OR Spectrum (2024) 46:1–27
https://doi.org/10.1007/s00291-024-00755-1

EDITORIAL

Predicting and optimizing marketing performance in dynamic markets

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Accepted: 29 January 2024 / Published online: 29 February 2024

Abstract
Our world is turbulent: ecological, social, political, technological, economic, and competitive business environments change constantly. Consumers have changing preferences, learn, build trust in brands, adopt new products, and are persuaded by advertising. Firms innovate and engage in and respond to competition. Exogenous events, such as changes in economic conditions and regulations, as well as human crises, also cause major shifts in markets. This special issue focuses on novel Marketing data and modern methodologies from different fields (e.g., Operations Research (OR), Statistics, Econometrics, and Computer Science), which help firms understand, utilize, and respond to market dynamics more efficiently. Here we propose a framework comprising analytical methods and data for dynamic markets that is useful for structuring research in this domain. Next, we summarize the history of the Marketing/OR interface. We highlight studies at the Marketing/OR interface from the last decade focusing specifically on dynamic markets and use our proposed framework to identify trends and gaps in the extant literature. After that, we present and summarize the papers of the current special issue and their contributions to the field against the backdrop of our framework and the trends in the literature. Finally, we conclude and discuss which future Marketing/OR research could tackle important issues in dynamic markets.

Keywords Dynamic markets · Marketing/OR interface · Analytical methods · Data analysis

1 Introduction

Our world is turbulent: natural, social, political, technological, economic, and competitive business environments change continuously and sometimes shift rapidly. By understanding such dynamics, companies can develop strategies that help them

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adapt while also taking advantage of new opportunities as they arise. The causes of these dynamics in demand and supply are many. Consumers have changing preferences, learn from the experience of and interaction with other consumers, build trust in brands, are persuaded by advertising, and adopt new technologies and sales channels (see, e.g., Zhang and Chang 2021). Firms introduce new products by developing or leveraging new technologies, grow, fail, merge with other firms, and respond to competition by innovating, lowering costs, adapting the Marketing mix, and improving efficiency. Fluctuations in demand and competition impact inventory levels, assortments, lead times, and transportation costs. Exogenous events such as changes in economic conditions (e.g., a stock market crash, inflation, recession), regulations (e.g., the General Data Protection Regulation—GDPR—in Europe, US-Chinese import tariffs, central banks raising interest rates), man-made crises (e.g., the Volkswagen diesel emissions scandal), as well as natural disasters (e.g., caused by climate change or the COVID19 pandemic), cause major shifts in markets.

Market turbulence has not only immediate effects on consumer behavior as well as innovation, manufacturing, distribution, pricing, and competition but also has long-term strategic consequences for firms having to anticipate and address the uncertainty caused by market dynamics. To understand dynamics and shifts in markets in a timely fashion, firms analyze and predict these changes and their impacts on market behaviors and reallocate resources accordingly. To this end, modern technologies (e.g., Machine Learning (ML), Artificial Intelligence (AI), Internet of Things, mobile and Global Positioning System technologies, virtual and other digital environments) enable firms to identify market shifts faster and better and track and capitalize on market dynamics.

In the past, Marketing data and modern methodologies from Operations Research (OR), Statistics, Econometrics, and Computer Science have helped companies understand market dynamics and shifts, enabling them to respond more rapidly and efficiently. Models from these fields have played different roles in supporting Marketing decision-making. Firstly, ML and AI methods help identify patterns in unstructured data that may indicate and predict trends (e.g., Random Forests, Deep Learning). Secondly, statistical/econometric models are used to analyze and test tabular data for time trends (e.g., dynamic linear models, dynamic discrete choice models, vector autoregression, hidden Markov models) and market shifts (e.g., regime-switching models), and their hypothesized antecedents. Specifically, Bayesian models have been applied to quantify uncertainty about (e.g., Bayesian learning) and heterogeneity in (e.g., Bayesian hierarchical modeling) market dynamics. Thirdly, econometric techniques support causal inferences from antecedents of market shifts in quasi or randomized field experiments (e.g., Difference-in-Differences, Instrumental Variables, Regression Discontinuity). Finally, OR techniques and analytical methods have helped businesses optimize their operations by finding optimal solutions to complex decision-making problems with multiple objectives and constraints (e.g., Markov Decision Models, Linear and Dynamic Programming, Simulations).

The use of these methodologies from OR and other fields in Marketing to understand market dynamics suggests there are numerous relationships between these areas. To assess the extent of ongoing cross-fertilization between Marketing and OR, we examine citations in several major journals in these two fields over the last

Table 1 Citation analysis

Percentage of papers in ...	...citing papers from ...						
	IJRM	JMR	MKSC	QME	EJOR	OPRE	ORSP
IJRM	74.1	88.9	68.8	15.5	4.4	2.3	0.5
JMR	33.1	94.6	70.3	18.3	2.3	2.1	0.3
MKSC	23.1	86.6	96.4	40.2	3.4	10.0	0.2
QME	17.3	71.9	87.8	54.0	3.6	4.3	0.0
EJOR	1.7	4.3	8.0	0.9	94.5	51.3	12.1
OPRE	1.3	5.2	10.0	1.1	38.5	85.3	2.9
ORSP	2.6	4.9	4.7	1.4	89.4	60.2	50.1

ten years. Some interesting patterns of cross-citations between Marketing and OR can be seen in Table 1. This table provides an overview of the percentage of papers with cross-disciplinary citations published in leading (quantitative) Marketing journals such as the *International Journal of Research in Marketing* (IJRM), the *Journal of Marketing Research* (JMR), *Marketing Science* (MKSC), and *Quantitative Marketing end Economics* (QME), and OR journals including the *European Journal on Operational Research* (EJOR), *Operations Research* (OPRE), and *OR Spectrum* (ORSP) that cite contributions from each other.[1]

The 2×2 block-diagonal pattern that emerges indicates that most papers in Marketing journals cite papers in other Marketing journals (e.g., 70.3% of papers in the JMR cite papers from MKSC), while, similarly, most papers in OR journals cite papers from other OR journals (e.g., 89.4% of papers in ORSP cite papers from EJOR). Notably, the self-citation rates of the journals in both fields are often high, exceeding 90% for EJOR, JMR, and MKSC. ORSP and QME present exceptions to this trend, exhibiting the lowest in-journal citation rates of approximately 50%. It is worth noting that cross-citations within disciplines are not always "symmetric." For example, among OR journals, while 89.4% of ORSP papers cite EJOR papers (as mentioned above), only 12.1% of EJOR papers cite ORSP papers. In the same fashion, among Marketing journals, while 71.9% of QME papers cite papers in JMR, only 18.3% of JMR papers cite QME papers. Cross-disciplinary citation percentages are even lower, with values below 5% in most cases. Papers published in OPRE and MKSC (both INFORMS journals) have the highest cross-disciplinary citation rates, citing each other in 10.0% of the papers. Interestingly, papers in OR journals cite Marketing papers slightly more than the reverse, especially citing papers from JMR and MKSC. The values are particularly low for ORSP; fewer than 1% of the papers in any of the Marketing journals cite ORSP papers. A somewhat similar pattern occurs for papers in OR journals citing QME. Thus, while the citation data shows that cross-fertilization continues to occur between the disciplines, especially between papers published in OR and MKSC, there are ample opportunities to strengthen these connections. That researchers in either field seem to utilize

[1] We compiled data from Scopus (https://www.scopus.com) and only used papers published since 2013.

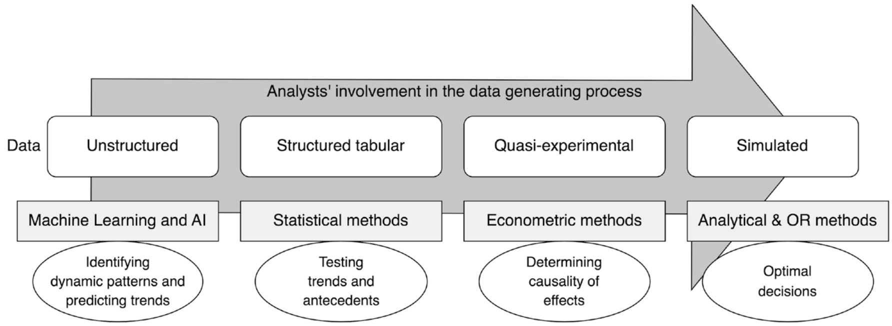

Fig. 1 Framework of data and methods for dynamic markets; inspired by Wedel and Kannan (2016)

developments in the other field quite modestly is a missed opportunity. Exploring sources beyond the few top journals within each discipline holds promise for researchers engaged in topics spanning both fields and may spawn more collaboration between researchers in those fields. Our special issue aims to help foster this connection between Marketing and OR.

Cross-fertilization between Marketing and OR research extends to the nature of the data used in both fields. Figure 1 places data to which methods in Marketing and OR are applied on a continuum of increasing analyst involvement in the data-generating process, from hardly any (unstructured data) to completely (simulated data). While ML methods are most suited to analyzing unstructured data for patterns and trends, analytical methods and OR often rely on simulated data for finding optimal decisions. In between these two extremes, statistical methods are traditionally applied to structured tabular data to test hypotheses about trends and their antecedents, while quasi-experimental methods, requiring more involvement of the analyst in their design, are most often analyzed using econometric methods to determine the causal effects of (dynamic) Marketing performance. Of course, the different types of data and methods are also often interrelated (e.g., data from previous forecasts and estimated demand models serve as input for simulations). Building on their comparative strengths, integrating these extant techniques in ways that aligns with the demands of a particular Marketing problem and the available data holds much promise for academic research and its application to business problems in the future (Bengio et al. 2021; Wedel and Kannan 2016). Researchers have integrated several of these approaches specifically at the Marketing/OR interface. Integration may involve combining models by averaging their predictions, using them sequentially, or incorporating aspects of one type of model into another to allow for the optimization of Marketing strategies as new data become available, enabling companies to adapt quickly and effectively to dynamic markets. Section 2 summarizes some of the history of these approaches at the Marketing/OR interface.

Academic research has been instrumental in integrating methods from Marketing and OR. In Sect. 3 we provide an extensive review of studies at the Marketing/OR interface over the last decade published in three leading OR journals, with a specific focus on dynamic markets. These more recent studies are placed within the framework provided in Fig. 1, with the purpose of identifying trends and gaps in the extant literature.

Large-scale applications of several of the methods in Marketing, OR, and the Marketing/OR interface have had direct relevance for business practice in industries such as retailing, transportation, energy, finance, inventory management, entertainment, and tourism. The literature review reveals that areas that lend themselves to further development include dynamics in multimedia budget allocation, consumer learning, pricing, brand Marketing strategies, customer relationship management, direct Marketing responses, firm competition, viral Marketing, assortment optimization, personalization of product recommendations, and new product innovation and introduction.

In Sect. 4, we summarize the contribution of the papers of the current special issue against the backdrop of our framework and the trends outlined in the literature. We show how each of these papers, at the intersection between Marketing and OR, contributes to a better understanding of market dynamics and their consequences for firm decision making. In Sect. 5, we conclude and discuss ideas for future Marketing/OR research that would tackle important issues in dynamic markets.

2 The history of the marketing/OR interface

From a management perspective, Marketing and OR are two related fields that have developed rapidly over the past 70 years. After World War II, the Marketing field started to broaden its view from being more or less sales and communication-centered to Marketing management-centered. OR, particularly mathematical programming techniques, were recognized as valuable tools in a management decision-making context. At that time, Marketing and OR were not completely separate from each other; for instance, Kotler's (1971) early editions of his seminal Marketing textbook included typical OR techniques, such as how to solve a traveling salesman's problem. In general, Marketing scholars began to pursue, on the one hand, behavioral (socio-psychological) centered research, and on the other hand, often followed economic principles that postulated that market actors maximize utility or profit. Obviously, maximizing goals under certain constraints points to the applicability of OR techniques. Several management schools in the USA, with MIT at the forefront, were pioneers in promoting this view. Little (1970) coined the concept of "decision calculus" which emphasized the management decision-making perspective. During these years, cooperation between Marketing and OR flourished, and many papers were published following the decision calculus principle.

Thus, Marketing and OR initially matured together at a rapid pace. As an illustrative example: Kotler removed more quantitative techniques from later editions of his *Marketing Management* textbook and coauthored another textbook devoted entirely to Marketing models (Lilien and Kotler 1983). At the same time, however, enthusiasm for using these methods declined because they did not always live up to the expectations of practitioners. The reason was a discrepancy between the reality of limited data and model complexity. In addition, managers sometimes had only a limited understanding of such methodologies.

The availability of market data (particularly scanner data) at a much broader scale changed the situation. We would like to emphasize at this point that researchers (e.g., Naert and Leeflang 1978; Parson and Schultz 1976)[2] established a link between Marketing and Econometrics. Econometrics (and multivariate Statistics) provided the necessary tools to extract meaningful and useful information from a magnitude of data. A prominent example of this is the research by Guadagni and Little (1983), which adapted an already existing model, the multinomial logit choice model, for an application in Marketing using scanner data. Since then, Marketing scholars have not strictly distinguished between methods borrowed from OR or Econometrics but refer to them as quantitative Marketing or "Marketing Science." The new edition of Lilien et al. (1992) was another comprehensive monograph at the intersection between Marketing, OR, and Econometrics.

It is worth mentioning that this academic progress was accompanied by changes in the organization of the field. The Harvard Institute of Basic Mathematics for Applications in Business first applied analytics to Marketing (Winer and Neslin 2014) which led to the founding of the Marketing Science Institute in 1961. That institute continues to play an important role in bridging the gap between Marketing in academia and in practice. In 1964, the first issue of the *Journal of Marketing Research* was published (complementing the *Journal of Marketing*), offering another top-tier journal to scholars in the field. In 1978, the first conference exclusively targeting quantitative researchers occurred at Stanford University. The first issue of *Marketing Science* was published in 1982. The Operations Research Society of America (ORSA) and The Institute of Management Science (TIMS) merged in 1995, forming the Institute for Operations Research and the Management Sciences (INFORMS). And in 2002, ISMS, the INFORMS Society of Marketing Science, was founded (see Winer and Neslin 2014, for further details).

At the beginning of the new millennium, several environmental forces changed the Marketing agenda dramatically, e.g., the high penetration of the internet and, later that of social media into the market; the plethora of data from different sources with different structures (cf. Fig. 1); the way of conducting omnichannel business and interacting with customers; and, the growth of computational power and storage capacity of electronic devices. Marketing research had to account for these changes and to do this, adapt its tools. In addition, concepts and methods from other disciplines, like Psychometrics and Computer Science, enhanced the field. This makes it more difficult to strictly distinguish between the interdisciplinary interaction of Marketing with OR and its interactions with other fields. However, this does not imply a lack of interaction but rather a different type of interaction. For example, Lilien and Rangaswamy (2004) stay within the framework of Marketing/OR but focus on certain problem-centered aspects of the field, e.g., targeting, segmentation, and positioning. The title of Lilien and Rangaswamy's textbook coins the term "Marketing engineering and analytics," which emphasizes the decision-making perspective.

[2] For many of the textbooks mentioned in this subsection, several editions (sometimes with other coauthors) have been published. For the sake of readability and space, we refrain from referring to these editions.

Lilien also set up the Marketing Practice Prize sponsored by ISMS in 2003. Applicants are expected to demonstrate that Marketing Science is applicable to a wide range of managerial problems in practice, using a diversity of analytical techniques, many of them borrowed from OR.

The recognition in economics that companies make profit-maximizing decisions (Dorfman and Steiner 1954), provided the impetus for the development of OR approaches towards optimal decision-making in such domains as advertising (Parsons and Bass 1971), sales force (Mantrala et al. 1994), direct Marketing (Bult and Wansbeek 1995), and online price customization (Zhang and Krishnamurthi 2004). Marketing scholars successfully applied OR methods developed decades ago, albeit sometimes under a different heading. As an illustrative example, what is nowadays called "qualitative comparative analysis" (e.g., Woodside, 2013) is based on fuzzy sets (e.g., Zadeh, 1965). Optimal decision-making was often derived from the application of OR methods formulated on top of econometric models of market behavior (see Zhang and Krishnamurthi 2004).

Finally, it has become common practice in business schools to hire incoming academics with specific quantitative expertise. In most cases, positions are not specifically designated as requiring expertise in OR, Statistics, or Econometrics, but in many cases, basic training in these areas offers advantages or may even be required. The steady influx of scholars with degrees in OR and other quantitative disciplines has further promoted the integration of these fields with Marketing and other disciplines, including OR, as these scholars have applied the analytical expertise from their domain to Marketing problems. Consequently, the degree of integration of Marketing and OR has reached a new level. Section 3 illustrates that integration using the recent literature and a sample of leading journals, focusing on methods that address market dynamics.

3 Recent OR literature on market dynamics

After reviewing some of the history of the Marketing/OR interface, we now provide a deeper insight into more recent research focusing on market dynamics. The goal is to identify recent trends and gaps in the literature, which helps us understand how the papers in this special issue contribute to the growing Marketing/OR literature on dynamic markets. For this purpose, we scanned the last decade of papers published in three leading OR journals: EJOR, OPRE, and ORSP. These journals are highly ranked (EJOR has an impact factor of 6.4, OPRE's impact factor is 3.9, and that of ORSP is 2.7) and are long-established core OR journals that have been outlets for Marketing-related research as well.[3]

[3] Certainly, more outlets are publishing research at the Marketing/OR interface, such as journals covering a broader range of research related to the theory and practice of management (e.g., *Management Science*), well-respected conference proceedings (e.g., the Operations Research Proceedings, see Grothe et al. 2023) or specific working groups (e.g., Euro Working Group on Retail Operations, Working group on Data Analysis and Classification in Marketing (GfKl e.V.)). However, we keep a narrow focus, only using OR journals and peer-reviewed research.

While we do not aim to provide a comprehensive literature review, we aim to highlight examples from the Marketing/OR interface, with a specific focus on dynamic markets from these three journals. In searching the journals, we used specific keywords (and combinations of them) related to types of data, methods, and topics, which allow us to categorize the recent literature using the framework outlined in Fig. 1. The resulting first list of papers was then examined more closely and further reduced to the papers summarized in Tables 2, 3, 4, and 5. While we tried to select papers that are prototypical for particular types of research, we acknowledge that there is some variation in the academic visibility and impact of the papers, as measured by the number of citations on Google Scholar (https://scholar.google.com/). While some papers have somewhat low numbers (e.g., Baumgartner et al. 2018 was cited less than ten times)—even when considering the relatively short time frame for the analysis of one decade—others are cited much more often than the impact factors of the respective journals would imply. In particular, papers related to ML methods and customer repurchasing behavior received an exceptionally high number of citations (e.g., De Caigny et al. 2018 has more than 400 citations, and Martínez et al. 2020 was cited almost 200 times). We see the high numbers as an indication that the topic of market dynamics at the Marketing/OR interface is highly relevant. Still, papers with lower citation counts highlight that not all sub-topics are equally popular. We hope this special issue and our framework not only help identify trends but also give a proper overview of the whole field of market dynamics.

The papers in Tables 2, 3, 4 and 5 span a range of different types of data and methods used for understanding dynamic markets and finding optimal solutions to Marketing problems. Several papers use *simulated data*, *numerical examples*, and *computational studies* to validate their approaches, find optimal solutions, or to further highlight specific properties of the models and results. These papers study topics such as dynamic pricing (e.g., Gönsch et al. 2018), advertising dynamics (e.g., Aravindakshan and Naik 2015), or production and inventory dynamics (e.g., Ketzenberg et al. 2022). A handful of papers use simulations to study the statistical properties of estimators or to benchmark proposed models against several alternative approaches (e.g., Guhl 2019; Sauré and Vielma 2019).

Various researchers *combine multiple types of data*. Some studies combine simulations with the analysis of market data for additional substantive insights (e.g., Boztuğ et al. 2014; Wang 2021). Aligning simulations with features of "real" data (e.g., size, structure, variables, amount of variation) enhances the credibility of the simulation results and their generalizability. Some papers use experimental data to augment readily available market data. For instance, Fikar et al. (2019) use a conjoint experiment to collect the relevant preference information as an input for their decision support system. Conjoint methods are popular data collection tools in both Marketing and OR research (Green and Srinivasan 1990). Several contributions to the literature over the last decade are related to the adaptive (i.e. dynamic) generation of questionnaires for optimal preference learning (e.g., Bertsimas and O'Hair 2013; Sauré and Vielma 2019). In quasi-experimental settings, MartínezdeAlbéniz and Belkaid (2020) exploit weather variation to study dynamics in footfall and sales for fashion retailers, and Chen et al. (2019) employ causal inference to identify social influences on product adoption.

Table 2 Overview of the selected papers in the *European Journal of Operational Research* (part 1)

Paper	Topic	Method	Data
Chen et al. (2019)	Social influence identification in social media for predicting new-product adoption, repeat buying and cross-selling	Learning-simulation coordinated method; 3 steps including treatment effect estimation (using ML), counterfactual simulations, and an adjustment strategy	High-dimensional Microblog database from Tencent Weibo, e.g., 73,209,277 historical records, demographics of 2,320,895 users
Chongwatpol (2015)	RFID-enabled tracking of visitors at trade exhibitions	Analysis of customer (customer profile, walking paths), sales, and inventory data using clustering and predictive modeling (ML methods)	Pilot experiment with customer profiles and walking paths of 140 attendees of a trade exhibition
Chou et al. (2021)	Customer repurchase prediction in an online retailing context	"Buy till you die" models (Beta-Geometric/Beta-Bernoulli) and different ML approaches (e.g., lasso and BG/BB (Beta-Geometric/Beta-Bernoulli) model), as well as combinations	1,250,587 transactions from 52,410 members of an online retailing service in Taiwan
De Caigny et al. (2018)	Customer churn prediction	Decision trees, logistic regression, and the logit leaf model	14 data sets from different industries; up to 602,575 observations and 303 features
Fikar et al. (2019)	Decision support system for e-grocery operations using product shelf-life data	Conjoint analysis and agent-based simulations	Survey data from 432 customers and extensive computational experiments
Guhl (2019)	Time-varying effects of price and promotion in a retailing context	Aggregated logit model, time-varying coefficients, heterogeneity, and price endogeneity, fitted with maximum simulated likelihood	4 canned-tuna brands and weekly store-level data for 337 weeks; simulated data of comparable size and structure
Ketzenberg et al. (2022)	Inventory data sharing in fresh food supply chains	Game theory model with the manufacturer as Stackelberg leader	Numerical analysis for sensitivity analyses

Table 3 Overview of the selected papers in the *European Journal of Operational Research* (part 2)

Paper	Topic	Method	Data
Liu et al. (2022)	Dynamic pricing strategies based on customers' patience times	A single-server queue system with homogeneous or heterogenous customers	Numerical simulations as validation and to highlight model features and results
Martínez et al. (2020)	Purchase predictions in a non-contractual setting	Various ML approaches (e.g., lasso or gradient-tree boosting) using high-dimensional and dynamic customer features	Monthly B2B transaction data of 10,136 customers from 125 countries; 192,470 orders from January 2009 to May 2015
MartínezdeAlbéniz and Belkaid (2020)	Visitor and sales forecasts for fashion goods during weather fluctuations (e.g., rain and temperature)	OLS regression with robust standard errors to adjust for heteroskedasticity and serial autocorrelation	Daily category sales and footfall data from 98 stores from 4 different European countries; detailed weather data
Salé et al. (2017)	Optimal introduction timing for new product generations (incl. pricing, production timing/quantities)	Integration of the Bass model for new product introductions and updates with the Wagner and Whitin dynamic lot-sizing model	Numerical experiments based on different parameter values, with a full factorial design including 65,536 combinations
Schlosser and Gönsch (2023)	Risk-averse dynamic pricing	Time-consistent mean-semivariance optimization; novel fixpoint-based Dynamic Programming approach)	Numerical analysis to demonstrate the applicability of the proposed approach
Tao et al. (2022)	Personalized dispatch in online-to-offline on-demand services	ML approaches (Boruta algorithm, Random Forest) for real-time delivery-speed prediction and capacity personalization of drivers	Order and delivery data from over 20 stores in Beijing from 14 July 2016 to 31 March 2019; about $\approx$ 1,800 orders per day

Table 4 Overview of the selected papers in *Operations Research*

Paper	Topic	Method	Data
Adelman and Uckun (2019)	Dynamic electricity pricing for smart homes	Price-load equilibrium in a large-scale market for smart appliances, with dynamic prices and customer responses	Several data sources for (sub-) model calibration (e.g., ComEd data, weather data) and policy analysis
Aravindakshan and Naik (2015)	Memory effects in pulsing advertising	Awareness formation model based on a delay differential equation	Numerical examples to illustrate shapes of optimal advertising policies
Bertsimas and O'Hair (2013)	Learning preferences in dynamic questionnaires	Robust and integer optimization in an adaptive conjoint analysis with conditional value at risk to address loss aversion	Data on recipe choice in an online dieting application
Bruce et al. (2022)	Optimal dynamic advertising for fashion products	Discrete-time dynamic system accounting for multiple styles of products and latent time-varying exclusivity; estimated using a Bayesian particle filter/smoother	Weekly sales, price, and advertising data for two styles of sunglasses and handbags from two brands (166 weeks, 2016–2019)
Gallino et al. (2023)	Effect of in-process delays in online services	Threshold regression models to estimate non-linear effects of website loading times; generalized Synthetic Control approach with elastic net for measuring (persistent) causal effects of website performance shocks	Novel data on website speed and sales of online retailers (apparel and personal hygiene)
Musalem et al. (2023)	Agent retention and waiting times in a call center for car insurance	Discrete choice models with flexible specification of waiting time variables	Data regarding the date and time of each quote, the acquisition channel, the customers, and car features
Sauré and Vielma (2019)	Dynamic questionnaires for adaptive choice-based conjoint analysis	Discrete choice model (mixed-logit model) and the ellipsoidal method for questionnaire updating	Several simulation experiments with 100 respondents and varying response accuracy and heterogeneity
Wang (2021)	Consumer choice, assortment planning, and pricing with market expansion	Discrete choice (multinomial logit model) and Poisson model; joint estimation using the alternating-optimization expectation-maximization method	50 weeks of store-level panel data (soft drinks); extensive numerical experiments to evaluate the performance of the approaches

Table 5 Overview of the selected papers in *OR Spectrum*

Paper	Topic	Method	Data
Baumgartner et al. (2018)	Time-varying effects of (internal) reference price, loss aversion and customer loyalty in a retailing context	Semi-parametric extension (P-splines) of discrete choice models to capture time-varying effects; restricted maximum likelihood estimation	Household panel data (32,468 purchases from 4,183 households over 53 weeks, 5 brands, ground coffee)
Boztuğ et al. (2014)	Price thresholds, (internal) reference price, and loss aversion in a retailing context	Semi-parametric extension (general additive model) of discrete choice models to capture flexible price effects; two-stage estimation	Household panel data (3,647 purchases from 876 households over 104 weeks, 7 brands, daily care products); simulated data of comparable size
Gönsch et al. (2018)	Dynamic pricing under risk aversion in markets where firms sell a single unit of capacity (e.g., real estate market)	Dynamic model with a risk-averse seller to optimize the conditional value-at-risk in a dynamic pricing environment	Extensive numerical study to validate and evaluate the proposed approaches for solving the dynamic optimization problem
Khare et al. (2020)	Predicting gasoline shortages during disasters using social media data	Combination of support-vector-machines, as well as ARIMA and Poisson regressions	Empirical data with about one million tweets from Florida during the onset and post-landfall of hurricane Irma
Klein et al. (2018)	Dynamic pricing for attended home delivery/online retailing	Approximation approach based on mixed-integer Linear Programming that is integrated into a dynamic pricing framework	Computational study to evaluate the proposed approach; 1,000 potential customers in a delivery region as a grid with a width and length of 10 km
Köhler et al. (2023)	Dynamic customer acceptance and vehicle routing for attended home delivery/online retailing	Sampling-based customer acceptance approach	Empirical data (i.e. historical) order data from two German cities served by an online grocery retailer

Causality is not often mentioned explicitly, but several papers use instrumental variables to address (price) endogeneity (e.g., Guhl 2019) or discuss endogeneity concerns (e.g., Musalem et al. 2023).

Most empirical applications in Tables 2–5 use *well-structured tabular data*. In particular, papers relating to (online) retail operations often utilize store-level or individual-level panel data to study reference price effects (e.g., Boztuğ et al. 2014), time-varying Marketing mix effects (e.g., Baumgartner et al. 2018; Guhl 2019), market expansion (e.g., Wang 2021), customer churn (e.g., De Caigny et al., 2018), or predictions of re-purchasing behavior in contractual settings (e.g., Chou et al. 2021; Martínez et al. 2020). While many use statistical/econometric methods (e.g., discrete choice models and classical or Bayesian estimation), there is an increasing trend toward the use of ML approaches, which have enabled researchers to handle growing data volumes and complexity (e.g., Chou et al. 2021; De Caigny et al. 2018).

Several papers use more or less *unstructured data* as an input for their research on dynamic topics. For instance, social media data, specifically millions of posts ("tweets"), have been shown to help predict gasoline shortages (Khare et al. 2020). Customers' high-dimensional real-time radio-frequency identification (RFID) position information has been used to support firms at trade show exhibitions (e.g., Chongwatpol 2015) and retailers with smart stores (e.g., Hauser et al. 2020). Blogging information has shed light on dynamic social influences on customer behavior, such as product adoption or repurchasing (e.g., Chen et al. 2019).

The selected papers allow us to identify commonalities, differences, and novel connections between the fields of Marketing and OR. Furthermore, the summary reveals the following *seven critical trends and gaps in the literature*.

First, while the papers in this review were selected based on whether they addressed market dynamics, most topics in Tables 2, 3,4 and 5 also align well with a wide range of popular and trending methodological themes at the Marketing/OR interface in general: choice modeling (e.g., Guhl et al. 2018; Kalouptsidis and Psaraki 2010; Méndez-Vogel et al. 2023; Morrow and Skerlos 2011; Pancras 2011; Silberhorn et al. 2008; Van Ryzin and Vulcano 2017), discrete choice experiments and preference measurement (e.g., Díaz et al. 2023; Falke and Hruschka 2017; Gensler et al. 2012; Hein et al. 2022; Kaluza et al. 2023; Maldonado et al. 2015; Paetz and Steiner 2017), causal inference (e.g., Cousineau et al. 2023; Gubela et al. 2020; Haupt and Lessmann 2021), and revenue management (e.g., Gönsch 2017; Strauss et al. 2018). Substantive themes that are covered include product line optimization (e.g., Bechler et al. 2021; Bertsimas and Mišić 2019), supply chain and assortment optimization (e.g., Roemer et al. 2023; Rusmevichientong et al. 2010), optimal pricing and advertising (e.g., Broder and Rusmevichientong 2012; Cataldo and Ferrer 2017; Karray and Martín-Herrán 2009; Krishnamoorthy et al. 2010; Su 2010; Schön 2010), direct Marketing and recommender systems (e.g., Aydin and Ziya 2009; Bose and Chen 2009; Gabel and Guhl 2022; Hruschka 2010; Jagabathula et al. 2018; Schröder and Hruschka 2016; Scholz et al. 2017). Thus, market dynamics are often not addressed in a monolithic fashion but rather are seen as an integral component of a wide range of substantive and methodological challenges and opportunities. These topics are classical substantive and methodological topics, and the use of trending AI/ML methods seems as yet underrepresented; there are also differences in the journals' tastes in publishing these developments.

Second, the need for causal inferences has spawned an entire domain of research, initially in Statistics and Economics (Pearl 2009), but increasingly embraced by Marketing and OR in the last decade. While still somewhat underrepresented in the OR journals, there are several examples at the Marketing/OR interface (e.g., Bokelmann and Lessmann 2024; Cousineau et al. 2023; Gubela et al. 2020; Haupt and Lessmann 2021). There is untapped potential in dynamic markets, where digital environments enable efficient experimentation for research on bandits (e.g., Rusmevichientong et al. 2010) and reinforcement learning (e.g., Kallus and Uehara 2022). Even with market data, quasi-experimental methods allow researchers, using explicit assumptions, to make causal statements about the effects of policy interventions (see, e.g., Gallino et al. 2023). This is crucial for firms conducting online business and with ongoing customer relationships (e.g., online retailers, streaming platforms, and apps), and a steady stream of research addresses the needs of companies in this regard. Researchers already collaborate with companies to design and analyze field experiments to assess the causal effects of Marketing interventions (Gordon et al. 2019, 2023) and develop approaches for doing so in a way that has a direct impact on Marketing practice (Malodia et al. 2023). And this is a trend that will no doubt gain in frequency in the future. Addressing Marketing dynamics in methods such as Difference-in-Differences, Double Machine Learning, Control Function Approaches, Synthetic Control Methods, and Regression Discontinuity Designs is one of the ongoing challenges (Imbens 2024; Papies et al. 2023).

Third, several papers use modern ML methods to handle large datasets (i.e. many observations or many variables) or address complex (non-linear) relationships between variables (e.g., Blumenstock et al. 2022; Chou et al. 2021; De Caigny et al. 2018; Martínez et al. 2020; Mena et al. 2023). As ML and Deep Learning methods continue to be developed and improved in Computer Science, this trend is likely to continue and (partially) replace traditional statistical or econometric methods in various domains, especially those where prediction is of paramount importance (e.g., Gabel et al. 2019; Hruschka 2014). The explainability of calibrated ML models is crucial, especially in the field of Marketing (Rai 2020), which poses a number of challenges and remains a very active domain of current and future research (De Bock et al. 2023). Future research is also likely to apply ML and AI to unstructured data for tasks like feature extraction, text, image, or video analysis, and as an aid in finding new solutions to high-dimensional optimization problems. While relatively little research has been devoted to the application of Generative AI (text, image, and video generation using ChatGPT, Dall-E, etc.), given the potential of these methods and their societal impact, that gap in the literature is expected to be addressed soon.

Fourth, retailing or retail operations are a substantial area of interest for research in Marketing and OR (Hübner et al. 2018). An ongoing stream of research, which has a long tradition in Marketing and OR (see Sect. 2), leverages retailer data (at the aggregate level via checkout systems or at the individual/household level via loyalty cards) to fit demand models (e.g., Baumgartner et al. 2018; Hruschka et al. 2002; Lang et al. 2015; Weber et al. 2017; Weber and Steiner 2021; Wensing et al. 2018).

This has allowed researchers to analyze the impact of the Marketing mix (e.g., price, product, promotion, place) on consumer behavior. This stream of research has been supported by several scanner data sets made publicly available by the retailing industry. As mentioned in Sect. 2, historically, the availability of well-structured market data has greatly contributed to this trend. Notably, the field of OR has focused on optimizing prices, products, advertising, and assortments and enhancing overall supply-chain efficiency, including product delivery (e.g., Klein et al. 2018; Köhler et al. 2023). The increasing volume of retailing data, especially from online and multi-channel retailers and facilitated by advances in tracking technology, is expected to sustain interest in this area. Bayesian methods, particularly those addressing consumer heterogeneity and data uncertainty, have become a mainstay for research in this domain, and are likely to remain widespread in the future, driven by ongoing improvements in algorithms and computing tools for better scalability (e.g., Stan and Hamiltonian Monte Carlo, or variational inference; Carpenter et al. 2017; Jacobs et al. 2021). Rather than a continued focus on models and algorithms, we see a trend towards the use of this type of data and existing methodologies to address various substantive problems in retailing. These include multi-channel retailing (Zhang et al. 2010), the customer journey (Lemon and Verhoef 2016), attribution, and sustainability (Vadakkepatt et al. 2021), while addressing market dynamics across broad ranges of brands, products, categories and assortments.

Fifth, digitalization, including online retail, smart stores, and new communication channels in virtual and augmented reality settings (Wedel et al. 2020), offers firms more opportunities to engage with and learn from consumers, through real-time analytics, e.g., via AI and chatbots (Ramesh and Chawla 2022). These trends often involve personalization and recommendations, including personalized promotions (Gabel and Guhl 2022; Zhang and Wedel 2009), and often require dynamic, optimized designs for online learning, which has been applied to website morphing (Hauser et al. 2014), adaptive conjoint designs (Sablotny-Wackershauser et al. 2024; Sauré and Vielma 2019), and adaptive personalization of music (Chung et al. 2009), amongst others. However, new forms of data and the ability to track consumers in space and time also raise concerns about data privacy, competition, and consumer trust in handling sensitive information (e.g., Bimpikis et al. 2023; Schrage et al. 2020; Tucker 2014). Research in Marketing and OR is expected to further provide governments and firms with insights into privacy policies (see, e.g., Johnson et al. 2023; Lin 2022).

Sixth, both Marketing and OR recognize consumer behavioral biases (i.e. not assuming the (full) rationality of decision-makers, see, e.g., DellaVigna, 2009; Dowling et al., 2019). Marketing scholars have analyzed reference-dependent utility, time-inconsistent preferences, and social preferences extensively (e.g., Jindal 2015; Jung et al. 2017; Milkman et al. 2009). While much of that research has taken a consumer psychology perspective and has been tested in lab experiments, quantitative researchers have made major strides in including bounded rational behavior in their models (e.g., Stüttgen et al. 2012; Yang et al. 2015; Yegoryan et al. 2020). This work has revealed that these improvements may result in the predictive and explanatory power of models that incorporate bounded rationality. OR research has similarly addressed such "biases," including reference prices, loss aversion, and risk aversion (e.g., Bertsimas and O'Hair 2013; Gönsch et al. 2018; Popescu and Wu 2007; Schlosser and Gönsch 2023), as well as non-standard decision-making processes in the form of lexicographic choice and elimination by aspects rule (e.g., Gilbride and Allenby 2004, 2006; Kohli and Jedidi 2017; Kohli et al. 2019; Maldonado et al. 2015). In many cases, such model formulations and optimization procedures require the recognition of dynamics in consumer decision-making. Both Marketing and OR are expected to develop further in response to the challenges posed by incorporating bounded rationality and rational inattention (Sims 2003) into assessing and optimizing the effectiveness of the Marketing mix (e.g., Boyacı and Akçay 2018; Joo 2023).

Seventh, research focusing on sustainability in both Marketing and OR shows strong growth, stimulated by widespread concerns over climate change, air and plastic pollution, deforestation, biodiversity loss, food waste, fast fashion, and other environmental problems. OR explores sustainable manufacturing, waste reduction, and energy-saving, aiming to enhance efficiency and reduce costs (e.g., Beullens and Ghhiami 2022; Saharidis 2017; Tirkolaee et al. 2023). Marketing emphasizes the consumer's willingness to pay for sustainable products (e.g., Gomes et al. 2023; Paetz and Guhl 2017; Vecchio and Annunziata 2015), various retail policies (Vadakkepatt et al. 2021), and even addresses degrowth (Lloveras et al. 2022). Future research is expected to integrate the supply and demand sides holistically. Smart devices at home (e.g., smart meters) enable consumers to understand and adapt their behavior to the prevailing situation, providing firms with opportunities for dynamic pricing, not only to conserve energy (Adelman and Uckun 2019; Bollinger and Hartmann 2019) but also to mitigate problems of food waste (Vadakkepatt et al. 2021). Sustainability is an area with widespread implications for Marketing and OR, and research into its antecedents and consequences has many facets of dynamics and adaptation that are likely to generate research well into the future.

We identify these seven areas of research as domains where, in the next five to ten years, much progress can be achieved by combining the power of Marketing methods to explain and predict market dynamics with the capabilities of OR methods to find optimal solutions to supply chain and Marketing mix allocation problems. The papers in the special issue may provide impetus for that future work, as explained in the next section.

4 Papers in the special issue

All the papers submitted underwent an initial screening to assess their alignment with the topic of this special issue (i.e. "dynamic markets"). Upon unanimous agreement among guest editors to include a paper in the regular reviewing process for *OR Spectrum*, we appointed two or more reviewers from the fields of Marketing *and* OR. Despite the original submission deadline being set for the end of 2021, we commenced the reviewing process after publishing the call-for-papers at the end of summer in 2020. Recognizing the value of a diverse set of contributions, we extended the submission deadline to the end of March 2022. This process explains the varying publication dates of the papers in this special issue. The six papers accepted

Table 6 Overview of papers in this special issue

Paper	Topic	Method	Data
Aschersleben and Steiner (2024)	Non-parametric and heterogeneous price effects and dynamic pricing in a retailing context	P-splines in a Hierarchical Bayes framework	Weekly store-level data for eight juice brands over 87 weeks from 81 stores (54,260 observations)
Baier and Voekler (2023)	Product-line design using one-stage heuristics, relevant for dynamic markets	Several approaches (e.g., Ant Colony Optimization, Genetic Algorithms, Particle Swarm Optimization, Simulated Annealing) are applied to 78 small- to large-size product-line design problems	Extensive numerical study using simulated product-line design problems based on commercial conjoint analysis
Hruschka et al. (2022)	The effect of dynamic variables based on purchase histories on category choice in a retailing context	Multivariate logit models, including dynamic variables (loyalty and inter-purchase times at the category level) and heterogeneity (finite-mixture); maximum pseudo-likelihood estimation	Market basket data from 1,500 households with 24,047 shopping trips buying grocery products from 31 categories (e.g., milk, coffee, toilet tissue)
Wamsler et al. (2023)	Dynamic in-store targeting	Bayesian category-level inter-purchase-time model using share-of-transactions	Transaction data from 3,335 loyalty program members of a European grocery retail chain with 149 stores
Weinmayer et al. (2023)	Corporate sustainability performance and its dynamic effect on advertising efficiency	Multi-directional efficiency analysis for obtaining firm-level advertising efficiency scores; Hierarchical regression for analyzing the relationship between advertising efficiency and corporate sustainable behavior	10 years of annual data for 195 firms from 5 industries; Compustat for firm-level financial data and data from Sustainalytics for ESG (environmental, social, and governance) scores
Yang and Wu (2022)	The effect of switching costs and competition in a dynamic duopoly	Discrete choice model and Dynamic Programming	Numerical simulations using estimates from published research

use structured, experimental, and simulated data and employ a wide range of analytical methods, addressing different topics that are highly relevant to dynamic markets. Table 6 briefly summarizes the papers, using the same structure and format as Tables 2, 3, 4 and 5. Next, we present each paper in greater detail.

Aschersleben and Steiner (2024) fit dynamic sales response data using a Hierarchical Bayesian P-Splines model that incorporates lagged prices and time-dependent covariates and which accommodates heterogeneity across stores. The model is calibrated using store-level scanner data from eight brands, in 81 stores, over 74 weeks or more. Optimal dynamic price paths are derived for each store using a discrete Dynamic Programming algorithm that mitigates boundary price solutions. The results show that the prices derived from the proposed dynamic approach yield higher-than-expected profits than those derived from several benchmark models that do not accommodate heterogeneity or dynamics. This paper exemplifies the ongoing trend of leveraging well-structured retailer data and Bayesian methods. The combination of empirical analysis with (dynamic) optimization underscores the importance of combining methods at the Marketing/OR interface and the implications that this may have for Marketing practice, in this case, dynamic pricing. Such dynamic pricing problems may arise in many other contexts, such as energy reduction in smart homes and food waste reduction in retailing.

Baier and Voekler (2023) address the product-line design problem, a classical topic at the Marketing/OR interface (Bertsimas and Mišić 2019; Steiner 2010). This problem remains highly relevant in practice, especially in dynamic and complex markets with changing consumer preferences and many products and features. Choosing attribute levels (e.g., flavors, ingredients, tastes) for a product line involves customer choice behavior modeled by either a first-choice or a probabilistic choice model, often estimated from (marketing-based) conjoint data. The purpose of the optimization is to maximize expected overall buyers' welfare, expected revenue, market share, and/or profits. Given the NP-hard nature of the product-line design problem, various heuristics have been developed over the decades (involving either one or two stages), catering to the typically large scales of these problems encountered in practice. The authors conduct a large-scale numerical experiment, testing different heuristics, including one-stage heuristics such as Ant Colony Optimization, Genetic Algorithms, Particle Swarm Optimization, and Simulated Annealing across 78 small- to large-size product-line design problems, generated according to a large sample of commercial conjoint analyses. The results are promising, with the newly introduced heuristics outperforming established ones. Such an extensive evaluation of algorithms is important as it provides clear directions for future research, pointing to a limited set of algorithms that can be subject to further improvements.

Hruschka (2022) uses multivariate logit models to analyze multicategory choice in a retailing context. The models are extended with dynamic variables based on individual-level purchase histories for each category, incorporating category loyalty and time since the last purchase from the category. Including dynamic variables improves in- and out-of-sample model fit, affecting substantive insights regarding the effectiveness of Marketing mix variables and category interdependencies. Notably, multicategory models lacking dynamic variables tend to overestimate the effects of Marketing mix variables on the purchase probability. This paper showcases ongoing research at the Marketing/OR interface, employing both econometric and ML tools to analyze well-structured data—a crucial focus for retailers in dynamic markets (aee, e.g., Boztuğ and Reutterer 2008; Gabel and Timoshenko 2022; Hruschka 2014; Jacobs et al. 2021). This research has important implications for Marketing practice, as it shows that overpromotion, a common problem for retailers, may arise from not sufficiently recognizing dynamics in the data. It sets the scene for future research that may address challenges for brick-and-mortar retailers operating in dynamic markets.

Wamsler et al. (2023) present a novel approach for personalized promotions in offline retailing, specifically targeting "live" promotions through in-store kiosk systems. The authors develop a targeting methodology recommending category-level discounts based on customers' inter-purchase times and an estimate of outside potential, introduced as the "share-of-transactions." Empirical comparisons with a recency, frequency, and monetary-value-based benchmark using loyalty-program and observational data reveal significant improvements in revenues, redemption rates, and frequency of purchasing. The paper utilizes a Bayesian category-level inter-purchase-time model, which addresses a critical incomplete data challenge for retailers, which is that information from their stores is available but not from competitors. Their Bayesian approach, augmented with real-time dynamic variables, aligns well with current Marketing/OR interface trends regarding digitalization, personalization, missing information, and turbulent markets. It is important because it addresses the issue of the effectiveness of offline promotions and points to the role redemption rates (Zhang and Wedel 2009). It sets the scene for future research at the Marketing/OR interface that seeks to improve personalization not only online but also in brick-and-mortar stores.

Weinmayer et al. (2023) study the dynamic impact of firms' environmental, social, and governance performance on their advertising efficiency. They use a two-step procedure scrutinizing ten years of data from almost 200 US firms across five industry sectors. The first step employs a multi-directional efficiency analysis to determine relative firm-level advertising efficiency scores. The second step involves a time-fixed effects panel regression and a three-level regression to investigate the impact of environmental, social, and governance activities on advertising efficiency. Their extensive analysis reveals the nuanced impact of corporate sustainability performance on advertising efficiency, showcasing variations across both time and industry sectors. The authors underscore the significance of consumer expectations in shaping this intricate relationship. This paper is an exemplary contribution to sustainability-focused research at the Marketing/OR interface, demonstrating the role played by advanced modeling techniques in teasing out the intricate effects of sustainability efforts on Marketing mix effectiveness. This paper thus aligns seamlessly with the trend identified and highlighted in the preceding subsection and may lead to further research on sustainability.

Yang and Wu (2022) examine the market dynamics between two firms in the presence of consumer switching costs. Switching costs are a crucial factor in dynamic markets. This research aligns with the trend towards service and platform business models. Using a dynamic game framework and a discrete choice model, the study considers switching costs related to customer transitions or product incompatibility.

The authors validate their findings with a simulation study, revealing that the impact of switching costs depends on a firm's market position. Larger firms benefit more, while smaller firms are motivated to reduce switching costs. While recognizing state dependence in consumer behavior has a history in Marketing and Economics (e.g., Keane 1997), optimizing the Marketing mix under these dynamics poses challenges (e.g., Dubé et al. 2009). Thus, applying OR tools to derive optimal solutions for firms in this context is a valuable contribution. This research also exemplifies the role that game theory has to play in addressing complex strategic Marketing problems and highlights the use of multi-method approaches to these problems.

In summary, the papers in this special issue exemplify research incorporating various elements of our proposed framework, employing innovative Marketing data, multiple data sources, and modern methods from different disciplines, including OR, Statistics, Econometrics, and Computer Science. Their collective objective is to enhance our understanding of market dynamics and shifts, and their consequences for the behavior of firms. Importantly, these papers address diverse forms of market dynamics in various research domains at the intersection between Marketing and OR.

5 Conclusion, discussion, and future outlook

In the face of turbulent dynamics and market shifts caused by natural, social, and technological changes, this special issue focuses on novel Marketing data and modern methodologies from OR, Statistics, Econometrics, and/or Computer Science that help companies respond to these market dynamics more efficiently. Future research building on the work presented in this special issue may incorporate models and methods that account for dynamics (e.g., dynamic linear models, vector autoregression, or hidden Markov models) and market shifts (e.g., regime-switching models), uncertainty (e.g., Bayesian learning, dynamic discrete choice models, Dynamic Programming), as well as heterogeneity (e.g., Bayesian hierarchical modeling). These will combine with methods from OR (e.g., Linear Programming, Optimization, Simulation, Greedy algorithms, Game theory) that enable one to derive optimal solutions to difficult problems such as dynamic pricing, the personalization of promotions, and product-line design. In addition, developments in AI/ML, particularly such methods as Random Forests, Topic modeling, and Deep Learning, have begun to realize their potential in large-scale prediction and optimization problems in Marketing and other fields of business. This special issue presents research that involves large-scale applications directly relevant to business practice in various industries.

The six articles in this special issue display the wide range of data, methods, and applications of the Marketing/OR interface, showcasing a representative sample of research on market dynamics at the Marketing/OR interface. However, our review of the history and literature highlights that the fields of Marketing and OR, after an initial period of convergence, seem to be currently diverging rather than converging. The cross-citation counts in Table 1 support this conclusion. Nonetheless, methods from OR (e.g., Linear Programming) have become part of the standard toolkit of Marketing researchers, and researchers in OR commonly use methods developed in

Marketing (e.g., choice modeling and conjoint analysis), which may not show up in cross-citation data. At the same time, there is a common growing trend towards using ML/AI methods, causal inference, and unstructured data in both academic fields, which may result in convergence between the fields in terms of methodology. Part of the reason for a divergence may be the increasing level of specialization in both fields. While cross-discipline citation occurs, there are ample opportunities to further strengthen this connection: researchers in Marketing could benefit from more recent developments in the use of, for example, AI in optimization and simulation, while those in OR could benefit from the latest developments in choice modeling, conjoint design and analysis, and the use of large unstructured data sets now commonly available in (digital) Marketing. An undesirable potential for further divergence of the two fields underlines the importance of the current special issue at the Marketing/OR interface. We hope that the articles in this special issue stimulate researchers to take a fresh look at the large value offered by integrating or combining methods from Marketing and OR, especially in the context of market dynamics. Both fields (i.e. Marketing and OR) are able to contribute extensively to understanding or steering firm behavior in the face of market turbulence. However, as the articles in the special issue show, combining these methods yields many additional benefits. As the level of specialization in both fields increases, an efficient route to realizing these benefits is for researchers from both fields to collaborate. Common trends at the Marketing/OR interface regarding the use of ML/AI methods, causal inference, and large amounts of available (unstructured) data can serve as a catalyst for further cross-fertilization and collaboration. Such collaboration has the potential to yield both profound insights into market dynamics and prescriptions for the optimal behavior of firms in the face of such dynamics. In addition, for both researchers from Marketing and OR, it would provide opportunities for new research directions and to tackle some of the main challenges currently faced by consumers, firms, and society as a whole.

Acknowledgements We would like to extend our profound thanks to the current Editor-in-Chief, Guido Voigt, and the former Editor-in-Chief, Rainer Kolisch, for allowing us to guest-edit this special issue. We also thank the various diligent reviewers whose valuable insights helped us select the papers. Furthermore, we acknowledge the insights provided by stimulating discussions and constructive feedback received during conferences and workshops. Special thanks are extended to the organizers of EMAC 2021 and DSSV-ECDA 2021 for allowing us to coordinate special sessions related to this special issue, including invited talks from Norris Bruce, Sahar Hemmati, and Robert Rooderkerk. We also benefited from the comments by Jochen Gönsch, Harald Hruschka, Stefan Lessmann, Anna Schulz, and Narine Yegoryan. Maria Lord helped with the copy editing of this paper. Daniel Guhl gratefully acknowledges the financial support from the German Research Foundation (DFG) through CRC TRR 190 (Project Number 280092119). All authors contributed equally to the project.

Funding Open Access funding enabled and organized by Projekt DEAL.

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