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Informational Challenges in Omnichannel Marketing: Remedies and Future Research

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Abstract

Omnichannel marketing is often viewed as the panacea for one-to-one marketing, but this strategic path is mired with obstacles. This article investigates three challenges in realizing the full potential of omnichannel marketing: (1) data access and integration, (2) marketing attribution, and (3) consumer privacy protection. While these challenges predate omnichannel marketing, they are exacerbated in a digital omnichannel environment. This article argues that advances in machine learning and blockchain offer some promising solutions. In turn, these technologies present new challenges and opportunities for firms, which warrant further academic research. The authors identify both recent developments in practice and promising avenues for future research.

Keywords

Despite the prevalence of new advertising and promotional channels and significant investments in data and technology, marketers are still struggling to generate and to prove sales results in an increasingly omnichannel world.

—Eric Solomon, Senior Vice President, Nielsen (Nielsen 2018)

Channels have traditionally been viewed as intermediaries that facilitate distribution and transfer of products from manufacturers to their customers.[1] Prior to the commercialization of the internet and subsequent digitization innovations, firms usually

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[1] Peterson et al. (1997, p. 334) identify three types of channel intermediaries: distribution channels, transactional channels, and communication channels. The distribution function is rooted in realizing efficiency (Stern et al. 1996) and often involves functions such as sorting, inventory holding, assortment management, and so on. Transaction channels "facilitate economic exchanges between buyers and sellers," while communication channels inform buyers about "the availability and features of the seller's product or service." Unless stated otherwise, in this article, we assume that channels serve all three intermediation functions.

employed one type of channel such as a physical store, a call center, or a catalog. However, there were also instances where firms employed multiple channels to serve their customers. For example, firms such as L.L. Bean, Sears, and Lands' End sold their products in brick-and-mortar stores, in catalogs, and by phone. This practice gave birth to the idea of multichannel marketing. Subsequently, the idea of multichannel marketing moved beyond product fulfillment to include a whole gamut of interactions between a firm and its customers. Neslin et al. (2006, p. 96) define multichannel marketing as the "design, deployment, coordination, and evaluation of the channels to enhance customer value through effective customer acquisition, retention, and development." Therefore, in a multichannel context, although customers may interact with the firm across multiple channels before a conversion occurs, the firm's focus is on managing and optimizing the performance of each channel separately.

The presence of multiple channels can alter how customers gather product information (e.g., Ansari, Mela, and Neslin 2008; Van Nierop et al. 2011) and where they purchase these products (Pauwels et al. 2011). In addition, a portfolio of channels allows customers to self-select into their preferred channel at each stage of the purchase journey (Bell, Gallino, and Moreno 2018; Vinhas and Anderson 2005), thereby allowing the firm to access a larger base of customers. Furthermore, when an online retailer expands into offline channels, the firm may also see some benefits of complementarity (e.g., Avery et al. 2012; Liang et al. 2019). As a result, operating additional channels might result in customers increasing their purchases (Li et al. 2015).

With continuing growth in digitization, consumers today interact with firms across online, mobile, and offline media channels. This, in turn, has led to a shift toward "omnichannel" marketing, which emphasizes a unified consumer experience rather than just facilitating transactions. Furthermore, as Teixeira and Piechota's (2019) study indicates, the growing popularity of omnichannel marketing has been fueled by the idea that the different stages of the customer journey can be decoupled and delivered by various entities. In effect, for firms, omnichannel marketing entails managing a combination of different types of channels such that they align well with the way their customers search, purchase, and consume their products and share those experiences (Ailawadi and Farris 2017).

Verhoef et al. (2015, p. 176) define omnichannel as the "synergetic management of the numerous available channels and customer touchpoints, in such a way that the customer experience across channels and the performance over channels is optimized." In the ideal scenario, customers interact seamlessly with the firm across channels both internal and external to the firm, and the firm has full information on all customer touchpoints to provide a single unified experience across channels.

However, this ideal faces several important hurdles in reality. As retailers adopt omnichannel marketing, it presents its own set of challenges and opportunities for the suppliers and other distribution channel partners. Ailawadi and Farris (2017, p. 120) note that omnichannel marketing "often encompasses

not just the channels of distribution through which a supplier's products reach the consumer but also the channels of communication—owned, paid, and earned."

As we see it, this important observation made in Ailawadi and Farris (2017) does not fit within the scope of Verhoef et al.'s (2015) definition of omnichannel marketing. We broaden the scope of previous definitions and define omnichannel marketing as the synergistic management of all customer touchpoints and channels both internal and external to the firm to ensure that the customer experience across channels as well as firm-side marketing activity, including marketing-mix and marketing communication (owned, paid, and earned), is optimized for *both* firms and their customers. Thus, whereas Verhoef et al. (2015) emphasize experience over transactions and Ailawadi and Farris (2017) emphasize communications over sales, our view of omnichannel marketing considers sales, experience, and communications. Note that the synergistic management of touchpoints and experiences might affect important outcomes for firms, such as market share, profits, and customer lifetime value (Ascarza, Fader, and Hardie 2017). The exact objective function is likely to vary across firms and its and customers' life cycle.

Given its promise, it is not surprising that firms have invested heavily in omnichannel marketing. The transformation to omnichannel marketing has gained prominence in a wide range of industries, including consumer packaged goods such as Unilever, fashion retailers such as Bonobos, service providers such as Bank of America, restaurants such as Starbucks, and pharmacies such as Walgreens. However, firms also need to consider the cost of implementing customer integration (for details, see Coughlan [2011] and Gustafson [2017]). In the end, firms have to assess whether additional costs are commensurate with the expected benefits of undertaking omnichannel marketing. Our treatment of omnichannel marketing in this article focuses more on the customer side and the ensuing impact on revenues rather than on the supply-side costs that firms may incur in achieving such integration.

Despite the promise of omnichannel marketing to manage how firms interact with their customers to drive growth, foster innovation, and improve long-term performance, we posit that this potential has not been fully realized. In our view, there are three main interrelated challenges that have prevented omnichannel marketing from realizing its full potential:

1. **Data Challenges:** To fully realize the potential of omnichannel marketing, firms need information on all their interactions with each customer during the different stages of the customer journey. We include consideration of the communications between the firm and its customers, activities where the customers interact with the firm (or its partners) while gathering information, making a purchase, receiving the product, making a return, and receiving postpurchase service. Such data might not be readily available or easily usable.

Table 1. Data-Related Challenges, Remedies, and Future Research.

Data Challenges	Data Remedies	Future Data Research
Gain Data Access		
1. Within the firm, information on various contact points by the same customer resides in silos.	1. Deploy federated learning to construct joint machine-learning model while keeping parties' servers' training data private.	1. Which machine learning methods are optimal and generalizable to impute missing pieces of information?
2. Many customer touchpoints not owned by firm.	2. Track customers on third parties: walled garden platforms, legacy media agencies, or syndicated providers.	2. What is the optimal means to collate information from different parties spanning different touchpoints?
Aggregate Data Across Sources		
3. Different databases use different rules, data formats, and reporting standards.	3. Deploy probabilistic tracking when information from different databases cannot be clearly combined.	3. What is the impact of data sharing and probabilistic tracking on consumers (price), firms, and policy makers (welfare)?
4. Data sources differ in reliability.	4. Use permissioned blockchains to allow firms to control who can see data and validate transactions.	4a. How can firms incentivize internal and external partners to participate in blockchains?
		4b. Do blockchain-enabled omnichannel marketing efforts increase or soften competition?

2. **Marketing Attribution Challenges:** For optimizing the customer experience across all channels, firms need to know the impact of various touchpoints on behavior and measure the return on investment of its marketing spend. In our opening quote from Eric Solomon, this is captured as "prove sales results." Such analysis may be challenging when the effect of a touchpoint can transcend multiple stages in the purchase funnel, when several occur concurrently, or when consumers go back and forth between different stages in their path-to-purchase journey.

3. **Customer Privacy Challenges:** The promise of omnichannel marketing relies on using data on all the interactions between the firm and its customers. However, this can come at the cost of infringing on customer privacy. Therefore, an important challenge for a firm is determining how to embrace an omnichannel strategy while respecting consumers' privacy.

Each section of this article elaborates on these challenges and discusses recent attempts to address them. We then propose promising avenues for future research in these areas.

Challenge #1: Data

Firms such as REI carefully plan for their customer experience to be unified across all touchpoints. While REI has a large physical footprint, it is mobile-centric and encourages its customers to use the app. For instance, if a customer clicks on a product in an email from REI and installs the mobile application, the app will note which nearest store has the product in stock. In addition, when customers visit a store, they are strongly encouraged to join the store Wi-Fi, log into the app, and check product availability. Disney and Bank of America are examples of other companies that have carefully integrated the customer experience across different channels (Fontanella 2020).

Data Challenges in Omnichannel Marketing

One of the main challenges that a firm might face in realizing the full potential of omnichannel marketing pertains to availability and usability of such data from various touchpoints. We can broadly classify such data-related challenges along two key dimensions: (1) gaining access to these data and (2) integrating these data from different sources. We elaborate on these points in the following subsections. The first column in Table 1 summarizes the key issues in each of these two dimensions.

Challenges in gaining access to data. As noted previously, in omnichannel marketing, firms interact with their customers at multiple touchpoints, some within the firm and some beyond it. Within the firm, often, information on various contact points by the same customer resides in silos. As a result, a given unit might not even know what data are being collected by other units. For example, a firm's e-commerce platform team may not know what information about a customer exists in other divisions within the firm, and vice versa. Thus, the first bottleneck for effective omnichannel marketing is knowing what kind of data exist on the same customer *within* the firm (Wilder-James 2016). The extent to which a firm is siloed depends on how it approaches the role of data-driven marketing. In some organizations, the role is centralized within a large data science team. In others, the individuals are spread out among smaller units that might specialize in that area.

Beyond the firm, the problem is compounded. For example, many of the touchpoints for a consumer interested in an automobile are not controlled by the manufacturer, which might use paid, owned, and earned media to engage with customers; provide product information; and possibly entice them to visit the distribution channel (i.e., its local dealership). Subsequent interactions such as test drives and price negotiations occur at these dealerships. However, neither the manufacturer nor the retailer has a complete view of the multiple interactions; worse, they may not even know whether such interactions occurred.

Thus, even if a firm is efficient in cataloging what data exist on a customer in each silo of the firm, it may not know what data exist on the same customer beyond the firm.

When a firm is aware of all the data that exist on a customer within (and even outside) the firm, the second challenge is the right to use it (Wathne and Heide 2000). One of the reasons for this bottleneck is that complicated administrative procedures can make data sharing between different departments with the same company very difficult, if not impossible. For example, in financial companies, one set of investments being made by customers may not be reported to other parts of the company. In addition, in industries such as health care and finance, regulations might impose restrictions on sharing of data across units. For example, Miller and Tucker (2014) showcase the presence of data silos in the context of health care. They find that even within a hospital system, there is evidence of incomplete sharing of patient and clinical data.

Integrating data from different sources. Even if firms can surmount the challenges related to awareness of and access to data, managers still need to integrate the data to produce insights. There are two main problems that can arise with such integration. First, because each touchpoint with the customer may be managed by different entities (both within and outside the firm), they may be stored in different databases, using different rules, data formats, and reporting standards. As a result, it can be extremely challenging to match data on the same customer across different touchpoints (Neumann, Tucker, and Whitfield 2019; Stuart, Rubinson, and Bakopoulos 2017).

The second problem is that data from diverse sources may differ in terms of their reliability. For example, the sales department within a firm might have accurate information on the various interactions it had with the customer. However, the information on the other interactions assembled by the marketing department might be less accurate, perhaps because its data are more aggregated and/or acquired from third-party vendors with their own rules and market definitions that may not overlap completely with those used by the firm. Similarly, data on some interactions might be missing some key information, which could arise, for example, from a firm's internal infrastructural limitations. For instance, a firm's interactions with its customers' via its call center/customer support channel often requires manual entry of the details of customers' inquiries, which makes it prone to transcription errors. This is in contrast to sales transactions channels, where state-of-the-art point-of-sale information technology systems reliably automate the process of obtaining reliable data on customers' purchase history and product returns.

Remedies to Address Data Challenges in Omnichannel Marketing

Remedies to gaining access to data. As noted previously, gaining access to data on different customer touchpoints can be difficult even if such data reside within the same organization. In such settings, is it possible to fuse customer data together without having to transport them across various departments within an organization?

In the past few years, developments in artificial intelligence (AI) have addressed this problem. One such example is federated learning. Unlike standard machine-learning practice, in which the training data sit on one machine or in a data center, federated learning enables multiple parties to use data from multiple decentralized data servers to collaboratively construct a machine-learning model while keeping their respective servers' training data private (Konecný et al. 2016). Over the course of several training iterations, the shared models get exposed to a significantly wider range of data than any single organization or department possesses in-house. Such an approach would be valuable in situations where regulations, such as those in the context of health care, preclude business units within a firm from sharing data.

Additional challenges are introduced when moving from situations where data reside within a company to those where outside entities own some of the customer information. This warrants reconsidering the boundary of the firm. Firms can form strategic partnerships or engage in acquisitions to ensure access to data. There are two broad situations where such partnerships have proved to be fruitful. The first situation involves tracking known customers on the so-called third-party "walled garden" platforms (Google, Facebook, and Amazon). Platforms such as Facebook and Google now allow firms to import their own "first-party" data, such as lists of email addresses or phone numbers. This can help firms identify consumers with whom they have previously had contact. Similarly, e-commerce platforms such as Amazon's "Amazon Publisher Services" enable a firm to understand how its customers engage on Amazon across products. Another example of a successful data partnership is the acquisitions of large data brokers by the legacy media agencies. In particular, the acquisitions of Epsilon by Publicis and Acxiom by IPG are two prominent mergers and acquisitions that have the potential to enable highly personalized omnichannel customer experiences when data from the data brokers are combined with the vast scale and breadth of complementary agency services. That said, the recent decisions by Google and Apple to stop supporting open-source identifiers such as third-party cookies and the identifier for advertisers can erode some of the benefits from these remedies.

The second situation pertains to tracking known customers and prospects across the open web. There have been some positive developments wherein third-party data providers enable retailers to track consumers' engagement with ad platforms such as Amazon, Apple, Facebook, Google, Verizon, and Walmart, among others. For instance, data brokers such as Experian, Acxiom, and LiveRamp have allowed firms to match information such as email addresses or cookies with other data sets, such as spending and demographic information. These examples point to the growing set of choices available for marketers and advertisers of all sizes to access and integrate customer data from different sources to successfully execute their omnichannel marketing campaigns.

An additional challenge is that even if firms can access data from several sources, they may face instances where some of the information is missing. New advancements in AI and novel predictive algorithms offer promising avenues for addressing these challenges. For example, in online purchases, product returns are a serious threat to the profitability of manufacturers and retailers, especially in the case of experience goods such as clothing. Dzyabura et al. (2019) have recently developed a machine-learning-based approach to predict the probability that an item will be returned. In a similar vein, many companies are now monitoring the use of products and enhanced product fulfillment even before the customer shows a need. For instance, Amazon has patented "anticipatory" shipping to cut down delivery times by predicting what buyers are going to buy before they buy it. This trend of using predictive models to forecast customer behavior might enable AI-powered companies to ship products to consumers before they are ordered (Agrawal, Gans, and Goldfarb 2018). While these algorithms have been developed to predict purchase and consumption behavior to curate products and content, they can also be used to identify missing pieces of information in the data. For example, if a firm observes purchase information, but not the consumption or product return information, the predictive power of such algorithms can be used to fill these data voids.

Remedies to integrating data from different sources. There are two main ways that firms currently track consumers across devices and media that the firm controls. The first is deterministic tracking, which occurs when the firm can identify a consumer from multiple databases. For example, a subscriber of *The New York Times* would log in to both the website and the app using the same email login, allowing for perfect identification of the same user.

However, it is common for firms to encounter situations where they cannot match customers across different databases. For example, a website that did not have a subscription model and did not require a login would not be able to easily track whether it was the same consumer visiting its desktop website, mobile website, or application. As cookie deletion becomes more prevalent, it will become increasingly difficult to track the same consumer returning to the website. Under such situations, probabilistic tracking is a promising approach to identify consumers as they browse across different devices. As the name suggests, probabilistic matching allows firms to use algorithms to probabilistically identify and track the same user across multiple touchpoints. Drawbridge, which was recently acquired by LinkedIn last year, is an example of a firm that uses probabilistic tracking. To implement probabilistic tracking, marketers have the option of deploying machine-learning models trained on user location data, triangulated from multiple devices. This would enable them to identify the best model for probabilistic matching.

A novel set of technologies that have the potential to help track customer data and its integrity are blockchain technologies, such as those inspired by smart contracts and shared tamper-evident ledgers. Blockchain-based solutions offer a way to coordinate among different entities in the supply chain

(e.g., different sources within a channel or even different channels per se).[2] A key feature of blockchain solutions to this challenge is an attempt to bring all the data into one protected location. If the standards are enforced when the data are entered, a well-designed blockchain system can provide data integrity as well. The data recorded in a blockchain may easily be made accessible to the participants.

Blockchain technologies have been developed mostly in response to the success and popularity of Bitcoin, in which all transactions are stored in a blockchain. Bitcoin's novelty was in creating a reliable digital currency system without any need for a centralized trusted party who would protect against copying of digital assets (Halaburda and Sarvary 2016). This is an example of a permissionless blockchain, as it operates without any gatekeepers—and thus, the number and identity of the participants is not known. A central feature of this type of blockchain is a shared ledger, which is reconciled among the participants via a consensus mechanism (Halaburda 2018). In contrast, permissioned blockchains allow firms to control who can see their data and validate the transactions (Halaburda 2018). From a firm's point of view, the key advantages of using a permissioned blockchain as opposed to a more regular means of storing data is that blockchain offers more data integrity, because by the nature of shared ledger, there cannot be discrepancy when two users see the same piece of data.

Permissioned blockchains require some asymmetry in authority because there must be a trusted party or consortium to give permissions to access the system.[3] The level of involvement of the trusted party in maintaining the records would depend on the structure of the system. The trusted parties may be either a private company or a government agency. It is important to note that while permissionless blockchains can be slow and expensive, permissioned blockchains are much faster and cheaper. In the world of digital ads, Lucidity is such a player, constructing and running a permissioned blockchain and controlling access to it. It is a trusted party in a similar way that Google is a trusted party in running keyword auctions.

Participants may be punished for "misbehavior" outside of the blockchain (e.g., with fines, access restrictions) and their permission to participate revoked. While there is still a need for a method to reach agreement between the participants, there is no need for such demanding consensus systems as with permissionless systems. However, it is important to emphasize that permissioned blockchains can also be viewed as a more efficiently run distributed database, rather than a distinctly different way of managing data. A distributed database is a database where multiple parties can make an entry (e.g., Google Docs, Dropbox). Here, the "multiple parties" are the parties representing different channels. From a firm's point of view, the key advantages of

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[2] For a discussion of blockchain technologies and their impact on operations management, see Babich and Hilary (2020).

[3] As an example, consider TradeLens, the shipping blockchain started by IBM and Maersk, which also has added several competitors to the system (Maersk 2019).

using a permissioned blockchain as opposed to a more regular means of storing data is that blockchain offers more data integrity, because by the nature of shared ledger, there cannot be discrepancy when two users see the same piece of data.

There are several advantages for storing data and safeguarding their integrity that result from adopting a blockchain. Blockchain-based systems can help with standardization and unification of data, leading to better data integrity in digital supply chains, such as in the adtech and martech world (Ghose 2018; Gordon et al. 2021). The current opaque and fragmented adtech supply chain does not allow for seamless cross-validation of ad campaign data from the different entities in the ecosystem that sit between the brand and the publisher, such as the demand-side platform, supply-side platform, ad exchanges and data management platform, that would ascertain the veracity of the data. One problem omnichannel advertisers often face is the reconciliation of a transaction in a given ad campaign when mapping it from a brand to a publisher—ensuring that the raw campaign data for a given transaction is the same across the different entities (e.g., the demand-side platform, ad exchange, and the supply-side platform) in the adtech supply chain (Gordon et al. 2021). A blockchain-related solution could allow for proper ad engagement tracking that will lead to more precise digital attribution. Higher data quality achieved through transparency and unification of data streams from the different entities in the adtech ecosystem will allow firms not only to track delivered messages but also to set up smart contracts to automatically execute intricate programmatic advertising strategies and eliminate redundancy and irrelevance, to the benefit of both the advertiser and the customer. With data standardization and integration across different parts of the adtech supply chain, marketing messages in an omnichannel environment can be delivered consistently and data can be verified.[4]

The adoption of blockchain-based data management systems can affect how customer data are combined and integrated in many other areas as well. Omnichannel marketers typically have a complex supply chain consisting of physical stores, home delivery, online browsing, and online commerce, all of which comprise a complex network of data points on different systems and in different entities. Despite the advances made, in today's world, retail agreements are largely manual and based on proprietary systems. To get integrated views of the inventory and the customer, this complex world of data and transactions needs to be merged. For example, if a retailer pilots a blockchain solution to trace the cotton being used for a line of T-shirts, its internal system needs to be able to communicate with its cotton suppliers' and contract manufacturers' systems

with a high degree of automation and accuracy to enable full end-to-end supply chain visibility.

In this context, blockchain-related systems offer several business benefits for retailers and their partners in the supply chain, both upstream and downstream, as they gather information from multiple channels in one system, inducing standardization and unification of data.[5] With transparent, real-time data access enabled by a shared database, retailers will know where their stock is at any point in time in that complex supply chain and where their customers interact with them at any touchpoint in that path to purchase. This real-time knowledge can lead to a faster, more transparent, and end-to-end integrated supply chain. Although the database is shared, it is not visible in its entirety by all players, thereby mitigating any privacy concerns.

Finally, the smart contracting feature of blockchains—due to automated execution of agreements—can drastically reduce the transaction costs within supply chains, thereby potentially lowering the cost of goods sold.[6] Harvey, Moorman, and Toledo (2018) highlight that blockchains could allow firms to use "micropayments to motivate consumers to share personal information—directly, without going through an intermediary." Such forms of micropayments could significantly negate the need for firms to pay third parties such as Google or Facebook to share customer information, as is currently undertaken by omnichannel firms. The extent to which this will enhance customer welfare will depend on the degree to which firms can use this information to provide the most relevant products or services for consumers. In summary, the increased integrity of the data resulting from standardization and unification through blockchain-related solutions also brings an indirect benefit by supplying both higher-quality data for advanced data analysis and predictive analytics about customers.

Future Research Opportunities for Investigating Data Challenges in Omnichannel Marketing

While many of the advancements discussed in the previous subsection have significantly improved firms' ability to acquire and utilize disparate data to have a unified view of a customer/prospect, they also present an interesting set of challenges and opportunities for future research. First, building on the work of Dzyabura et al. (2019), how can one decide which machine-learning methods may be best and are generalizable to impute

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[4] An important caveat to keep in mind is that the larger digital platforms will need to be appropriately incentivized to adopt a blockchain-based mechanism that can alleviate issues of data inconsistency across supply chain and opacity in how money is shared between the different entities that sit between the brand and the publisher.

[5] The visibility here does not need to mean that all players see all entries in the shared database. For example, for the blockchain solution developed by IBM and used by Walmart to operate its supply chain for leafy greens, only Walmart and selected validators have access to all the data. The supplier can see only the data related to its interaction with the supply chain, but not competitors'. However, information stored in the blockchain can be available upon request (e.g., for auditing, allowing the consumer to check the provenance of a particular head of lettuce by scanning a QR code).

[6] Blockchain-enabled smart contracts are virtual agreements that remove the need for validation, review, or authentication by intermediaries (Cong and He 2019).

missing pieces of information using data already available to the firm? One challenge with typical imputation algorithms is that they are context-specific. For instance, Chen and Steckel (2012) model the incomplete information problem faced by credit card companies by using the interpurchase time distributions. While the model works well for a credit card application, its use may be limited for other applications where interpurchase times are less regular. Developing a more general approach that accommodates situations that do not occur periodically is a promising opportunity for future research.

Second, to aggregate and manage data from different firms and/or units within a firm that track different customer touchpoints, it might be useful to have matchmakers who can deliver that function. Firms such as A.C. Nielsen have been successful in delivering this for a part of the customer journey. However, increasing the scope of such data collection efforts would require significant changes in how these data integration platforms are designed. In this regard, future research could discuss the optimal design of matchmakers/platforms that will collate information from different parties spanning different customer touchpoints.

Third, what is the impact of data sharing within and across firms on consumers (e.g., prices they pay), firms (e.g., supply-chain efficiency, profit margins), and policy makers (e.g., market structure, efficiency, overall surplus)? Chen, Narasimhan, and Zhang (2001) suggest that the answer might depend on the precision of customer-level information. They model two firms that each have their own set of loyal (price-insensitive) customers and are competing with prices for switchers. Each firm can classify its own loyal customers and switchers correctly with some probability (this is the imprecision in targeting). The key insight from their study is that while individual marketing is feasible but imprecise, improvements in targetability can be a win-win for competitors. The intuition behind this result is that when a firm becomes better at distinguishing its loyal customers from the switchers, it is motivated to charge a higher price to the former group. However, targeting is imperfect. Therefore, firms can make mistakes such as classifying price-sensitive switchers as price-insensitive loyal customers and charging them a higher price. These mistakes allow the competitor to acquire the mistargeted customers without lowering prices and, thus, reduce the rival firm's incentive to cut prices. Therefore, the study reveals that firms may be better off sharing information with their competitors. However, the kinds of incentives that will facilitate data sharing are still unclear. In this regard, it would be worthwhile to explore what kinds of mechanisms should be put in place to incentivize firms to share data with their up- and downstream partners as well as with their competitors.

Fourth, if one were to deploy blockchains, how could one incentivize internal and external partners to participate in the blockchains? The existing commercial success stories typically rely on the strength of large players—for example, Walmart uses its bargaining power to force all its suppliers to use its blockchain. For such an incentive design problem, one needs to measure and quantify the economic benefits enabled by blockchain technology in interorganizational environments. These benefits include the decentralized management of digital assets, the algorithmic enforcement of agreements in the form of software programs, and the verification of data records in an adversarial environment. These benefits can incentivize internal and external partners to work collaboratively on the development and deployment of different blockchain-based solutions for their interorganizational environments. Certain applications of blockchain technology such as smart contracts could significantly influence the level of challenges and transaction costs between upstream and downstream partners within a supply chain. Smart contracts can also be adopted to reduce routine processes to a set of articulated conditions and facilitate frictionless execution. Research should consider whether these actions would mean that blockchain can have a measurable impact on transaction costs, firm boundaries, and interfirm governance.

Fifth, a blockchain's decentralized consensus feature can eliminate information asymmetry as a barrier to entry and facilitate greater competition (Cong and He 2019). Increased competition can, in turn, enhance welfare and consumer surplus. However, decentralized consensus affords greater information transparency, which, in turn, can foster tacit collusion. Tacit collusion can, in turn, result in higher prices and erode consumer surplus. Consequently, would blockchain-enabled omnichannel marketing efforts result in increasing or softening competition?

Challenge #2: Marketing Attribution

Attribution Challenges in Omnichannel Marketing

Unlike multichannel marketing, where marketing investments are optimized on a channel-by-channel basis, in an omnichannel setting, such optimization needs to be done jointly across all distribution and communication channels (Zhang, Pauwels, and Peng 2019). This becomes challenging when the purchase funnel has many stages and/or is traversed by customers in a nonsequential manner, as is often the case in the digital economy. That is, a customer might begin their search process in a brick-and-mortar store, form an initial consideration set, and then at some point in the near future restart their search process on a website leading up to a new consideration set and eventually make a purchase.

Before omnichannel marketers can optimize their marketing efforts across various customer touchpoints, they need to understand the effectiveness and role of each touchpoint in the consumer decision journey and its incremental role on the overall sales conversion (Kannan, Reinartz, and Verhoef 2016). Attribution is more complicated in an omnichannel setting because consumers self-select into different channels, and part of the difference in response to marketing interventions

might be a result of such self-selection (Mulpuru 2011). As a result, inferring the causal effect of interventions, which is essential for attribution, might be difficult or probably even impossible. The potential number of communication paths is incredibly large, and there is no way to have sufficient causal variation. Not surprisingly, the Marketing Science Institute (MSI) has consistently highlighted attribution as the number-one priority in its research priorities since 2016.

Attribution-related bottlenecks in omnichannel marketing stem from three key sources. First, a touchpoint in the customer journey might have an effect on multiple subsequent stages in the purchase funnel. Even if each marketing intervention can be uniquely linked to a transition from one stage in the purchase funnel to the next, it might not be appropriate to view the effect of the intervention as being restricted within the boundaries of a stage in the purchase funnel. For example, if search advertising resulted in a customer clicking on it and arriving at a firm's website, should it be given credit only for reaching the website or also for all subsequent on-site activities, including purchase, either in the same session or at a later point in time? There are two potential implications of this challenge. One implication pertains to the contract between the advertising platforms (and/or publishers) and the advertiser. The price that the advertiser is charged (and/or should be willing to pay) needs to reflect the downstream impact of the exposure. This issue is not specific to the context of omnichannel marketing. A second implication, which is more relevant in the context of omnichannel marketing, regards the appropriate allocation of resources across different touchpoints. For instance, the impact of a marketing intervention in one channel at an early stage in the purchase funnel might interact with the impact of another intervention in a different channel, possibly at a subsequent stage.

Second, consumers may be interacting with the firm via multiple touchpoints simultaneously. For example, there is ample evidence that people frequently consume several media at the same time (see Danaher and Dagger 2013; Liaukonyte, Teixeira, and Wilbur 2015; Lin, Venkataraman, and Jap 2013; Tonietto and Barasch 2020). Multihoming in digital platforms is a well-documented phenomenon. In such settings, marketing efforts are likely to be concurrently directed at the consumer across different channels (Ghose and Todri 2016; Godfrey, Seiders, and Voss 2011; Naik and Raman 2003; Sridhar and Sriram 2013). Under such a scenario, the challenge is to apportion credit among different omnichannel marketing activities for a conversion. As noted previously, this requires firms to reconsider the design of contracts as well as the appropriate allocation of resources across different touchpoints.

Third, many attribution methods are largely focused on quantifying which touchpoint gets credit when a purchase happens. However, if a purchase does not happen, which touchpoint(s) needs to be held accountable? The question of what is *ineffective* as a marketing touchpoint should take priority in a firm's marketing measurement approach, as that is an appropriate place to start the conversation around reallocation of marketing budgets from one channel to another. This can become more problematic if that touchpoint's failure to drive purchase also led other touchpoints to fail. For example, if a customer had a poor retail store experience, it might lead them subsequently to decide against buying products on the firm's mobile app; however, identifying that chain of causality can be challenging. A related problem arises when a firm uses only a subset of potential touchpoints. Under such a scenario, the effectiveness of unused touchpoints cannot be assessed. Together, these two scenarios highlight some key limitations of the traditional multitouch attribution (MTA) approaches.

Fourth, another challenge with attribution is when the data belonging to different stages of the purchase funnel are aggregated at different levels. For example, television advertising investments may be available only at the market level, while search information may be available at the individual level (Joo et al. 2014; Lee and Venkataraman 2019). Therefore, although we can infer whether an individual customer was exposed to search advertising, we may not have equivalent information for television advertising. Consequently, we can potentially relate actions by individual customers to their search behavior, but not for television advertising. The first column in Table 2 summarizes the key issues related to each of these challenges.

Remedies to Address Attribution Challenges in Omnichannel Marketing

How should firms resolve the first attribution challenge—that the effect of a marketing intervention can carry over to subsequent stages? One way to address this problem is to employ extant methods that have focused on modeling long-term effects (e.g., Dekimpe and Hanssens 1999; Hanssens and Pauwels 2016; Jedidi, Mela, and Gupta 1999; Mela, Gupta, and Lehman 1997; Sriram and Kalwani 2007). While traditional attribution modeling has used aggregate metrics (e.g., overall TV ad budget, number of website visits, net social media sentiment), more recent research uses individual-level path-to-purchase data. This has enabled researchers to obtain a richer understanding of carryover and spillover effects across channels (Dalessandro et al. 2012; Ghose and Todri 2016; Li and Kannan 2014; Shao and Li 2011).

Abhishek, Fader, and Hosanagar (2015) model customers' states in their decision processes using a hidden Markov model to assess the impact of various channels at different stages of the decision process. Anderl et al. (2016) propose a graph-based attribution model that maps the sequential nature of customer paths as first- and higher-order Markov walks and shows the idiosyncratic channel preferences (carryover) and interaction effects both within and across channel categories (spillover). Zantedeschi, Feit, and Bradlow (2017) develop a hierarchical Bayesian model for individual differences in purchase propensity and marketing response across channels, finding that catalogs have a substantially longer-lasting purchase impact on customer purchase than emails.

The second challenge pertains to the case in which firms might employ multiple touchpoints simultaneously (i.e., within each stage in the purchase funnel) and/or when consumers

Table 2. Attribution-Related Challenges, Remedies, and Future Research.

Attribution Challenges	Attribution Remedies	Future Attribution Research
Across Multiple Touchpoints		
1. Estimate downstream and interaction impact of each touchpoint when it has an effect on multiple subsequent stages in the purchase funnel.	1a. Assess touchpoints' long-term impact and synergies in marketing-mix model. 1b. Deploy hidden Markov models to assess the impact of various channels at different stages of the decision process.	1. What is the value of assembling a rich data set that tracks customers across different stages of the purchase funnel and links them to various interactions between the firm and customers at each of these stages?
2. Apportion credit among different omnichannel marketing activities when customers interact with them simultaneously.	2. Develop MTA models to attribute the individual-level purchase conversion to exposures to individual marketing messages.	2. How can firms exploit differences in flexibility among communication channels to change communication touchpoints on short notice for attribution?
3a. Identify ineffective marketing touchpoints based on purchases that did not occur if the failure of that touchpoint to drive purchase also led other touchpoints to fail.	3. Undertake carefully curated randomized field experiments and leverage advanced machine learning (e.g., multi-armed bandits) and econometric methods to evaluate the effectiveness of marketing interventions.	3a. What is the value of obtaining verifiable fine-grained data on consumer exposure to touchpoints via blockchain technology in improving attribution?
3b. Identify effectiveness of unused touchpoints if a firm uses only a subset of potential touchpoints.		3b. Can we develop modeling approaches that are scalable to touchpoints that are large in dimensionality?
Across Aggregation Levels		
4. Identify the set of marketing touchpoints that each customer is exposed to when the data on these exposures are aggregated at different levels.	4. Develop models that combine information on touchpoints across different levels of aggregation.	4. Can we develop approaches that can integrate MTA (individual) with aggregate marketing-mix models?

might be multihoming. In such settings, firms tend to use heuristics such as first touch and last touch to infer attribution. In recent years, several "digital native" companies have developed intricate ways to uncover and influence online consumer decision journeys and attribute the individual-level purchase conversion to the individual exposure to specific marketing messages. As a result, MTA has come into prominence in recent years (Li et al. 2015). This body of research has demonstrated the limits of heuristics such as last- and first-click attribution shortcuts. For example, De Haan, Wiesel, and Pauwels (2016) find evidence that last-click attribution can underestimate the effectiveness of some types of interventions and lead to suboptimal budget allocation. In addition, research has explored mapping and visualizing different consumer journeys in the digital space across display and search ads (Ghose and Todri 2016), examining the impact of offline channel opening on consumers' online shopping behaviors or vice versa (Bell, Gallino, and Moreno 2018; Forman et al. 2009; Liang et al. 2019; Pauwels and Neslin 2015) and developing more efficient ways to analyze and store big data (Bradlow et al. 2017).

However, MTA runs into problems when companies also use more traditional marketing communication channels such as TV, radio, print, and billboards, as even digital native companies such as Amazon and Kayak do. Individual-level exposure and response data are either not available for these channels or their collection is severely constrained by costs and/or privacy concerns.[7] Likewise, MTA typically does not

account for nonpaid influences on individual consumers, such as online and offline word of mouth (Fay et al. 2019).

Next, we consider the third issue related to attribution: understanding the effectiveness of unsuccessful and unexplored interventions. To this end, advertisers are increasingly undertaking carefully curated randomized field experiments and leveraging advanced machine learning and econometric methods to evaluate the effectiveness of marketing interventions. Methods such as multi-armed bandits (Schwartz, Bradlow, and Fader 2017) have the potential to address some of these challenges. Multi-armed bandit experimentation is good for situations where conditions can change over time. This is essentially an optimization-driven approach where the omnichannel marketer creates a series of ads, which can be delivered to users by running multiple concurrent combinatorial tests of the creative, and offers to find the combinations that deliver the best results (e.g., click, conversion, revenue) (Thomas 2017). Multi-armed bandit experimentation can be slower than traditional A/B testing, but it is more robust in dynamic contexts and thus has the potential to lead to a more reliable digital attribution analysis.

Future Research Opportunities for Investigating Attribution in Omnichannel Marketing

While these innovations in attribution modeling have significantly improved firms' ability to assign credit to a specific marketing touchpoint, several challenges remain, which serve

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[7] The problems arise because with traditional analog media, it would be difficult to match individual customers and their touchpoints with the firm. This is somewhat aided by the advent of programmatic television and

addressable television markets, but there are still many media (e.g., billboards) for which it is nearly impossible to get individual data.

as the basis for future research. First, attribution models still cannot link the transition across stages of the purchase funnel to a single marketing intervention. They typically presume that the impact of the previous intervention stops with the next step within the purchase funnel and that this impact does not carry over to subsequent steps within the funnel. This assumption is inconsistent, for example, with aggregate-level findings that content-related (vs. content-separated) ads generate site traffic that is more likely to convert in the add-to-cart and checkout stages (De Haan, Wiesel, and Pauwels 2016). This attribution challenge can be addressed by assembling a rich data set that tracks customers across different stages of the purchase funnel and can link them to their various interactions with the firm at each of these stages. If such data have sufficient variation in terms of the extent of firm–customer interactions at different stages of the purchase funnel, we should be able to map the short- and long-term impacts of marketing interventions at different stages of the purchase funnel and beyond.

Second, in many settings, omnichannel marketers may have access to customer-level data for some channels and only aggregate data for other channels. There is a well-established tradition in marketing that combines aggregate and disaggregate data (Berry, Levinsohn, and Pakes 2004; Besanko, Dubé, and Gupta 2003; Chintagunta, Gopinath, and Venkataraman 2010; Christen et al. 1997; Petrin 2002; Tenn 2006). These studies have shown that the combination of customer-level and aggregate data (usually market-level sales data) allows for a better, much richer understanding of consumer heterogeneity than either micro or macro data alone. To the best of our knowledge, we are unaware of any attribution models that leverage aggregate and disaggregate data.

Third, as omnichannel marketers adopt technologies such as blockchain, these firms will realize greater transparency and more reliable integration of consumer data across touchpoints within and outside the firm. Precise MTA modeling and empirical analyses require access to atomic user-level data, some of which come from touchpoints on assets owned by the firm (e.g., the data that the brand may own about a consumer surfing on its website or mobile app) and some from touchpoints on external sources (platform-owned data about a consumer created when that consumer interacts with the brand's ads on Google, Instagram, Amazon, and others). Examples of such granular information include details about the various touchpoints in the consumer path to purchase, the sequence of touchpoints, the kind of content published on a given touchpoint and time spent interacting with that content, the kind of ads (e.g., search, display, video) on a given touchpoint and the time spent interacting with ads, the time lag between different touchpoints, and how frequently the consumer visited that touchpoint in the past. Such fine-grained omnichannel data about consumer response to digital advertising eventually need to be verified, collated, and made accessible. In implementing marketing-mix and attribution models, it is important to verify the various customer touchpoints. Blockchain technologies can serve this purpose. This naturally warrants a better understanding of how the attribution effects change (in terms of both magnitude and reliability) with and without blockchain-enabled marketing platforms.

Fourth, as discussed previously, one challenge relates to assessing the effectiveness of unexplored intervention options. Because marketers can potentially have a plethora of intervention options, exploring the effectiveness of each of these options presents a unique challenge. Approaches that balance the trade-off between exploration and exploitation (e.g., the multi-armed bandit approach) have proved to be promising ways to address this issue. However, their ability to scale to a large set of alternatives faced by a typical decision maker is unclear. Developing approaches that are scalable to interventions that are large in dimensionality might be a worthwhile avenue for future research.

Fifth, the channels through which firms interact with their customers may differ in terms of the flexibility of contracts. For example, let us consider the communication touchpoints that a firm may employ to inform its customers about products. Historically, television advertising contracts are negotiated in advance and are largely irreversible (Wilbur 2008). In contrast, keyword advertising can be changed instantaneously. Low flexibility limits how quickly a firm can experiment with the nature and volume of its interactions with customers, which is required for attribution. In instances where firms concurrently use multiple channels with varying levels of flexibility, can one exploit the differential flexibility as a new source of identification for attribution?

Challenge #3: Privacy/Intrusiveness

Until recently, questions of privacy and questions of channel structure were far removed from each other. This is because, in general, channel management was associated with a lack of insight into customers' desires, purchases, and feedback. Lack of insight was very much bound up with the lack of data as firms had different experiences with different aspects of consumer behavior.

However, in the omnichannel environment, which relies on a fully integrated view of the various customer touchpoints, privacy issues are becoming a crucial question in any discussion of channel management. The ability to use first-party data and match them with external activity on digital touchpoints not owned by the firms is both novel and attractive for firms, but such practices have been challenged by privacy activists (Venkatadri et al. 2019). In particular, control of a customer's data that may give insight into future sales opportunities is something that, in theory, should be available to all channel participants due to the widespread nature of a customer's digital footprint. However, in practice, channel conflicts can arise when one channel partner claims ownership over these data and tries to exclude other channel partners. Such claims often rely on certain interpretations of privacy regulations and customer privacy preferences. As such, customer privacy concerns can often be in surprising conflict with channel coordination.

There are several reasons why privacy will become an important factor in omnichannel marketing. First, the types

of products sold via omnichannel marketing will expand. At the moment, many of the key examples of omnichannel marketing are products, such as coffee, that tend to have short customer decision journeys and for which customers are generally untroubled if their shopping habits are visible to others. Omnichannel marketing may ultimately be most useful, however, for high-involvement products that involve many stages of deliberation and research by the customer. Often, high-involvement products fall into sectors that most naturally give rise to privacy concerns, such as health and finance. Consumers may not be troubled if Starbucks can link coffee-browsing profiles across an app and a store, but they might feel differently about their blood-pressure profile being linked to their features via facial recognition.

Second, as technological capacity improves, the trade-off between personalization and privacy concerns will sharpen. Existing research has emphasized that there are natural trade-offs between a customer's acceptance of personalization and the degree of their privacy concerns and sense of control over their data (Ghose 2017; Tucker 2014; White et al. 2008). Given the natural technological challenges of merely tracking a customer across different touchpoints in their customer decision, as of yet most technological investments have been focused on syncing and tracking. However, once this natural technology barrier has been resolved, firms will soon have to face key decisions about how much personalization they attempt, and how acceptable such personalization will be, given customer privacy concerns. For example, one of the primary goals of matching omnichannel marketing to the customer journey is to link earlier stages in the decision process with prior purchase decisions. However, will customers find it acceptable for firms to remind them of their prior purchase decisions or their product search history across different digital touchpoints?

This leads to three major potential challenges for firms aiming to conduct effective omnichannel marketing while being mindful of consumer privacy concerns. The first challenge is that customers may not be willing to allow the focal firm to collect, parse, and sync their data across devices and touchpoints for use in marketing. The marketing literature has emphasized that one way of addressing this natural privacy concern is to improve perceived consumer control over data. Typically, it is the combination of lack of control and perceived privacy intrusion that is most problematic in customers' minds (Tucker 2014). Therefore, many managerial solutions to these constraints imposed on omnichannel marketing by customer privacy concerns may come in the form of improving customer control over their data.

The second challenge is that customers may not be willing to allow *other* firms that they interact with in their decision journey to collect, parse, and sync their data across devices and share these data with the focal firm. In general, omnichannel marketing has focused on questions of how to piece together disparate fragments of customer data (Neumann, Tucker, and Whitfield 2019), in the absence of privacy concerns. However, as of yet, little research has investigated how firms can share customer data with channel partners in a way that reflects consumer privacy concerns.

The third challenge is that regulators may not be willing to allow firms to share, sync, and collect customer data across different firms, devices, and touchpoints. Since May 2018, firms throughout the world have had to grapple with the General Data Privacy Regulation (GDPR), a European Union (EU) regulation designed to ensure that firms document that they have obtained consent from customers to use their data. One of the most striking novelties of this regulation is its global reach. For example, if a Malaysian website served EU citizens, then it is subject to the regulation and needs to ensure that its use of cookies was compliant. Furthermore, penalties for contravening the regulation are large—4% of worldwide turnover. There are already examples of how such regulation has restrained firms' attempts at omnichannel marketing. Firms such as JD Wetherspoon, a restaurant chain, had to take steps antithetical to the ambitions of an omnichannel retailer, such as deleting over 800,000 email addresses and halting email marketing, in anticipation of the regulation (Manthorpe 2017).

Although the GDPR is focused on EU data subjects, there is some evidence that even firms based in the United States are choosing to implement its strictures rather than go through the complex process of identifying which website visitors are or are not affected (Marthews and Tucker 2019). By contrast, the new California Privacy Act in the United States could potentially affect U.S. firms directly. Because the California Privacy Act has some data-use restrictions that resemble that of the GDPR, there may be similar negative effects on firms' ability to pursue omnichannel strategies in the United States. However, at the time of writing of this article, the act is still being litigated and its actual effects are uncertain.

Another effect of the GDPR for omnichannel marketing has been its impact on firms' ability to engage in probabilistic matching. Probabilistic tracking uses data on the visit (e.g., the IP address, the device used, the browser used, the timing, the location) to predict whether it is the same customer. The GDPR has restricted the collection of IP addresses as potentially personally identifiable information. As such, the regulation has restricted one of the major ways that probabilistic matching is done. It has also given incentives to firms to pursue more deterministic forms of tracking, such as forcing the use of login credentials, which may, in turn, be more privacy-intrusive than probabilistic tracking methods.

Many of the potential costs of this regulation for omnichannel markets stem from its focus on obtaining and documenting consent. This means that firms are prioritizing their use of technologies such as customer data platforms for compliance reasons, rather than focusing on the potential for such technologies to provide a more complete picture of a customer or theorizing how that customer might feel about the combination of data the firm is collecting. Customer data platforms are therefore being marketed as a way of tracking the consent status and origins of disparate pieces of information about a customer, rather than their initial aim of enabling seamless omnichannel marketing. It is not clear, however, whether

Table 3. Privacy-Related Challenges, Remedies, and Future Research.

Privacy Challenges	Privacy Remedies	Future Privacy Research
1. Customers unwilling to allow the focal firm to collect, parse, and sync their data across devices, touchpoints for marketing in high-involvement settings.	1a. Make predictions about a customer's likely future purchases based on aggregated actions of other customers instead of storing data about a particular customer. 1b. Use blockchain technology to provide incentives to customers in the form of a share in the profits derived from using their data.	1a. How can researchers build a predictive model whose suggestions are unlikely to be perceived as intrusive? 1b. What are the types of industries, products, and patterns of consumer behavior for which offering incentives (facilitated by blockchain technology) will encourage customers to share their data?
2. Customers are unwilling to allow the other firms that they interact with to share their data with the focal firm.	2. Develop data exchange platforms that allow organizations to match data sets with deidentified information and without ever having to leave the firm's secured servers.	2a. What are the effects of deploying methods such as blockchain-enabled federated learning architecture on tempering privacy concerns and implementing more efficient omnichannel marketing programs? 2b, What are the adverse consequences of identifiable data in inducing algorithmic biases and discriminatory practices?
3. Regulators are unwilling to allow firms to share and sync customer data across different firms, devices, and touchpoints.	3. Use regulations such as GDPR to give customers control of their data.	3. What is the extent of privacy regulation compliance among firms and what are its implications for consumer welfare and the firm–consumer relationship?

documentation of compliance with the law supplants the ideal use of such technology, which is to ensure that firms track customers across the decision journey in a manner that makes customers feel comfortable. The first column in Table 3 summarizes the key issues related to each of these challenges.

Technological Remedies to Help Protect Customer Privacy in Omnichannel Marketing

In general, the technological frontier on marketing is at odds with maintaining customer privacy. In this subsection, we discuss the source of this tension and offer potential future remedies.

Machine learning and predictive analytics privacy remedies. Recent advances in machine learning and other predictive technologies are primarily focused on allowing firms to make predictions about an individual customer's future behavior. This contrasts with previous marketing analytics, which have been focused on predicting aggregate behavior. To address privacy concerns while conducting omnichannel marketing, a firm can either try to guarantee not to predict behavior using only an individual's data or, if they do predict behavior at the individual level, try to ensure that these data and predictions are anonymized. For example, rather than storing data about a particular customer, a firm could make predictions about customers' likely purchase path going forward on the basis of the aggregated actions of other customers. Alternatively, a firm could ensure that all data it stores about an individual are anonymized and depersonalized.

We argue, though, that eventually privacy in omnichannel marketing will become less a question of where data are stored and more a question of whether a customer *feels* that the predictions made by data are intrusive. Although

predictive analytics can be conducted in a way that focuses on using aggregated, anonymized, and depersonalized data, it is not clear that it directly addresses customer privacy concerns, even if it is compliant with privacy regulation. For example, imagine that a customer is browsing a web supermarket storefront, and a predictive analytics suite that uses privacy-compliant aggregated and anonymized data that associates mobile data with desktop website–based data predicts that, in line with her browsing behavior, she is also likely to be interested in contraception. The customer may still find such a suggestion intrusive, even though the suggestion itself was made using privacy-compliant analytics.

As another example, in the world of adtech, Data Republic is a data exchange platform that allows organizations to deidentify and match data sets without personally identifiable information ever having to leave the firm's secured servers. Again, privacy compliance is focused on the question of how and where data are stored and how anonymous the data are when stored.

Blockchain privacy remedies. Blockchain technology may provide customers better (or at least decentralized) ownership rights over their data. In advertising, an example of this is Brave, a "privacy browser" that is combined with blockchain-based digital advertising. The underlying idea is that Brave users will own the rights to their data and share in the profits of firms advertising to them (Brave 2019). The role of blockchain technology is to allow the immutability of "basic attention tokens," which is the currency by which Brave users are rewarded for their attention to advertising. Although Brave has solved some concerns, recently it has been criticized for trying to monetize

its users' attention through steering their browsing behavior (Stevens 2020).

Although this example is focused on advertising rather than full omnichannel marketing, it does illustrate the potential challenges of using blockchain technology to resolve privacy concerns in a context where multiple firms are trying to track users across multiple touchpoints. The challenges that exist between blockchain technology and data privacy requirements include, at a minimum, the following three use cases: (1) different perspectives on anonymity and pseudonymity, (2) identification of data controllers and data processors in various blockchain technology implementations and how they affect the applicability of various data protection and privacy laws, and (3) reconciling transaction immutability and data preservation in blockchain applications with individuals' rights.

First, it is often believed that transparency afforded by blockchain-related solutions may help mitigate such consumer concerns by giving consumers information on how advertisers have used their data (Ghose 2018; Werbach 2018). Blockchains are often designed so that all transactions are visible to everyone. They are pseudonymized, meaning that only addresses are visible on the blockchain, and anyone can get an unlimited number of addresses. Still, even in this system, it is possible to identify individuals by examining transactions linked by the addresses (Haeringer and Halaburda 2018) and statistically predicting the characteristics and identity of an individual by combining these transaction data. Furthermore, it would be very difficult to prevent the visible information from being copied and used in a different way on a different system. Therefore, current blockchain technology that emphasizes visibility and the reduction of asymmetric information may not prevent marketers from selling customer data.

Second, blockchain technology's distributed peer-to-peer network architecture can also put it at odds with data privacy laws such as the GDPR and California Consumer Privacy Act. This is because a law such as the GDPR relies on the idea of centralized controller-based data processing or a distinct firm that oversees and manages data processing. By contrast, blockchain is explicitly decentralized, and part of its merit is that there is not a single controlling firm or body. This disconnect can make it difficult to reconcile current data protection laws with blockchain's other core elements, such as the lack of centralized control, immutability, and perpetual data storage. Regulatory guidance on reconciling this and other potential conflicts is currently a work in progress.

Finally, many of the privacy concerns associated with blockchain stem from the fact that its major virtue is to ensure data integrity and ensure that data are immutable. However, preserving data in an immutable form is itself a privacy challenge.

As we have discussed, blockchain technology can be either permissionless or permissioned. Typically, permissionless blockchains are explicitly decentralized without a governing or controlling body. One potential solution to some of these challenges of protecting privacy in a blockchain environment is to move to permissioned blockchains, such as the IBM technology used by Walmart. IBM Food Trust is a permissioned blockchain that Walmart's suppliers of leafy greens are required to use. However, unlike the more traditional permissionless blockchain, simply participating in the blockchain does not provide any visibility into the data recorded there. Walmart has access to all the information, but suppliers can see only the information they have provided themselves. Such blockchain-based systems provide only constrained transparency, however. The information in the blockchain is more transparent to Walmart than the previous record-keeping methods. The suppliers obtain more information than before, but the system is not fully transparent for them. In other words, concerns about data visibility can be addressed by moving blockchain toward a permissioned format, which loses some of the unique benefits of decentralized blockchains that have often attracted blockchain enthusiasts. However, it is not clear that the permissioned blockchain format addresses issues of immutability of data or the fact that blockchain is essentially a technology focused on preserving and ensuring the integrity of data, which naturally puts it at tension with privacy.

Future Research Investigating Customer Privacy in Omnichannel Marketing

Our discussion highlights that although it is possible to use tools such as machine learning and blockchain to address privacy concerns, the use of these technologies creates different privacy concerns. This insight suggests fruitful avenues for future research. We highlight several possibilities.

First, is there a way of using predictive analytics in a manner that is conscious of customers' likely privacy preferences? For example, is it possible to build a predictive model that ensures that any suggestions made in an omnichannel context are never likely to be perceived as intrusive? To achieve this goal requires a deep understanding of what customers consider a privacy-invasive touchpoint or suggestion in an omnichannel context (Athey, Catalini, and Tucker 2017). We highlight that this kind of research—whether it be done through surveys, data analysis, or A/B testing—is going to be crucial to ensure that predictive analytics are not just privacy-compliant but actually privacy-conscious. Toward this direction of future research, Macha et al. (2019) build on the principle of location data obfuscation to provide a framework that allows, for example, a reduction in a firm's probability of being able to infer a customer's home address, with no reduction in actual targeting accuracy for advertising.

Second, can research uncover ways to emulate existing blockchain-based ecosystems in an omnichannel context? For example, can a firm use blockchain to create a token that establishes a currency allowing the consumer to be rewarded for sharing their data as a part of an omnichannel marketing effort? More ambitiously, is there a way that multiple firms can coordinate around a single-token-based scheme to help kick-start a larger ecosystem? As with any time firms work together, there will be interorganizational challenges, especially if the firms are competitors and these proposals involve sharing data. These

interorganizational challenges may lead to useful theoretical modeling opportunities for marketing academics. For example, theory work could examine what would give rise to incentive-compatibility issues in a blockchain-fueled data exchange system in an omnichannel context, which would uncover the likelihood and drivers of firms being willing to share data with competitors and channel partners. This would illustrate the types of industries, products, and patterns of consumer behavior offering the largest incentive-compatibility issues in terms of data sharing.

Third, how successful are adtech initiatives that have helped omnichannel marketers become privacy-regulation compliant? Are they inherently just a cost that interrupts the accurate processing of information, or are there benefits in terms of enhanced consumer trust of that firm? For example, if a firm offers an array of privacy-compliance tools, does it actually have a measurable effect on the consumers' relationship to the firm, in terms of measurable purchase behavior or measured attitudinal change? The recent spate of privacy regulation, and in particular regulation in California, has led to a large number of startups that are trying to help firms comply with new regulations (International Association of Privacy Professionals 2019). These vendors span functionalities such as activity monitoring, assessment management, consent management, data discovery, data mapping, deidentification, and privacy management. Each of these functionalities is likely to be core to a privacy-compliant omnichannel future. Yet these are also technologies whose role the academic marketing community knows little about. It strikes us that useful partnerships between academics and firms in this space could help provide an early assessment of the usefulness of such tools, and how to improve them, for firms, consumers, and regulatory compliance.

Fourth, as discussed in the previous section, recent developments in machine learning aim to provide privacy controls. For example, "federated learning" trains a machine-learning algorithm across multiple decentralized devices such as mobile phones that hold local data samples, without exchanging the data. These leakages can stem from loopholes in collaborative machine-learning systems, whereby an adversarial participant can infer membership as well as properties associated with a subset of the training data. Kim et al. (2018) propose a block-chained federated learning (BlockFL) architecture, where the local-learning model updates are exchanged and verified using a blockchain. Might such developments temper privacy concerns and lead to more efficient omnichannel marketing programs?

Fifth, public policy has thus far focused on the deleterious effects of machine-learning-induced algorithmic biases in the form of racial or gender discrimination. Scant research or policy has examined the use of personal information in algorithms. For example, does greater transparency into customers' path-to-purchase journey, even with the explicit consent of the customer, result in the unintended consequence of giving omnichannel firms room to price discriminate efficiently and, in doing so, erode consumer welfare? This would be particularly problematic if these data led groups of different socio-economic backgrounds or different races to pay different prices. As a starting point, it would be useful for research to document the extent to which having more individualized data leads to more price discrimination and, if so, whether that price discrimination appears to be associated with any historically disadvantaged groups.

Conclusion

How does omnichannel marketing differ from how firms have interacted with consumers in the past? In this article, we argue that, to realize the full potential of omnichannel marketing, firms need to track the *same* consumer across multiple channels. Obtaining such a 360-degree view of the customer experience would require hitherto unimagined consumer tracking capacity by firms. We have highlighted the root causes of three key sources of informational challenges that might prevent firms from realizing the potential of omnichannel marketing—data access/integration, marketing attribution, and protection of consumers' privacy—and discuss how emerging technologies such as machine learning and blockchain can help address these challenges. We establish that while these technologies have promise as solutions, they also create new challenges and opportunities. In addition, we discuss fruitful avenues for future research in each of the three challenge areas. Next, we highlight several possibilities of future research that integrate the three areas.

First, obtaining a 360-degree view of the customer experience, on the one hand, while maintaining customer privacy, on the other, seem to be at odds. However, a firm might need only a subset of information on customer touchpoints to make effective inferences about attribution. If some of these data that firms might not need for attribution are also those for which customers have serious privacy concerns, the firm could collect only the subset that is useful for its internal purposes, thus giving customers a semblance of privacy. Identifying such data represents a potential win-win and therefore is a useful area of research. This is likely a process that will need to be ongoing as consumer education and government regulation increases.

Second, related to the previous point, are there some types of data that are only needed in the short run for attribution purposes about which customers have privacy concerns? Identifying such data is a useful area of research from a public policy perspective, as countries could mandate potentially attractive regulations limiting retention of such data.

Third, while more information is always beneficial to the firm from the perspective of managing customer experience, there may be diminishing returns. Therefore, might it be worthwhile to quantify the incremental benefit of additional data or data from multiple sources for attribution? If we believe it is the combination of data that represents the greatest privacy risk, it would be beneficial for future research to identify instances where there are swift diminishing returns to incremental data in companies, as these data could be removed from regular collection.

Fourth, could there be a marketplace for consumer data that results in fair valuation while preserving privacy, thus creating a win-win situation? Many consumers are increasingly willing to share their personal data (e.g., their location) with brands in

return for some economic incentives (e.g., discounts). This comes from the belief that their data are their asset, and just like a property right, they should be able to exchange this asset with brands for monetary compensation from marketers (Harvey, Moorman, and Toledo 2018). Some consumers, however, hesitate to participate because they believe that brands and marketers may not appropriately compensate them for their data. Future research could consider how platform design can inspire consumer confidence and how various mechanisms, such as auction, might be useful in clearing such a market.

Fifth, can blockchain-based technologies be used in facilitating the market for customer information? The hope is that when such a blockchain-based marketplace emerges, consumers will have a transparent overview of how their data are valued and which brands might be willing to enter an exchange with them. It would be beneficial for future research to identify the hurdles (both from consumers and firms) to participating in such markets, and how to overcome them.

In summary, our thesis is that while omnichannel marketing promises to open up new opportunities for firms, firms need to be cognizant of the tension between obtaining a 360-degree view of the customer (and the challenges therein) and alleviating concerns about loss of privacy. We hope that our article helps spearhead future research solving these challenges in omnichannel marketing.

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