LINKING CUSTOMER VALUE AND ENGAGEMENT BEHAVIORS IN A CUSTOMER SATISFACTION SURVEY

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Acknowledgements:
The authors thank warmly Numberly 1000mercis Group, for the dataset and its support.

Cite as:
VILLENET Tom, SABADIE William (2023), LINKING CUSTOMER VALUE AND ENGAGEMENT BEHAVIORS IN A CUSTOMER SATISFACTION SURVEY . *Proceedings of the European Marketing Academy*, 52nd, (114554)

Paper from the 52nd Annual EMAC Conference, Odense/Denmark, May 23-26, 2023

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Customer satisfaction surveys are often analyzed through the ratings of satisfaction or NPS. We analyze the various engagement behaviors in a customer survey by studying their link with purchasing behaviors of 188 642 customers of a fashion & footwear company. We empirically demonstrate that customer engagement behaviors in N can be linked to lower churn rates and higher future customer value in N+1. We highlight a hierarchy between the engagement behaviors and identify click-through and elaboration to an open-ended question as the most important behaviors to identify the company's best customers. We also compare engagement behaviors to declarative data (NPS and satisfaction ratings) and show that survey-based attitude scores don't bring any significant additional value on future value compared to the reaction to the satisfaction survey request and more specifically the click-through behavior.

Keywords: *customer engagement, satisfaction survey, customer value*

Track : Relationship Marketing

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Introduction

In a recent McKinsey report (2021), "*93% of the managers use survey-based metric as their primary means of measuring customer experience performance*". However, practitioners call for new ways of measuring customer feedback metrics as 15% of their respondents "*were fully satisfied with how their company was measuring CX*". This report echoes MSI's Top tier research priority for 2020-2022 to determine "*which key performance indices (KPI)/metrics should be used to guide Marketing strategy?*" and the sub-question "*What KPIs best capture behavior, attitudes, and values?*". Both the Net Promoter Score (NPS) and the satisfaction score are widely used measurement scales used in satisfaction surveys (Baehre, O'Dwyer, O'Malley & Lee, 2022). These items measure components of the relationship quality (Palmatier et al., 2006) and have been linked to future customer loyalty (Baehre et al., 2022; de Haan et al., 2015;2021).

Providing feedback to a company and answering a customer survey have been previously identified as engagement behaviors (Kumar et al., 2010; Van Doorn et al., 2010; Maslowska, Malthouse & Collinger, 2016; Harmeling, Moffett, Arnold, Carlson, 2017; Eigenraam, Eelen, Van Lin et Verlegh, 2018) although as such, its impact of future value and loyalty remains to be demonstrated. As a feedback behavior, academics and practitioners consider exclusively the score to gauge satisfaction or attitudinal loyalty. However, in line with the behavioral conception of engagement, we plead in favor of analyzing the different behaviors composing the reply to a customer survey. By doing so, we respond to the call for a larger use of behaviors for measuring attitudes (Pauwels & van Ewijk, 2020; Gupta & Zeithaml, 2006) to combine declarative data to behavioral measures . Especially in a more and more digitized world characterized by a profusion of data, Kunz et al., (2017) called to identify which data deserves to be prioritized because they are likely to be more "valuable" in an engagement approach. Furthermore, fewer individuals provide feedback to a company by taking the time to complete a customer survey (de Haan, Verhoef & Wiese, 2021; Han and Anderson, 2022; PewResearch, 2012). Accordingly, we anchor our work on the social exchange theory (Thibaut and Walker, 1975) and consider the customer behaviors toward the satisfaction study as efforts that reflect his/her attitude towards the firm. Providing feedback to a company (or not) via customer survey offers a wide variety of behaviors, sending a signal to the company which varies depending on levels of intensity -from being contactable (need for an opt-in to the relationship program), to receiving a survey request and opening the email, to clicking on the email, to choosing or not to provide feedback, to filling only the rating questions or taking the time for an open-ended question.

Analyzing the purchasing behaviors of 188 642 customers between 2017 and 2019 of a fashion & footwear company in Europe, results show higher turnover and lower churn rates among customers displaying engagement behaviors such as click-through in the email containing the satisfaction survey request and elaboration to an open-ended question. Customers who give higher satisfaction or NPS ratings do not have significantly higher turnover or lower churn rates compared to the clickers.

First, we contribute to the customer satisfaction-loyalty literature by considering the impact of customer engagement toward satisfaction survey on churn and customer value. Second, adopting a behavioral lens to analyze customer feedback helps overcome the challenge of low-response rates underlined by de Haan, Verhoef & Wiesel (2021) or Han and Anderson, (2022) as a lack of response is a signal to the company about the levels of customer's engagement. Third, we contribute to the customer engagement literature (Eigenraam et al., 2018) highlighting a pyramid of engagement behaviors in the customer survey with varying impacts of future churn and customer value. Fourth, we add to the debate about a behavioral conception of customer engagement vs an attitudinal one (Harmeling et al., 2017), and the complementary of the two variables types to predict future customer value (Pauwels & van Ewijk, 2019; Gupta & Zeithaml, 2006) by comparing the NPS score and customers' behaviors toward the satisfaction survey. This paper also brings several managerial implications. The first one is, analyzing customer survey engagement behaviors as a driver of firm performance. We also highlight the different engagement behaviors in the customer survey and demonstrate which are the most predictive of future churn and customer value. Finally, we underline the potential of mixing the traditional attitudinal approach with engagement behaviors to identify the future best customers and the customers at risk.

Theoretical framework

We define customer engagement in line with Harmeling et al., (2017) and Van Doorn et al., (2010) as a customer's voluntary resource contribution to a firm's marketing function, going beyond financial patronage. Customer engagement behaviors can further help identify the future best customers (e.g. Bowden, 2009; Venkatesan et al., 2018). Venkatesan, Petersen, and Gussoni (2018) suggested that the consumer's previous engagement behaviors could be relevant and meaningful indicators of subsequent engagement behaviors. The answer to a satisfaction survey and overall customer feedback behaviors have previously been identified as engagement behaviors (Kumar et al., 2010; Van Doorn et al., 2011; Maslowska et al., 2016; Eigenraam et al., 2018).

Providing customer feedback and overall helpful behaviors hence replying to customer surveys has been previously linked with a positive attitude (Nambisan & Baron, 2010), commitment (Bettencourt, 1997; Bove et al, 2009; Choi & Lotz, 2018), satisfaction (Groth, 2005) or relationship quality and relationship strength (Balaji, 2014; Burnham et al., 2020). The explanation lies in the social exchange theory as demonstrated by Bettencourt (1997) and more recently by Burnham et al. (2020). Customers balance inputs, what they provide, and outputs, what they receive, which can justify reciprocity when they feel that they receive more than they gave, justifying efforts toward the firm that surpass their basic role obligations (Blau, 1964; Morgan and Hunt, 1994; Bagozzi, 1995). As De Wulf, Odekerken-Schröder & Iacobucci (2001) have shown, investing time, effort, and other "sunk" resources creates a psychological bond that motivates the individual to maintain a relationship and sets expectations for reciprocity.

Founding customer engagement articles theorized engagement with various levels of intensity (Hollebeek, 2011, Brodie et al., 2011; Maslowska et al., 2016). Park et al., (2010) conceptualized a "behavioral hierarchy" depending on whether they require more or less efforts and resources from the customer. In line with the attitudinal perspective of the customer-firm relationship, the strength of this bond will drive a consumer to use his resources for the benefit of the firm. Customer survey offers various behaviors which involve more or less efforts (i.e cognitive, temporal) which we classified into a pyramid of engagement - appendix 1 - ranging from being able to receive the marketing request that contains the survey to opening the email to clicking on the link to answering the survey to using the open-ended question and providing more or less elaborate feedback. First, we consider these different behaviors according to the extent they require more or less effort from the customer.

- **opt-in**: in Europe, as of May 2018, to receive a satisfaction survey, as it involves personal data, a consumer needs to opt-in to the company's marketing program (General Data Protection Regulation "GDPR", 2016). As a behavior, opt-in is an engagement behavior (Eigenraam et al., 2018); showing a willingness to interact with the firm (Kumar, Zhang & Luo, 2014).
- **Opening the email**: reacting to the firm's emails has been identified as an engagement behavior (Eigenraam et al., 2018; Venkatesan, Petersen, and Gussoni, 2018). Zhang, Kumar & Cosguner (2017) demonstrated that opening rates were on average positively correlated with purchases.
- **click-through**: there's always a loss of customers between those who opened the email and those who clicked (Kumar et al., 2014) and clicking is another reaction to an email hence qualifying as an engagement behavior (Eigenraam et al., 2018; Venkatesan, Petersen, and Gussoni, 2018).
- **filling out a survey**: Completing a survey takes time and requires cognitive efforts (Dholakia, Vicki G. Morwitz, and Robert A.Westbrook, 2004). Fewer individuals provide feedback to a company by taking the time to complete a customer survey (de Haan, Verhoef & Wiesel, 2021; Han and Anderson, 2022; Pew Research, 2012). As stated above, it sends a signal of a good attitude toward the company.
- **filling out an open-ended question**: Reja, Manfreda, Hlebec & Vehovar (2003), found that open-ended questions resulted in "significantly larger item nonresponse" compared to quantitative items, stating that they require "more efforts from respondents". Bone et al. (2017) highlighted a "mere-measurement plus effect" wherein customers who reply to a positive open-ended question request will purchase more in the coming year compared to the customers who completed a survey without the positive solicitation. Malthouse, Calder, Kim & Vandenbosch (2016) found that higher levels of elaboration, i.e the number of words written - reflected greater engagement of the customer.

Additionaly, we analyze the value of these behavioral indicators compared to satisfaction and net promoter scores to address the question of the incremental value of Customer Feedback Metrics (CFM) vs engagement behaviors. Considering that online behaviors are manifestations of attitudes (Pauwels & van Ewijk, 2019; Batra & Keller, 2016), customers' engagement behaviors toward a satisfaction survey should be a strong predictor of their future value. However, Pauwels & van Ewijk (2019) found that survey-based attitudes and digital behaviors were rarely correlated and therefore used a combination of both. We answer their recent call in line with the one from Gupta & Zeithaml (2006) to combine declarative data with behavioral measures.

Among the various CFM metrics, the Net Promoter Score (NPS) is a widely used metric (Baehre et al., 2022) which allows for comparisons between firms. The NPS, described as a proxy for measuring customer attitudinal loyalty (Fornell, Morgeson III, Hult & VanAmburg, 2020), is linked with future sales (Reichheld, 2003). Furthermore, some studies showed that NPS is a predictor of sales growth but not superior to other customer metrics (Baehre et al., 2022; de Haan et al., 2015, van Doorn, Leeflang & Tijs (2013). For instance, de Haan et al. (2015; 2021) and Otto et al. (2019) found that transforming satisfaction ratings into top-2 box is a good predictor of retention across industries.

Methodology and results

We used data from a large European fashion & footwear company that sends post-transaction satisfaction surveys comprising satisfaction ratings, NPS questions, and several open-ended questions to its customers without any incentive. As reminded by Baere et al. (2022), this choice of industry is justified because NPS works best to predict sales growth in industries where customers are more likely to give recommendations, such as those with high emotional involvement in the purchase decision. Gruca and Rego (2005) also note that customer feedback metrics work particularly well to predict future cash flow in consumer goods industries where customers have short inter-purchase cycles, such as the apparel, athletic shoes, or beer industry. Our dataset combines annual customer-level transactional data (turnover and churn) as well as the reactions to post-satisfaction requests and satisfaction survey data aggregated by year for 188 642 customers between 2017 & 2019. As in Flynn et al. (2017), to be included in our sample frame, consumers must have (1) had a transaction and (2) completed a post-transaction survey. In that observation period, 82 960 customers opted-in to receive a request (44% of the active customers), 49.8% opened for a 25.9% click-through rate; out of the 16 872 respondents (20% of customers solicited), 72.3% went into the effort of filling an open-ended question for a total of 19 963 surveys completed.

Past customer value plays an important role in future customer purchases (Gupta, Hanssens, Hardie, Kumar, Lin, Ravishanker, Sriram, 2006; Kumar, 2008). In line with Flynn et al. (2017) or Zeithaml, Rust & Lemon (2001) we decomposed our active customer sample into 2 tiers based on their purchases (turnover) per year (see appendix 1 for descriptive statistics on the different segments). This approach allows us to evaluate the reliability of the results by taking into account heterogeneity in customer value.

We then conducted 3 types of comparisons. To assess the impact of customer engagement toward the satisfaction survey en N on customer value en N+1, we analyzed the differences in turnover and churn in N+1 for each customer's behaviors in N (opt-in, opening…).
First, comparing customer value (future turnover and churn rate) between the customers who displayed the engagement behaviors vs those who didn't.

Engagement behaviors in a customer satisfaction survey	Heavy customers (10% of customers based on their turnover N)		Light customers (50% customers based on their turnover)	
	ΔTurnover*	ΔChurn	ΔTurnover	Δ Churn
Purchase + opt-in (vs purchase + opt-out)	-/=	+/+	=/=	+/+
Opens the email (vs not)	+/+	+/+	+/+	+/+
Clicks in the email (vs not)	+/+	+/+	+/+	+/+
Answers the survey (vs not)	=/+	=/=	=/+	=/=
Answers the open-field question (vs not)	=/=	=/=	=/=	=/=
Elaborate answer (top 2 deciles of nb of characters used vs flop 5 deciles)	+/+	=/+	=/+	=/=

** + (behavior presence > behavior absence) ; = (behavior presence = behavior absence) ; - (behavior presence < behavior absence) ; p<.05 and p<.1 if underlined*

Future turnover and churn rates of the customers who opened the email requesting feedback and of those who clicked through are consistently better (higher for the turnover, lower for the churn rate) for both customer segments. Opt-in has also a significant positive effect on the churn rate as well for heavy and light customers but we found no impact on future turnover, except for a lower turnover of opt-in compared to the opt-out customers in 2017 that we explain with the coming into force of the GDPR in 2018 which impacted how companies collect customers data and opt-ins. Elaboration in the open-ended questions, measured by the total number of characters used in their feedback, has a positive though non-systematic effect on future turnover and churn rates for heavy customers. In other words, a heavy customer with a very elaborate response has a higher turnover and a lower churn rate than a heavy customer who provided lesser elaborate feedback. On the other hand, this effect is almost not existent for light customers. We note that the differences in turnover or churn rates are not significant for the response behavior to the survey (in itself or to the open-ended question) regardless of the type of customer.

We then compared the behaviors among them to create a hierarchy, by comparing future customer values (N+1) associated with the behaviors displayed in N. Among the heavy customers, the respondents to open-ended questions who provide elaborate answers, have the highest turnover (e.g $M_{Turnover2019}$ = 430€) compared to other engagement behaviors ($p<.05$). These results confirm those from Bone et al., (2017), however, these highly engaged customers represent only a fraction of the database (e.g 2.3% of the heavy customers in 2018). Besides this behavior, the click-through in the email request is a strong signal of future value. We see significantly higher levels of turnover and lower churn rates for clickers (e.g for 2019 $M_{Turnover}$=330€; M_{churn} = 46.5%) compared to heavy opt-in customers and heavy openers ($p<.05$). Furthermore, We didn't find any significant difference between the future turnover or churn rate between clickers and respondents of the survey or with those who provided an answer to an open-ended question ($p>.05$), the only exception being with those who provided an elaborate answer on future turnover (e.g $_{MTurnover2019}$ = 430€, $p<.05$). This finding holds for both 2018 and 2019. Among light customers: we observe the highest levels of sales and lowest levels of churn among clickers ($M_{Turnover}$=141.6€; M_{churn} = 42.2%). Turnover and churn of these customers are better compared to those of opt-in customers or openers ($p<.05$). For this segment of customers, respondents of the survey and respondents to an open-ended question, no matter their level of elaboration don't have a significantly different level of churn or turnover ($p>.05$)

Finally, we compared the various engagement behaviors to the attitudinal measures: our results are on par with Seiders et al. (2005) or Flynn et al. (2017) who previously found no significant effect of customer ratings on future purchase behaviors. Overall, the attitude ratings don't bring any significant additional value compared to the reaction to the satisfaction survey request and more specifically the click-through behavior. Satisfaction Top2Box or NPS Promoters don't have a significantly different turnover or churn rate compared to the clickers, for both heavy and light customers (p.>.05). The only exception is for the churn rate of light customers in 2018 ($M_{ChurnTop2Box}$ = 75.9%; $M_{ChurnPromoters}$ = 75.3%) which was lower ($p<.05$) than the churn rate of clickers to the request ($M_{Churnclickers}$ = 77.1%).

Discussion and limits

First, results show to what extent customer engagement in a satisfaction survey in N can be linked to churn rates and future customer value en N+1. We demonstrate the relevance of considering engagement behaviors in the satisfaction survey as they have different effects on future customer value. Secondly, we contribute to the customer engagement literature

highlighting a hierarchy of engagement behaviors in the customer survey. Encompassed in the feedback category of behaviors (Eigenraam et al., 2018), click-through is the behavior associated with an improved turnover and churn rate. Because requests for satisfaction survey are often phrased in a way asking the customer to help the company improve its offer, clicking in the email appears to be a signal of a positive favorable attitude. The fact that the click-through is as good of a signal than the other behaviors suggests that as long as the favorable disposition is present, positive customer outcomes will happen. Even if Kumar et al. (2014) who found no correlation between the total number of emails clicked and the average purchase amount, although they suspected the emailing program they studied was not optimized for conversion. We bring a new lens to the results to further analyze clicks depending on the type of marketing content sent. Furthermore, elaboration in an open-ended question appears to be a strong signal of heavy customers in terms of future value. Thirdly, we demonstrate that the response rates are not the only relevant KPIs to monitor, clickers in the satisfaction survey request are more numerous than respondents with the same turnover and churn rates. Fourth, by comparing the NPS, the top2box satisfaction scores and customers' behaviors toward the satisfaction survey, results concur with Petersen, Kumar Polo & Sese (2017) who demonstrated that customers with positive mindsets are not necessarily more profitable than customers with less positive mindsets.
Despite our contributions, our research has several limitations. Firstly, customer value can be analyzed with more than the turnover (i.e. the number of articles purchased, cross-selling,...) as a consequence of loyalty (Bowden, 2009; Van Doorn et al., 2010). Studying the consequences of engagement in a customer survey could have differential effects that would provide more granular results. Secondly, several authors studied the impact of marketing communication pressure on the answer to a survey (Dong, Janakiralan & Xie, 2014; Flynn, Court Salisbury & Seiders, 2017) hence studying the engagement in a satisfaction survey depending on the level of (over) solicitation could bring more nuanced results. Thirdly, we adopted a static point of view to analyze the impact of customer's engagement. A dynamic approach (Zhang & Chang, 2020) permettrait de mieux appréhender l'impact des comp d'engagement to measure their respective impact on predicting future customer value and customer retention. Accordingly, our analysis could benefit from such a dynamic approach as active customers get more opportunities to reply hence more solicitations and can be multi-respondents (10% of the respondents in our sample) and could offer future promising insights to identify the company's best customers.

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Appendix 1 - Descriptive statistics

Heavy customers are the top 10% (10th decile) of the active customers based on their annual turnover
Light customers are the flop 50% (first 5 deciles) of the active customers based on their annual turnover

	Total (2017+2018)	**Heavy customers**	**% Heavy**	**Light customers**	**% Light**	**sig. p-value**
Total active customers	188 642	31 462	100%	157 180	100%	-
Nb of opt-in customers	82 960	16 892	**53.7%**	66 068	**42.0%**	**.000**
Nb of openers	51 030	12 563	**39.9%**	38 467	**24.5%**	**.000**
Nb of clickers	21 479	6 745	**21.4%**	14 734	**9.4%**	**.000**
Nb of respondents	16 872	5 421	**17.2%**	11 451	**7.3%**	**.000**
Nb of multi-respondents	1 683	1 553	**4.9%**	110	**0.1%**	**.000**
Nb of open-ended respondents	12 205	4 307	**13.7%**	7 898	**5.0%**	**.000**

p-value were computed with the prop.test function in Rstudio which provides a test of Equal or Given Proportions (confidence level = 0.95)

	Heavy customers	**Light customers**	**sig. p-value**
Turnover 2017 (SD)	502.1€ (141.6)	63.6€ (27)	**.000**
Average purchase frequency 2017 (SD)	2 (0.8)	1.1 (0.2)	**.000**
Nb of active customer N+1	6 798	16 128	**.000**
Turnover N+1 (SD)	314.9€ (240.6)	142.9€ (137.5)	**.000**
Turnover 2018 (SD)	512.4€ (149.6)	61.3€ (26.2)	**.000**
Average purchase frequency 2018 (SD)	2.1 (0.8)	1.1 (0.3)	**.000**
Nb of active customer N+1	7 515	17 549	**.000**
Turnover N+1 (SD)	307.7€ (237)	137.6€ (132)	**.000**

Differences in means were computed with the wilcox.test function in Rstudio which provides a Wilcoxon-Mann-Whitney test for unpaired two samples (chosen over a t-test because transactions data do not follow a normal distribution)

p-value for the difference between the 2 groups of customers regarding the nb of active customers N+1 were computed with the same prop.test function mentioned above