Leveraging Customer Conversion Behavior in Hyperconnected Networks

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Abstract: *This paper focuses on how leveraging conversion rates in hyperconnected networks can help retailers face the challenge they face to meet customer expectations with efficient and effective supply chains with increased. The conversion rate is the percentage of visitors to an online platform who finalize a purchase, and understanding and estimating such curves help sh*

challenge to weigh these tradeoffs and decide on the combination that best meet their customers' needs and maximize the profit.

Because conversion rates are affected by various factors including pricing, user experience, shipping and delivery, examining the relationship between any single factor and the conversion rate is a challenging task. Further, as most companies log sales data but do not log demand data, conversion data is sparse, and the existing data is oftentimes unreliable, further skewed by other factors.

In this paper, we focus on conversion rates as a function of quoted lead time that affect the resulting demand. We challenge the notion that all customers ubiquitously desire to get the products as soon as possible, in line with early research in Montreuil et al. (2013) and explore how this concept can be leveraged in hyperconnected networks with the Physical Internet (PI).

Since faster delivery usually requires more expensive modes of transportation (for example, air cargo, less-than-truck services, or parcel delivery vans) the trade-off between delivery speed and lost demand from not meeting customer delivery expectation must be studied to maximize the overall profit while maintaining high customer satisfaction. However, while decision making in the industry have generally assumed that all customers want the products as soon as possible, some customers might be either insensitive to the quoted lead time or have specific time window such that getting the product delivered earlier than the start of the time window could in fact decrease the conversion rate. Such complexity in customer conversion behavior can be observed for different product types, customer groups, seasonality, and whether the products are customized or not.

In the past decade, some retail industry leaders, namely Amazon or InstaCart, have begun to offer specific time windows for product deliveries, since customers in these industries tend to be more time-sensitive than those in other industries. For these products, the time of delivery could be a deal breaker for most customers (they do not want food items to be spoiled, etc.). For most other industries, guaranteed delivery in a certain time window is more expensive and logistically difficult, especially for retailers selling big and bulky products with high costs such as furniture, large electronics, or vehicles. However, the Physical Internet and the interconnectivity it provides with the hyperconnected logistic networks and supply chains allows a more flexible, efficient, and responsive logistical system in which we could leverage the understanding and estimates of customer conversion behavior to maximize profit and/or customer utility.

In this paper, building on a systemic literature review, we first provide a characterization of diverse types of customer behaviors relative to delivery/pickup time sensitivity. Second, we develop in deeper mode the Physical Internet levers usable for enhancing conversion rates. Third, we analyze how leveraging the different customer behavior types in the Physical Internet may lead to even higher conversion rates in an efficient and sustainable way. We contrast the relative impact of PI's interconnectivity levels on conversion with three representative scenarios: independent retailer, independent retailer with flexible mode options, and retailers in a hyperconnected network. We finally provide conclusive insights and avenues for further research.

2 Literature Review

The concept of the Physical Internet, introduced by Montreuil (2011), is an approach to allow and enable an open, hyperconnected logistics system grounded on interconnectivity on multiple layers including but not limited to physical, digital, and operational levels. For an introduction to and formalization to the concepts of the Physical Internet and hyperconnected logistics systems, refer to Montreuil (2013).

Best to our knowledge, the role of conversion rates in hyperconnected networks has not been formally studied. However, with e-commerce shaping the landscape of retailing in the past few decades, an abundance of literature on conversion rates study methods to improve conversion rates, either through artificial intelligence and machine learning algorithms or through creating a better user experience (UX) design. The former takes advantage of the now available data on customer behavior and preferences to improve personalized recommendations and targeted marketing. Childers et al. (2001) and McDowell et al. (2016) are examples for the latter in which the authors study how web design and enhancing online shopping experiences relate to conversion rates. Zimmermann and Auinger (2022) also provide a marketing optimization framework for driving sales through optimizing the conversion rates. While various factors contribute to conversion rates (e.g., website design, user experience, marketing), we primarily focus on the time-sensitive aspects and how the lead times impact the conversion rates and thus sales.

Traditionally, researchers have recognized the role of lead times in customer utility and thus sales (Brynjolfsson et al. 2009, MH&L 2016, and Kumar et al. 2000, So and Song 1998, de Treville et al. 2014, to name a few). The relationship between lead times and conversion rates have been studied by researchers in different disciplines with the notion that by decreasing the wait times, customer utility increases, including methods to offer quick delivery to remain competitive (Kumar et al. 1997 and Brynjolfsson et al. 2009). Following this assumption, researchers have modeled demand or sales as a linear decreasing function of time (either wait times or lead times) as shown in the early models of intertemporal choice such as the work by Samuelson (1937).

However, more recent works show that such assumption might be over-simplifying the time-sensitivity. For instance, Thaler (1981) showed that consumers have a higher sensitivity for low-priced products. In fact, in addition to prices, other product attributes are linked to varying lead time sensitivities as Cui et al. (2020) shows. Xia and Tahagopalan (2009) study how lead time sensitivity differs for various product categories. Lead time sensitivity also varies by customer groups and thus it is important to adjust the impact of quoted lead times on demand accordingly for each group of customers (Jin 2013, Fisher 2019). Montreuil et al. (2013) creates different client profiles and purchasing behaviors as a function of lead times for each client profile. With the representation of such client behaviors, they provide a simulation approach aiming to estimate a business's ability to meet delivery deadlines in a make-to-order environment.

Further, Montreuil et al (2013) challenge the notion that all customers prefer shorter waiting times in all of their purchases – depending on the client profile, some are either less sensitive or insensitive to the lead times, or would prefer a certain time window rather than getting the products as soon as possible. Marino et al. (2018) also notes that in some instances, “consumers might prefer to delay an event’s occurrence”. In this paper, we continue to challenge the idea that all customer groups share the same behavior and desire for products as quickly as possible. Instead, we show how retailers can leverage the characterization and analysis of customer conversion behavior with varying lead time sensitivities in hyperconnected networks.

Building on the early work of Montreuil et al. (2013), we provide exemplary models of customer behavior profiles with utility, and thus the likelihood of purchase, as a function of lead time. The assumption that all customers have pre-determined preferences relative to lead time which varies by different customers and different products is made. Sales is represented as conversion rates, or the fraction of website visits that translates to a purchase in e-commerce retailing. In such settings, lower conversion rates correspond to lost sales from potential clients, whether because of pricing, product attributes, user experience, etc. We focus on the time-sensitivity aspect of conversion rates, and aim to represent the change in customer preferences and thus the fraction of actual purchase from change in lead times.

Three customer behavior patterns are introduced as a basis for representing more complex customer conversion behaviors in response to lead times: as soon as possible customers, target time, customers and patient up to a threshold customers. The design and characteristics of each customer behavior pattern is now explained.

3 Characterizing Customer Group Behaviors

3.1 As Soon As Possible Customers

We first present the as soon as possible customers, that desire the product to be delivered to them immediately. Customers in this group exhibit decreasing utility and thus decreased likelihood of purchase as the waiting time increases for them. The curves are represented as concave curves that exhibit the maximum sales in the lowest lead times, and the conversion rate decreasing in decreasing increments as the lead time increase – such shape represents the higher time-sensitivity closer to the desired delivery time (in this case, 0). Figure 1 shows example conversion curves with varying parameter values, with the horizontal axis representing quoted lead times shown on an e-commerce website, and the vertical axis representing the conversion rate. The leftmost curve (labeled ASAP 1) represents the most impatient customer as the curve sharply drops to null value after the desired delivery time of 0. The rightmost curve (labeled ASAP 8) represents the most patient customers with the conversion rate dropping by the least amount compares to all other customers. The curves in the middle represent the customers with time-sensitivity between the first and the last ones, with decreasing time-sensitivity as we move to the right.

This group of customer behavior represents the assumption that has been made in many of the past studies, that the customers want the products as soon as possible, and the utility decreasing as the delivery time shifts further from the time the order is placed. In fact, adjusting the parameters so that the curve becomes completely linear, we would get the conversion rate graph as a linear function of lead times, the equation that had been used in studies from multiple fields to represent customer behavior.

Note that in these illustrative examples, we assume that the conversion rates are function of a lead time only and thus all customers will purchase after a visit if and only if the quoted lead time is acceptable for them, thus the maximum value of 100% attained at some point in all scenarios. However, in reality, multiple factors affect conversion rates and even if the quoted lead time is acceptable for the customer, a visit does not always lead to a purchase. In fact, the average conversion rate is only around 4% (Lee et al. 2012). The rates shown in these illustrative graphs should thus be understood as relative fractions of the maximum attainable conversion rates given all other factors, and estimated from empirical examples.

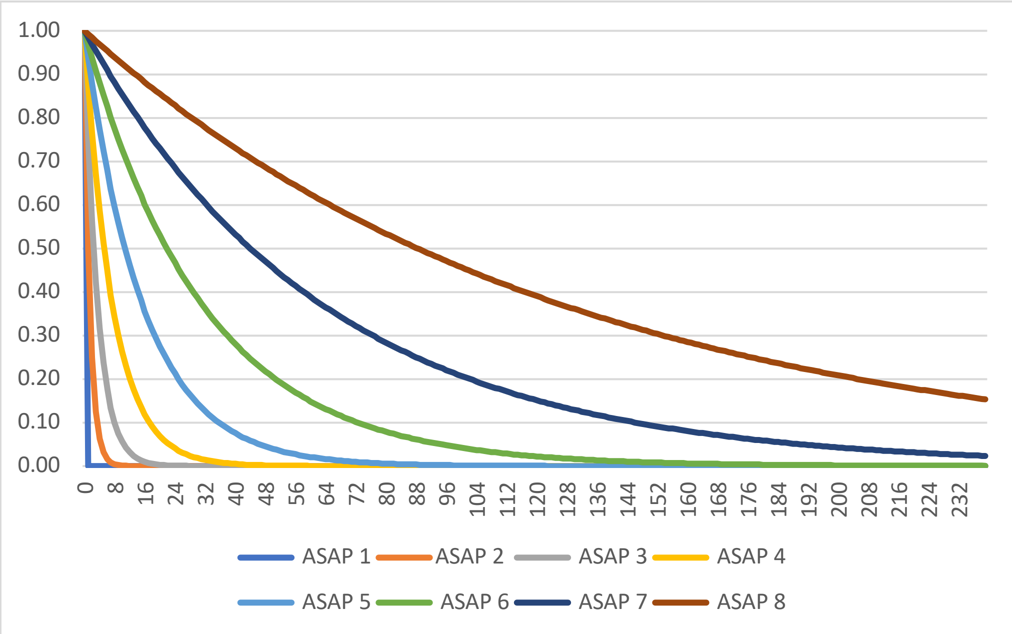

Figure 1: Example Curves for As Soon As Possible Customers

3.2 Target Time Customers

Challenging the common assumption made for the as soon as possible customer group that customers want the products immediately after they make an order, the second customer group profile represents the customers that ideally desire to receive the product at some point in the future. The utility and thus the conversion rate for these customers is the maximum at the points near their desired delivery time, and decreases as we deviate in either direction from this point. In fact, the conversion rate starts at a certain value (determined by the parameters) at lead time of 0, and then increases until the desired lead time is reached. Then as the lead time increases after that point, the conversion rate drops to eventually reach a null value. Note that the second portion of the graph consisting of the point in which the target time is reached until the end of the graph is similar to the first customer group curve for the as soon as possible customers. Varying levels of time-sensitivity is observed for either portion of the graph similar to the first set of curves illustrated.

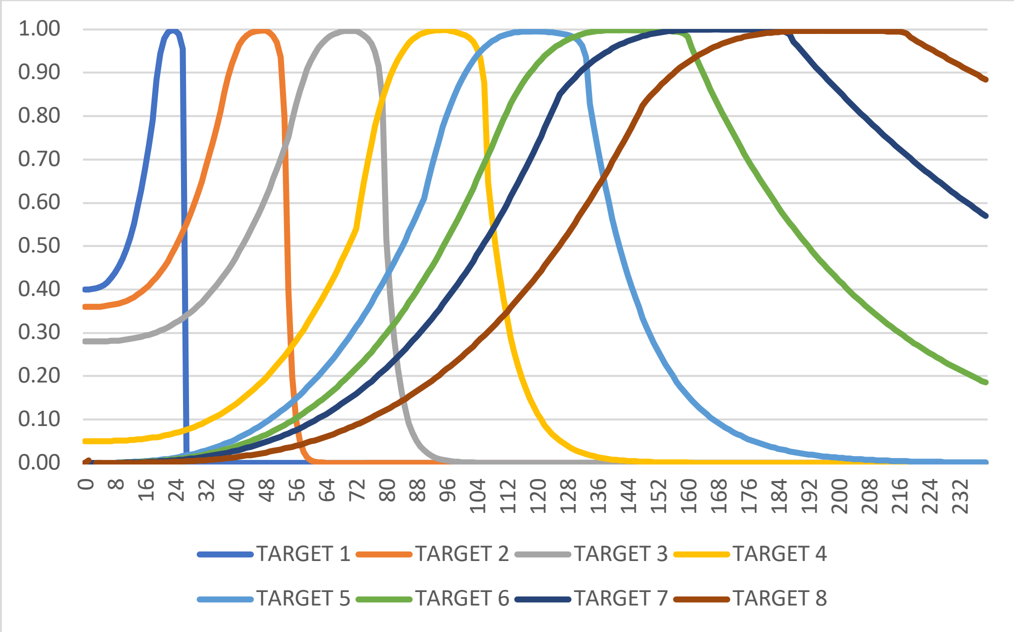

Figure 2: Example Curves for Target Customers

3.3 Patient Up To a Threshold Customers

The third type of customer conversion behavior is patient up to a threshold customers (PUTT) who ideally desire the product immediately, similarly to the as soon as possible customers, but are more willing to wait up to a certain point. These customers are patient until this set point and thus the first leg of the curve is concave. However, once that threshold point is reached, the conversion rate drops rather sharply. The second part of the curve, from the threshold point to the remaining lead times, is again similar to the as soon as possible customer group curves with concave curves of varying sensitivities that eventually reach the null value.

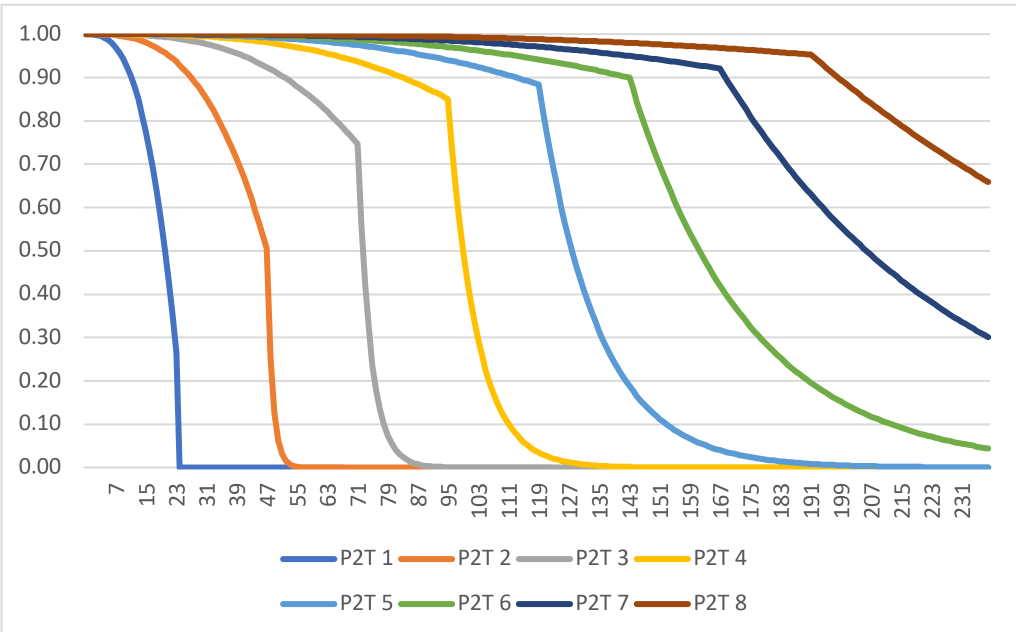

Figure 3: Example Curves for Patient Up to a Threshold (PUTT) Customers

4 Physical Internet Levers

Universal interconnectivity (interconnectivity in multiple layers including physical, digital, operational, transactional, and legal interconnectivity) is key to making the Physical Internet an open, global, efficient and sustainable system (Montreuil et al. 2012). With the Physical Internet, interconnectivity in the following levels can be achieved, that are particularly relevant in the context of conversion rates:

1. Physical Interconnectivity: With physical interconnectivity, physical objects (trucks, parcels, etc.) are able to flow seamlessly across parties, facilities, and modes through the hyperconnected networks, in which they are "moved, handled, and store ubiquitously" while meeting regulatory, security, and other operational constraints. Thus, in a supply chain in which the physical interconnectivity is ensured, the orders customers place online would be flowing seamlessly and at a greater flexibility in terms of when and how the items are delivered from the source (manufacturer, supplier, etc.) through intermediate nodes (hubs, warehouses, etc.) to the final delivery point (retail stores for pickup, customer homes, etc.).
2. Digital Interconnectivity: With digital interconnectivity, information is shared seamlessly across the entire network and with all stakeholders and entities. This informational interconnectivity allows transparency including tracking the status and location of the objects moving in the network, as well as real-time update on the changes in customer demand and the availability of the products demanded from the supply side. Such real-time information is openly available not only among the virtual agents, but human actors (truck drivers, decision makers, etc.) as well, and would allow a more dynamic supply chain in response to any changes in conversion rates.
3. Operational Interconnectivity: Interconnecting the networks on an operational level among multimodal logistics and transportation service providers ensures consolidation and synchronization (Crainic et al. 2016). These synchronized in-the-field operational and business processes include using standardized business contracts as well as the operational protocols (Montreuil et al. 2016). For conversion rates, e-commerce retailers could gather crucial information on how the quoted lead time affects sales by offering a standardized procedure of asking the desired time window for when the customers desire to receive the products.

Dynamic, synchronized deployment of physical items further increases the availability of products across the hyperconnected network. With an open and transparent network of warehouses, hubs, distribution centers, and fulfilment centers, retailers can deploy the right products at the right places at the right times as the required information is readily available and with seamless delivery through different transportation modes. Sohrabi et al. (2016) and Yang et al. (2017) provide optimization and simulation-based experiments showing that such interconnected distribution result in up to 30% increase of "efficiency, responsiveness, resilience, and security, through a dynamic network approach securing supplies without duplication of safety stocks and fast fulfillment in line with market expectations" (Ballot et al. 2021).

The efficiency and responsiveness in hyperconnected networks allow for delivery speeds that are not currently achievable in many realistic cases – depending on the type of items being shipped, air cargo might not be an option and even if it is, it is usually a costly option. Moving through different phases of the Physical Internet thus provides a greater flexibility in delivery options, allowing for a full exploitation of the conversion curves. With faster delivery, the left-side boundary of the conversion curve shifts to further left, and with effective deployment, delivery can be delayed and even finetuned as needed.

We now contrast the three representative scenarios: independent retailer, independent retailer with flexible mode options, and retailers in a hyperconnected network.
The independent retailer can only access one mode of delivery. Since it is limited to a single mode, the lead time cannot be adjusted based on the conversion rate to maximize the profit based on expected sales. Orders are shipped to the customer as soon as they are placed. Then, we have the independent retailer with flexible mode options – we can now leverage premium shipping options to increase demand when the net revenue is worth the change. In hyperconnected networks, different retailers now collaborate with real time sharing of information. For non-time sensitive goods, or products with higher conversion rates with delayed delivery, shipments are consolidated to save delivery costs. With hyperconnected network, faster deliveries allow us to use the lower lead time portions of the conversion curve.

5 Conclusion

This paper focuses on the impact of quoted lead time on customer conversion rates, which affects demand and sales by challenging the assumption that all customers desire immediate delivery. We explore how this concept can be leveraged in hyperconnected networks with the Physical Internet (PI) -- leveraging the PI's interconnectivity can lead to a more efficient, flexible, and responsive logistical system. To fully take advantage of the interconnectivity the PI provides, different customer behaviors and thus varying conversion curves are acknowledged. We thus provide a characterization of three types of customer behaviors relative to delivery/pickup time sensitivity, namely As Soon As Possible (ASAP) customers, Target Time customers, and Patient Up to a Threshold (PUTT) customers. We then develop Physical Internet levers that can enhance conversion rates, and analyze how leveraging different customer behavior types in the PI may benefit the retailers in an efficient and sustainable way. We contrast the relative impact of PI's interconnectivity levels on conversion with three representative scenarios: independent retailer, independent retailer with flexible mode options, and retailers in a hyperconnected network. This paper provides insights into how retailers can balance the tradeoff between delivery speed and lost demand from not meeting customer delivery expectation to maximize profit while maintaining high customer satisfaction.

Further research directions include further exploration of customer behavior to include more complex scenarios to refine the understanding of conversion behavior. Methods on the specification of the parameters that determine the scale and shape of the curves should be further studies as well. While the paper briefly touches on sustainability, additional research could explore the potential impact of leveraging the conversion rates in the Physical Internet settings on supply chain sustainability, including quantifying the degree of efficient use of resources, or the reduction in carbon emissions. Finally, with the potential to disrupt traditional business models in logistics and e-commerce, future works could explore the impact of the system on different types of businesses models and industries. Such continuations of work in this area can provide a better understanding of how customer conversion behavior can be leveraged in hyperconnected networks to enhance the efficiency and sustainability of the logistics system, and benefit both the customers and the retailers.

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