Understanding touchpoint criticality in customer churn journeys

Roelof Hars
University of Groningen
Hans Risselada
University of Groningen
Jaap Wieringa
University of Groningen

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Abstract

Understanding and managing customer journeys is a key goal for firms that has received significant attention in the literature. Current empirical work has focused on customer purchase journeys, yet much less is known about the post-purchase stage. Since post-purchase customer journeys are equally relevant for firms, the authors introduce customer churn journeys to the literature. In doing so, this paper proposes a typology of key touchpoints, and uses a state space approach to study whether the effect of these touchpoints on customer churn depends on a customer's prior journey. Using a unique longitudinal dataset from the insurance industry which covers internal touchpoints, external touchpoints, competition and transactional data on the individual customer level, the authors assess the added value of a journey-based approach in comparison to a more 'traditional' approach to churn. Initial results suggest that a journey-based approach adds important contextual information that can improve managerial understanding of churn.

Keywords: churn, customer journeys, touchpoints

Track: relationship marketing

1. Introduction of Paper

Properly understanding, predicting and managing customer churn has been at the forefront for managers and academics alike for several decades. Many firms face significant churn rates (Blattberg, Kim & Neslin 2008), and retaining customers is a key ingredient in establishing growing customer lifetime value (Bolton, Lemon & Verhoef 2004). Taking a customer journey perspective, managers have recently shown interest in understanding and managing churn based on individual customers' churn journeys. This is not without reason, as a journey-based approach to understanding, predicting and managing churn holds the promise of making churn- and touchpoint management event-driven, geared towards where individual customers currently are in their own journey and amenable to early intervention. Despite these benefits however, a recent report by Bain & Company (2014) finds that many firms currently do not follow a journey-based approach to churn. The report argues that not approaching churn from a customer journey standpoint can significantly hinder firm performance due to focusing on the wrong target (the final touchpoint), since churn is –according to the report– inherently journey-driven.

Despite the ostensible benefits of approaching churn from a journey-based perspective and the managerial interest in what we refer to as customer churn journeys, the marketing literature currently does not provide any guidance to managers. It is therefore unclear how journey-driven customer churn truly is, nor is it clear how firms should identify or model such journeys. In this paper, we therefore introduce and model customer churn journeys. We use a unique and rich dataset in the insurance industry, which contains daily level information on internal touchpoints, external touchpoints, and market context at the individual customer level. This data allows us to provide a relatively complete overview of customers' churn journeys. We follow a three-pronged approach where we 1) identify key touchpoints and establish how strongly their effects depend on prior journey steps, and 2) assess the added value of a journey-based approach in comparison to a more 'static' approach to predicting and understanding churn. In doing so, we enable firms to identify key red flags to act upon in individual churn journeys. In the following sections, we first discuss our research framework. Afterwards, we discuss our data and methodology, and discuss some preliminary findings.

2. Research Background

2.1 Relation to existing literature

While prior work in the marketing literature has not discussed churn journeys, there is significant work suggesting that a journey-perspective is a promising avenue to explore. For example, recent work on commitment and satisfaction suggests that customer relationships depend not just on the level, but the evolution of key antecedents (Van Doorn & Verhoef 2008, Palmatier et al. 2013). A similar perspective emerges from work on usage under contract (Ascarza & Hardie 2013). Finally, empirical work has already established that customer relationships are state-dependent, and that key touchpoints can influence transitions between relationship states (Netzer et al 2008, Zhang et al. 2016).

By taking a customer journey perspective, our work adds to this literature stream by proposing that the relationship between key touchpoints and a customer's churn probability is dependent on which touchpoints have been previously visited by the customer. In other words, in addition to studying main effects of key touchpoints, our work explicitly recognizes and studies interaction effects between prior touchpoints and current touchpoints, and assesses how much adding such information improves our capability to understand and predict churn.

2.2 Conceptual model

Since we view churn journeys as part of the 'overall' customer journey, we base our conceptual model on the theoretical customer journey literature. In our definition, churn journeys consist of a collection of touchpoints that customers visit throughout their lifetime at a firm. We view a customer's decision to churn as ultimately being determined by their experience. While Lemon & Verhoef (2016) argue that customer experience is measurable in theory, to the best of our knowledge, no measure of the construct has been developed. Since our work takes an individual customer journey perspective, we treat customer experience as latent. We view customer experience as a time- and customer-specific construct that is shaped by the set of touchpoints that a customer visits (De Keyser et al. 2020). This suggests that firms can use knowledge about such touchpoints to infer customers' current experience. Therefore, we ultimately view the combination of touchpoints (a customer's journey) as influencing their churn probability through influencing their (latent) customer experience at every time point. Prior empirical work in the purchase journey literature has recognized that the inferences a firm can make about touchpoint effects are highly context-dependent, and depend on other touchpoints a customer has visited (Anderl, Schumann & Kunz 2016) and market context (De Keyser et al. 2020). We therefore take this into account in our conceptual model, see Figure 1.

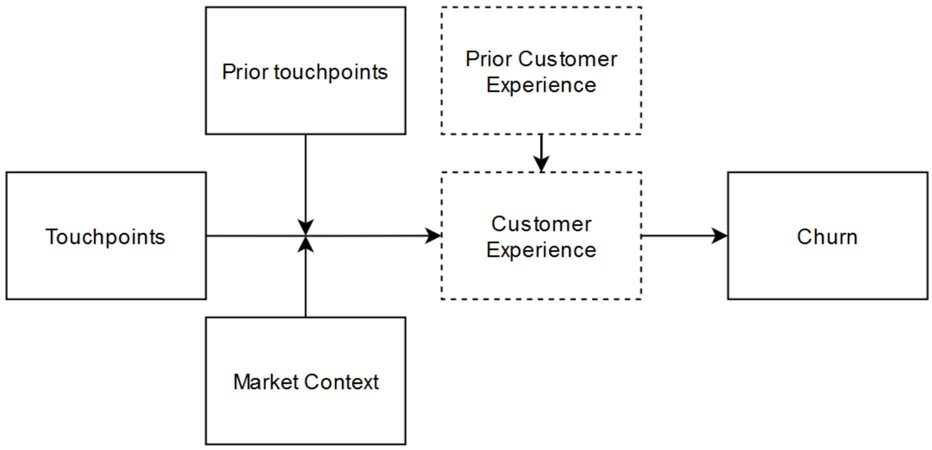

Figure 1. Conceptual model

2.3 A touchpoint typology for customer churn journeys

Significant work has been done on identifying different types of touchpoints in customer journeys (Anderl et al. 2016, De Keyser et al. 2020). An essential difference between purchase journeys and churn journeys is that whereas firms typically have 'macro' level information on purchase journey touchpoints (i.e. channel, such as SEO or SEA), information on touchpoints relevant to churn journeys is available on a much more fine-grained 'micro' level. This is due to the fact that existing customers are the object of study. For example, a firm's website alone may contain hundreds of potentially relevant pages related to different customer motivations and goals, leading to a myriad of touchpoints.

In this paper, we deal with this complexity by proposing a marketing funnel-type taxonomy. In doing so, we combine touchpoints that we expect to contain similar signals about the current status of a relationship. Our approach is inspired by the 'consumer decision journey' framework by Edelman & Singer (2015). Based on this framework, we propose four types of touchpoints in post-purchase customer relationships. We specifically identify 1) relationship (re-) evaluation, 2) relationship expansion/contraction, 3) bonding/commitment, and 4) relationship re-initiation.

We define (re-)evaluation touchpoints as any touchpoint that suggests the customer is re-evaluating their relationship with the firm. Typical examples that occur in our data are searches for alternatives through product- and price comparisons. In the relationship expansion/contraction stage, customers increase their relationship breadth by purchasing more insurance products from the same firm. In contrast, customers can decrease their relationship breadth by partially churning, thus decreasing their number of insurances, while still remaining a customer. Bonding/commitment type touchpoints are types of behavior that suggest a customer is committed to and bonding with the firm. For example, in our dataset, a surprising number of customers are active on the firm's website in order to read the firm's online magazine, and to respond to the firm's (engagement-)marketing initiatives. Finally, we identify relationship re-initiation. This type of touchpoint signals a 'resetting' of the clock, where customers signal that they have actively chosen to remain in their current relationship. A typical example is a contract extension, but our insurance context contains other such touchpoints as well. For example, making a claim against their car insurance typically also signifies a resetting of the clock. This is related to the fact that, due to the way insurance works in the focal country, making an insurance claim subsequently makes premiums at other insurance firms less attractive (and thus the focal insurer more attractive) due to the fact that the number of years a customer has not claimed insurance determines the best insurance premium offered by competitors.

We treat these four touchpoints are signals, which may occur in any order, and even simultaneously. We pose hypotheses for touchpoints and touchpoint combinations in Table 1, but do not discuss these in detail for the sake of parsimony.

2.4 Hypotheses[1]

Starting with relationship (re-)initiation events, we expect that customers who experience these events have a lower churn probability. We expect this based on two mechanisms. First, relationship initiation and re-initiation (e.g. contract extension decisions) typically follow from a purposeful choice for a specific option. Moreover, in our dataset, some relationship re-initiation events (e.g. claiming insurance) has negative consequences for the availability and attractiveness of other alternatives (competitor prices increase after a claim), thus increasing switching costs (Burnham et al. 2003). Thus we hypothesize:

H1: relationship re-initiation events are associated with a lower churn probability

Relationship (re-)evaluation is closely related to searching for alternatives. We expect that customers who are (re-)evaluating their relationship have a higher propensity to churn. Bendapudi & Berry (1997) propose that information search by customers depends on whether the relationship with their current firm is constraint-based or dedication-based. The less

[1] As relationship expansion/contraction, transactional events and competitor information are not yet in our preliminary model and results, we do not discuss these variables here for the sake of parsimony.

dedication-based (i.e. customers wanting to stay) and the more constraint-based a relationship is (customers having to stay), the more customers tend to search for alternative options. This suggests that if customers are in relationships in which they want to be, less search for alternatives should ensue. While there are also other, more positive reasons that customers search for alternatives such as involvement (Maity, Dass & Malhotra 2014), or motivations of relationship expansion, we expect most search to be driven by 'negative' reasons, since committed customers may expand their relationship with a focal firm without explicit relationship re-evaluation (Edelman & Singer 2015). We therefore hypothesize:

H2: relationship (re-)evaluation touchpoints are associated with higher churn probability.

Finally, we expect 'bonding' touchpoints to be indicative of long-term relationship commitment, and thus reflective of a good customer experience and lower propensity to churn. We base this hypothesis on commitment theory (Morgan & Hunt 1994, Palmatier et al. 2013), and on the notion that customers who visit commitment-type touchpoints rather than 'transaction-based' touchpoints are ultimately investing time in their relationship with a firm, and such time investments have been known to be a clear signal of commitment (Le & Agnew 2003).

H3: bonding touchpoints are negatively related to churn.

In general, we expect prior touchpoint effects to moderate the effect of current touchpoint effects. While space limitations prevent us from discussing our complete set of hypotheses here, our general reasoning is based on consideration of whether the combination of a prior touchpoint and current touchpoint is convergent or divergent in terms of underlying motivation. If prior touchpoints are divergent in comparison to current touchpoints, we expect weaker effects of current touchpoints, and vice versa. For example, if a 'relationship re-evaluation' touchpoint is preceded by a 'bonding' touchpoint, we expect that the 'relationship re-evaluation' touchpoint is a less critical indicator of a poor customer experience/churn, since the fact that a customer has previously visited a 'bonding' touchpoint indicates their commitment to the relationship with the firm, which suggests that the cost-benefit trade-off for this customer may be different. Thus:

H4: Divergent combinations of current touchpoints with prior touchpoints weaken the effect of current touchpoints, while convergent combinations strengthen the effects of current touchpoints.

3. Data

In order to estimate the model that we introduce below, we use 15a unique dataset from a European car insurance provider, and combine it with data from an insurance comparison website. In doing so, we obtain daily panel data for 10.000 customers over 3.5 years (June 2015-January 2019). Our dataset contains information on online touchpoints, such as visits to the focal firm's website, the insurance comparison website, and emails. Our database also includes offline touchpoints (calls) and has information on firm-to-customer contacts. Based on the customer's insurance details, we also know (or can rather accurately predict) what a customer's market context is at any specific time. In addition, our database contains typical transactional data such as the number of products a customer has, demographics, and socio-economic data. Finally, for customers who have filled in NPS surveys during this time period, NPS scores are available.

4. Methodology

4.1.Model

We estimate our churn journey model using a state space approach. Our touchpoint data is on the daily level. However, we are not necessarily interested in a customer's daily churn probability. In our experience, firms need time to identify churners and to determine an appropriate cause of action, which implies that the relevant level for managers is not daily, but a more aggregate level. Based on the current churn literature (e.g. Ascarza & Hardie 2013), we argue that the monthly level is most interesting for managers.. At the same time, aggregating touchpoint level information to a monthly level leads to a loss of information, as the intra-month development of customers' experience would not be accounted for (Ascarza & Hardie 2013). We therefore define a mixed frequency model (e.g. Harvey & Pierse 1984).

Specifically, we define $p_{i,t}$ as a firm's estimate of the end-of-month churn probability of customer i given information available up to and including time (i.e. day) t. As such, if nothing in a relationship changes, a firm's estimate will remain relatively constant, but when new touchpoint information comes in, a firm can update their estimate of a customer's churn propensity. Given our focus on individual customer journeys and customer experience, the churn propensity of customer i at time t is a function of an individual customer's (latent) experience at time t $\alpha_{i,t}$ and measurement error $v_{i,t}$. That is:

$$p_{i,t} = \alpha_{i,t} + v_{i,t} \; v_{i,t} \sim N(0, \sigma_v^2) \; (1)$$

Subsequently, given our conceptual model, we view a customer's current experience (state) as a function of their past experience ($\alpha_{i,t-1}$), plus an updating of their past experience based on recent touchpoint visits, including the interaction of these touchpoint visits with prior touchpoint visits and market context.[2] This allows individual customer experiences to build over time. Given that our focal firm typically updates their database at the end of the day, and in order to prevent churn being predicted by churn, we only include lagged touchpoint effects.

$$\alpha_{i,t} = \alpha_{i,t-1} + \theta_1 TP_{1,i,t-1} + \cdots + \theta_k TP_{k,i,t-1} + \eta_{i,t}, \eta_{i,t} \sim N\left(0, \sigma_\eta^2\right) \quad (2)$$

Where $\alpha_{i,t-1}$ is a customer's prior experience, and $TP_{1,i,t-1\ldots}$ $TP_{,k,t-1.}$ are effects of touchpoints. The parameter estimates for our touchpoint effects represent how much the visiting of a certain touchpoint changes $\alpha_{i,t-1}$ (a customer's prior experience), on average. While we show a main effects equation above, our model allows for the straightforward inclusion of interaction effects with prior touchpoints and market context in the parameter vector. We include interactions with prior touchpoints in our initial results, and will include additional predictors before the conference. We estimate our model using the Kalman filter and maximum likelihood.

5. Results

Our initial results are shown in Table 1 below. This preliminary model does not yet include the full set of predictors. Results show that, as expected, reconsideration touchpoints are positively associated with churn. Contrary to expectations, commitment touchpoints are not significantly associated with churn, and renewal touchpoints are negatively associated with churn. We suspect the latter results might be related to the fact that we include both contract renewals and other customer-initiated changes (e.g. changes in coverage and other product details) in this touchpoint, which might be heterogeneous in their effects, in the sense that when many customer-initiated product changes occur in a short time span, this might be a signal for poor product fit rather than relationship renewal.

In terms of interaction effects, we find that effects of reconsideration are weakened when preceded by any of the other touchpoints, which coincides with the interpretation that the 'signal value' of reconsideration touchpoints can change, in the sense that searching for alternatives is a negative signal for relationships by default, but can become a 'neutral' signal for committed customers, or customers who have recently reinitiated their relationships. Effects of commitment are not significantly different from zero, neither as main effects, nor when

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[2] Additional observed predictors will be included in an observation drift vector in equation 1 in a future version of this model.

commitment touchpoints are preceded by other touchpoints. Effects of renewal are weakened when preceded by a commitment touchpoint, but strengthened when preceded by another renewal touchpoint. We will further study, expand and explore these results before the conference.

Table 1. Parameter estimates

Variable	B	Interpretation
reconsideration,t-1	0.0146**	Associated with greater churn probability
commitment, t-1	-0.0031	n.s.
renewal, t-1	0.0224**	Associated with greater churn probability
reconsideration, t-2	0.0035*	Associated with greater churn probability
commitment, t-2	0.0007	n.s.
renewal, t-2	-0.0022	n.s.
reconsideration,t-1*reconsideration,t-2	-0.0093**	If a reconsideration touchpoint precedes another reconsideration touchpoint, effects are weakened.
reconsideration,t-1*commitment,t-2	-0.0090**	If a commitment touchpoint precedes a reconsideration touchpoint, effects are weakened
reconsideration,t-1*renewal,t-2	-0.0087*	If a renewal touchpoint precedes a reconsideration touchpoint, effects are weakened
commitment,t-1*reconsideration,t-2	-0.0006	n.s.
commitment,t-1*commitment,t-2	0.0008	n.s.
commitment,t-1*renewal,t-2	-0.0062	n.s.
renewal,t-1*reconsideration,t-2	-0.0074	n.s.
renewal,t-1*commitment,t-2	-0.0108**	If a commitment touchpoint precedes a renewal touchpoint, effects are weakened
renewal,t-1*renewal,t-2	0.0196**	If a renewal touchpoint precedes a renewal touchpoint, effects are strengthened

6. Literature

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