chose this timeframe as the majority of IRD apps were published after 2020[3]. In order to identify all existing apps we screened the article abstract

[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 timeframe.

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), at presence, are targeting the adoption 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.

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)*	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)*	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)*	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)*	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)*	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)*	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)*	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.
Humphreys, Isaac, and Wang (2021)*	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)*	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)*	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)*	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)*	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)*	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)*	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)*	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)*	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) *	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 integrate passive voice analysis in their research (e.g., as control variables).
Warren et al. (2021)*	Optimizer	Clarity Calculator	Adaption and Integration	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.

Note. JCR = Journal of Consumer Research, JCP = Journal of Consumer Psychology, JM = Journal of Marketing, JMR = Journal of Marketing Research, MS = Marketing Science.
*Author participated in survey

Motivations and Barriers to Develop Interactive, Research-Driven Apps

To address RQ_1 and obtain a better understanding of the motivations and barriers when developing IRD apps, we interviewed 21 authors that have been 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 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 opted often times to build the IRD apps 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), 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.

App development was frequently described as challenging by the authors, 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 post-development. 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 integrate novel methodological approaches, visualize relationships, or apply findings directly. Students are another key target group that benefit from IRD apps' dynamic environment, offering tangible educational experiences that make abstract theories more tangible. Importantly, many authors also identify practitioners; IRD apps can help to 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 timeframe and the same journals as before, we retrieve 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 in order to have potential for an IRD app. First, we inspected whether the research solves an important marketing science problem by addressing real-world issues that impact managers, researchers or stakeholders, or by targeting a specific issue (e.g., advertising attribution) that is relevant (Van Heerde et al. 2021). Second, we inspected whether the article offers actionable solutions to solve this problem (i.e., predict, optimize and recommend, explore, or convert). Finally, we inspected 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.

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 (2023) who use large-language models to optimize e-mail 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

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

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 interactive, research-driven apps in marketing papers in a citation analysis that is detailed in Web Appendix D. Eight of 11 papers that contain an IRD app published in 2022 and 2023 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 filed.

Second, we recruited 146 marketing managers using the research platform Prolific that passed an instruction check (60.3 % female, $M_{age} = 38.77$) for a 4x2 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, Kihal, and Ellsaesser 2023; Dew, Ansari, and Toubia 2022; Farace et al. 2025; Humphreys, Isaac, and Wang 2021). For each article, the respective IRD app is randomly either provided or not, in addition to the abstract and an excepts of the article. We checked whether this manipulation was successful after each article ("To what extent do you think the research paper is interactive?"). In order to measure interestingness and relevance, we used a 3-item scale for interestingness ($\alpha = 0.88$) and a 4-item scale for relevance ($\alpha = 0.90$), 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 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? 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_{App} = 5.32, SD = 1.42, $M_{Control}$ = 3.88, SD = 1.32, $F(1,35)$ = 9.814, p = .004), useful (M_{App} = 4.79, SD = 1.32, $M_{Control}$ = 3.76, SD = 1.09, $F(1,35)$ = 6.379, p = .016) and

[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 interactive, research-driven app to the research paper.

relevant (M_{App} = 4.58, SD = 1.43, $M_{Control}$ = 3.71, SD = 1.26, $F(1,35)$ = 3.741, p = .061) compared to 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 these find papers with an IRD app more interesting, useful, and relevant. However, while IRD apps are an emerging phenomenon potentially closing 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 to 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.

Developing Interactive, Research-Driven Apps

Identifying the core audience for the interactive, research-driven app

IRD apps can help overcoming the adaption and integration gap as well as the adoption and implementation gap. While the former focuses mostly on fellow researchers valuing the possibility of integrating knowledge in their own research, the latter focuses on practitioners valuing 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 having a quick insight about the fit of a campaign goal with its actual content. As Table 2 shows, most published IRD apps target both gaps. But targeting both gaps can expose pitfalls. While enhancing their potential impact, researchers might "fall between the chairs". For example, researchers prefer rigor over usability, whereas practitioners tend to appreciate usability more. Therefore, researchers should carefully assess what contributions their articles possess (e.g., does it have a more research or practical orientation?), and adapt the development of their IRD app accordingly.

Assessing the cost of the interactive, research-driven app development

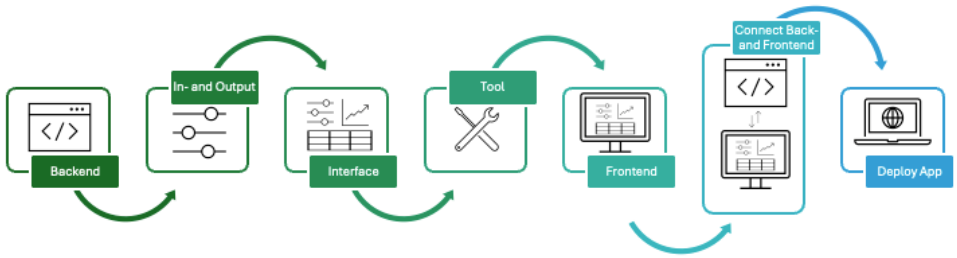
Assessing costs plays also a crucial role in the decision to whether develop an app or not. While internal development is cheaper and sometimes can be supported by University's resources (such as IT departments), it requires significant time to acquire the skills necessary for development. Though app 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 in the development. While most develop internally, some authors report external development through agencies or freelancers. We did not get cost estimates from these authors, but we expect them 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 adaption 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 backend, (2) deciding on input and output parameters, (3) designing the graphical user interface and widgets, (4) choosing the implementation tool, (5) building the frontend, (6) connecting backend and frontend, 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/).

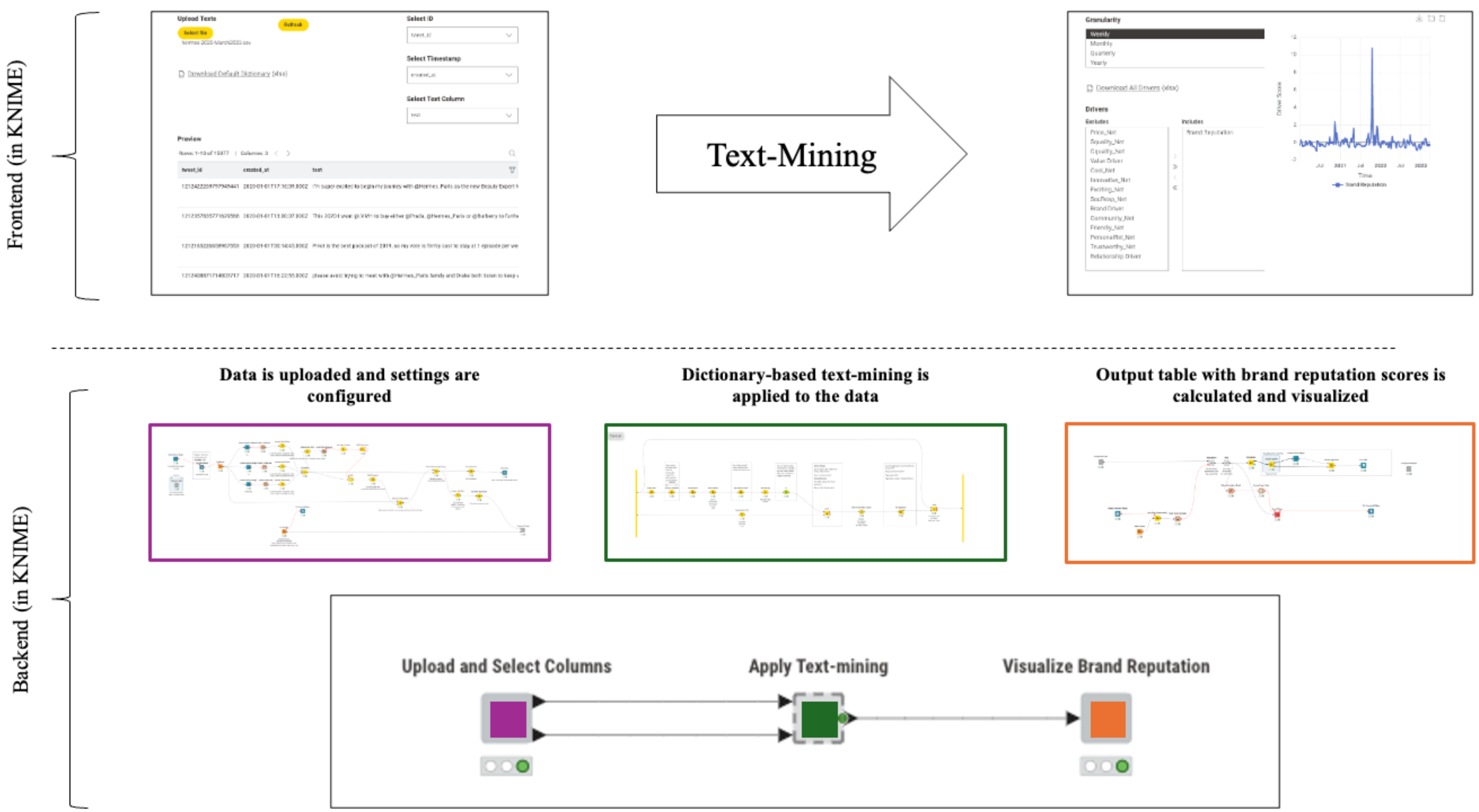
Table 3: Process to Develop Interactive, Research-Driven Apps



Step	Description	Example: Brand Reputation App
1. Specifying the IRD app type and preparing the backend	Choosing 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 backend from the empirical analysis.	The main contribution is the brand reputation score from social media data. The backend converts social media posts to brand reputation scores, using word lists per brand attributes. Results can be visualized, making it viable for an explorer app.
2. Deciding 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. Choosing the implementation tool	Tool depends on researcher capabilities and scope of the app. Decision is taken on existing backend, researcher preferences, and budget.	KNIME and Streamlit because of existing codebase, free open-source frameworks, text-mining and visualization capabilities.
5. Building the frontend	Using the widgets from the selected tool, the frontend is built based on design heuristics (e.g., top-left organization of buttons based on importance).	Using the lay-out editor in KNIME and the column structures in Streamlit, the IRD app is structured from top left to bottom right.
6. Connecting backend and frontend	The backend analysis is triggered through interactive widgets in the frontend. The logic of execution is clarified.	Computational heavy text-processing and mining is triggered only on demand and is designed to not be re-triggered when the user interacts with the interface.
7. Deploying 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, offer sufficient computational power and contained costs (free for academic use).

We use 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 adaption 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. (2021) 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.

Figure 2: The Brand Reputation App



Note. 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 1: Specifying the IRD App Type and Preparing the Backend

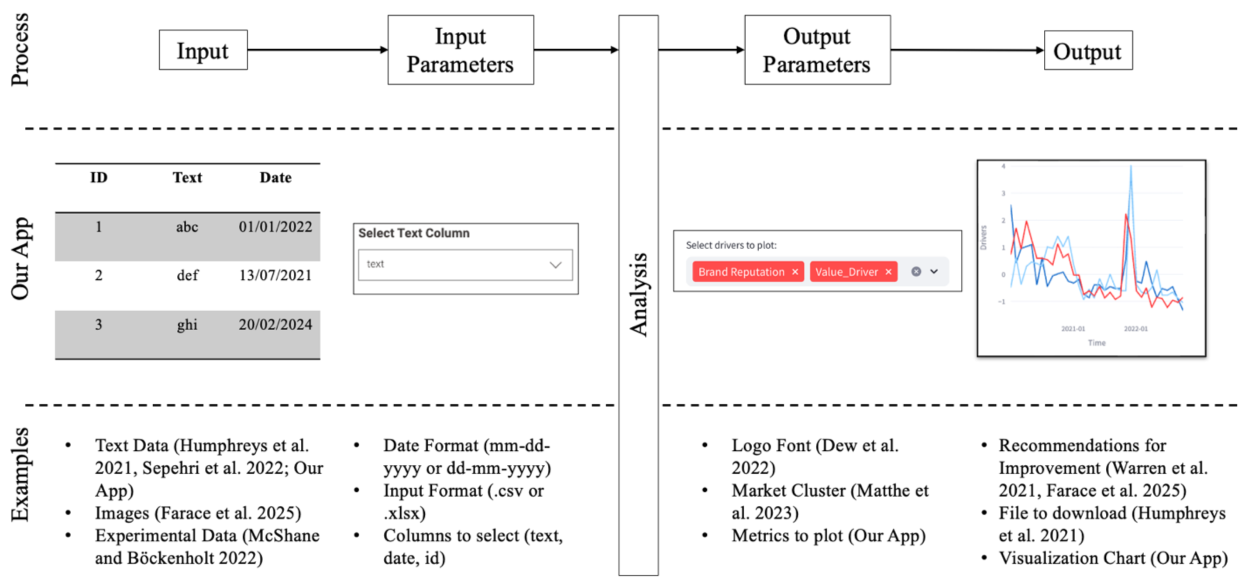
Marketing researchers must first decide on the type of IRD app they want to develop: predictor, optimizer and recommender, explorer, or converter. This decision is linked to the key contributions of the paper, and the flowchart in Web Appendix C can guide in finding the appropriate IRD app type. Importantly, 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 tend to be easiest to develop. Researchers targeting the adaption 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 fit for researchers that 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 and recommender apps are even more complex and interactive as these tend to have multiple inputs and multiple 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 adaption 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 2022).

The choice of app type can determine not only its functionality but also how they tighten the gaps in the marketing science value chain. Once the type of the app and hence its contribution has been specified, the researcher needs to prepare the backend. The backend 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 (2022) the backend is composed by a set of grammatical rules that scores the level of passive voice in text, making it a converter app. The backend of the predictor “Mindminer” consists of a machine-learning model that processes textual consumer-generated content, such as customer reviews, and predicts the extend of mind perception in smart objects (Hartmann, Bergner and Hildebrand 2023). Similarly, in the optimizer and recommender app “Syntactic Surprise Calculator”, the backend processes marketing messages and analyses their syntax (Atalay, Kihal and Ellsaesser 2023) and then scores how surprising the syntax is and creates recommendations for the right range of syntactic surprise in a marketing message. Technical details are provided in Web Appendix G.

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 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.

Figure 3: From Input to Output via Configuration Parameters



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 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 the 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 backend, and the researcher's programming skills. Most tools are frameworks that are based on specific programming languages, like Python or R. All frameworks offer pre-made function that are simplifying the coding process, by offering prebuilt functions, for example the multiselect widget in Streamlit which is based on Python. If the existing analysis of the backend 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 that 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 low-code solution (Villarroel Ordenes and Silipo 2021). Web Appendix J provides an overview of different implementation tool options.

Step 5: Building the Frontend

The frontend represents the graphical layer where the user interacts with the IRD app. It is comprised of the widgets that have been defined and chosen in Step 3. Web-apps are normally structured around a top-left-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 site. 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 frontend (see an example in Web Appendix K). When programming is strictly done via code (e.g. in R or 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 2025a). However, LLMs can offer an easy way to adapt code to different frameworks and used to understand the code (Nam et al. 2024). When generating code (Chen et al. 2021), for example for backend tasks, researchers should still proceed with caution and test the proposed solutions (Nejjar et al. 2025).

Step 6: Connecting Backend and Frontend

To render the IRD app interactive, back- and frontend need to be connected. Technically, the connection between front- and backend is based on variables and data frames. In the case of an input parameter, to connect front- and backend, 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 the Dew, Ansari, and Toubia 2022 logo app) and the settings are chosen (both mandatory and optional). The analysis is then triggered, for example, through a button widget. The backend now analyses the data. In the 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 computational heavy calculations (e.g., topic model algorithms), it makes sense to split Python code in multiple pages to make sure that the code is sequentially executed. If not, any interaction triggers the user interface to be updated and re-executed. 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 re-executing 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 taking two decisions: How to share the IRD app and how much computational resources it will need. This will then determine the budget needed and help to choose the platform on which the IRD app should be deployed on. For this, the researcher should think about whether the IRD app should be published privately or publicly. Publicly 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.

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

Conclusion: Interactive, Research-Driven Apps in Marketing

Summary and Contributions

In this paper, 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 adaption 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 adaption 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 three main benefits of them. First, they facilitate adaption 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 students to improve the appreciation of scientific research; as many interviewed authors report, students are often using 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-steps 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, Boegershausen 2024), and implementing open science standards (Deer et al. 2025).

The Future of Interactive, Research-Driven Apps

We think 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 the development of apps (Ratnayake and Wang 2024), researchers still need guidelines supporting the development of IRD apps.

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 towards the end of the customer funnel; Humphreys, Isaac, and Wang 2021). So far, we are also 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 researchers could inspect less researched links in its framework to stimulate new research ideas.

Despite 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 NDAs 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, researcher's incentive systems are geared towards publications, and not IRD apps (Haenlein and Jack 2025). Researchers that must concentrate their scarce time resources might be inclined to decide against development of an app. Furthermore, if researchers developing an IRD app lack rigor in their findings or app development, the multiplication and easier access to might backfire. One can imagine the reputational damage that a popular IRD app based on wrong or sloppy implemented findings could imply 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 an 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 IRD apps issue in the *Journal of Marketing* (Chintagunta et al. 2022), the special issue on methodological advances in the *Journal of Marketing Research* (Hamilton et al. 2024), or initiatives that include industry grants (OpenAI 2025b) or university grants (AI & Wharton Analytics Initiative, https://ai-analytics.wharton.upenn.edu/) could stimulate 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 to narrow the research-practice gap.

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

WEB APPENDIX

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These materials have been supplied by the authors to aid in the understanding of their paper. The AMA is sharing these materials at the request of the authors.

Web Appendix A. Unique Benefits of Interactive, Research-Driven Apps

Format	Audience	Benefits	Limitations	Best Use Case	How IRD Apps Complement
Research Article	▪ Academics	▪ Rigor through peer review	▪ Limited accessibility ▪ Hard to read for managers ▪ No interactivity	▪ Establishing credibility ▪ Academic exchange	IRD apps translate static findings into dynamic, actionable simulations that foster deeper understanding and faster implementation.
Article in Business Magazine	▪ Practitioners	▪ Concise ▪ Broad reach	▪ Limited space and depth ▪ Risk of oversimplification	▪ Influencing non-academic or inter-disciplinary audience	IRD apps provide evidence-based depth behind managerial insights, enabling exploration and application of the discussed ideas.
Podcast	▪ Practitioners	▪ Engaging storytelling ▪ Low entry barriers	▪ Audio only ▪ No interactivity	▪ Sharing stories, interviews, or broad implications	IRD apps add a visual and interactive dimension that deepens engagement and supports hands-on learning or decision-making.
Video	▪ Practitioners ▪ Students ▪ General Public	▪ Easy to consume ▪ Highly accessible	▪ Limited depth ▪ Limited interactivity	▪ Communicating concise, audio-visual messages	IRD apps allow users to move from watching to experimenting, increasing comprehension and the likelihood of real-world implementation.
Sharing Code and Data	▪ Academics	▪ Supports transparency ▪ Centralized, modifiable resources	▪ Static format ▪ Requires technical expertise	▪ Long-term visibility and reproducibility	IRD apps turn repositories into living, interactive resources, allowing adaptation, exploration, and scenario testing.
Interactive App	▪ Academics ▪ Marketing intermediaries ▪ Practitioners ▪ Students	▪ Hands-on ▪ Personalization ▪ Scenario testing	▪ Requires development resources ▪ Requires maintenance resources	▪ Training ▪ Decision support ▪ Translating research into practice	Core format providing the interactivity and engagement other formats lack.

Web Appendix B: Participants and Insights of the Author Interviews

Participants of the Author Interviews

Author	Interactive Research-Driven App
Amir Sepehri; ESSEC	PassivePy
Andrea Luangrath, University of Iowa	PARA Language
Arash Laghaie, NOVA SBE	BFMediate_APP
Bernd Skiera, Frankfurt University	Coupon Calculator
Blakeley McShane, Northwestern University	MCSM
Christian Hildebrand, University of St. Gallen	DICE (Digital In-Context Experiments)
Daniel Ringel, UNC Kenan-Flagler	Evo Map, mapXP
Federico Mangio, University of Bergamo	BUMOLDS MAPPER
Francisco Villarroel Ordenes, University of Bologna	Text Overlay App
Giovanni Luca Cascio Rizzo, USC Marshall	Hand Movement Classifier
Grant Packard, Schulich School of Business	When Language Matters
Jochen Hartmann, Technical University of Munich	Mindminer
Nils Wlömert, WU Vienna	NADE
Rebecca Wang, Lehigh University	Construal Score Tool
Ryan Dew, University of Pennsylvania	Logo Explorer
Shane Wang, Virgina Tech University	AI Meta Analysis
Siham El-Kihal, WU Vienna	Syntactic Surprise Calculator
Simon J. Blanchard, Georgetown University	GPT-Coder
Stephan Ludwig, Monash University	Linguistic eXtractor (LX) *(not online)*
Tianyu Gu, University of Utah	Clarity Calculator
Verena Schoenmueller, ESADE	Social Listening

Insights of the Author Interviews[1]

Why did you decide to invest time and resources into the development of your app?

The motivations for developing IRD apps reveal a shared aspiration to bridge the gap between academic research and its broader application in both scholarly and managerial contexts. Across the 21 authors, five motivations were frequently named: enhancing research accessibility and impact, democratizing methodological tools, demonstrating practical relevance, advancing methodological innovation, and responding to external drivers.

First, a dominant motivation among authors was to make research more accessible, engaging, and actionable for diverse audiences. Many noted that traditional academic outputs—papers, tables, and static figures—limit the exploration and dissemination of insights. By contrast, IRD apps offer a more dynamic and interactive format that allows users to visualize data, test scenarios, and explore findings from new angles. Several authors viewed their apps as vehicles for broader knowledge dissemination, helping both fellow researchers and practitioners engage with research outputs without technical barriers. For some, the apps served as a bridge between academia and practice, transforming abstract concepts into tangible tools that promote adoption and real-world relevance.

Second, authors also emphasized inclusivity in research methods. They saw IRD apps as a way to democratize access to complex analytical tools and reduce the need for programming expertise. By transforming sophisticated models and statistical methods into user-friendly interfaces, authors hoped to empower others—particularly those without technical backgrounds—to apply advanced approaches in their own work. This theme was particularly salient among author teams who developed R and Python packages and later translated them into IRD apps for ease of use.

Third, authors were motivated by a desire to show that their research had practical value beyond the publication itself. IRD apps were seen as proof of concept—living demonstrations of how theoretical or methodological advances can be implemented in real-world contexts. This included, for example, showcasing gesture-based interfaces, enabling emotion detection, or helping small businesses evaluate platform promotions.

Fourth, authors developed IRD apps to overcome existing methodological limitations in their fields. For example, one author team sought to combine experimental control with ecological validity, addressing trade-offs in traditional study designs. Other authors created apps to capture or analyze previously underexplored constructs—such as textual paralanguage or syntactic features in marketing content. These IRD apps emerged not only as research dissemination tools but also as platforms that extend methodological boundaries and invite other researchers to innovate upon them.

Finally, some motivations stemmed from institutional, collaborative, or review-driven factors. One project was funded under a national initiative with an explicit mandate for public engagement. Other authors developed their apps in response to reviewer or editor suggestions aimed at increasing managerial applicability. In another case, peer interest in early prototypes encouraged further development and refinement, turning a private research tool into a shared resource of the academic community.

[1] We used ChatGPT 5 to summarize all answers from the 21 authors but carefully double-checked, changed, and edited the text provided here.

How did you develop your app? Please indicate the tools, software, outsourcing (i.e., freelancer), or collaborations (i.e., business partnership) that you used to develop your app.

Most authors reported developing their IRD apps independently or within their immediate research teams, drawing on widely accessible open-source frameworks. Commonly used tools included R with Shiny, Python with Streamlit, or Gradio, JavaScript-based environments such as React, Vercel, or Bootstrap, and, in a few cases, KNIME or Excel. These platforms enabled the authors to design both front- and back-end components without specialized engineering support. To further help with development, several researchers incorporated AI at different stages of development. Some authors used large language models such as GPT to assist in coding, debugging, and web programming. Others embedded AI directly into their analytical pipelines, employing ChatGPT, Google's Gemini 1.5 Pro, and LLaVA-NeXT for tasks such as gesture detection and automated classification.

A substantial subset of authors relied on collaboration with student programmers, research assistants, or university data science units. Such collaborations were instrumental in handling tasks that required additional technical or design expertise while preserving academic oversight of app logic and purpose.

Another smaller group of respondents described outsourcing elements of app development to freelancers or professional agencies. Outsourcing typically addressed the creation of user interfaces, the deployment of web hosting environments, or the translation of research code into production-ready software. Even in these cases, however, researchers maintained conceptual control to safeguard methodological integrity.

What is also noteworthy is that several authors emphasized adherence to open-science and transparency principles. They used collaborative repositories such as GitHub and frameworks like oTree or KNIME Analytics to facilitate reproducibility and public sharing of source code.

What were the biggest challenges and barriers you encountered while developing and deploying your app? Please also indicate estimated number of hours in development and an estimate of the overall cost of creating and hosting the app (in USD).

The challenges and barriers came from six different areas: limited technical expertise, time intensity, costs and infrastructure management, maintenance and scalability, data processing and model performance, and balancing usability with academic demands.

First, many authors described difficulties stemming from limited programming experience and the need to acquire new technical skills. They emphasized steep learning curves in languages such as R, Python, or JavaScript, and in integrating frameworks like Shiny, Streamlit, or KNIME. For some, deployment and compatibility issues added further complexity, especially when combining R and C++ through Rcpp or setting up server environments. These challenges often required considerable self-training and experimentation before achieving a stable implementation.

Second, the development process was widely characterized by high time intensity and extensive iteration. Reported development times ranged from 20 to 150 hours for most projects, with a few large-scale initiatives spanning hundreds of hours or multiple years. Iterative testing, debugging, and responding to reviewer feedback were common, as was continuous refinement of user interfaces and model accuracy. One author described 120–150 hours spent on iterative prompting and manual validation, while other authors emphasized the cumulative time costs of balancing app design with academic responsibilities.

Third, the authors reported substantial variation in financial and infrastructural costs. While some small-scale IRD apps were developed and hosted at negligible cost using free or low-cost services such as Hugging Face or serverless hosting, others incurred notable expenses. Reported development costs ranged from a few hundred dollars for simple tools to several thousand for research-oriented platforms, with one large project exceeding USD 200,000 due to computational and data-handling demands. Typical hosting expenses for most IRD apps fell between USD 13 and 200 per year, reflecting moderate yet recurring infrastructure needs.

Fourth, several authors mentioned maintenance and scalability as continuing challenges. These included keeping apps functional amid software updates, ensuring stability under heavier traffic, and managing long-term hosting. Authors with Shiny or Python-based apps noted the importance of minimizing dependencies and performing iterative testing to prevent crashes and user errors.

Fifth, some challenges were tied to data processing and model performance. Author teams working with multimodal data, such as gesture or paralanguage detection, cited high computational loads and the need for extensive human validation. Integrating AI and vision-transformer models was also noted as technically demanding.

Finally, several authors reflected on the academic opportunity costs of app development. Time invested in coding and interface design often came at the expense of publication output or grant writing, and some complained that their fields offered limited recognition for such work.

What is the primary target group(s) of your app (i.e., practitioners, other researchers, students)? Please also indicate for what purpose your app is used by the target group(s).

Four principal target groups were named by the authors, including researchers, students, practitioners, and specialized audiences. Their answers indicate that most IRD apps are designed not only to support scholarly inquiry but also to extend the reach of research to broader educational and professional communities.

First, researchers were the primary intended users in most cases. Authors described their IRD apps as tools to explore, analyze, or visualize research data and as vehicles to make research outputs “more accessible” or to “inspire others” to develop similar tools. Many saw their apps as extensions of scholarly work—supporting replication, method dissemination, and collaborative experimentation across institutions.

Second, students formed a major target group. Several authors described their IRD apps as educational tools designed to illustrate complex concepts or analytical procedures interactively. Such apps allowed learners to test research ideas, engage with data in real time, and better grasp theoretical constructs. The authors noted that IRD apps helped make abstract theories more tangible, fostering more active learning.

Third, practitioners were identified as an important audience, particularly in cases where IRD apps were designed to demonstrate the practical relevance of research findings. Such apps aimed to show how academic insights could be translated into managerial or professional applications. Several authors described instances where their apps were adopted or tested by industry professionals, highlighting the potential of IRD apps to inform real-world decision-making. These examples reflect an explicit effort to make research actionable and to position apps as interfaces between conceptual development and practical application.

Finally, specialized users were mentioned less frequently. These included journalists, merchants, and other professional groups who could use the IRD apps for decision-making or applied communication. Such apps translated research insights into intuitive interfaces that supported practical use while maintaining scientific rigor.

How many visitors / users does your app approximately have?

Some authors described limited or early-stage usage of their IRD app, often linked to recent launches or pending publications. In such cases, usage remained minimal—typically ranging from dozens to a few hundred users—while authors expected growth as visibility increased through associated papers or conferences. Other authors reported moderate usage levels, with estimated user numbers in the hundreds or low thousands. These IRD apps often have user activity concentrated within a limited audience and without indications of broader public uptake. A small number of authors reported relatively high levels of user engagement, with estimated figures ranging from over one thousand to nearly ten thousand unique visits or downloads. Although hosting platforms were not always specified, these IRD apps were generally made publicly accessible through dedicated websites or open repositories, and their visibility was often amplified by academic publications.

It is important to note that many authors reported the absence of user analytics. Authors indicated that they did not track user data due to privacy concerns, technical limitations, or hosting constraints. Some authors deliberately avoided collecting usage information to protect user anonymity or comply with open-science norms. Others hosted their IRD apps on static servers or GitHub pages, where analytics were not readily available.

Finally, several authors relied on indirect indicators of use, such as paper citation counts, download statistics, or anecdotal feedback from collaborators.

Web Appendix C: Selection and Classification of Articles

Keywords for Selecting the Articles

natural language processing, social media, artificial intelligence, branding, language, machine learning, meta-analysis, online search, relevance, text analysis, abstract vs. concrete mindsets, agentic ai, ai acceptance, algorithm aversion, automated text analysis, bayes factor, bayesian estimation, between-study variation, big data, causal direction, causal model identification, citations, cohen's d, communication, competitive market structure, competitive market structure visualization, conditional independence, construal level, consumer decision journey, context effects, customer service, data mining, deep learning, deep representation learning, detailing, digital marketing, drugs (prices control) order, dynamic images, dynamics, ecological validity, emojis, emotions, event study, experimental methods, experiments, feeds, goal progress, grammatical voice, group sequential designs, heterogeneity, hierarchical, human-ai interaction, image processing, in-context testing, information retrieval, interpretable machine learning, language models, logos, mapping, market evolution, market structure analysis, measurement, mediation, mediation analysis, meta-science, methods, mind perception, mixture model, multilevel, multiview learning, natural languageprocessing, neural product embedding, overlapping clustering, passive voice, pharmaceutical price regulation, political marketing, political polarization, power analysis, processing fluency, random effects, readability, regression discontinuity in time, regulated molecules, representation learning, salience, search queries, sentiment analysis, smart objects, social media engagement, standardized mean difference, statistics, structural heterogeneity, syntactic surprise, syntax, synthetic controls, technology acceptance, text mining, text overlays, theory of mind, topic modeling, trajectories, user-centered design, user-generated content, visual appeal, warmth and competence, writing

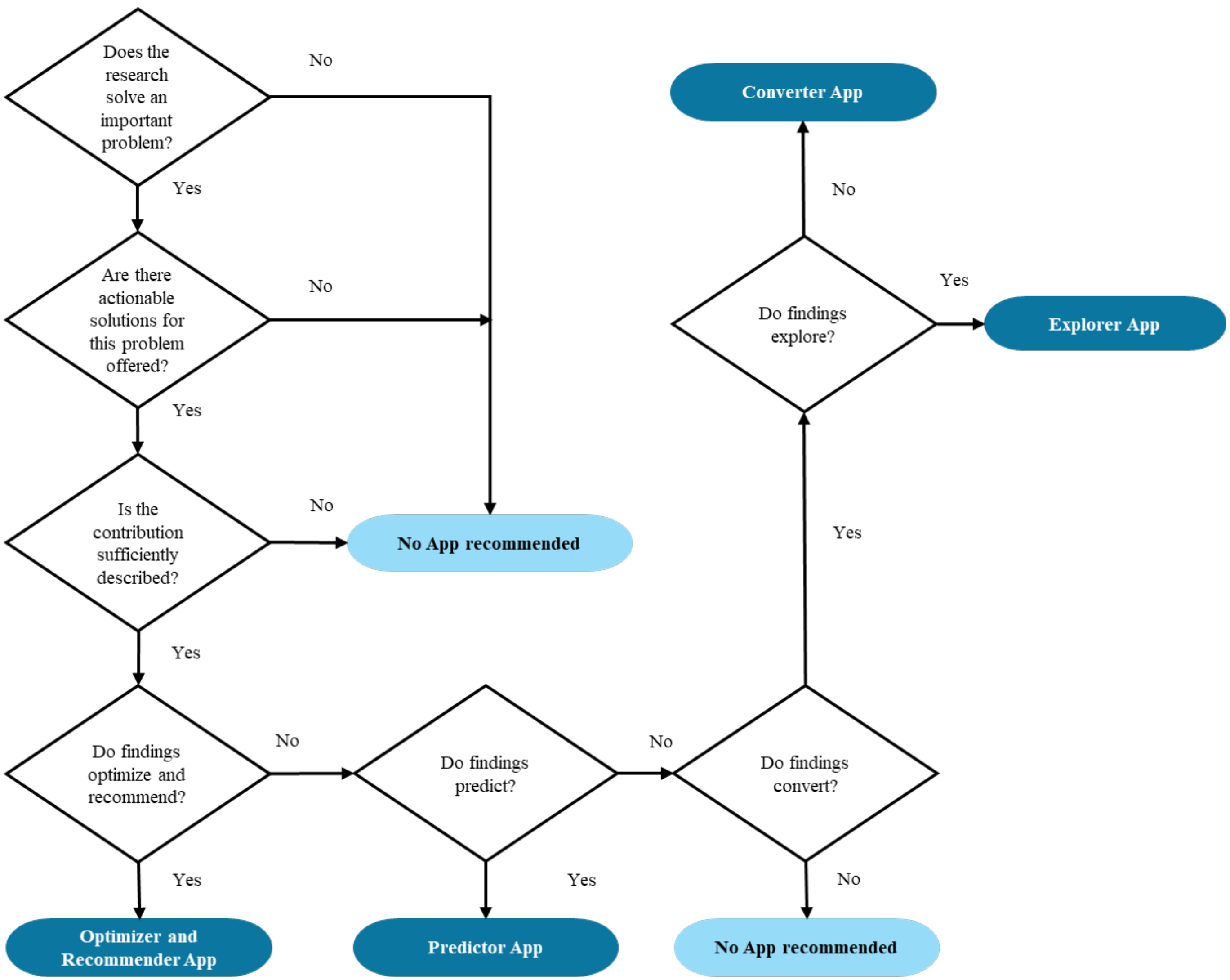
Journals in the Sample

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

Robustness Test

To test the robustness of our findings, we classified 100 randomly selected articles that did not match with the keywords using the same timeframe (2020 to September 2025) and journals as in the main analyses reported in the paper. We found that 23% (23 articles) had potential for IRD app development, including 4% (4) predictors, 5% (5) optimizers and recommenders, 13% (13) explorers, and 1% (1) converter.

Flowchart for Classifying Interactive, Research-Driven Apps



Web Appendix D: Citation Statistics for Interactive, Research-Driven Apps

Article	Citations	Year	Citations > Impact Factor
Cascio Rizzo, Berger, and Zhou (2025)	3	2025	Not enough data
Blanchard et al. (2025)	6	2025	Not enough data
Roggenkamp, Boegershausen, and Hildebrand (2025)	2	2025	Not enough data
Farace et al. (2025)	3	2025	Not enough data
Hotz-Behofsits, Wlömert, and Abou Nabout (2025)	3	2025	Not enough data
Li, Lai and, Wang (2025)	1	2025	Not enough data
Packard, Li, and Berger (2024)	17	2024	Not enough data
André and Reinholtz (2024)	6	2024	Not enough data
Jaikumar, Chintagunta, and Sahay (2024)	7	2024	Not enough data
Atalay, Kihal, and Ellsaesser (2023)	25	2023	No
Hartmann, Bergner, and Hildebrand (2023)	30	2023	Yes
Laghaie and Otter (2023)	13	2023	Yes
Matthe, Ringel, and Skiera (2023)	19	2023	Yes
Ringel (2023)	9	2023	Yes
Schoenmueller, Netzer, and Stahl (2023)	68	2023	Yes
Sepehri, Mirshafiee, and Markowitz (2023)	19	2023	Yes
Dyachenko and Allenby (2023)	5	2023	No
Dew, Ansari, and Toubia (2022)	93	2022	Yes
McShane and Böckenholt (2022)	23	2022	No
Yang, Zhang, and Kannan (2022)	71	2022	Yes
Hovy, Melumad, and Inman (2021)	32	2021	No insights on IF
Humphreys, Isaac, and Wang (2021)	114	2021	No insights on IF
Jedidi et al. (2021)	33	2021	No insights on IF
Warren et al. (2021)	79	2021	No insights on IF

Note. We assessed whether articles published in 2022 and 2023 received higher citation counts in 2024 than the 2024 impact factor of their respective journals.

Web Appendix E: Additional Details for the Online Experiment

All Stimuli

Control Condition (No IRD App)

Construal Matching in Online Search: Applying Text Analysis to Illuminate the Consumer Decision Journey

This study suggests that the language in online search queries reveals consumer goals (information or purchase). Consumers use more abstract language when they have an informational goal, and more concrete language when they have a purchase goal. Matching search engine ads to these goals increases clicks and user satisfaction by giving the perception of achieving their goals.

Article Highlights

Concreteness of Search Result	Concreteness Score	Informational Stage	Comparison Stage	Transactional Stage
Abstract ("See What's New From Surface")	307.15	25.8%	22.8%	23.4%
Intermediate ("Which Surface Works For You")	362.93	61.4%	67.3%	37.9%
Concrete ("Free Next Day Delivery")	390.93	12.9%	9.9%	38.7%

Treatment Condition (IRD App)

Construal Matching in Online Search: Applying Text Analysis to Illuminate the Consumer Decision Journey

This study suggests that the language in online search queries reveals consumer goals (information or purchase). Consumers use more abstract language when they have an informational goal, and more concrete language when they have a purchase goal. Matching search engine ads to these goals increases clicks and user satisfaction by giving the perception of achieving their goals.

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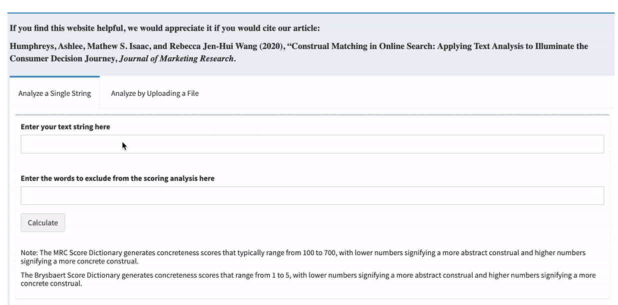
Concrete ("Free Next Day Delivery")	390.93	12.9%	9.9%	38.7%

Demonstration of the App

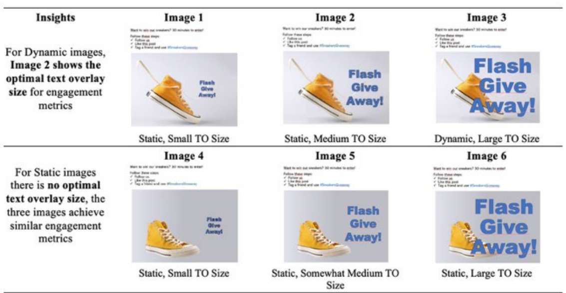


Control Condition (No IRD App)

Creating Effective Multimodal Social Media Communication

This research studies how to use text overlays (i.e., text inserted in an image) to improve social media engagement. The study finds that well-designed text overlays can increase engagement by 43%. The size and placement of text overlays matter especially in images depicting an action (i.e., dynamic), while the characteristics of text overlays do not significantly impact engagement with static images.

Article Highlights

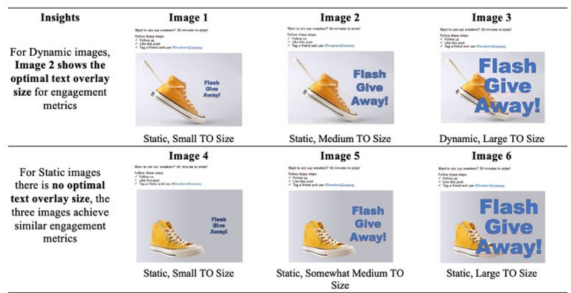


Treatment Condition (IRD App)

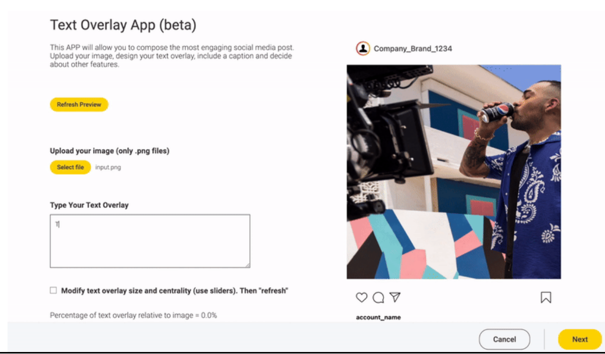
Creating Effective Multimodal Social Media Communication

This research studies how to use text overlays (i.e., text inserted in an image) to improve social media engagement. The study finds that well-designed text overlays can increase engagement by 43%. The size and placement of text overlays matter especially in images depicting an action (i.e., dynamic), while the characteristics of text overlays do not significantly impact engagement with static images.

Article Highlights



Demonstration of the App

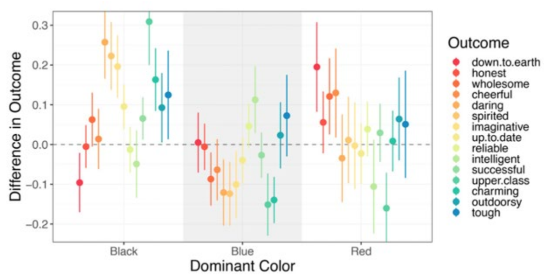


Control Condition (No IRD App)

Letting Logos Speak: Leveraging Multiview Representation Learning for Data-Driven Branding and Logo Design

This study develops an algorithm that analyzes logos by breaking them down into detailed components and linking them to a brand's identity and public perception. It applies this algorithm to a wide range of brands to observe which logo features are favored and how they shape consumer views of a brand's character. Additionally, the study shows how this algorithm can help generate new brand identities and suggest logo designs that are likely to resonate with customers.

Article Highlights



Treatment Condition (IRD App)

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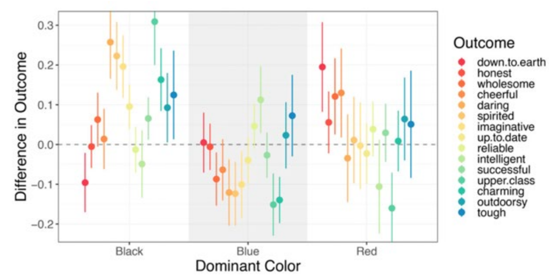
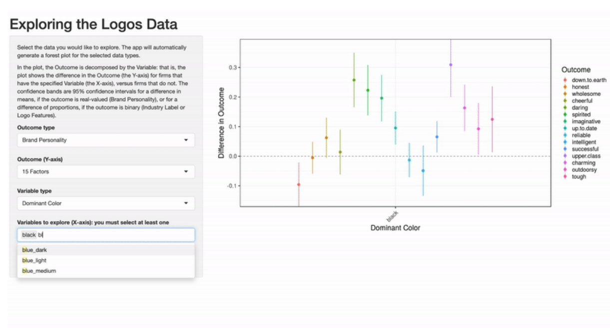


Demonstration of the App

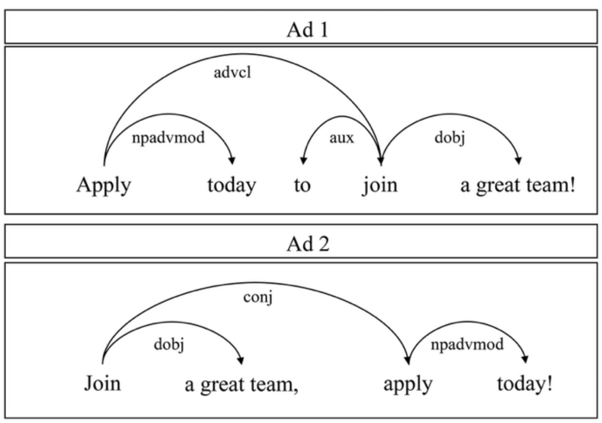


Control Condition (No IRD App)

Creating Effective Marketing Messages Through Moderately Surprising Syntax

This study looks at how a surprising sentence structures in marketing messages can grab people's attention. The researchers created a way to measure this "syntactic surprise" and checked that it works both in theory and in the real world. They found that ads with a not-too-simple, not-too-complex sentence structure get more clicks. Working with two companies, the study proved that ads with a medium level of surprising sentence structures are more effective than those that are either too plain or too complicated.

Article Highlights (Ad 2 is more surprising)



Treatment Condition (IRD App)

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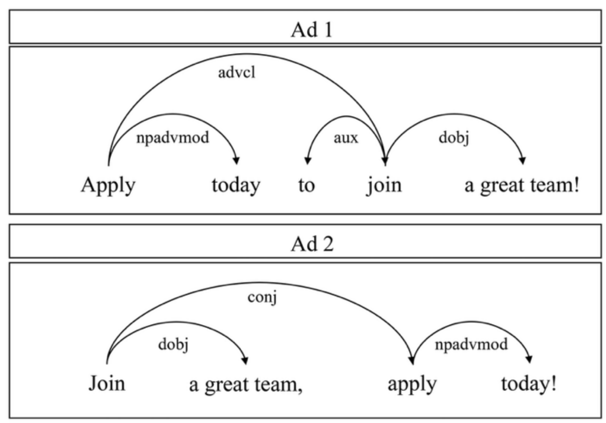
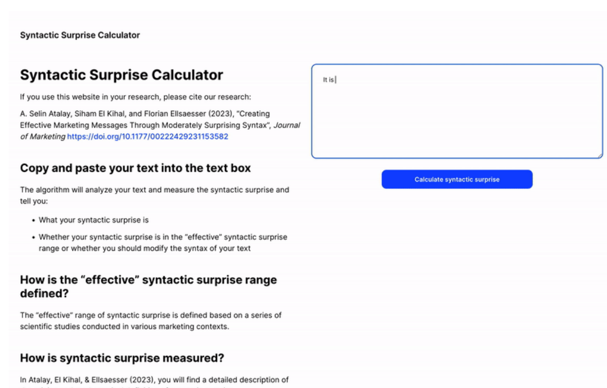


Demonstration of the App



Scales

Interactivity

To what extent do you think the research paper is interactive? (Not interactive at all = 1, Very interactive = 7)

Interestingness (Schauerte et al. 2017)

In your opinion, how interesting, useful, and easy is it to implement the findings from this research? (Not at all = 1, Very = 7)

- Interesting
- Useful
- Easy to implement

Relevance (Schauerte et al. 2017)

How relevant do you find this research paper? (Not at all relevant = 1, Very relevant = 7)

- For companies in general
- For your own industry
- For your own company
- For your own position

Descriptive Statistics

Dependent Variables	N	Minimum	Maximum	Mean	Std. Deviation
Interestingness	584	1	7	5.111	1.376
Relevance	584	1	7	4.917	1.462

Work Experience	Count	Percentage
Less than 5 years	68	11.6
More than 5 years	516	88.4
Education	**Count**	**Percentage**
Secondary education or lower	84	14.4
Vocational or technical training	72	12.3
University degree (Bachelor’s, Master’s or equivalent)	408	69.9
Advanced Degree (PhD, MD or equivalent)	20	3.4

Discrete Variables by Conditions

	Control		Treatment	
	Count	**Percentage**	**Count**	**Percentage**
Gender				
Diverse	2	0.7	6	2.1
Female	170	58	182	62
Male	120	41	104	36
Work Experience				
< 5 years	29	9.9	39	13
≥ 5 years	263	90	253	87
Education				
Advanced Degree (PhD, MD or equivalent)	14	4.8	6	2.1
Secondary education or lower	39	13	45	15
University degree (Bachelor's, Master's or equivalent)	210	72	198	68
Vocational or technical training	29	9.9	43	15
Observations	292		292	

Regression

Interestingness – No Controls

	Dependent variable: Interestingness	
	Coefficient	**SE**
Intercept	4.987***	(.080)
Condition		
App present	.248**	(.114)
Observations	584	584

Note:* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Interestingness – Controls

	Dependent variable: Interestingness	
	Coefficient	**SE**
Intercept	5.330***	(.360)
Condition		
App present	.255**	(.111)
App Type (Converter as Base)		
Predictor	.604***	(.156)
Explorer	-.299*	(.156)
Optimizer	.313**	(.156)
Work Experience: >5 years	-.045	(.174)
Education		
Secondary or lower	-.401	(.334)
University	-.506*	(.307)
Vocational/Technical	-.408	(.341)
Observations	584	584

Note:* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Relevance – No Controls

	Dependent variable: Relevance	
	Coefficient	**SE**
Intercept	4.801***	(.085)
Condition		
App present	.234*	(.120)
Observations	584	584

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

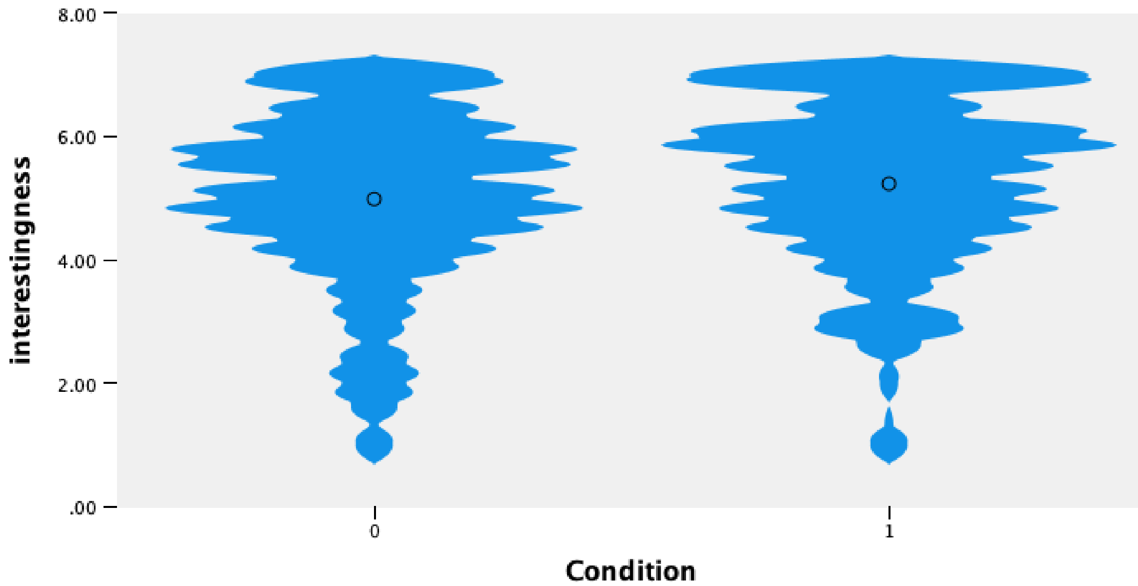
Relevance – Controls

	Dependent variable: Relevance	
	Coefficient	**SE**
Intercept	5.237***	(.390)
Condition		
App present	.265**	(.120)
App Type (Converter as Base)		
Predictor	.440***	(.169)
Explorer	-.036	(.169)
Optimizer	.313*	(.169)
Work Experience: >5 years	-.109	(.188)
Education		
Secondary or lower	-.475	(.361)
University	-.503	(.332)
Vocational/Technical	-.945**	(.368)
Observations	584	584

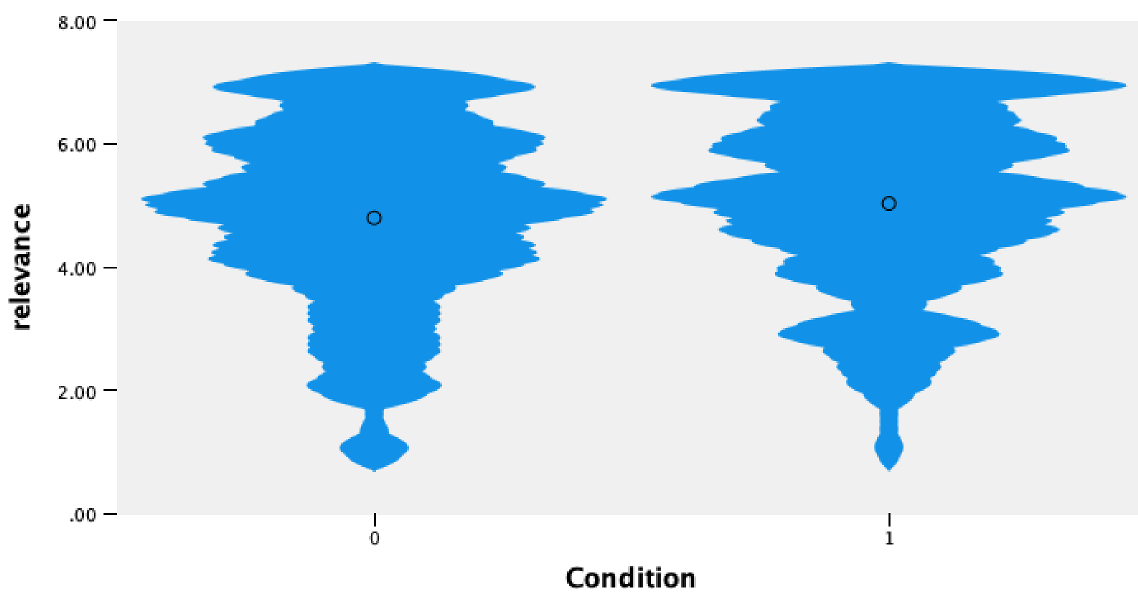
Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Additional Visualizations for the Online Study

Interestingness



Relevance



Web Appendix F: Additional Details for the A/B Test

Control Condition (No IRD App)

Data-Driven Branding and Logo Design

Short introductory lecture on Data-Driven Branding and Logo Design, referring to the paper from Dew, Ansari, and Toubia (2022).

Letting Logos Speak: Leveraging Multiview Representation Learning for Data-Driven Branding and Logo Design

Ryan Dew,[a] Asim Ansari,[b] Olivier Toubia[b]
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Received: November 25, 2019
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Abstract. Logos serve a fundamental role as the visual figureheads of brands. Yet, because of the difficulty of using unstructured image data, prior research on logo design has largely been limited to nonquantitative studies. In this work, we explore the interplay between logo design and brand identity creation from a data-driven perspective. We develop both a novel logo feature extraction algorithm that uses modern image processing tools to decompose pixel-level image data into meaningful features and a multiview representation learning framework that links these visual features to textual descriptions, consumer ratings of brand personality, and other high-level tags describing firms. We apply this framework to a unique data set of brands to understand which brands use which logo features and how consumers evaluate these brands' personalities. Moreover, we show that manipulating the model's learned representations through what we term "brand arithmetic" yields new brand identities and can help with ideation. Finally, through an application to fast-food branding, we show how our model can be used as a decision support tool for suggesting typical logo features for a brand and for predicting consumers' reactions to new brands or rebranding efforts.

Task (10 minutes)

Please engage with the topic "Letting Logos Speak" to answer to the questions distributed in class.
You can use the following materials when engaging with the topic:

1. One page summary of scientific paper
(but not sufficient to answer to the questions)

2. Scientific paper
https://pubsonline.informs.org/doi/abs/10.1287/mksc.2021.1326

Treatment Condition (IRD App)

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1. One page summary of scientific paper
(but not sufficient to answer to the questions)

2. Scientific paper
https://pubsonline.informs.org/doi/abs/10.1287/mksc.2021.1326

3. Research-driven app
The authors also developed a research-driven app to make the findings easier accessible for readers.
https://dr19.shinyapps.io/explore_logo_data/

Questions

In your opinion, how interesting is it to implement the findings from this research? (Not at all interesting = 1, Very interesting = 7)

In your opinion, how useful is it to implement the findings from this research? (Not at all useful = 1, Very useful = 7)

How relevant do you find this research paper? (Not at all relevant = 1, Very relevant = 7)

Web Appendix G: Additional Details for Brand Reputation App

Step 1 – Brand Reputation Scoring

After the data is uploaded from social media, the text data is preprocessed by converting the text column into the appropriate "document" format, converting all text to lowercase, stemming words, and creating a bag-of-words representation. The app then applies the dictionaries from Rust et al. (2021) to obtain a score for each social media post. These scores are aggregated according to a specified timeframe (e.g., weekly or monthly), normalized for better comparison, and then visualized. While the brand reputation could be classified as a converter app, by visualizing the results and making them available for interactive exploration, we classified it as an explorer app.

Step 2 – Input and Output

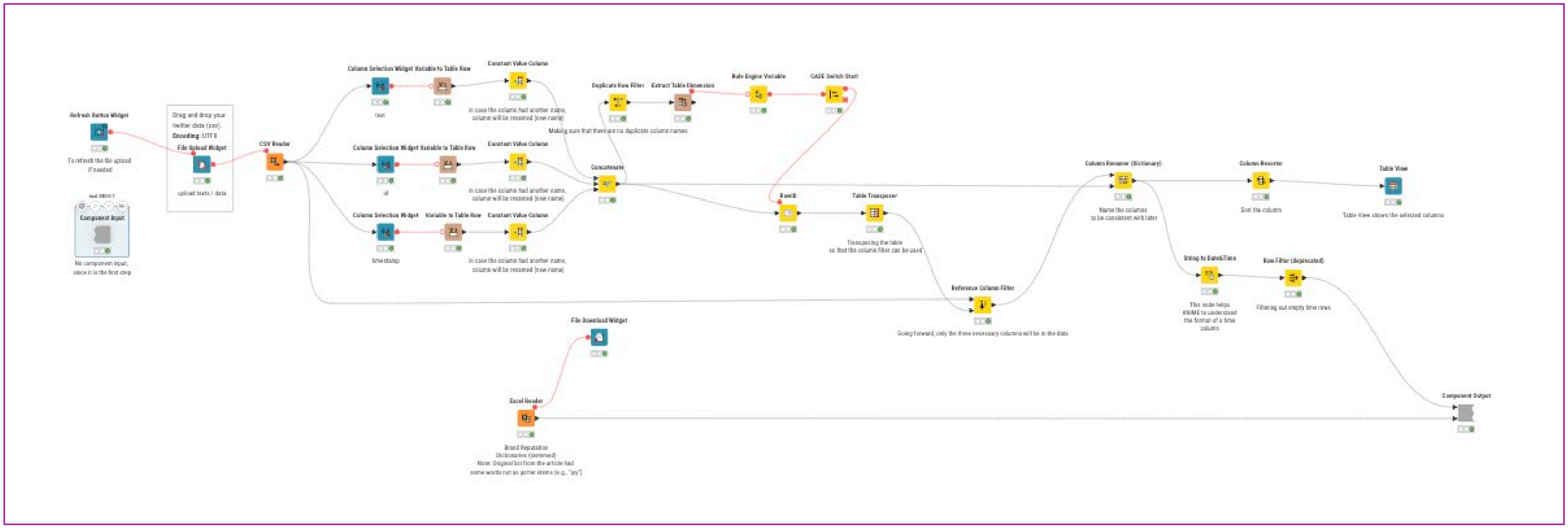
In the brand reputation tracker, the input would be the social media text data that is uploaded, where the columns to be considered for the analysis are selected. For example, to specify the time dimension in the analysis, one needs to select the column "created at" containing the time at which a social media post was created. Additionally, parameters for the text and ID column are needed. Together, these are the input parameters. When the results are processed, the user of the app can adjust and explore results based on output parameters, for example by changing the aggregation type from weekly to monthly.

Step 3 – Applied Heuristics

We apply the heuristics as close as possible in the brand reputation tracker. First, an obvious start with a consistent logic: the user can upload a proprietary dataset for analysis (via "Edit" on Streamlit or "Select file" in KNIME) and can then click a prominently placed button ("Compute and Visualize Brand Reputation" on Streamlit or "Next" in KNIME). Clicking this button then leads to immediate feedback in the form of a loading screen. To facilitate user interaction visually, we seek to group related widgets (such as those that set input and output parameters) together. For example, when the user needs to set-up the data fields (ID, time and text-field) for the uploaded data, they are found close to the upload widget. In the same way, the parameters for the visualization (what to visualize, time dimension to be aggregated on) are grouped together with the chart that is visualized. Last, to minimize errors within the process, the app has a default social media dataset.

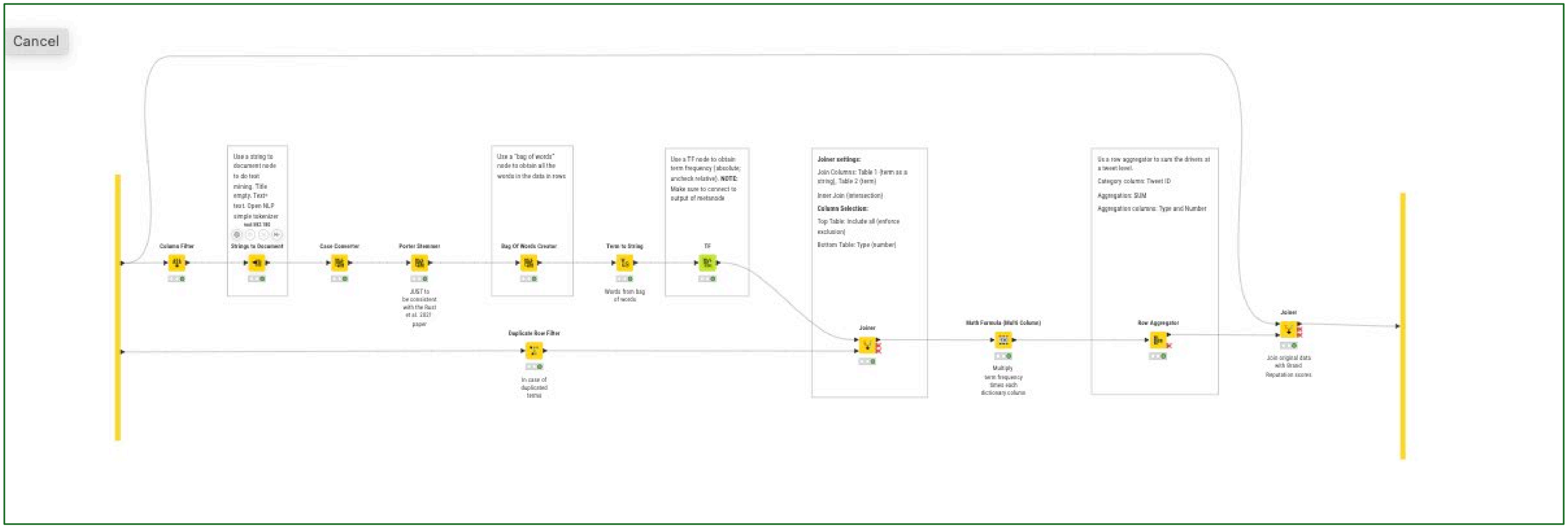
While the forementioned heuristics should guide the design process, superior user experience and good interactivity of an app is eventually created through iterative development and the well-planned interplay of widgets. A widget is an element of a graphical user interface that displays information or provides a specific way for a user to interact with an application (Kirvan 2022). Widgets can be used to input data (e.g., file upload, set a parameter), trigger actions (e.g., execute button), or output data (e.g., graphs, download files). The choice of input widget depends on the inputs chosen in a previous step. In general, a widget can be picked by identifying the type of input (such as table data, string, number, or Boolean), by assessing the number of options available (e.g., a limited and small list, a continuous or discrete set, or a numeric range) or by determining whether the selection should be single or multiple (e.g., "select all that apply"). Web Appendix I displays some of the widgets from the brand reputation app.

Uploading Data and choosing columns



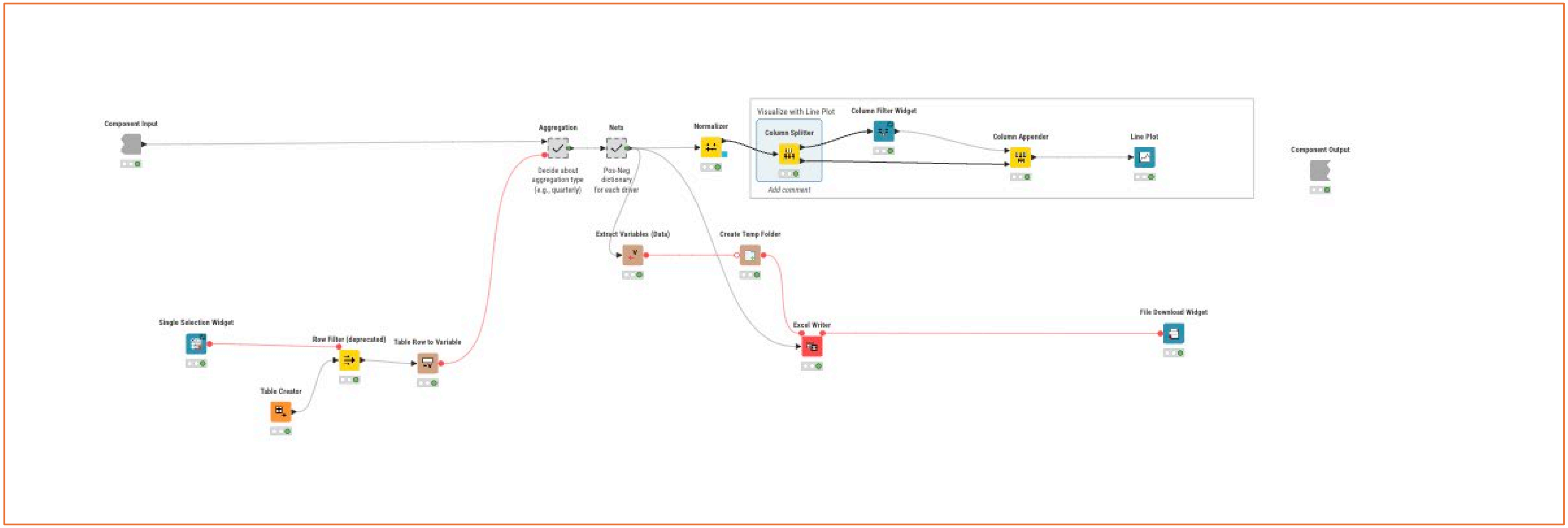
This component of the workflow handles the input (social media), along with the configuration parameters (field, id, data). This information is then used to create a data preview table. The data is then sent to the text-mining workflow.

Dictionary-based text-mining is applied to the data



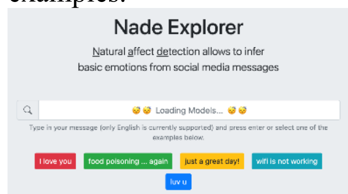
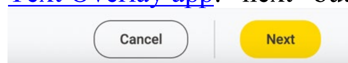
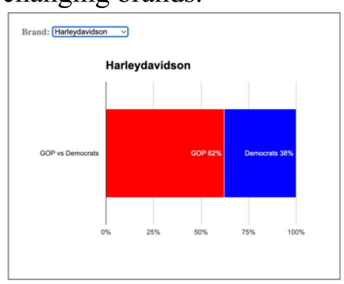
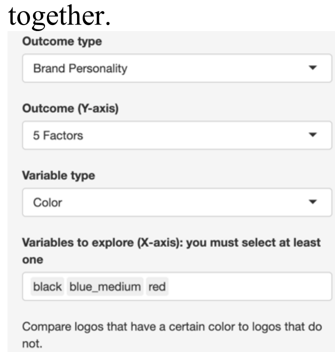
This component of the workflow handles the preprocessing of the text document (converting data to lower-case, stemming the data, creating a bag of words). Then, the dictionaries are applied, i.e. the messages are scored based on words. The data is then handed over for brand reputation score calculation and visualization.

Output table with brand reputation scores is calculated and visualized



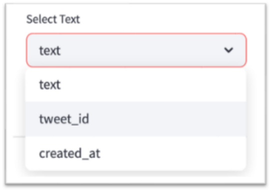
The brand reputation score is calculated based on the aggregation periods that are chosen via the user interface (weekly, monthly, quarterly, yearly. Those scores are then used to visualize the results and prepared for download.

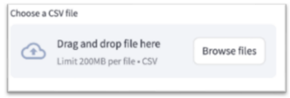
Web Appendix H: Important Heuristics to Design a Graphical User Interface

Heuristic	Explanation	Example
Obvious start	The user should immediately know where to start	NADE: directly offers a text field including examples. 
Consistent logic and flow	The next step should be clear to the user.	Text Overlay app: "next" button on the bottom right. 
Immediate Feedback	When the user interacts, he should have immediate feedback.	Social Listening app: directly adapts charts when changing brands. 
Proximity	Related settings should be grouped together.	Logo explorer: output parameters are grouped together. 
Error prevention	User experience should be designed to reduce mistakes.	ConcretenessScoringTool: offers tool tutorial and various options for input (e.g. single strings or complete files). 

Note: Selected heuristics from the user experience literature (Blair-Early and Zender 2008; Molich and Nielsen 1990)

Web Appendix I: Widget Examples from the Brand Reputation App





Widget	Selectbox	File uploader	Line chart
Description	Select columns in the dataset (specifying description, options and default)	Upload proprietary data (specifying description and filetype)	Visualize data from tables
Code	`selected_column = st.selectbox("Select Text", [”text", ”tweet_id", ”created_at"], index=1)`	`uploaded_file = st.file_uploader("Choose a CSV file", type=("csv"))`	`st.line_chart(df_drivers[selection2])`

Notes: We show examples of widgets from the Streamlit (Python) framework along with a short description and example code. The full code can be found here. The configuration for the KNIME nodes can be inspected in the online repository.

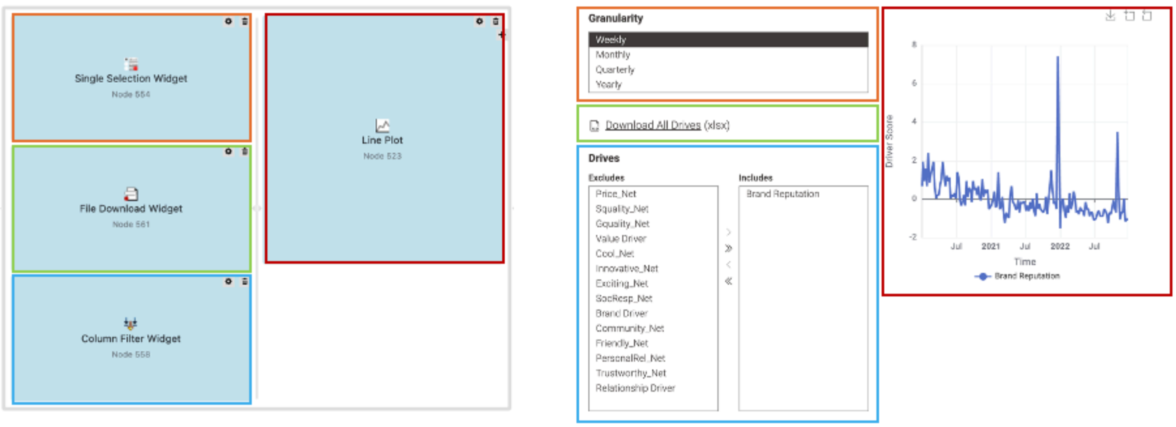
For example, if the users select an aggregation method from a predefined list of three options (weekly, monthly, yearly) and only one selection is allowed, the appropriate widget would be a dropdown menu, implemented as a “Single Selection Widget in KNIME” or a “st.selectbox()” in Streamlit. If users are asked to select multiple brand metrics from a longer list, a multi-select widget would be appropriate, such as the “Column Selection” Widget in KNIME or “st.multiselect()” in Streamlit. The widgets for the expected outputs also depend on the typology of app chosen. For example, with converter apps, the final results are often made available to download (e.g., Hovy, Melumad, and Inman 2021; Humphreys, Isaac, and Wang 2021). In these cases, a download widget should be included. The combination of widgets determines the visual appearance and user experience of the app. The resulting design can be improved based on the order in which the user is expected to interact with the settings and additional elements that are added for subsequent actions: triggering the analysis with a button, displaying a loading bar, and finally reviewing the results in a graph.

Web Appendix J: Overview of Implementation Tool Options

Tool	Description	Free option	Programming Language and Framework	Widgets
Gradio	Python-based open-source framework, specialized on machine learning.	Via Hugging Face	Python, git	Limited
KNIME	Low-code analytics tool offering R and Python integrations. WYSIWG editor for front-end editing.	No, but academic options available	No	Extensive
Netlify	Composable platform for hosting web apps	Yes	Git, Node.js	Extensive
Observable	Open-source framework focused on complex data visualizations.	No	R or Python, git, npm, Javascript	Unlimited due to JavaScript
Plotly Dash	R-based open-source app framework specialized in visualizations rich applications.	Via Render	R, git, flask, virtualenv,	Extensive
Shiny	R and Python-based open-source framework.	Yes	R or Python	Extensive
Streamlit	Python-based open-source framework.	Yes	Python, git	Limited

Web Appendix K: Layout Editor and Frontend Results

Layout Editor **Frontend**



The KNIME layout editor offer a drag&drop editor to position the widgets on the screen. Mandatory settings are aligned on the left part of the frame (selection widget), along with optional settings (column filter widget).

The frontend is rendered according to the KNIME layout editor. Note that when the widgets are rendered the file download widget is smaller than in the layout editor.

Notes: This figure demonstrates the functionality of a drag&drop editor for visualization purposes. On the left, how it is configured, and on the right, how it is rendered in the front-end.

Web Appendix L: Commonly used Deployment Frameworks

Framework	Costs for Public Deployment	Selected Examples	Comments	Required Programming Experience
Streamlit	Free for first app, only when publicly deployed	Sepehri, Mirshafiee & Markowitz (2022) Hovy, Melumad, Inman (2021)	Widely used, based on Python. Extensively documented.	Medium
Shiny	Free for 25 hours of usage	André and Reinholtz (2024) Dew, Ansari & Toubia (2022)	Based on R, often used for research-driven apps.	Medium
KNIME	Free for academic use	Farace et al. (2025)	Easy to use low code solution with active community.	Low
Netlify	Free until 100GB bandwidth	Matthe, Ringel & Skiera (2022)	Fit for scalable apps that expect high traffic.	High

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