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Refocusing loyalty programs in the era of big data: a societal lens paradigm

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Abstract
Big data and technological change have enabled loyalty programs to become more prevalent and complex. How these developments influence society has been overlooked, both in academic research and in practice. We argue why this issue is important and propose a framework to refocus loyalty programs in the era of big data through a *societal lens*. We focus on three aspects of the societal lens—inequality, privacy, and sustainability. We discuss how loyalty programs in the big data era impact each of these societal factors, and then illustrate how, by adopting this societal lens paradigm, researchers and practitioners can generate insights and ideas that address the challenges and opportunities that arise from the interaction between loyalty programs and society. Our goal is to broaden the perspectives of researchers and managers so they can enhance loyalty programs to address evolving societal needs.

Keywords Loyalty programs · Inequality · Privacy · Sustainability · Big data

1 Introduction

Firms are increasingly turning to loyalty programs (LPs) to manage customer relationships. Such programs help firms identify the most valuable customers, improve customer retention, and enhance the efficiency of marketing communications. Customers also often benefit because participating in these programs allows access to customized products and services, relevant promotions, and enable more personalized and efficient interactions with the firm. This paper takes these positive features as given and focuses on often overlooked societal consequences of LPs.

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The growth of LPs and the increased availability and analysis of "big data" are tied through a virtuous circle: Big data enable firms to make LPs more effective, and LPs are an ideal vehicle for collecting data such as purchase transactions that can in turn enhance the profitability of LPs and other marketing actions (e.g., Kopalle et al. 2012; Venkatesan and Farris 2012). Since rewards are often calculated from transaction data, LPs encourage customers to self-identify when making a purchase. Furthermore, data collection via LPs can lead to a rich 360-degree view of the customer both online and offline, not hampered by typical handicaps such as device switching or the need to match offline sales to specific customers.

The inter-related growth in LPs and big data applications increases the importance of the societal consequences that accompany the many benefits of this virtuous circle. While societal concerns would exist even in the absence of an LP, LPs have the potential to exacerbate these issues. Hence, it is important for firms and researchers to take societal concerns into consideration when designing and managing LPs to the benefit of all stakeholders. This paper ties key aspects of LPs to three major societal concerns: inequality, privacy, and sustainability.

Potential danger to *inequality* stems from the LP/big data capability to target consumers with precision. Not only can personal data be analyzed to identify which types of customers should be targeted with specific offers or services, but such personalized marketing actions can also be implemented with ease because the members are "accessible." This more precise targeting within LPs, enhanced by big data, intensifies the distinction between beneficiaries and non-beneficiaries of LPs. As Lacey and Sneath (2006, p. 458) note, "Firms... are explicitly shifting resources away from non-participating customers in favor of customers who participate in their LPs, which may lead to accusations of discriminatory customer treatment."

Potential danger of infringing on customer *privacy* is based on how personal data are collected, stored, processed, and shared, and is intensified by the completeness of LP data. With the help of big data capabilities, LPs now collect more data than ever, tracking customer behavior both offline and online, including through mobile and connected devices. The result is a heightened threat to data privacy. Lacey and Sneath (2006, p. 458) indicate that for LP members, there is potential for misuse of personal information and for loss of control over how information is being collected and disseminated.

Sustainability is impacted by the power of LP/big data partnership because rewards depend on demand. Therefore, LPs thrive on changing consumption patterns. Big data collected through LPs allow firms to analyze the impact of these programs on demand, and to rely on psychological mechanisms (e.g., Stourm et al. 2015) to more effectively impact consumer choices on what and when to buy and redeem. While some consumption patterns can exert positive externalities on society (e.g., purchase of healthy food), major users of LPs such as retail, consumer electronics, hotels, and airlines are increasingly evaluating the impact of their reward incentives on pollution (Kugel 2020). Clearly, individuals' consumption patterns not only change their own physical and mental health, for better or worse, but also affect those around them.

In summary: (1) Big data enhance the effectiveness of LPs by enabling more precise targeting and deeper insights. (2) LPs and big data reinforce each other, contributing to the growth of both. (3) The power of the LP/big data combination has clear implications for society, particularly for inequality, privacy, and sustainability.

The goal of this paper is to show how researchers and practitioners can enhance both research and practice by viewing the LP/big data union through a societal lens. We propose a framework to enable academics and practitioners to consider carefully the societal impact of an LP's design and its management. The framework, illustrated in Fig. 1, places a *societal lens* between research and practice to refocus our view by serving as a central perspective by which researchers seek guidance from practice, and by which practitioners seek to implement research findings in LPs.

The rest of the paper proceeds as follows. Sections 2, 3, and 4 elaborate on three facets of our societal lens perspective: inequality, privacy, and sustainability. In each section, we first elaborate how LPs in the big data era impact that specific facet and then provide suggestions on how the adoption of the societal lens may generate ideas for future directions on how researchers and practitioners can address the societal challenges. Section 5 briefly discusses the interdependences across the three facets and section 6 concludes with a summary of our contributions and a discussion of how the framework may be applied to related settings.

2 Inequality

2.1 How LPs impact inequality

This section outlines how data-driven LPs can impact inequality using three examples: (1) when LPs use reward thresholds and tiers to offer certain benefits exclusively to consumers that reach a certain spending amount or status and not to others, (2) when LPs use personalized targeting of marketing activities enabled by customer-level score metrics, and (3) when LPs integrate big data across domains and/or companies where inequality in one domain and/or company carries over to another (unrelated) one. We elaborate on each example below.

First, the reward structure of LPs can increase inequality. For example, status and reward tiers create a hierarchy among consumers by providing improved services, prices, and rewards for consumers who spend above certain thresholds. The labels of
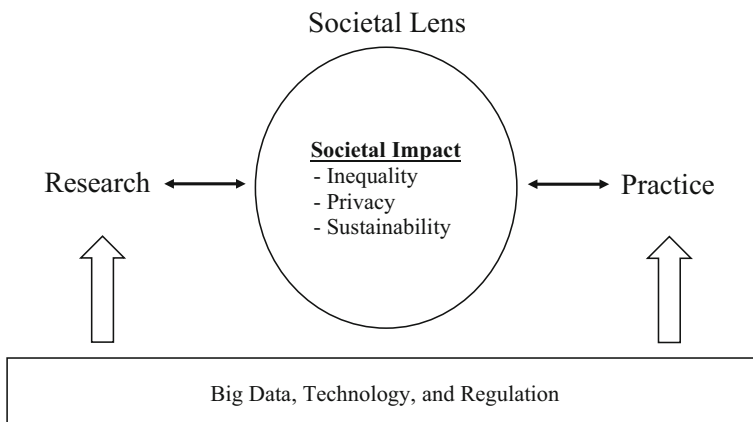

Fig. 1 A societal lens framework to guide loyalty program research and practice

tiers often reflect luxury and hierarchy, such as "silver," "gold," and "platinum" for tiers of increasing exclusivity. Big data enable firms to identify customers who are best prospects to be targeted with offers that either move them into upper tiers or reduce membership fees. Such exclusive offers can lead to a substantial degradation of service for the remaining customers, or those who qualified for the benefits through their regular consumption patterns, perhaps explaining why non-tiered programs seem to enjoy higher overall customer retention (Gopalakrishnan et al. 2020).

Second, firms often personalize products, prices, and communications using customer-level scoring metrics that rely on big data collected through LPs. Such metrics are becoming more fine-grained as programs increasingly track individual behavior, including measures of consumer engagement (Safdar 2018). In turn, these metrics allow firms to separate consumers into more fine-grained segments, often through statistical scoring algorithms. Serving customers differently based on their scores may exacerbate social inequality by refusing the poor what is necessary and giving the rich what is superfluous. While this may be unintended, personalized targeting may increase wealth inequality, which may perpetuate inequalities in other domains. In the extreme, wealth inequality may curtail access to education or even political influence (Stiglitz 2019).

Third, metrics such as customer lifetime value (CLV) that are used to compute customer-level scoring metrics often reflect income inequality because of the "triple-jeopardy" phenomenon (Ehrenberg et al. 1990): wealthy customers are more valuable to the firm, and this may manifest itself in three key components of CLV: lower churn rate, more frequent orders, and larger expenditure per order (e.g., Fader et al. 2007).

As LPs expand to track transactions at multiple retailers across domains, customer-level scoring metrics may beget even more inequality. For example, lower income consumers who start out with low scores with one set of retailers can have difficulty in improving their scores with other retailers due to data sharing across firms. An example of this cross-effect is the Chinese Social Credit System, which uses big data to measure the trustworthiness of individuals. Citizens with low scores may not only have trouble accessing credit, but also risk sanctions and travel restrictions, as well as potential losses to social capital, which refers to resources from a personal network (Coleman 1988). Therefore, a low score on one component of the system translates into lower scores on other components of the system, potentially further distancing those citizens from mainstream society (Kuhnreich 2018). The Chinese Social Credit System is not an LP, but illustrates a theoretical impact of data sharing across retailers[1]. A customer who has accumulated few points at retailer A's LP will be identified as low potential when retailer A shares data with retailer B, and hence not targeted with special rewards. This may accentuate the unequal treatment of lower versus higher income consumers.

2.2 Opportunities for addressing inequality

Having identified key ways in which LPs can impact inequality, a natural direction for future research and practice is to investigate how LPs can address the negatives inherent in amplifying inequality. We draw on the three elements that generate inequality discussed above.

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[1] Firms including Baidu, Alibaba, and Tencent share data on individuals' purchase histories, private messages, gaming behavior, networks, dating behavior, preferred newspapers, browsing behaviors, as well as offline behavior.

First, to improve the impact of the design of LP rewards and fee-based membership on inequality, research is needed to investigate design solutions that most consumers would consider fair (and at the same time be profitable). A classical approach would be to utilize the "veil of ignorance" (Rawls 1999) to specify quality and prices across reward tiers. For LPs with different tiers, this means designing the conditions to access tiers ex-ante in such a way that the design team and different customer segments would find the quality differences acceptable if they were to ex-post find themselves in any tier, including the lowest one. One challenge, however, is that perception of fairness and tolerance for disparities across tiers can be primed by cues, which differ across and within cultures (Wang and Lalwani 2019).

For example, airlines often nudge or simply offer high-value customers the opportunity to buy into a higher tier status (Liu-Thompkins et al. 2020). This accentuates inequality. Management can address this by considering actions that improve the perceived fairness of the LP by limiting inequalities in service quality across segments. For instance, an airline can set up a more comfortable waiting area and boarding procedure for non-tiered members, or implement policies allowing low-tier members who are seniors or are accompanied by children to either board early or have guaranteed carry-on baggage space to mitigate the stress they would ordinarily experience by boarding last.

Second, to improve the impact of personalized targeting on inequality, research and practice need to identify and evaluate solutions to limit (unintended) inequality produced by automated algorithms. While algorithms for big data are being developed to be easy to understand and interpret (e.g., Lee et al. 2019), increased transparency is not always viable since many LPs consider their scoring algorithms to be protected by intellectual property rights, such as trade secrets. Thus, research is needed to identify ways to communicate how personal data are used to score users, and the subsequent impact on prices and service access. It would also be valuable to better understand how personalization, based on fine-grained segmentation, can be implemented to benefit consumers to better balance the negative impact on inequality with the positive benefits of differential treatment across all. Given the new availability of big data, reward tiers could be designed in a way that accommodates differences across customers' needs.

Third, to improve the impact of the integration of data sources across firms, we advocate research on when allowing consumers to start from a "blank slate" would alleviate inequality and at the same time benefit firms. Such an approach could entail refraining from processing and transferring personal data of consumers who are anticipated to be penalized by their own data. Purposefully removing data of disadvantaged consumers from processing (especially "old data") may protect firms from unintentional discrimination when using automated personalized algorithms (Speicher et al. 2018). Research is also needed on when personal information should be shielded from other industries, or how to calculate scores across industries in ways that address inequality differences.

3 Privacy

3.1 How LPs impact privacy

This section examines how data-driven LPs challenge privacy. The increasing complexity of LPs brings consumers both anticipated and unanticipated privacy risks

(Hosanagar 2019). Some consumers may not have concerns with sharing data with their preferred retailer. Despite this, they may not desire their data to be processed by or transferred to third parties. Privacy concerns also vary by the types of personal data collected, e.g., transactions, text messages, information on a customer's network, location, and biometric data (i.e., pictures of faces for recognition). While some consumers are more concerned about privacy than others, privacy risks deter some consumers from participating in LPs (Hinz et al. 2007).

The era of big data has further exacerbated the concerns and risks connected to privacy, as it has given rise to more complex programs that involve multiple data processors and partners (Turow 2017). For example, parties that often collaborate to process personal data collected through complex LPs include partner retailers, platforms that connect retailers, data processors (e.g., Fintech and ledgers used to record blockchain transactions), and other marketing partners (e.g., social media platforms). Furthermore, as LP-based firm actions become more real-time, aided by technology, big data become relevant. Big data and technology provide firms a large scale of personalization opportunities using LP data that were not possible earlier, and have implications for privacy, and thus place LPs under increasing scrutiny from regulators.

For example, a national data protection authority in the European Union (EU) recently audited 12 LPs and found that 11 of them contained multiple breaches to privacy pursuing to the EU's General Data Protection Regulation (GDPR), which applies to any firm that processes data of people in the EU. In particular, they found that (1) most LPs processing personal data for direct marketing and profiling tended not to collect consumers' consent, (2) 40% of LPs did not provide clear and easy-to-use options to opt-out from direct marketing such as text messages or emails, (3) 40% of LPs collected excessive amounts of data, and more than half of these did not indicate specific third parties to which they shared the data with, thus misleading customers and failing to provide them with clear and transparent information, and finally, (4) 60% of LPs either did not have specific terms for the storage of personal data or had terms that were unreasonably long (GDPR Register 2018).

3.2 Opportunities for addressing privacy

Researchers need to develop and analyze solutions that assist firms to take a proactive and preventative approach to protect consumer privacy by default, rather than to craft remedies ex-post once weaknesses have been exposed (Monreale et al. 2014). This is even more important since "privacy-by-design" has become a regulatory requirement for firms subject to GDPR. Two common privacy-by-design IT solutions worth investigating in an LP context are encryption (restricting access to the sensitive data only to specific authorized individuals within an organization) and pseudonymization (anonymizing a customer's identifiers for the purpose of processing them across multiple parties or subcontractors, while storing in a separate location the information that can re-identify the customer). Privacy-by-design also conveys a managerial dimension: to include privacy concerns from the conception of an LP and ensuring that any mechanisms it relies upon have been thought to be privacy-preserving.

Another direction to address privacy is to understand under what conditions consumers should reveal personal data to firms in order to receive personalized marketing and how to compensate consumers through rewards for access to

data. Blanco-Justicia and Domingo-Ferrer (2016) propose an information protocol through linked tokens that enables consumers to enroll in an LP and earn rewards without having their personal information or even payment histories revealed to the firm. Customers choose how much personal data to reveal for the purposes of profiling, if any, and such data is compensated with points. The protocol emulates the incognito mechanism of punch-card LPs that offer rewards without the need for identifying information.

Regardless of whether retailers should purposefully blind themselves and others from identifying information, there is an increasing need for both research and practice to create and adopt methods to retain the value from LP data without requiring personal identifiers. One such method is provided by Kakatkar and Spann (2019). They develop a methodology for analyzing anonymized and fragmented data, which allows retailers to approximately recover individual-level heterogeneity and derive meaningful variables from the raw data. Another solution is called deep anonymization, which stochastically alters individual-level data while preserving the distribution of data across people. For example, startup WeData helps healthcare researchers access patient data from hospitals, while preserving privacy, by creating new "avatar" patients with characteristics equal to weighted averages from small clusters of very similar patients. Such methodologies could guide LP design by using both dependent and independent variables constructed from fragmented or anonymized retail datasets that cannot easily be traced back to identifiable individuals.

4 Sustainability

4.1 How LPs affect sustainability

Our notion of sustainability broadly refers to the quality of our collective lives, encompassing both the environment and the health and well-being of people (see Barrington-Leigh and Escande 2018). LPs can impact sustainability through their influence on consumer demand. While researchers have not clearly established that LPs increase *primary* demand, the economic and psychological impetus for LPs to increase primary demand is well-researched (e.g., Zhang and Breugelmans 2012; Kopalle et al. 2012; Taylor and Neslin 2005).

Regulators are increasingly more concerned that the excessive consumption of certain goods and services through LPs may be detrimental to the environment. The UK's Committee on Climate Change (Carmichael 2019, p. 35) recently recommended regulators to "introduce a ban on air miles and frequent flyer loyalty schemes that incentivize excessive flying," thereby following Norway, which introduced taxes on reward miles (Skapinker 2019).

In addition, many sustainability-minded customers are already making decisions based on environmental friendliness, and indeed there are companies that have unique selling propositions related to serving society at large. Hence, the customer relationship created through LPs can benefit from positioning such companies alongside sustainability targets.

4.2 Opportunities for addressing sustainability

Many companies are currently seeking ways in which LPs lead to a win-win outcome for consumers, companies, and society at large. LPs can adapt technology to monitor and reward decreases in the carbon footprint of transaction patterns (Groening et al. 2015), or target other behaviors that promote sustainability. Academic research is required to provide the much-needed theoretical backbone to support recent initiatives undertaken by companies. For example, the South Korean government has introduced rewards for credit card purchases that reflect more sustainable consumption, such as purchasing products with low carbon footprints and using public transportation (UN ESCAP 2016). The Australian air carrier Qantas has introduced "Fly Carbon Neutral," a new reward program that allows frequent flyers to earn points for each dollar's worth of carbon offsetting, with the money being used to fund non-profit projects selected by the airline, including initiatives to protect the Great Barrier Reef and power renewable energy (Banis 2019). Other airlines use approaches such as analyzing customer data to profitably decouple the reward from an incentive to overconsume, for example, by "allowing customers who are approaching next-tier status to pay for it without hopping on wasteful flights" (Kugel 2020).

As to the promotion of healthier behavior, Lympo (2017) aspires to build an ecosystem where consumers are rewarded with crypto-points by insurance companies for patterns in fitness and wellness data tracked by health apps and wearable technologies. Similar partnerships exist between insurance companies and supermarkets to reward healthy purchase habits (Mochon et al. 2017; Tuzovic and Mathews 2017). With the rise of geo-location tracking technologies, insurance companies could provide rewards in addition to discounts on insurance premiums for safer driving behaviors (AXA 2015).

While advanced tracking technologies enable the use of rewards to address sustainability concerns, research is needed on how to limit possible adverse consequences. Extrinsic incentives on responsible consumption can sometimes backfire and lead to unintended consequences on consumer satisfaction and guilt (Giebelhausen et al. 2016). Furthermore, rewarding any type of consumption, even those of eco-friendly products, may increase total consumption and thus lead to an overall higher carbon footprint.

One final promising avenue for sustainable LP design is to explore partnerships between businesses and municipal governments, allowing them to integrate LP data with external measures of impact on the environment and well-being. For example, LPs may reward customers for sustainable behaviors, such as the propensity to properly recycle at the local level. Partnerships with utility companies could help firms design rewards that raise awareness for responsible consumption habits with respect to electricity and water usage.

5 Interdependencies across the different societal aspects

Interdependencies among inequality, privacy, and sustainability provide challenging but promising opportunities to utilize the societal lens in designing LPs. Thus, both researchers and practitioners should be aware of these interdependencies when

considering LPs. We illustrate these intersections for privacy-inequality and sustainability-inequality.

Privacy and inequality are interdependent, as access to privacy in LPs may become a luxury that only a few can afford. For example, firms may offer LP members the opportunity to consent to having their data collected, while non-members may have their data collected without consent. But LP membership may be practical only for higher income consumers, as lower income consumers may not consume enough to earn rewards. Thus, making discounts contingent on consent increases inequalities across people's ability to protect their right to privacy. The practice of combining rewards and discounts to obtain consent has been challenged in recent popular literature as "coercion" (O'Neil 2017) and using rewards to obtain consent as "bribes" (Turow 2017). In fact, the California Consumer Privacy Act of 2018 (Paragraphs 1798.125(a)(1)) limits firms from charging different prices and discounts for consumers who take actions to protect their privacy. However, this practice is allowed if the price difference is directly related to the value provided by the consumer's data (Paragraphs 1798.125(a)(2)). Thus, if high-income consumers' data are more valuable simply because they purchase more, they can access lower prices and more rewards.

Sustainability and inequality are also interdependent. For example, rewarding environmentally-friendly behaviors may exacerbate inequality when such behaviors are systematically more difficult for low-income households to adhere to. Also, rewards that successfully promote environmental sustainability and well-being for some consumer segments can at the same time encourage the opposite for others. For instance, pricing insurance based on detailed personal health information leads people to pay in advance for their expected risks, which can price out vulnerable consumers instead of pooling risks across the population (e.g., Tirole 2019; O'Neil 2017). To address this interdependency, assessment reports by firms would not only help to determine whether a majority of customers are improving their behavior as intended but could also help to anticipate and monitor the behavior of savvy consumers who often exploit special "point hacking" opportunities to maximize the value of free rewards received, and who even resort to stockpiling points through manufactured spending schemes (e.g., Studer 2014; Herreria 2016; Tahara 2016). Future research in LPs, in particular for emerging LPs linked to health data and insurance rewards, is needed to encourage mindful consumption by consumers for whom pricing based on personal information could adversely discriminate against vulnerable consumers.

6 Conclusion

Loyalty programs have advanced dramatically in their design and management in response to technological advances that enable them to leverage big data. Modern programs allow points to be redeemed anytime and across select partners (Stourm et al. 2017; Gardete and Lattin 2018), and some crypto-points can even be exchanged with other crypto-currencies, as well as between consumers (Fromhart and Therattil 2016). As big data fuels the expansion of LPs, LPs in exchange fuel the collection of big data through rewards. This evolving, symbiotic relationship between big data and LPs impacts not only consumers and firms but also society at large. Thus, as interdisciplinary research fueled by the growth of LP data raises the sophistication of LPs, such as by

informing firms when to reward consumption based on quantity vs. expenditure (Chun and Ovchinnikov 2019), or on how to dynamically set prices on services redeemable in points (Chung et al. 2020), we hope that the next generation of research applies the societal lens to refocus these advances in the era of big data.

This paper aims to motivate and guide researchers and practitioners to apply the societal lens as they leverage big data to develop their LPs. We developed a framework that encourages researchers and managers to identify, evaluate, and improve the impact of LPs on inequality, privacy, and sustainability. A key aspect of the framework is that research should inform practice and practice should inform research through the societal lens. We illustrated the framework to identify key areas for research and practice based on the societal lens. To strengthen customer relationships by designing LPs to become more equitable, adhere more to privacy, and be more sustainable, we have discussed some suggestions:

- Adapt the reward and fee structure based on demographics (income, need, etc.) to facilitate the access of rewards for people in need.
- Develop analytic methods that only utilize certain information in rewarding and targeting customers to allow concerned consumers to preserve privacy while benefitting from rewards.
- Adapt metrics derived from LP data and reward points to encourage consumers to develop habits of sustainable product consumption. For example, while CLV could be optimized using the conventional metrics in an LP, the externalities of expected future purchase patterns on the dimensions of inequality, privacy, and sustainability could also be increasingly considered.

With the growing concentration of market power driven by connecting LPs and big data, it is increasingly important for business and society that market leaders implement socially responsible LPs. While much research is needed to show how firms can benefit from refocusing LPs through the societal lens, we posit that LPs that address the key societal challenges of inequality, privacy, and sustainability can generate competitive advantages for firms and thus contribute to improved brand value in the long run. A promising direction for future research lies in the interplay among consumers, firms, and society. For instance, public agencies and local government may partner with corporate LPs to encourage behaviors such as recycling and bike sharing.

While some of the societal issues we discuss here also apply to other marketing activities, LPs are unique and different from other marketing activities in their *inherent* link to big data. This relationship is mutually reinforcing: LPs enable the collection of big data, and big data can be used to enhance and expand LPs—a virtuous circle. As a result, LPs trigger (1) privacy concerns related to the collection and usage of fine-grained, identifiable data on consumers, (2) inequality concerns related to the design of the program where consumers can or cannot enter/benefit, and (3) sustainability concerns related to the usage of rewards. So, the inherent link between LPs and big data naturally links LPs to a variety of societal issues that makes this marketing instrument a worthwhile focus for the application of the societal lens.

Still, we consider it worthwhile to expand the framework to consider other societal facets, other big data era consequences that impact privacy, inequality, and sustainability, or on how new datasets such as biometrics, social media text, and social network information are

changing LPs' societal impact. We hope that our work inspires related fields that share characteristics similar to LP design and management, such as referrals, subscriptions, and social media marketing to incorporate the societal lens (Iyengar et al. 2020).

To conclude, this paper has tied key aspects of LPs to inequality, privacy, and sustainability. While LPs alone are not the cause of the negative externalities that we identify across the three dimensions, we argue that through LPs, firms can increase the effectiveness of their efforts in diminishing these concerns, and perhaps even more successfully compared with other marketing instruments due to the unique nature of the increasing quality of consumer data that is collected linked to incentives offered in LPs.

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