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INFORMATIONAL CHALLENGES IN OMNICHANNEL MARKETING:

REMEDIES AND FUTURE RESEARCH

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INFORMATIONAL CHALLENGES IN THE WAY OF OMNICHANNEL MARKETING: REMEDIES AND FUTURE RESEARCH

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 potential challenges in realizing the full potential of omnichannel marketing: 1) data access and integration; 2) marketing attribution; and 3) protecting consumer privacy. While these challenges predate omnichannel marketing, they are exacerbated in a digital omnichannel environment. This article argues that advances in machine learning (ML) and blockchain offer some promising solutions. In turn, these technologies present new challenges and opportunities for firms, which warrant future academic research. We identify both recent developments in practice and promising avenues for future research.

Keywords: Omnichannel, attribution, privacy, machine learning, blockchain

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, SVP, Nielsen

INTRODUCTION

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 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 Land’s End sold out of stores, as well as catalogs and by phones. 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, while customers may interact with the firm across multiple channels before a conversion occurs, the focus of the firm is on managing and optimizing the performance of *each* channel separately.

[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 like sorting, inventory holding, assortment management, etc. 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 the rest of the paper, we will assume channels serve all three intermediation functions.

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 towards "omnichannel" marketing, which emphasizes a unified consumer experience rather than just facilitating transactions. Furthermore, as Teixeira and Piechota (2019) 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 touch points, in such a way that the customer experience across channels and the performance <u>over</u> 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 touch points 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 the Verhoef et al. (2015) definition of omnichannel marketing. We broaden the scope of previous definitions and define omnichannel marketing as the "*synergistic management of all customer touch points and channels both internal and external to the firm to ensure that the customer experience across channels and firm-side marketing activity, including marketing-mix and marketing communication (owned, paid and earned), is optimized for both firms and their customers*." Thus, while 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 touch points and experiences might impact outcomes that firms may care about, 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' lifecycle.

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, and restaurants such as Starbucks and pharmacies such as Walgreens. However, firms also need to consider the cost of implementing customer integration (Coughlan 2011).[2] In the end, firms have to assess if 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, innovation, and improve long-term performance, we posit that this potential has not been fully realized. In our view, there are three main inter-related 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 as they traverse 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, product fulfillment, returns, and post-purchase service. Such data might not be readily available or easily usable.
2. **Marketing Attribution Challenges:** For optimizing the customer experience across all channels, firms need to know the impact of various touch points on behavior and measure the ROI of its marketing spend. This is captured as 'prove sales results' in our opening quote from Eric Solomon. Such analysis may be challenging when the effect of a touch point can transcend multiple stages in the purchase funnel or when several occur concurrently or when consumers go back and forth between different stages in their path to purchase journey.

[2] See https://www.cnbc.com/2017/02/22/an-overwhelming-amount-of-retailers-are-losing-money-chasing-amazon.html for details.

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 how to embrace an omnichannel strategy while, at the same time, also respecting consumers' privacy.

In what follows, each section elaborates on these challenges and discusses recent attempts to address them. We then propose promising avenues for future research in these areas. Tables 1, 2, and 3 summarize the challenges, remedies, and future research challenges.

CHALLENGE #1: DATA

Firms like REI carefully plan for their customer experience to be unified across all their touch points. While it 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 phone application, it will note which nearest store has it in stock. And when customers visit a store, they are strongly encouraged to join the store WiFi, 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.[3]

[Insert Table 1 here]

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 these touch points. We can

[3] https://blog.hubspot.com/service/omni-channel-experience

broadly classify such data-related challenges along two key dimensions: a) gaining access to these data and b) integrating these data from different sources. We elaborate on these points below.

Challenges in gaining access to data. As noted above, in omnichannel marketing, firms interact with their customers at multiple touch points, 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 ecommerce platform team may not know what information on the same customer exists in other divisions within the firm, and vice versa. Hence, the first bottleneck for effective omnichannel marketing is knowing what kind of data exist on the same customer *within* the firm.[4] The extent to which a firm is siloed depends on how they approach 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 touch points for a consumer interested in an automobile are not controlled by the manufacturer, who 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 if such interactions occurred. Thus, even if a firm is efficient in cataloging what data exist on a customer in each silo of the firm, they may not know what data exist on the same customer beyond the firm.

[4] https://hbr.org/2016/12/breaking-down-data-silos

Even if 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 behind 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 some industries such as healthcare 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 of awareness of data and access to them, managers still need to integrate the data to produce insights. There are two main problems that can arise with such integration. First, since each touch point 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 touch points (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 their data are more aggregated and/or acquired from third-party vendors with their own rules and market definitions which may not overlap completely with that 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 example, a firm's interactions with its customers' via their call center/customer support channel often warrants manual entry of the details of customers' inquiries which is make it prone to transcription errors. This is unlike the sales transactions channels where state-of-the-art point-of-sale IT 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 above, gaining access to data on different customer touch points 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, we have seen developments in AI that address this problem. One such example is *federated learning*. Unlike standard machine-learning practice, in which the training data sits on one machine or in a datacenter, *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 healthcare, preclude business units within a firm to share data.

Moving from situations where data reside within a company to those where outside entities own part of the customer information can introduce additional challenges. 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 proven 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," allow a firm to understand how its customers engage on Amazon across products. Another example of a successful data partnership are 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 examples of M&A that have the potential to enable highly personalized, omnichannel customer experiences when data from the data brokers get combined with the vast scale and breadth of complementary agency services. With that being said, the recent decisions by Google and Apple to stop supporting open-source identifiers such as third-party cookies and IDFA can erode some of the benefits from these remedies.

The second situation pertains to tracking known customers as well as prospects across the open web. There have been some positive developments wherein syndicated providers such as Kenshoo allow retailers to track consumers' engagement with ad platforms such as Amazon, Apple, Facebook, Google, Verizon and Walmart, among others.[5] For example, Mercedes Benz was able to use the Kenshoo platform to re-engage audiences on Facebook that had searched for relevant keywords on Google—leading to better quality leads.[6] Similarly, data brokers such as Experian 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

[5] https://kenshoo.com/

[6] https://kenshoo.com/case-studies/mercedes-benz-omd-social/

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 A.I.-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 obtains a persistent login identifier for that consumer. 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 perfect identification of the same user.

By contrast, 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 their 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 touch points. Drawbridge, which was recently acquired by LinkedIn last year, is an example of a firm that uses probabilistic tracking. In order 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 with tracking of 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.[7] 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 is 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. The novelty of Bitcoin system was in creating a reliable digital currency system without any need for a centralized trusted

[7] Please see Babich and Hilary (2019) for a discussion of blockchain technologies and their impact on operations management.

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). The key advantages from a firm's point of view 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.[8] The level of involvement of the trusted party in maintaining the records would depend on the structure of the system. The trusted parties may either be 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. They are 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 or 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

[8] As an example, consider TradeLens, the shipping Blockchain started by IBM and Maersk, which also has added several competitors to the system. See here: https://www.maersk.com/news/articles/2019/07/02/hapag-lloyd-and-ocean-network-express-join-tradelens

permissioned blockchains can also be viewed as a more efficiently run distributed database, rather than a distinctly different way of managing data. Distributed database is a database where multiple parties can make an entry—Google docs or Dropbox are examples. Here the "multiple parties" are the parties representing different channels. The key advantages from a firm's point of view 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.

There are several advantages for storing data and safeguarding its integrity emerging from adoption of 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 ad-tech supply chain does not permit 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 (DSP), Supply Side Platform (SSP), Ad Exchanges and Data Management Platform (DMP) that would ascertain the veracity of the data. One problem often faced by omnichannel advertisers 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 (for instance, the DSP, Ad Exchange and SSP) in the adtech supply chain (Gordon et al. 2021). A Blockchain-related solution could ensure 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 consistently delivered and data can be verified.[9]

The adoption of blockchain-based data management systems can affect how customer data is 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. In order 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 a number of 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.[10] 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

[9] 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 these issues of data inconsistency across supply chain and opacity in how money gets shared between the different entities that sit between the brand and the publisher.
[10] The visibility here does not need to mean that all players see all entries in the shared database. For example, the blockchain solution developed by IBM and used by Walmart to operate its supply chain for leafy greens, it's only the Walmart and the selected validators who have access to all the data. Supplier can only see the data related to their interaction with the supply chain, but not competitors. At that same time, information stored in the blockchain can be available upon request, for auditing, or e.g., allowing the consumer to check the provenance of a particular head of lettuce by scanning a QR code.

them at any touch point in that path to purchase. This real-time knowledge can lead to a faster, more transparent and end-to-end integrated supply chain. While 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.[11] 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 like Google/Facebook to share customer information, as is currently undertaken by omnichannel firms. The extent to which this will be welfare enhancing will depend on the degree to which firm can use this information to provide the most relevant products or services for consumers.

In sum, the increased integrity of the data resulting from standardization and unification through blockchain-related solutions also brings an indirect benefit by supplying higher quality data for advanced data analysis, and predictive analytics about customers.

Future Research Opportunities Investigating Data Challenges in Omnichannel Marketing

While many of the advancements discussed in the previous section 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 missing pieces of information using data already available to the firm? One challenge with typical imputation algorithms is that they

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

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 have periodic occurrence 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 touch points, it might be useful to have matchmakers who can deliver that function. Firms such as A.C. Nielsen have been successful 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 can discuss the optimal design of matchmakers/platforms that will collate information from different parties spanning different customer touch points.

Third, what is the impact of data sharing within and across firms on consumers (prices they pay), firms (supply-chain efficiency, profit margins), and policy makers (market structure, efficiency, and overall surplus)? The work of Chen, Narasimhan and Zhang (2001) suggests that the answer might depend on the precision of customer-level information. 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. While previous studies have shown the benefits of data-sharing, the kinds of incentives that will facilitate data sharing are still unclear. In this regard, it will be worthwhile to explore what kinds of mechanisms should be put in place to incentivize firms to share data with their up- and down-stream 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 economics benefits enabled by blockchain technology in inter-organizational 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 inter-organizational 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 inter-firm 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, might 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. This becomes challenging in instances where the purchase funnel has many stages and/or is traversed by customers in a non-sequential 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 touch points, they need to understand the effectiveness and role of each touch point 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) highlights attribution as the No. 1 priority in its research priorities summary for 2016–2018.

[Insert Table 2 here]

Attribution-related bottlenecks in omnichannel marketing stem from three key sources. First, a touch point 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, is regarding the appropriate allocation of resources across different touch points. 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 touch points 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 2010; Tonietto and Barasch 2020). Multi-homing 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 2015). Under such a scenario, the challenge is to apportion credit among different omnichannel marketing activities for a conversion. As noted above, this warrants firms to reconsider the design of contracts as well as the appropriate allocation of resources across different touch points.

Third, many attribution methods are largely focused on quantifying which touch point gets credit when a purchase happens. However, if a purchase does not happen, which touch point(s) needs to be held accountable? The question of what is *ineffective* as a marketing touch point should be first-order 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 the failure of that touch point to drive purchase also led other touch points to fail. For example, if a customer had a poor retail store experience, it might lead them subsequently to decide against buying products on a mobile app, but identifying that chain of causality can be challenging. A related problem arises when a firm uses only a subset of potential touch points. Under such a scenario, the effectiveness of unused touch points cannot be assessed. Together, these two scenarios highlight some key limitations of the traditional multi-touch attribution 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, while we can infer if an individual customer was exposed to search advertising, we may not have equivalent information for television advertising. Consequently, we potentially can relate actions by individual customers to their search behavior, but not for television advertising.

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; Jedidi, Mela, and Gupta 1999; Mela, Gupta, and Lehman 1997; Hanssens and Pauwels 2016; Sriram and Kalwani 2007). While traditional attribution modeling has used aggregate metrics (e.g., overall TV ad budget, number of website visits, and 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 (HMM) 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 touch points simultaneously (i.e., within each stage in the purchase funnel) and/or when consumers might be multi-homing. 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, multi-touch attribution (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 sub-optimal 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; Pauwels and Neslin 2015; Liang et al. 2020), and developing more efficient ways to analyze and store big data (Bradlow et al. 2017).

Multi-touch attribution, however, 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.com 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.[12] Likewise, MTA typically does not account for non-paid influences on individual consumers, such as online and offline word-of-mouth (Fay et al. 2019).

Let us now 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 based on running multiple

[12] The problems arise because with traditional analog media, it would be difficult to match individual customers and their touch points with the firm. This is somewhat aided by the advent of programmatic television and addressable television markets, but there are still many media, such as billboards, where it is nearly impossible to get individual data.

concurrent combinatorial tests of the creative and offers to find the combinations that deliver the best results (click, conversion, revenue, etc.) with users.[13] Multi-armed bandit experimentation can be slower than traditional A/B testing, but they are more robust in dynamic contexts and hence have the potential to lead to a more reliable digital attribution analyses.

Future Research Opportunities Investigating Attribution in Omnichannel Marketing

While these innovations in attribution modeling have significantly improved firms' ability to assign credit to a specific marketing touch point, several challenges remain, which serve as the basis for future research.

First, attribution models suffer the limitation that they 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 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 dataset that tracks customers across different stages of the purchase funnel and can link them to the various interactions between the firm and customers 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 impact 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 remaining channels. There is a well-established

[13] https://www.liesdamnedlies.com/2017/01/solving-the-attribution-conundrum-with-optimization-based-marketing.html

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) enables 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 like blockchain, these firms will realize greater transparency and more reliable integration of consumer data across touch points within and outside of the firm. Precise multi-touch attribution modeling and empirical analyses requires access to atomic user level data. Examples of such granular information include details about the various touch points in the consumer path to purchase, the sequence of touch points, the kind of content published on a given touch point and time spent interacting with that content, the kind of ads (e.g., search, display, video) on a given touch point and the time spent interacting with ads, the time lag between different touch points, and how frequently the consumer visited that touch point in the past. Such fine-grained omnichannel data about consumer response to digital advertising eventually needs to be verified, collated and made accessible. In implementing marketing mix and attribution models, it is important to verify the various customer touch points. Blockchain technologies can serve this purpose. This naturally warrants a better understanding of how the attribution effects change (both in terms of magnitude and reliability) with and without blockchain-enabled marketing platforms.

Fourth, as discussed earlier, one challenge relates to assessing the effectiveness of unexplored intervention options. Since marketers can potentially have a plethora of intervention options, it presents a unique challenge to explore the effectiveness of each of these options. Approaches that balance the tradeoff 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 their 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—their desires, purchases and feedback. Lack of insight was very much bound up with the lack of data as firms had different experiences with different aspect of consumer behavior.

However, in the omnichannel environment, which relies on a fully integrated view of the various customer touch points, privacy issues are becoming a crucial question in any discussion on channel management. The ability to use first-party data and match it with external activity on digital touch points 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 which, 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 seeks 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.

[Insert Table 3 here]

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 also where 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 consumers might feel differently about our blood-pressure profile being linked up 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 touch points 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, how acceptable will customers find it for firms to remind them visibly of their prior purchase decisions or what they have researched across different digital touch points?

This leads to three major potential challenges for firms who want to both conduct effective omnichannel marketing, but also be 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 touch points 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 the 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 this data with the focal firm. In general, omnichannel marketing has focused on questions 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 best for firms to share customer data with channel partners in a way which 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 touch points. Since May 2018, firms throughout the world have had to grapple with the General Data Privacy Regulation (GDPR), an 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 make sure 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.[14]

Although GDPR is focused on EU data subjects, there is some evidence that even firms based in the U.S. are choosing to implement its strictures rather than going through the complex process of identifying which website visitor is affected and which visitor is not (Marthews and Tucker 2019). By contrast, the new California Privacy Act in the U.S. could potentially affect US firms directly. Since 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 U.S. However, at the time of writing of this article, the act is still being litigated and its actual effects are uncertain.

[14] https://www.wired.co.uk/article/wetherspoons-email-database-gdpr

Another effect of the GDPR for omnichannel marketing has been its effect on firms' ability to engage in probabilistic matching. Probabilistic tracking uses data on the visit (such as the IP address, the device used, the browser used, the timing, and the location) to predict whether it is the same customer. 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 allow a more complete picture of a customer or how that customer might feel about the combination of the 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 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.

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 section, we discuss the source of this tension and then discuss 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 marketing analytics in the past, which was 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, to try and ensure that this data and prediction is anonymized. For example, rather than storing data about a particular customer, a firm could make predictions about customers' likely purchase path going forward based on the aggregated actions of other past customers. Or a firm could ensure that all data it stores about an individual is anonymized and depersonalized.

We argue, though, that eventually privacy in omnichannel marketing will become less a question of where data is stored, but instead a question of whether a customer *feels* that the predictions made by data are intrusive. Though 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 a customer is browsing a web supermarket storefront, and a predictive analytics suite that uses privacy-compliant aggregated and anonymized data that associates mobile with desktop, website-based data predicts that based on her browsing behavior, she is likely to be also interested in contraception. The customer may still find such a suggestion privacy-intrusive, even though the suggestion itself was made using privacy-compliant analytics.

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

Blockchain privacy remedies. Blockchain technology may allow customers better (or at least decentralized) ownership rights over their data. An example of this, focused on advertising, is Brave, which is 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.[15] 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. While solving some concerns, recently Brave has been criticized for still trying to monetize its users' attention through steering their browsing behavior.[16]

Though 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 touch points. The challenges that exist between blockchain technology and data privacy requirements include the following three use cases, at a minimum: (i) different perspectives on anonymity and pseudonymity; (ii) 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 (iii) 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 their data has been used by advertisers (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

[15] https://brave.com/brave-tap-Blockchain/
[16] https://decrypt.co/31522/crypto-brave-browser-redirect

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 through combining data on these transactions. Further, 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 GDPR and California Consumer Privacy Act (CCPA). This is because a law such as 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 one 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.

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

As we discussed, blockchain technology can either be 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 only can see 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 the visibility of data can be addressed by moving blockchain towards a permissioned format which loses some of the unique benefits of decentralized blockchains which have often attracted blockchain enthusiasts. However, it is not clear that they address issues of immutability of data or the fact that blockchain is essentially a technology focused on preserving data and ensuring its integrity, 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 is construed by customers as a privacy-invasive touch point or suggestion in an omnichannel context. And we highlight that this kind of research—whether it be done by surveys or analysis of data, or A/B testing—is going to be crucial to ensure that predictive analytics are not just privacy-compliant but actually privacy-conscious. Towards opening up this direction of future research, Macha et al. (2019) build on the principle of location data obfuscation to provide a framework which allows, for example a reduction in the probability of a firm 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 that allows the consumer to be rewarded for sharing their data as a part of an omnichannel marketing effort? And more ambitiously, is there a way that multiple firms can coordinate around a single-token-based scheme to help kick start a larger ecosystem? Evidently, as with any time firms are working 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, we can imagine theory work that examines what would give rise to incentive-compatibility issues in a blockchain-fueled data exchange system in an omnichannel context which examines the likelihood and drivers of firms being willing to share data with competitors and with channel partners. This would illustrate the types of industries, products and patterns of consumer behavior offering the largest incentive compatibility issues in terms of the sharing of data.

Third, how successful are ad-tech 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.[17] These vendors span functionalities such as "Activity Monitoring," "Assessment Management," "Consent Management," "Data Discovery," "Data Mapping," "De-identification" and "Privacy Management". Each of these functionalities is likely to be core to a privacy-compliant omnichannel future. But these are also technologies whose role we as the academic marketing community know little about. It strikes us that useful partnerships between academics and firms in this space can help provide an early assessment of the usefulness and how to improve the usefulness of such tools for firms, consumers, and regulatory compliance.

Fourth, as we discussed in the prior 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 blockchained 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 so far focused on the deleterious effects of machine-learning induced algorithmic biases, be they in the form of racial or gender discrimination. Scant research or policy looks at the use of personal information in algorithms. For example, does greater transparency into the customers' path-to-purchase journey, even with the explicit consent of the

[17] https://iapp.org/media/pdf/resource_center/2019TechVendorReport.pdf

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 this data led groups of different socioeconomic backgrounds or different races to pay different prices, based on data. 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 associated with any historically disadvantaged groups.

CONCLUSION

What is unique about omnichannel marketing compared to how firms were interacting with consumers before? In this article, we argue that, in order 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 protecting consumers' privacy—and discuss how emerging technologies like machine learning and blockchain can help allay these challenges. We establish that while these technologies have promise as solutions, they also raise new challenges and opportunities. In addition, we discuss fruitful avenues for future research in each of the three challenge areas. In what follows, we highlight several possibilities of future research that integrate the three areas.

First, obtaining a 360-degree view of the customer experience and maintaining their privacy at the same time appear to at odds with each other. However, a firm might need only a subset of information on customer touch points in order to make effective inferences about attribution. If some of these data that firms might not need for attribution are also those where customers have serious concerns about privacy, the firm can collect only the subset that is useful for its internal purposes, while 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 point above, 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 useful area of research from a public policy perspective as countries could mandate potentially attractive regulations limiting data retention over 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, it might 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, which represents the greatest privacy risk, it will 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, can there be a marketplace for consumer data that results in fair valuation while preserving privacy and thus create a win-win for all? 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 is their asset and just like a property right, they should be able to exchange it with brands for monetary compensation from marketers (Harvey, Moorman, and Toledo 2018). Some consumers, however, hesitate to participate because of the belief that they may not get appropriately compensated for their data by brands and marketers. Future research can 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 when such a blockchain based marketplace emerges, consumers will have a transparent overview of how their data is valued and which brands might be willing to enter an exchange with them. It will be quite beneficial for future research to consider what are the hurdles (both from consumers and firms) to participate in such markets and how to overcome them.

In sum, our thesis is that while omnichannel marketing promises to open up new opportunities for firms, they 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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TABLE 1A: DATA-RELATED CHALLENGES, REMEDIES AND FUTURE RESEARCH

Challenge	Remedies	Future Research
Gain Data Access 1) Within the firm, information on various contact points by the same customer resides in silos 2) Beyond the firm, many touch points not controlled by firm	*1) Federated learning* constructs joint machine-learning model while keeping parties' servers' training data private 2) Tracking customers on 3P matchmakers: walled garden platforms, legacy media agencies or syndicated providers	1) Which ML methods best and generalizable to impute missing pieces of information? 2) What is the optimal design of matchmakers that will collate information from different parties spanning different touch points?
Aggregate Data across Sources 1) different databases, using different rules, data formats, and reporting standards. 2) data sources differ in reliability	1) *deterministic tracking*, which occurs when the firm obtains a persistent login identifier for that consumer 2) *probabilistic tracking* identifies consumers as they browse across different devices. *3) permissioned blockchains* allow firms to control who can see data & validate transactions	1) What is data sharing impact on consumers (price), firms, and policy makers (welfare)? 2) How to incentivize internal and external partners to participate in blockchains? 3) Does blockchain-enabled omnichannel marketing efforts increase or soften competition?

TABLE 1B: ATTRIBUTION-RELATED CHALLENGES, REMEDIES AND FUTURE RESEARCH

Attribution Challenge	Attribution Remedies	Future Attribution Research
Across multiple touchpoints 1)Estimate downstream and interaction impact of each touchpoint 2) Simultaneous touch points 3) channels have different flexibility	1) Long-term impact and synergy in marketing mix model 2) Hidden Markov Chains, 3) Hierarchical Bayes and MultiTouch Attribution (MTA)	1) How to include non-paid (e.g. ffline WOM) in marketing mix models 2) How to bring memory into Markov Chain models? 3) How to exploit different channel flexibility for attribution?
What is *ineffective* as a marketing touch point?	1) Field Experiments 2) Multi-armed bandits	1) Can Block chain resolve field experiment limitations? 2) How to Scale multi-armed interventions?
Across Aggregation Levels Some offline media don't have individual exposure data	Sequentially combine models across aggregation levels	Integrate MTA (individual) with aggregate marketing mix models and Customer Life Time Value

TABLE 1C: PRIVACY-RELATED CHALLENGES, REMEDIES AND FUTURE RESEARCH

Privacy Challenge	**Privacy Remedies**	**Future Privacy Research**
Customers unwilling to allow *focal firm* to collect, parse and sync their data across devices, touch points for marketing in *high involvement* settings	1) Regulation (eg GDPR) to give customers control of their data 2) Deterministic tracking and Customer Data Platforms	1) How to build a predictive model whose suggestions are unlikely to be perceived as intrusive? 2) How to emulate existing blockchain-based ecosystems in an omnichannel context?
Customers unwilling to allow *other* firms that they interact with to share this data with the focal firm	1) Data Exchange Platforms 2) Blockchain Federated learning and Privacy browsers allow customers decentralized ownership rights 3) Machine Learning to predict individual consumers' next actions	1) How to reconcile perspectives on anonymity and pseudonymity? 2) How to identify data controllers and processors in blockchain? 3) How to reconcile transaction immutability and data preservation with individuals' rights?
Regulators unwilling to allow firms to share and sync customer data across different firms, devices, touch points	Help advertisers to get higher returns while using less consumer data, and consumers to get better deals	How to quantify consumer welfare and firm-consumer relationship benefits of ad-tech initiatives on privacy-regulation compliance?