UNDERSTANDING THE DIFFERENTIAL VALUE OF VARIOUS RELATIONSHIP MARKETING METRICS ON FIRM PERFORMANCE

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ABSTRACT

The motivation for this dissertation stems from the relationship marketing literature, and how marketing as a field has evolved from viewing marketing decisions as transactional in nature to a better understanding of the value firms provide their customers. Even more specifically, this dissertation intends to focus on the accuracy of the various marketing metrics that purport to measure the impact of relationship marketing efforts. This idea of relationship marketing is not confined to being purely academic or theoretical in nature, as the vast majority of public firms are measuring their relationships with customers. Specifically, I focus on metrics that have received a great deal of interest among academics and practitioners alike. The first essay investigates the usefulness of the Net Promoter Scores (NPS), and intends to answer questions as to the validity of the metric that have been raised by academics, while also attempting to best understand what tactics practitioners can employ to increase its predictive ability of firm performance. The second essay more broadly focuses on a range of measures that firms collect on their customers to understand the value derived from their offering, and to better be able to predict whether they will cease or continue the relationship. The second essay takes the next step as well in investigating which measures impact the efficacy of specific actions taken by employees to attempt to increase retention. In essence, the two essays together attempt to provide a better understanding of the impact of marketing metrics on firm performance. These effects are shown across two main dependent variables of interest in both sales and retention.

DEDICATION

I dedicate this dissertation to my parents. You have molded me into the person that I am today, and without your endless support and encouragement I would not be in this position. You have stoked my inquisitive nature and fostered my persistence. Without your loving support along the way, I feel I would not be where I am today. I greatly appreciate the effort you have spent in molding me into the individual I am today. I know I have not always made it easy on you, I am very grateful for you. Additionally, thank you for all of the life-enriching opportunities you have allowed me to pursue, even if you would not have done them yourselves (such as living with a German family as a 15 year old). Both of you are phenomenal parents, and I cannot thank you enough.

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ABSTRACT

This article utilizes a multi-method design, which intends to better understand the NPS metric and provide a diagnostic test of its effectiveness. Some authors claim it is the most important metric for tracking growth (Reichheld 2003), while others claim that it is an inferior metric compared to other measures such as satisfaction (Keiningham et al. 2007a). Despite the contradictions in the academic literature, NPS remains one of the most commonly used marketing metrics among practitioners with over 2/3 of Fortune 1000 firms tracking NPS (Colvin 2020). Therefore, the first article focuses on better understanding the value of the metric, reasons why it may not work in every situation, and potential avenues for its improvement. First, this article establishes what the literature has previously investigated on the topic through a meta-analysis to better conceptualize the current level of knowledge in the field. These findings are then supplemented with a secondary data analysis from within a single firm to provide a diagnostic test of the measure in comparison to typical satisfaction metrics. Overall, this article establishes that the transformation of the Net Promoter Score decreases its predictive validity in estimating firm sales, and that the metric's usefulness is contingent upon practitioners' customer orientations. This research covers a topic that is of great interest to marketing managers given the expensive cost of implementing NPS systems and contributes to the current academic literature as to the success of the metric.

INTRODUCTION

In 2003, one of the most popular marketing metrics was introduced, termed the Net Promoter Score or NPS (Reichheld 2003). Calculated by asking how likely a customer would be to recommend a firm to a friend or a colleague, in less than 20 years NPS has become one of the top marketing metrics. Recent estimates state that at least two-thirds of Fortune 1000 firms use NPS (Colvin 2020), presenting evidence of its popularity. The adoption spans across firms of just about every industry, from airlines such as Southwest and Delta, to technology firms such as IBM. Its use is so widespread at IBM that the executive that oversees its use has stated "It is more than a metric, one could use the word 'religion'" (Murray and Dunn 2020). This fanfare is driven by a few key elements of NPS.

First, is the intuitive appeal of the metric, as each firm is scored from -100 to 100 making it easy for executives to understand. Quite simply the score is calculated by taking the responses from 0–10 on the likelihood to recommend question, and taking the percentage of "promoters" (those that score the likelihood to recommend as a 9 or 10) minus the percentage of "detractors" (those that score the firm from 0 to 6). Second, NPS has been shown to effectively predict firm growth. In particular, with a dataset of over 400 companies across over 12 industries, a strong correlation was found between Net Promoter Scores and firm growth rates in almost all of the industries (Reichheld 2003). Coupling its simplicity with its predictive power, NPS was rapidly adopted.

Despite the early adoption by a number of firms, academics were largely critical of the new metric. Specifically, a number of academics have argued that typical satisfaction metrics are more predictive of firm growth than NPS (Morgan and Rego 2006; Keiningham et al. 2007a; Kornetta 2018; Van Doorn, Leeflang, and Tijs 2013; Marsden, Samson, and Upton 2005).

Generally, the papers argue against the way the scores are transformed rather than the value of asking a likelihood to recommend question in general (Keiningham et al. 2007b; Morgan and Rego 2006), and a summary of the current literature is provided in Table 1. Newer literature (Baehre et al. 2021; 2022) investigate different ways to measure the NPS and Likelihood to Recommend questions. Their findings are novel in that top 2 box LTR questions emerge as the dominant predictor of sales above and beyond NPS measures (Baehre et al. 2022). However, their papers collect the NPS data from a firm's entire *possible* customers (in their case, the entire sportswear industry market), as opposed to collecting the likelihood to recommend data from the current customers only, which is more in line with previous academic research and industry practice.

Overall, research has explained how relatively effective or ineffective the NPS is relative to other marketing metrics like satisfaction, but the studies suffer from a few key shortcomings. First and foremost, the current literature stops short of explaining why NPS is or is not effective. Therefore, firms are not sure whether they should do away with NPS completely or if it can be salvaged. This is a critical question as these NPS programs are incredibly expensive when implemented by consulting firms (Reichheld 2003) and sold into the firm at the C-Suite level. Second, a key tenet of the value of NPS is managerial appeal and buy-in and limited research has examined if NPS is being utilized by managers and if this can contribute to top line sales. Finally, with a topic as hotly debated as NPS there are risks of researcher biases across studies influencing outcomes. As a result, a review is needed across studies to try and alleviate these concerns.

I address these gaps by first conducting a meta-analysis to provide cumulative insights across research teams about the effects of NPS on firm sales. This provides a baseline of studies

going forward. Second, I validate the effects of the meta-analysis using a large scale dataset across 2,087 retail outlets. For the results presented in the dissertation, I will utilize Hierarchical Linear Modeling (HLM) to distinguish between which effects are driven either between or within retailers. Then, I decompose the metric and demonstrate that the question: "How likely would you be to recommend firm XX to a friend or colleague?" is not flawed, but its underlying transformation hinders its ability to predict sales. Finally, I demonstrate that NPS can be a useful tool for predicting sales, but its effectiveness can be decreased by other managerial customer-oriented behaviors.

Table 1: Review of Empirical Research on NPS to Firm Sales Growth

Reference	Independent Variables	Dependent Variable	Includes Diagnostics	Contingency Factors	Major Findings
Morgan and Rego (2006)	Satisfaction (Mean and Top 2 Box)[1] NPS (Proportion Promoters, Proportion Detractors)	Total Sales Growth	No	None	Managers should not abandon typical satisfaction metrics to focus on net promoters when predicting firm growth.
Keiningham et al. (2007a)	Satisfaction (Mean, Top Box, Top 2 Box)[2] NPS (Typical Transformation)	Total Sales	No	None	Satisfaction outperformed the Net Promoter in predicting sales growth.
Keiningham et al. (2008)	Satisfaction (Mean) NPS (Typical Transformation)	Total Sales	No	None	Satisfaction outperformed the Net Promoter in predicting sales growth, with the data from Reichheld (2003).
Jeanjean (2011)	Willingness to Pay (Measured by Spokes Model (Chen and Riordan 2007)) NPS (Typical Transformation)	Total Sales	No	None	The correlation between NPS and WTP is very strong, but the correlation between NPS and sales is less pronounced.
Kornetta (2018)	NPS (Typical Transformation)	Total Sales ROA ROS ROE	No	None	Nothing confirmed the impact of NPS on the sales growth of the analyzed companies. NPS did have a significant impact on ROA, ROS and ROE profitability measures.
Van Doorn, Leeflang, and Tijs (2013)	Satisfaction (Mean, Top Box, Top 2 Box) NPS (Typical Transformation)	Total Sales	No	None	Satisfaction outperformed the Net Promoter in predicting sales growth.
Marsden, Samson, and Upton (2005)	NPS (Typical Transformation)	Total Sales	No	None	Every 1 point increase in the net promoter score correlated with a 8.82 million increase in sales.
Pingitore et al. (2007)	NPS Satisfaction Commitment Likelihood to Recommend Net Committed Net Delighted Net Satisfied	Change in Revenue	No	None	NPS does not outperform other customer feedback metrics in predicting customary outcome measures.
Kristensen and Eskildsen (2014)	NPS Satisfaction (EPSI and ACSI)	Customer loyalty Customer satisfaction	Yes – Groupings of promoters, neutrals and detractors is	No	The precision of NPS is found to be low compared to other measures of loyalty, the groupings of responses is flawed, NPS is extremely sensitive to changes in the underlying scale, and a “No Answer”

			shown to be flawed		option should be included in the response.
Baehre et al. (2021)	NPS Sales Growth Average Selling Price Number of Categories Market Growth HHI[3]	Sales Growth	Yes – An all "potential" customer sample outperforms the current customer sample	Two Samples: Current Customers All Potential Customers	Only the more recently developed concept of brand health measure of NPS (based on the all potential customer sample) is effective at predicting future sales growth.
Baehre et al. (2022)	NPS (regular, top 1, and top 3) LTR (average, top 1, top2, and top 3)	Sales Growth	Yes – Measures that are focused on the top points of the scale outperform the current NPS measures	No	LTR top 2 box is the most predictive measure of sales growth, as it does not distinguish between passives and detractors
Current Research (Studies 2–4)	Satisfaction (Mean) NPS (Typical Transformation and Raw Scores)[4]	Total Sales	Yes	Manager Customer Orientation	The transformation is problematic. Effects of NPS question increase with manager engagement with NPS dashboard.

[1] Top 2 Box refers to Percent of respondents that responded 4/5 or 5/5 on satisfaction
[2] Top Box refers to percent of respondents that responded 5/5 on satisfaction
[3] Herfindahl-Hirschman Index – common measure of industry concentration
[4] Raw Scores refer to NPS on 0-10 scale

In the following pages, I introduce the conceptual background, then review the results of the meta-analysis and the procedures used. Then, I discuss the dataset that provides the backbone for my primary analyses, reveal a series of tests, and finally conclude with implications.

CONCEPTUAL BACKGROUND

The theory of competitive advantage serves as the overarching theory guiding the effects of Net Promoter Scores and other loyalty metrics on firm sales, and thus is discussed first. Second, I delve into how relational advantage is measured and the measures of customer satisfaction specifically. Then, I discuss how customer loyalty is a unique concept under the theoretical umbrella of customer satisfaction. Finally, I examine the intention to recommend literature which spawned the Net Promoter Score. Additionally, I propose a series of hypotheses that the current investigation intends to address through a multi-study design.

Theories of Competitive Advantage

The reliance on metrics such as the Net Promoter Score can be traced back to theories of competitive advantage. Specifically, I focus on the Source-Position-Performance (SPP) framework created by Day and Wensley (1988). This framework introduces that firms can compete both on informational and relational advantages to outperform their competitors. These relational advantages stem from how firms perceive their customers and the value they attach to them. Firms either treat their customers as valuable assets to be retained or simply as transactional partners (Day and Van den Bulte 2002). The second component of competitive advantages firms can enjoy is their informational advantage. A firm's informational advantage stems from being better able to collect and share the information that they have on customers that they can incorporate into their products and services to improve offerings (Day and Van den

Bulte 2002). While informational and relational advantages refer to two distinct concepts, in reality relational advantages stem from informational advantages.

Satisfaction and NPS metrics can both be regarded as pieces of the puzzle that serve to create sources of informational advantages for firms. As firms are able to increase their informational advantage, this improves their ability to create relational advantages by better honing in on customers' preferences and incorporating them into their offerings. The benefits of informational advantages have previously been documented by showing that investments in Customer Relationship Management (CRM) systems results in improved understanding of a customer base (Reimann, Schilke, and Thomas 2010). In essence the superior knowledge collected from informational advantages allows for firms to create relational advantages.

This reliance on establishing a relational advantage to outperform competitors has led to the introduction and widespread adoption of certain relationship marketing metrics to better analyze the extent of relational advantages. The relationship marketing metrics have been focused on the two concepts of satisfaction and loyalty. Satisfaction is defined as a fairly temporal post usage state for one-time consumption, while loyalty refers to an attained state of enduring preference to the point of determined defense (Oliver 1997). Therefore, it is difficult for a firm to experience customer loyalty without having established some sense of satisfaction.

Customer Satisfaction

Satisfaction emerged as a concept in the marketing literature as a key driver of purchase intention. Satisfaction was first shown to be significant at the individual level of transactions. The evaluation of a level of satisfaction was shown to be dependent upon the individual's expectations, while satisfaction was shown to influence attitude change and purchase intention (Oliver 1980). Then, it was demonstrated at a more micro level, that satisfaction can drive

revenue for firms. Empirical work has indicated that firms which enjoy higher satisfaction enjoy higher economic returns related to firm performance, stock price, and market share (Bolton 1998; Aaker and Jacobson 1994). This revenue to satisfaction link is a result of satisfaction determining future usage behavior (Bolton and Drew 1999). This focus on satisfaction in the marketing literature eventually led to the creation of the American Customer Satisfaction Index (ACSI). The ACSI for a given firm represents its customers' overall evaluation of actual and anticipated total purchases and consumption experiences (Anderson, Fornell, and Lehmann1994; Fornell 1992; Johnson and Fornell 1991). However, the ACSI has been used to measure not only the link between firm satisfaction levels and revenue, but also as an indicator of macro-economic growth (Fornell 1992).

As there has been evidence of empirical work demonstrating the effectiveness of satisfaction on sales, it is important to understand the theoretical rationale behind these results. First and foremost, customer satisfaction leads to greater customer loyalty (Fornell 1992; Anderson and Sullivan 1993; Bolton and Drew 1991). Through this increase in loyalty, customer satisfaction results in future revenues (Bolton 1998; Fornell 1992). This increase in loyalty results in not only higher future revenues, but it reduces the costs of future transactions (Reichheld and Sasser 1990), decreases price elasticities (Anderson 1996) and minimizes the likelihood that a customer will defect if the quality decreases (Anderson and Sullivan 1993). For these reasons, an increase in satisfaction results in increases in firm sales through an increase in customer loyalty.

Customer Loyalty

The ACSI models always demonstrated that satisfaction was critical, because it reduced complaints and increased loyalty. While satisfaction scholars focus on satisfaction as the key

lynchpin, loyalty researchers started gravitating toward the measurement of the ultimate outcome of loyalty. Specifically, loyalty is achieved when a customer has both a favorable attitude that is high compared to potential alternatives and intentions to continue doing business with the firm (Dick and Basu 1994). It is important to note that loyalty cannot be looked at in a vacuum as this attitude is contingent upon the alternative options and this attitude must be examined in relation to relevant brands or products.

Theoretically, customer loyalty stems from a few key psychological components. There are cognitive, affective, and conative antecedents to customer loyalty representing those referring to informational determinants, feelings states, and behavioral dispositions, respectively (Dick and Basu 1994). The cognitive elements refer to the availability and ability with which a consumer can process and differentiate offerings from providers (Dick and Basu 1994). The affective antecedents to loyalty include emotions, which are intense states of arousal (Mandler 1976), moods, which are more transient than emotions (Clark and Isen 1982), primary affect, which is defined as being physiological in nature (Zajonc 1980), and satisfaction. Finally, the conative antecedents of loyalty refer to switching costs, defined as the onetime cost associated from switching from one supplier's product to another (Porter 2008), sunk costs, which are defined as costs already incurred (Arkes and Blumer 1985), and expectations, which reflect the current and expected fit between marketplace offerings and consumer needs (Dick and Basu 1994). In essence, satisfaction is a necessary but not sufficient component of loyalty formation (Oliver 1999). While the original loyalty literature focused on these antecedents of repurchase intentions and attitudes, the literature expanded into willingness to recommend as a behavioral intention of loyalty (Zeithaml, Berry, and Parasuraman 1996).

Net Promoter Score as a Measure of Intention to Recommend

With this expanded lens on loyalty, Reichheld (2003) focused on willingness to recommend. Given evidence across multiple business disciplines that firms should focus on supplementing financial measures when evaluating the value of customer loyalty (Kaplan and Norton 2001), there was a need for a new metric measuring the impact of Word of Mouth (WOM) marketing. WOM as a focal metric is simultaneously able to capture an evaluation of how a customer feels in the present and also how their behavior projects into the future. Moreover, the will to recommend constitutes a higher level of loyalty as it indicates consumers putting their own reputations on the line for a firm. As such, there was a need to package this metric in a managerially relevant way.

Evidence suggests that customer feedback metrics that are easy to comprehend and communicate while still maintaining simple and direct predictive relationships with future business performance are highly valued by managers (Ittner and Larcker 2003; Reichheld 2003). That is one of the main offerings the Net Promoter Score provides in that it is relatively easy to comprehend and is scored overall for a firm from -100 to 100. The metric's simplicity provides intuitive appeal for marketing management, but the simplicity of the metric is not the only reason it has been adopted so widely.

The Net Promoter Score's widespread adoption within industry is related to the overall displayed success of intention to recommend metrics in general. The literature has previously established the benefits of firms focusing on positive word of mouth intentions to understand drivers of their success, as this metric is predictive of multiple firm level measures of success (Morgan and Rego 2006). Specifically, positive word of mouth intentions have been found to

lead to higher profits and gross margins (Keiningham et al. 2007a; Van Doorn, Leeflang, and Tijs 2013). These are the same outcome measurements that NPS is claimed to predict.

Yet, the academic literature has provided some pushback as to the value of the metric. Literature has compared NPS to other customer feedback metrics such as customer satisfaction (Morgan and Rego 2006; Keiningham et al. 2007b; Pingitore et al. 2007), brand consideration (Baehre et al. 2022) and purchase intent (Morgan and Rego 2006; Baehre et al. 2022). In general, other measures outperform NPS when predicting sales growth. A few of the key arguments against its use refer to the grouping and subsequent calculation based upon the responses of the customers. Firstly, the cut-off points applied to group the responses into three categories of promoters, passives, and detractors appear arbitrary (Grisaffe 2007; Kristensen and Eskildsen 2014). Secondly, the calculation excludes the "passives" which unnecessarily ignores their responses, and finally the response variability is significantly diminished by grouping the 11 points into only three categories (Grisaffe 2007; Kristensen and Eskildsen 2014).

Therefore, the academic literature has taken some initial investigations into the validity of the metric, but this article intends to provide a few key contributions. First, no paper has provided a meta-analysis within this topic area. This meta-analysis will provide a better understanding of the current state of the literature, as well as help identify gaps that have yet to be addressed. Second, not only is the validity of the mean likelihood to recommend question shown, as has been done previously (Baehre et al. 2022), but a new transformation of the NPS responses is examined for the first time. Finally, I will demonstrate that managers high in customer-oriented behaviors can provide benefits to their firms beyond those indicated by the Net Promoter Score.

In the following section, I focus on the hypotheses that flow from the frameworks presented above.

HYPOTHESIS DEVELOPMENT

The following hypotheses flow from the logic of the Source, Positions, Performance (SPP) framework, and the benefits of informational and relational advantages (Day and Wensley 1988). Satisfaction and NPS metrics are indicators of increased relational advantage, while also providing a firm with an informational advantage. As the theories of competitive advantage, specifically the SPP, provide a theoretical background explaining the reasoning behind tracking customer loyalty, the satisfaction, intention to recommend, and loyalty literature provide evidence as to the success of various loyalty metrics.

From a theoretical point of view, satisfaction leads to higher revenues for firms through the growth of customer loyalty (Fornell 1992; Anderson, Fornell, and Lehmann 1994). As customer loyalty grows for a firm, their cost of future transactions decreases as they can rely on current customers to buy new products or services, instead of paying to acquire as many new customers. In addition, as customer loyalty goes up, even when a loyal customer has a bad experience, they will be less likely to defect to a rival firm's offering.

Higher satisfaction and NPS scores have both been found to lead to better performing firms. Specifically, satisfaction metrics have been previously linked in the literature to higher firm sales (Morgan and Rego 2006; Van Doorn et al. 2002; Keiningham et al. 2007a), and as such are widely used within industry. In a similar vein the Net Promoter Score, has also been linked to higher firm revenues. This stems from evidence suggesting that a firm's Net Promoter Score leads to higher willingness to pay for consumers (Jeanjean 2011). So, the NPS metric can measure not only the likelihood that customers will refer friends and colleagues, but also their

own willingness to pay for the product at different price points. This is the rationale why to varying degrees, other papers in the literature have found similar evidence of NPS's predictive power in estimating firm growth variables (Marsden and Samson 2005; Van Doorn et al. 2013; Kornetta 2018; Keiningham et al. 2007a).

The first hypothesis is focused on better understanding and summarizing the state of the current literature in the field and the relative effectiveness of satisfaction and NPS measures on revenue. Currently the literature provides evidence for both satisfaction and NPS having positive and significant effects on sales.

H1a: *Satisfaction scores have a positive and direct effects on sales.*

H1b: *NPS scores have a positive and direct effects on sales.*

The functional form of NPS to firm revenue also needs conceptual refinement. As a reminder, the NPS score is calculated by taking the proportion of responses that rate a firm as a 9 or 10 on a likelihood to recommend question minus the proportion that rate a firm as a 0 to a 6. Theoretically, with the way that the NPS is constructed, a drop of a customer or firm's response from a 7 to a 6, is just as harmful to a NPS score, as a drop from a 7 to a 0. The way this transformation is calculated does not allow for an understanding of the impact of this 7 to 0 versus 7 to 6 change. Thus, despite Reichheld's (2003) claim, logic suggests a non-linear relationship, and empirical research on other measures supports this claim.

Previous empirical research has demonstrated that satisfaction to repurchase intentions follows a highly nonlinear form with the satisfaction to repurchase intention link showing increasing returns (Mittal and Kamakura 2001; Gomez, McLaughlin, and Wittink 2004). Mittal and Kamakura (2001) demonstrate that different customer characteristics create heterogeneity in the various thresholds for consumers' satisfaction and repurchase intents. Additionally, Mittal

and Kamakura (2001) demonstrate that moving from a rating of 4 ("somewhat satisfied") to a 5 ("very satisfied") has a disproportionately larger impact on repurchase behavior than a corresponding move from a 3 ("neither satisfied or dissatisfied") to a 4. Expanding on these findings, Gomez, McLaughlin, and Wittink (2004) find further evidence of non-linearities and asymmetries in the satisfaction to sales performance link. They provide evidence that sales performance is more sensitive to negative than positive changes in overall satisfaction, and that the degree to which a positive or negative change of the same magnitude changes performance is dependent upon the beginning level of satisfaction.

The results of Mittal and Kamakura (2001) and Gomez, McLaughlin, and Wittink (2004) mirror the results expected to be found in this study. Similar to the satisfaction to sales performance literature, the NPS is expected to behave more as an ordinal, as opposed to an interval scale, as a one unit increase in NPS may have a differential impact on sales performance dependent upon the beginning value of NPS. Overall, the responses to the likelihood to recommend question answered on an 11-point scale are not expected to follow the path currently conceptualized. Specifically, I do not expect to find any values above the mid-point of the scale (i.e., 5s and 6s) to significantly *negatively* influence sales for retailers, as consumers would generally view those as slightly positive or neutral scores, and similarly, I expect to find that responses of 8 *help* retail firms' sales figures, as consumers would view those as positive scores. Overall, I anticipate the transformation of the NPS scores to result in information loss as some responses are not included in the calculation.

> ***H2:*** *The current NPS transformation results in information loss to the extent that it overlooks variance across the continuous range of respondent scores when predicting sales.*

The final hypothesis relies on the evidence that customer-oriented employees and firms lead to better firm sales. Customer orientation refers to a firm focusing their activities on the needs of their customers, and firms that follow this orientation outperform those that do not (Donavan, Brown, and Mowen 2004). Firms that practice a customer orientation focus on assisting customers to meet their own needs and help them buy what they really need, even if it is less income generating (Hamzah, Othman, and Hassan 2016). I hypothesize that the NPS scores are the most predictive of firm success in the retailers in which managers are not frequently viewing customer metric dashboards. I suggest a substitutive interaction where the ability of NPS to predict sales weakens as managers become more actively involved in their dashboards. This basically means that as managers are more active participants in monitoring scores and customer responses to surveys, the actual metrics become less predictive. In essence, for the highly customer-oriented managers their actions can essentially replace or substitute for NPS scores. Customer-oriented behaviors are still warranted, and I predict a positive and significant effect of these behaviors on sales, but they can diminish the value of the NPS scores.

The opposite is hypothesized for the managers that are not as engaged in viewing the NPS dashboards. For those less engaged managers who may not monitor customer data and provide supplemental relational efforts, then NPS is more strongly related to sales. Overall, those managers who are more arm's length with respect to relationship management, NPS will be a strong indicator of sales. However, for more involved managers, the effect of NPS is still positive, but it has relatively less influence.

> ***H3:*** *Managers' customer-oriented behaviors negatively moderate the effects of NPS on sales to the extent that the positive effect of NPS is weakened as the number of dashboard views increases.*

METHOD

Research Method

A mixed methods approach that combines a meta-analysis and a large-scale secondary data analysis is used to test H1 through H3. With this multi-method approach, I am able to summarize the extent of the current literature within the topic area and provide a quantifiable estimate of the previously examined effects, as well as to introduce new contingency factors into the literature. I will start with the meta-analysis, in Study 1, to better conceptualize the current state of the literature. Then, I will transition into the secondary data analysis using hierarchical linear modeling (HLM). First, Study 2 will focus on validating the results of the meta-analysis as to the differential effects of satisfaction and NPS on sales. Then, Study 3 will decompose the transformation of the NPS metric, and test the effectiveness of a newly transformed NPS Score. Finally, Study 4 will test the interaction effect of NPS scores and customer-oriented behaviors to see if the ability of NPS to predict sales weakens as the number of dashboard views increases. Table 2 presented below summarizes the design of the following studies and their findings.

Table 2: Overview of the Research Studies and Key Findings

Study	Design	Hypotheses	Key Findings
Study 1	Meta	*H1a: Satisfaction scores have a positive and direct effects on sales.* *H1b: NPS scores have a positive and direct effects on sales.*	Satisfaction is found to be a more significant driver of sales than NPS.
Study 2a Study 2b	HLM Studies	*H1a: Satisfaction scores have a positive and direct effects on sales.* *H1b: NPS scores have a positive and direct effects on sales.*	Comparison of NPS to satisfaction measures and Raw NPS to Satisfaction measures to show similarities and differences

Study 3a	HLM Studies	*H1a: Satisfaction scores have a positive and direct effects on sales.* *H1b: NPS scores have a positive and direct effects on sales.* *H2: The NPS transformation results in information loss to the extent that it overlooks variance across the continuous range of respondent scores when predicting sales.*	This decomposes the transformation of the NPS metric. I test the individual counts of the NPS responses and examine their effectiveness in predicting sales. Essentially, the NPS transformation is found to be mis-calibrated as the results do not match that of Reichheld's (2003) conceptualization, thus resulting in information loss.
Study 3b			A supplemental analysis shows that my newly transformed version of NPS is predictive, but even an ideal transformation underperforms relative to raw data.
Study 4	HLM Study	*H3: Managers' customer-oriented behaviors negatively moderate the effects of NPS on sales to the extent that the positive effect of NPS is weakened as the number of dashboard views increases.*	The effects of raw NPS scores are found to be decreased as views of the NPS dashboard increases.

STUDY 1 META-ANALYSIS

The purpose of this meta-analysis is to provide a quantifiable estimate as to the current literature's understanding of the NPS and satisfaction to sales links. Specifically, it is conducted to summarize the previous literature, and arrive at a conclusion as to which measures best predict sales in the previously conducted studies.

Collection and Coding of Studies

The seminal article that introduced the Net Promoter Score (Reichheld 2003) and the articles that referenced it, served as a starting point for a thorough review of the literature through meta-analytic estimates. There are two main independent variables, satisfaction and Net Promoter Score, and their bivariate correlations with revenue growth that will be investigated. Specifically, I will constrain my focus to the years 2003 through 2022, as 2003 is the year that

NPS was introduced. Relevant studies were identified by searching both Google Scholar and Business Source Complete. As search terms I included "satisfaction" "sales" "revenue" and "Net Promoter Score." Given that the numbers being investigated are observed variables, there are no predictor or criterion reliabilities to include in the analyses. I report the sample weighted r's and their 95% confidence intervals. Before applying the sample weights, the r's were adjusted to variance stabilizing Fisher's z-scores (Rosenthal 1994; Shadish and Haddock 1994). Following standard procedures (Shadish and Haddock 1994), I reconverted the Fisher's z-scores back to r's to report the sample weighted r's and their 95% confidence intervals. The random effects Meta-analytic effect size estimates are reported (Borenstein et al. 2010), given the evidence of heterogeneity.

Results

Which loyalty metric is a better predictor of revenue growth?

The main research question that I intend to answer in Study 1 is to assess whether satisfaction or NPS is more highly related to revenue growth for firms across multiple industries. To understand whether the Net Promoter Score is truly superior to satisfaction as a metric to predict revenue, two different Random Effects Meta-Analytic Effect Sizes are reported.

Satisfaction and revenue growth

Meta-analytic effect size estimates

The Random Effects MAES (r) for satisfaction on revenue growth is r = .38, with a 95% confidence interval of (.07 to .62). As the 95% confidence interval does not cross zero, this provides evidence that satisfaction to revenue studies show a significantly positive effect (Suurmond, van Rhee, and Hak 2017). These numbers are based on correlations from 63 different studies with an overall sample size of 2,843 firm time periods.

Evidence of heterogeneity

Both the *Q*-statistic and the I^2 values in the meta-analysis performed on the relationship between satisfaction and revenue growth suggest substantial heterogeneity ($Q = 1924.15$, $p < .001$; $I^2 = 96.78\%$) confirming the need for reporting the Random Meta-analytic effect size estimates that were reported above (Borenstein et al. 2010). These results reveal a high amount of heterogeneity, which suggests that there is a high likelihood of unaccounted for moderators affecting these relationships.

Subgroup analyses: Different measures of satisfaction

Specifically, the moderating effects that I examine are those that are due to different measurement of the satisfaction variables. However, the different measures of satisfaction all provided relatively similar results for their impact on sales. Specifically, the ACSI was found to be the most predictive with r = .69, confidence interval (.40 to .85), while the mean measure [r = .33 (-.34 to.78)], top 2 box [r = .4 (-.33 to .83)], and top box [r = .31 (-.22 to .70)] all provided non-significant estimates.

NPS and Revenue Growth

Meta-analytic effect size estimates

The Random Effects MAES (r) for NPS on revenue is r = .32, with a 95% confidence interval of (-.08 to .64). As the 95% confidence interval passes zero, these studies show statistically insignificant effect (Suurmond, van Rhee, and Hak 2017). These numbers are based on correlations from 32 different studies with an overall sample size of 1,433 firm time periods.

Evidence of heterogeneity

The *Q*-statistic and the I^2 values in the meta-analysis performed on the relationship between NPS and revenue growth also suggest substantial heterogeneity ($Q = 809.5$, $p < .001$; I^2

= 96.17%) confirming the need for the random meta-analytic effect size estimates analyses (Borenstein et al. 2010). Additionally, this suggests a high level of heterogeneity and the need to investigate moderating variables in this relationship.

Subgroup analyses by industry

The heterogeneity present in the meta-analysis for the NPS to sales link indicated that there is evidence of moderating relationships. As such, I investigate whether these effects vary by industry, following both the original Reichheld (2003) paper, and practitioner norms in comparing companies against competitors within industries. Banking had the highest correlation (r = .79 (.22 to .96), while the miscellaneous industries had a relatively high correlation (r = .48 (.31 to .63), and the gasoline industry actually had a negative correlation (r = -.84, (-.99 to .42). Theoretically, the results might not have held in the gasoline industry given that it is a commodity and as such customers will not be as brand loyal.

Discussion of results of meta-analysis

These results provide further credence to similar studies by Keiningham et al. (2007a) and Morgan and Rego (2006) indicating that the NPS may not be the most predictive loyalty metric. These results indicate quite a substantial difference between the two estimates and their respective relationships with revenue for firms across different industries. Satisfaction was found to have a positive significant effect on revenue growth, while from the literature analyzed in the current meta-analysis, NPS was not seen as having a statistically significant effect on revenue growth for firms.

The main takeaway from this meta-analysis is the overall Random Meta-Analytic Effect Size Estimates providing evidence of satisfaction, in all its various forms as being a more predictive estimate of revenue than NPS. This is evidenced not only by the higher correlation,

but also by the 95% confidence interval being positive, versus crossing zero for NPS to revenue, providing evidence that the Net Promoter Score does not provide a statistically significant effect on revenue, despite Reichheld's (2003) claims. This meta-analysis provides support for the first hypothesis that satisfaction scores have a positive and significant effect on sales, and rejects H1b that NPS scores have a positive and significant effect on sales.

OVERVIEW OF SECONDARY DATA ANALYSES

Given the initial evidence presented above that satisfaction metrics in various forms are better predictors of sales than the Net Promoter Score measures, studies two through four intend to extend the literature by trying to better understand the variables driving the relationships found in the meta-analysis. To provide a controlled diagnostic test of NPS, I designed a series of studies with a few goals in mind. First, I attempt to minimize noise and heterogeneity in the data presented in the meta-analysis by focusing on a set of retail outlets that belong to the same parent-distribution network in Studies 2 through 4. This controlled look increases confidence that variance found across the relationship marketing investments is due to the nature of the measurement and not outside influences or other sources of heterogeneity. Second, it is important to examine these effects over time. Most NPS studies look at large gaps in time in their panels—typically one year or more and usually for only a few time periods [Reichheld 2003 (3 years), Morgan and Rego 2006 (7 years), and Van Doorn, Leeflang, and Tijs 2013 (3 years)]. However, I focus on tighter measurement windows examining NPS and sales in closer and more numerous time periods (11 quarters). Study 2 compares two different NPS and satisfaction measures and their effects on sales. Study 3 decomposes the responses of the metric, and supplements these findings by testing a newly transformed version of NPS that more closely resembles the results of the effects of the individual accounts. Finally, Study 4 investigates the

ability of customer-oriented managers to substitute the effectiveness of NPS with customer-oriented behaviors.

Data Overview

Given these anchor goals, I partnered with a large consumer durables manufacturer with numerous retail stores located throughout the United States. Consistent with my design priorities the data provided includes data from 11 quarters of NPS and sales data nested within 2,087 retail outlets, for a useable sample size of 22,957.Given the nested structure of the data with time within retail outlets, I will utilize hierarchical linear modeling (HLM). HLM allows a researcher to analyze variables at multiple levels of analysis in a series of regression equations (Bryk and Raudenbush 1992). Specifically HLM explicitly takes into account the nesting of data in multiple levels such that individuals within a particular group may be more similar to each other, than individuals in other groups and as such cannot truly be treated as independent observations (Hofmann 1997). In the present example, satisfaction metrics, including NPS, will be treated as level one variables, while the retailer characteristics, such as retailer size and retailers by ZIP code will be treated as level 2 variables.

Measures

Given that the data for studies 2 through 4 are all from the same source, I will first provide a comprehensive discussion of the measures. In the following table, I will explicitly discuss the means (μ) and standard deviations (σ) of the following measures, as well as the bivariate correlations of the items at Level 1.

Table 3: Coverage of Measures

Variable	Definition/Measurement	Representative Citation
LnSales μ = 14.429, σ = 1.059	Natural log of total revenue for retail outlet (i) at time (t)	Becker, Wiegand, and Reinartz (2019)
Retailer Satisfaction (RetailerSAT) μ = 8.873, σ = .756	11 – point Likert scale measuring an individual's satisfaction with the retailer (i) at time (t)	Morgan and Rego (2006)
Product Satisfaction (ProductSAT) μ = 8.912, σ =.517	11 – point Likert scale measuring an individual's satisfaction with the product for retailer (i) at time (t)	Wang and Wallendorf (2006)
Net Promoter Score (NPS) μ = 69.871, σ = 12.791	Percentage of promoters ('s and 10's) minus percentage of detractors (0–6) for retail outlet (i) at time (t)	Reichheld (2003); Keiningham et al. (2007a; 2007b); Van Doorn, Leeflang, and Tijs (2013); Marsden, Samson, and Upton 2005
Raw Net Promoter Score (RawNPS) μ = 8.862, σ = .252	Mean of the 0–10 response to the Likelihood to Recommend Question for retail outlet (i) at time (t)	Baehre et al. (2022)
Transformed NPS (TransformedNPS) μ = 83.88, σ = 11.20	Re-transformed NPS Score (percent of 8–10, minus percent of 0–3) for retail outlet(i) at time (t)	Unique to this study
Number of 0's (NPS0) μ =..721, σ = 1.228	Count of the number of 0's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 1's (NPS1) μ =.21, σ = .52	Count of the number of 1's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 2's (NPS2) μ =.28, σ = .63	Count of the number of 2's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 3's (NPS3) μ =.31, σ = .66	Count of the number of 3's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)

Number of 4's (NPS4) μ =.32, σ = .68	Count of the number of 4's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 5's (NPS5) μ =1.63, σ = 2.20	Count of the number of 5's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 6's (NPS6) μ =1.14, σ = 1.67	Count of the number of 6's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 7's (NPS7) μ =3.17, σ = 4.06	Count of the number of 7's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 8's (NPS8) μ = 9.27, σ = 10.58	Count of the number of 8's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 9's (NPS9) μ =8.62, σ = 9.76	Count of the number of 9's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Number of 10's (NPS10) μ =30.62, σ = 33.95	Count of the number of 10's on the Likelihood to Recommend Question for retail outlet (i) at time (t)	Kristensen and Eskildsen (2013)
Dashboard Views (DashboardViews) μ = 3.12, σ = 13.74	Total number of views of the NPS dashboards by managers for retail outlet (i) at time (t)	Customer-oriented behaviors – Franke and Park (2006)
Retailer Age μ = 25.25, σ = 18.76	Years the retailer has been open for retail outlet (i)	Yi and Jeon (2003)
Retailers by Zip μ = 8.46, σ = 5.14	Total number of industry retailers within the ZIP code of retailer (i)	Competitive Intensity – Luo and Homburg (2007)

Table 4: Means, Standard Deviations, and Correlations

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	LnSales	14.43	1.06																	
2	Retailer Satisfaction	8.87	0.76	-.25*																
3	Product Satisfaction	8.91	.52	-.04*	.46*															
4	NPS	69.87	12.79	-.04*	.41*	.56*														
5	NPSRaw	8.86	0.25	-.22*	.51*	.39*	.42*													
6	Transformed NPS	83.88	11.20	-.09*	.46*	.63*	.60*	.86*												
7	NPS (Number of 0s)	.72	1.23	.44*	-.30*	-.20*	-.13*	-.24*	-.27*											
8	NPS (Number of 1s)	.21	.52	.29*	-.20*	-.14*	-.09*	-.17*	-.19*	.33*										
9	NPS (Number of 2s)	.28	.64	.33*	-.19*	-.13*	-.10*	-.16*	-.20*	.37*	.25*									
10	NPS (Number of 3s)	.31	.66	.35*	-.20*	-.13*	-.11*	-.17*	-.21*	.40*	.27*	.32*								
11	NPS (Number of 4s)	.32	.68	.34*	-.19*	-.12*	-.10*	-.16*	-.21*	.38*	.25*	.30*	.30*							
12	NPS (Number of 5s)	1.63	2.20	.52*	-.23*	-.12*	-.15*	-.20*	-.18*	.53*	.35*	.42*	.43*	.43*						
13	NPS (Number of 6s)	1.14	1.67	.48*	-.21*	-.10*	-.14*	-.18*	-.17*	.49*	.34*	.40*	.42*	.40*	.63*					
14	NPS (Number of 7s)	3.17	4.06	.55*	-.23*	-.10*	-.15*	-.19*	-.18*	.56*	.39*	.46*	.47*	.47*	.72*	.70*				
15	NPS (Number of 8s)	9.27	10.58	.60*	-.20*	-.06*	-.14*	-.15*	-.03*	.59*	.40*	.47*	.49*	.49*	.76*	.73*	.85*			
16	NPS (Number of 9s)	8.62	9.76	.60*	-.16*	-.02*	.007	-.11*	-.02*	.58*	.41*	.48*	.49*	.49*	.75*	.71*	.83*	.90*		
17	NPS (Number of 10s)	30.62	33.95	.61*	-.10*	.04*	.06*	-.02*	.02*	.57*	.38*	.46*	.47*	.47*	.74*	.70*	.82*	.90*	.91*	
18	Dashboard Views	3.62	13.74	.21*	-.04*	.01	.04*	-.05*	.01	.19*	.13*	.14*	.15*	.14*	.19*	.18*	.20*	.23*	.25*	.27*

* Correlation is significant at the 0.05 level (2-tailed)

Analysis

Partitioning of variance components

Before I test the hypothesized models with HLM, I investigate whether systematic differences existed within and between individuals within the criterion variables variance. To investigate the variances for within and between individuals I ran a null model for the criterion variable of the natural log of total sales. The null model partitions the total variance of the dependent variable into within- and between-individual components, and the intercept for each null model represents the average level of the variable across individuals. HLM would not be appropriate if there exists only between-individual variance to explain (Judge, Scott, and Illies 2006). To figure out whether HLM is a suitable form of analysis, I will thus calculate the Intraclass-Correlation Coefficient (ICC). ICC: .84627/(.84627 + .15968) = .8412. So, 84.12% of the variance in sales is between-retailers (at level-2). That means that 15.88% of the variance in sales is within-retailers. In all, I have a substantial amount of variability at both levels (Bliese 1998), which establishes that HLM is an appropriate method to test my effects.

STUDY 2A – VALIDATING THE META-ANALYSIS

The purpose of study 2a is to replicate the results of the meta-analysis with data from within a single firm to investigate the significance of satisfaction variables and NPS on sales. I attempt to minimize noise and heterogeneity in the data presented in the meta-analysis by focusing on a set of retail outlets that belong to the same parent-distribution network. This controlled look increases confidence that variance found across the relationship marketing investments is due to the nature of the measurement and not outside influences or other sources of heterogeneity. Following standard procedures (Aguinis, Gottfredson, and Culpepper 2013), the level 1 predictor variables will be group mean centered, while the level 2 variables will be

grand mean centered. The relationships will be estimated using the dataset described above with 11 quarters of data across a network of 2,087 retailers. This study will serve as test of hypothesis 1 that a) satisfaction scores and b) NPS scores both have significant positive effects on sales, and it will be examined from within a single firm.

Measurement

Study 2 uses both satisfaction, and the typical NPS measure noted in the opening discussion as well as the natural log of sales as the outcome variable. These variables were included to investigate whether the satisfaction variables provide significant and independent value beyond the NPS measure.

Analysis

Given the nested nature of the data and results of the variance partitioning discussed earlier, I proceeded by estimating a multi-level model in HLM. Specifically the following system of equations were estimated:

Level 1 Model

$$LnSales_{ti} = \pi_{0i} + \pi_{1i} * (NPS_{ti}) + \pi_{2i} * (RetailerSAT_{ti}) + \pi_{3i} * (ProductSAT_{ti}) + e_{ti}$$

Level 2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(RetailerAGE_i) + \beta_{02}*(RetailerByZip_i) + r_{0i}$$
$$\pi_{1i} = \beta_{01}$$
$$\pi_{2i} = \beta_{20}$$
$$\pi_{3i} = \beta_{30}$$

In this model, π_{1i} captures the effect of NPS on LnSales, π_{2i} captures the effect of Retailer Satisfaction on LnSales and π_{3i} captures the effect of Product Satisfaction on Sales. Additionally, β_{01} captures the effect of retailer age on sales and β_{02} captures the effect of competitive intensity on LnSales. Error terms e_{ti} and r_{0i} are also included in the model.

Results

The results provide evidence that product satisfaction (π_{3i} = .026, *SE* = .008, *t* = 3.180, *p* < 0.01) is a significant predictor of sales, but retailer satisfaction (π_{2i} = .001, *SE* = .010, *t* = .100, *p* = 0.920) is not. NPS (π_{1i} = .004, *SE* = .000, *t* = 14.247, *p* < 0.01) is also found to be a significant driver of sales. As outlined in these estimates above, NPS emerges as the dominant predictor of sales followed by product satisfaction, as a one standard deviation increase in NPS is related to a .05 increase in sales, while a one-standard deviation increase in product satisfaction is equal to a .01 increase in sales. Retailer age (β_{01} = .002, *SE* = .001, *t* = 2.070, *p* < 0.05) and dealers by ZIP code (β_{02} = -.002, *SE* = .004, *t* = -.558, *p* =.577) were also included in the analysis as control variables. Retailer age had a significant and positive effect on the outcome variable of sales, which is to be expected, the older and more established the retailer, the higher the sales. The -2 Log Likelihood (deviance) = 29427.61, indicates a significant improvement over the null model (Raudenbush and Bryk 2002). The results are presented in table format below with the estimates and standard errors.

Table 5: Study 2a Results

Predictor	Estimate	Robust S.E.
Intercept	14.529**	(.020)
Retailer Age	.002*	(.001)
RetailersByZip	-.002	(.004)
NPS	.004**	(.001)
Retailer Satisfaction	.001	(.010)
Product Satisfaction	.026*	(.013)

Notes: * p < .05; ** p < .01.

Discussion

The results presented above provide slightly different results than the meta-analysis in that NPS can effectively predict sales, and, only product, but not retailer satisfaction still offers

significant and independent value in predicting future sales. Retailer age was also found to have an extremely large impact on the sales of a retailer. Overall, study 2a served as a confirmation of the first hypothesis that both some a) satisfaction and b) NPS measures can significantly predict sales. Yet, study 2a does not get at the crux of the issue as to providing a diagnostic examination of the measure. The followings series of studies will focus on how can NPS be improved or amplified. The next study will focus on understanding the way the NPS is calculated and transformed from its raw 0–10 score.

STUDY 2B – ASSESSING VALIDITY OF RAW NPS METRIC

Given diagnostic evidence that the transformation is severely limiting the predictive ability of NPS, I examine the effectiveness of the raw NPS, which is the mean response on the 0–10 scale. Essentially, Study 2b is an extension of Study 2a as it investigates the extent to which a raw or non-transformed NPS score can estimate sales versus the same previous satisfaction metrics included in study 2. In essence, Study 2b is re-estimating study 2a with the non-transformed NPS variable. This study serves as a test of Hypothesis 1 in comparing the similarities and differences between the a) satisfaction and b) Net Promoter Score effects on sales.

Analysis

Given the nested nature of the data and results of the variance partitioning discussed earlier, I proceeded by estimating a multi-level model in HLM. Specifically the following system of equations were estimated:

Level 1 Model

$$Sales_{ti} = \pi_{0i} + \pi_{1i} * (NPSRaw_{ti}) + \pi_{2i} * (RetailerSAT_{ti}) + \pi_{3i} * (ProductSAT_{ti}) + e_{ti}$$

Level 2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(RetailerAGE_i) + \beta_{02}*(RetailersByZip_i) + r_{0i}$$

$$\pi_{1i} = \beta_{01}$$

$\pi_{2i} = \beta_{20}$
$\pi_{3i} = \beta_{30}$

In this model, π_{1i} captures the effect of NPS raw scores on sales, π_{2i} captures the effect of retailer satisfaction on sales and π_{3i} captures the effect of product satisfaction on sales. Additionally, β_{01} captures the effect of retailer age on sales and β_{02} captures the effect of retailers by ZIP code on sales. Error terms e_{ti} and r_{0i} are also included in the model.

Results

Table 6: Study 2b Results

Predictor	Estimate	Robust S.E.
Intercept	14.529**	(.020)
Retailer Age	.002*	(.001)
Retailers By Zip	-.002	(.004)
NPS Raw	.093**	(.013)
Retailer Satisfaction	.002	(.010)
Product Satisfaction	.016	(.017)

Notes: * p < .05; ** p < .01.

The raw NPS score is now the only one of the metrics that was a significant driver of sales (π_{1i} = .093, *SE* = .009, *t* = 10.626, *p* < .001) and it outperforms the satisfaction metrics of the retailer (π_{2i} = .002, *SE* = .007, *t* = .262, *p* = .793) and of the product (π_{3i} = .016, *SE* = .009, *t* = 1.677, *p* = .094) which are not significant drivers of sales in this model. Retailer age (β_{01} = .002, *SE* = .001, *t* = 2.070, *p* =.039) was a significant positive predictor of sales and retailers by ZIP code (β_{02} = -.002, *SE* = .004, *t* = -.558, *p* = .577) was not a significant predictor of sales, as they were once again included in the analysis as control variables. The -2 Log Likelihood (deviance) = 29510.15, indicates a significant improvement over the null model (Raudenbush and Bryk 2002).

The above results suggest that the main likelihood to recommend questions used for calculating the NPS is a good one. Asking customers to rate the likelihood that they would recommend a product or service to a friend or colleague clearly can be highly predictive of sales success. The raw NPS score is shown to be highly predictive of sales, and it actually subsumes the predictive variance of both satisfaction measures. Thus, by using the raw score, managers can predict sales in a manner that does not require supplemental satisfaction questions, while the transformed NPS score couldn't fully replace the variance from the satisfaction metrics. This could be due to information loss due to the transformation.

These results indicate that Reichheld (2003) focused on a correct question in terms of likelihood to recommend. However, the transformation of the scores results in information loss. As a result, the next study will shift the focus to the behavior of the individual responses and their effects on sales.

STUDY 3A – DECOMPOSING THE NPS TRANSFORMATION

The purpose of study 3a is to understand the effects of the NPS calculation as currently conceptualized (Reichheld 2003). Study 3a was conducted to better understand the effect of the transformation of the raw NPS score from 0–10 into the labels of "promoter", "detractor" or "neutral". This is being used as a test of hypothesis 2 that this transformation results in information loss and that unaccounted for variables in the NPS calculation have significant effects.

Analysis

Given the nested nature of the data and results of the variance partitioning discussed earlier, I proceeded by estimating a multi-level model in HLM. Specifically the following system of equations were estimated:

Level 1 Model

$LnSales_{ti} = \pi_{0i} + \pi_{1i} * (NPS0_{ti}) + \pi_{2i} * (NPS1_{ti}) + \pi_{3i} * (NPS2_{ti}) + \pi_{4i} * (NPS3_{ti}) + \pi_{5i} * (NPS4_{ti}) + \pi_{6i} * (NPS5_{ti}) + \pi_{7i} * (NPS6_{ti}) + \pi_{8i} * (NPS7_{ti}) + \pi_{9i} * (NPS8_{ti}) + \pi_{10i} * (NPS9_{ti}) + \pi_{11i} * (NPS10_{ti}) + e_{ti}$

Level 2 Model

$\pi_{0i} = \beta_{00} + \beta_{01}*(RetailerAGE_i) + \beta_{02}*(RetailersByZip_i) + r_{0i}$
$\pi_{1i} = \beta_{01}$
$\pi_{2i} = \beta_{20}$
$\pi_{3i} = \beta_{30}$
$\pi_{4i} = \beta_{40}$
$\pi_{5i} = \beta_{50}$
$\pi_{6i} = \beta_{60}$
$\pi_{7i} = \beta_{70}$
$\pi_{8i} = \beta_{80}$
$\pi_{9i} = \beta_{90}$
$\pi_{10i} = \beta_{100}$
$\pi_{11i} = \beta_{110}$

In this model, π_{1i} captures the effect of NPS scores of 0 on Sales, π_{2i} captures the effect of NPS scores of 1 on Sales, π_{3i} captures the effect of NPS scores of 2 on Sales, π_{4i} captures the effect of NPS scores of 3, π_{5i} captures the effect of NPS scores of 4, π_{6i} captures the effect of NPS scores of 5, π_{7i} captures the effect of NPS scores of 6, π_{8i} captures the effect of NPS scores of 7, π_{9i} captures the effect of NPS scores of 8, π_{10i} captures the effect of NPS scores of 9, and π_{11i} captures the effect of NPS scores of 10 on sales. Additionally, β_{01} captures the effect of retailer age on sales and β_{02} captures the effect of retailers by zip on sales. Error terms e_{ti} and r_{0i} are also included in the model.

Results

Table 7: Study 3a Results

Predictor	Estimate	Robust S.E.
Intercept	14.529**	(.020)
Retailer Age	.002*	(.001)
RetailersByZip	-.002	(.004)
NPS 0	-.006*	(.003)
NPS 1	-.008	(.005)
NPS 2	-.016**	(.004)
NPS 3	-.013**	(.004)
NPS 4	-.000	(.004)
NPS 5	-.001	(.002)
NPS 6	-.003	(.002)
NPS 7	-.001	(.001)
NPS 8	.002**	(.001)
NPS 9	.005**	(.001)
NPS 10	.010**	(.000)

Notes: * p < .05; ** p < .01.

First and foremost, the Reichheld (2003) implies that 0 – 6 will all hurt sales, so for the transformation to be valid, these should all have comparably strong negative, direct effects on sales. Namely, this pattern holds for the counts of 0 (π_{1i} = -.006, *SE* = .003, *t* = -2.133, *p* = .033), 2 (π_{3i} = -.016, *SE* = .005, *t* = -3.349, *p* < 0.01), and 3 (π_{4i} = -.013, *SE* = .005, *t* = -2.725, *p* < 0.01) which negatively predict sales. However for the counts of 4 (π_{5i} = -.000, *SE* = .004, *t* = -.064, *p* =.949), 5 (π_{6i} = -.001, *SE* = .002, *t* = -.298, *p* =.766) and 6 (π_{7i} = -.003, *SE* = .002, *t* = -1.231, *p* =.218) there is no effect, so penalizing firms for these scores is inconsistent with the untransformed data.

The transformation would also imply that the scores of 7 and 8's have no effect. This pattern holds for the scores of 7 (π_{8i} = -.001, *SE* = .001, *t* = -.476, *p* =.634), however the counts of 8 (π_{9i} = .002 *SE* = .001, *t* =3.155, *p* < 0.01) show strong significant and positive effects.

Reichheld (2003) was correct in asserting that 9's and 10's had significant positive effects, as the counts of 9 (π_{10i} =.005, *SE* = .001, *t* = 6.146, *p* < .01), and 10 (π_{11i} = .010, *SE* = .000, *t* =37.988, *p* < 0.001) positively impact sales. Yet, the counts of 10 are shown to have an exponential impact on sales, and thus this suggests that if one were to create a weighted average, that 10's would have to be given more weight.

Retailer age (β_{01} = .002, *SE* = .001, *t* = 2.073, *p* < 0.05) was a significant positive driver of sales and retailers by ZIP code (β_{02} = -.002, *SE* = .004, *t* = -.556, *p* = .579) was not a significant driver of sales, as they were once again included in the analysis as control variables. The -2 Log Likelihood (deviance) = 257786.64 , indicates a significant improvement over the null model (Raudenbush and Bryk 2002).

Discussion

The results presented above in Study 3a provide support that the current transformation as applied when calculating the NPS of transforming 0–6 as detractors, 7's and 8's as neutral, and only 9 and 10's as promoters does not appear to be accurate and serves as a test of hypothesis 2. First and foremost, I provide evidence that the counts of 8 actually prove to be significant positive drivers of sales, as opposed to being classified as neutral. Additionally, the counts of 4, 5 and 6 are not significant drivers neither positively or negatively and should not be classified as detractors. Retailer age was also found to have a significant impact on the sales of a retailer. As establishing that the transformation of NPS appears to be flawed, the next study will use a new transformed NPS score, and then the final study will investigate how the raw NPS score's predictive ability can be enhanced in determining the relationship to sales.

STUDY 3B – INVESTIGATING THE TRANSFORMED NPS

Study 3b's purpose is to investigate whether a new NPS transformation is valid that more closely resembles the results presented above in Study 3a. In essence, the new transformed NPS score is calculated similarly, but with different cut-off points. Specifically, the scores of 8–10 will be considered promoters, 4–7 will be neutral, and only the scores of 0–3 are detractors. Then, the NPS will be calculated as the percent promoters minus the percent detractors. This serves as a direct test of H2, to better understand if a more ideal transformation of the NPS scores provides better results.

Analysis

Given the nested nature of the data and results of the variance partitioning discussed earlier, I proceeded by estimating a multi-level model in HLM. Specifically the following system of equations were estimated:

Level 1 Model

$$Sales_{ti} = \pi_{0i} + \pi_{1i} * (RetailerSAT_{ti}) + \pi_{2i} * (ProductSAT_{ti}) + \pi_{3i} * (TransformedNPS_{ti}) + e_{ti}$$

Level 2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(RetailerAGE_i) + \beta_{02}*(DealersByZip_i) + r_{0i}$$
$$\pi_{1i} = \beta_{01}$$
$$\pi_{2i} = \beta_{20}$$
$$\pi_{3i} = \beta_{30}$$

In this model, π_{1i} captures the effect of retailer satisfaction on sales, π_{2i} captures the effect of product satisfaction on sales and π_{3i} captures the effect of transformed NPS on sales. Additionally, β_{01} captures the effect of retailer age on sales and β_{02} captures the effect of retailer size on sales. Error terms e_{ti} and r_{0i} are also included in the model.

Results

Table 8: Study 3b Results

Predictor	Estimate	Robust S.E.
Intercept	14.527**	(.021)
Retailer Age	.002*	(.001)
RetailersByZip	-.008	(.004)
Retailer Satisfaction	.012	(.010)
Product Satisfaction	.051**	(.016)
Transformed NPS	.002**	(.001)

Notes: * p < .05; ** p < .01.

The transformed NPS score (π_{3i} = .002, *SE* = .001, *t* = 2.882, *p* < .01) and the product satisfaction (π_{2i} = .051, *SE* = .016, *t* = 3.234, *p* < .01) are both significant drivers of sales. They outperform the satisfaction measure of the retailer (π_{2i} = .012, *SE* = .010, *t* = 1.269, *p* = .205) which is not a significant driver of sales in this model. Retailer age (β_{01} = .002, *SE* = .001, *t* = 2.232, *p* <.05) was a significant positive predictor of sales and retailers by ZIP code (β_{02} = -.008, *SE* = .004, *t* = -1.932, *p* = .053) was not a significant predictor of sales, as they were once again included in the analysis as control variables. The -2 Log Likelihood (deviance) = 29725.95, indicates a significant improvement over the null model (Raudenbush and Bryk 2002).

Overall, these results demonstrate that transformation to the underlying distribution of NPS score responses may be misguided. It results in information loss, as a large portion of the scale, 4–7, are not considered in the transformation at all. This presents similar issues to dichotomizing continuous variables, which has been shown to reduce statistical power, and to often lead to spurious results (Fitzsimmons 2008). These transformations are simply ignoring portions of the data that could be meaningful, and these results provide support for Hypothesis 2.

STUDY 4 – MODERATING EFFECT OF OVER-RELIANCE ON THE METRIC

As study 2b provides evidence that the non-transformed NPS can be a significant positive predictor of sales, study 4 is conducted to investigate the moderating effect of a retailer's attention paid to the metric on the raw NPS to sales relationship. One of the main appeals of the NPS metric is its simplicity and managerial appeal, however the benefits of managers accessing NPS has not yet been studied. Therefore, for this study, the attention paid to the metric will be operationalized by the total number of views of the satisfaction dashboard by the managers of the firm under investigation, and this study will serve as a test of Hypothesis 3.

Analysis

Given the nested nature of the data and results of the variance partitioning discussed earlier, I proceeded by estimating a multi-level model in HLM. However, to run this system of equations, I had to first mean-center the independent variables and the moderator outside of the HLM software, and multiply the mean-centered version of the variables together to create the interaction term. The mean centering generally would change the interpretation of these results, as the coefficients should be interpreted in regards to their deviance from the mean, as opposed to their absolute values, yet this follows the rest of the analyses, as the level-1 variables were all group-mean centered. Specifically the following system of equations were estimated:

Level 1 Model

$$LnSales_{ti} = \pi_{0i} + \pi_{1i} * (DashboardViews_{ti}) + \pi_{2i} * (NPSRaw_{ti}) + \pi_{3i} * (DashboardViews*NPSRaw_{ti}) + e_{ti}$$

Level 2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(RetailerAGE_i) + \beta_{02}*(RetailersByZip_i)$$
$$\pi_{1i} = \beta_{10}$$
$$\pi_{2i} = \beta_{20}$$
$$\pi_{3i} = \beta_{30}$$

In this model, π_{1i} captures the effect of dashboard views on sales, π_{2i} captures the effect of raw NPSs scores on sales and π_{3i} captures the effect of the interaction between the two on sales. Additionally, β_{01} captures the effect of retailer age on sales and β_{02} captures the effect of retailer's by Zip on sales. Error terms e_{ti} and r_{0i} are also included in the model.

Results

Table 9: Study 4 Results

Predictor	Estimate	Robust S.E.
Intercept	14.530**	(.020)
Retailer Age	.002*	(.001)
Retailers By Zip	-.002	(.004)
Dashboard Views	.006**	(.001)
NPS Raw	.090**	(.009)
NPS Raw * Dashboard Views	-.003**	(.001)

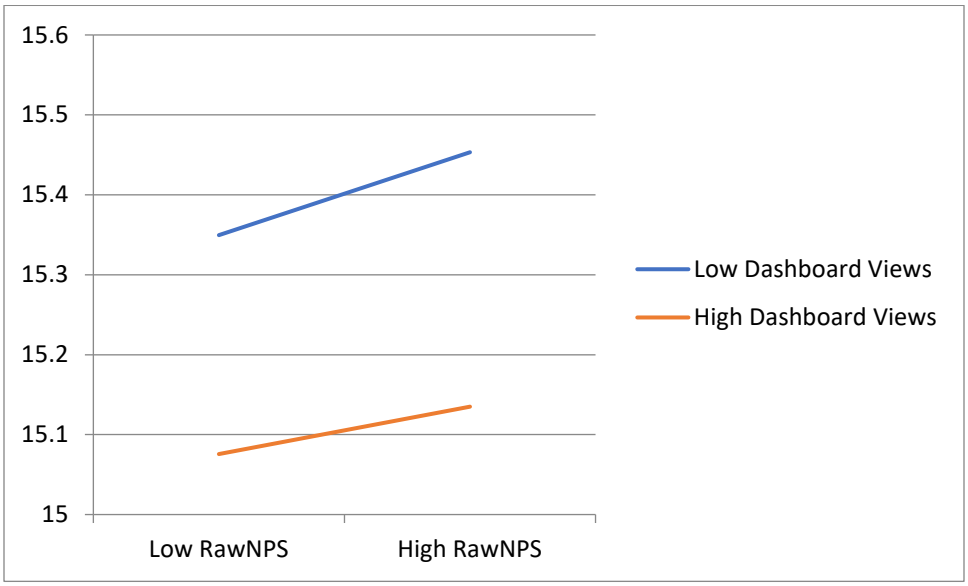
Notes: * p < .05; ** p < .01.

The raw NPS score remains a significantly large driver of sales (π_{2i} = .090, *SE* = .009, *t* = 10.312, *p* < .001) as are the dashboard views (π_{1i} = .006 , *SE* = .001, *t* = 7.461, *p* < .01). Interestingly, the interaction effect of the dashboard views and the raw NPS measure is significantly negative on sales (π_{3i} = -.003 , *SE* = .001, *t* = -2.930, *p* < .05). Retailer age (β_{01} = .002, *SE* = .001, *t* = 2.152, *p* =.032) was a significant negative predictor of sales and retailers by ZIP code (β_{02} = -.002, *SE* = .004, *t* = -.597, *p* = .550) was not a significant driver of sales, as they were once again included in the analysis as control variables. Additionally, the -2 Log Likelihood was 28737.52. This indicates that the model does a reasonable job of explaining the variance in sales. A graphical depiction of the interaction effect is depicted below.

The value of the raw NPS score is shown to be strong and significant, even for those managers that are not frequently keeping track of the measure. The results show that there is a substitutive effect. For the dis-engaged manager, NPS is an even stronger predictor of sales. For

a more engaged manager who utilizes the reporting system, the effects of NPS are still strong and significant, but relatively lower as the managerial action and commitment to customer relations replaces some of the predictive power of NPS. These results are in line with literature extolling the virtues of customer orientation. This serves as confirmation of Hypothesis 3, that the positive benefits of NPS are weakened as the number of dashboard views increases.

Figure 1: Graphical Depiction of Moderating Effect of Customer Orientation on Raw NPS to Sales



Discussion

The main results of study 4 are twofold. First, as established in study 2b, the raw NPS score is still a significant positive driver of sales. Secondly, as hypothesized in H3, the effects of NPS decrease as the number of dashboard views increases. However, I am not advocating that managers rely on NPS in lieu of exhibiting customer-oriented behaviors. The results instead demonstrate that the customer-oriented behaviors themselves do have a positive and direct effect on sales. Rather, I suggest a modest substitutive effect, that for the engaged managers the effects of NPS are still strong and significant, but relatively lower as the managerial action and commitment to customer relations replaces some of the predictive power of NPS.

GENERAL DISCUSSION

The purpose of the present investigation is to better understand whether the Net Promoter Score (NPS) is as powerful in predicting sales for firms as it is espoused to be (Reichheld 2003). Given that a large majority of firms in the Fortune 500 use this metric to better understand the success of their customer loyalty programs (Shevlin 2009), it is important that this metric's predictive accuracy is better understood. Previous literature (Morgan and Rego 2006; Keiningham et al. 2007a; Keiningham et al. 2007b) has investigated the relationships between NPS and different outcome variables for firms such as revenue, but this research marks the first attempt in the literature to provide a meta-analysis that summarizes all of the previous work to end up with effect size estimates. In addition to the meta-analysis, hierarchical linear modeling was employed from studies 2 through 4 to replicate the meta-analysis findings, decompose the effect of the transformation of the raw NPS scores from 0–10, and finally to demonstrate empirically the benefits customer orientation can provide beyond that of the NPS scores.

Managerial Implications

As the Net Promoter Score has been adopted by myriad firms across vastly different industries and is treated in some as sacred, this article intends to fill some gaps in managerial knowledge on the metric. Although, previous work has investigated NPS's significance on sales (Morgan and Rego 2006; Keiningham et al. 2007a; Korneta 2018), this is the first attempt at a meta-analysis of the current literature. The literature included in the meta-analytic estimates helped elucidate the effectiveness of NPS, but stopped short of explaining why it was not effective. In addition to the meta-analytic estimates, my secondary dataset allowed me to examine the flaws of the transformation of the NPS scores, as well as behaviors managers can engage in to substitute the effectiveness of NPS scores.

Effect of the Transformation

One of the main managerial contributions of this article is that the transformation of the customer responses to the likelihood to recommend question is flawed. Although some managers might logically understand that an individual's likelihood to recommend score decreasing from a 7 to a 6 out of 10 is vastly different than it decreasing from a 7 to a 0, this article provides evidence that this is what is flawed about the metric. Overall, the transformation is found to be unnecessary and managers can use the individual scores from 0–10 to track their loyalty success. The reasoning behind these results is due to the information loss inherent in the transformation. The transformed scale only uses a portion of the total available data to create the variable. The only reason that the NPS measure is at all predictive, is that the scores of 10 drive the extreme positive effects, but information is still lost. So, a better predictor that can truly replace satisfaction measures and give firms "one number to grow" is the non-transformed version of the same question.

These marketing managers should still rightly prioritize receiving positive word of mouth. Positive word of mouth has been found to be highly swayed by both customer satisfaction and loyalty (Brown et al. 2005). Therefore, if a firm is scoring well in positive word of mouth metrics such as NPS, then they are most likely scoring well on satisfaction and loyalty variables. Additionally, one could argue that positive word of mouth is the cheapest marketing tool. If managers are taking care of their current customers and retaining them, while those current customers are recruiting new customers, then in general revenue will grow. So, the intuitive appeal of the NPS metric is clear.

The main takeaway for managers however, is that the transformation reduces the predictive power of the NPS metric, and given the exorbitant costs some consulting firms will

charge to survey, organize, and measure responses (Reichheld 2003), it may not be the best way to track their customer loyalty. At the least, managers should be aware of this finding and re-estimate relationships with their non-transformed NPS scores as well.

NPS is More Predictive for Dis-engaged Managers

The value of the raw NPS score is shown to be strong and significant, even for those managers that are not frequently keeping track of the measure. These results are in line with literature extolling the virtues of customer orientation. The results show that managers can substitute customer-oriented behaviors for better NPS scores. I do not advocate relying on the NPS measures alone for managers, but to supplement these measures with more customer-oriented behaviors. The results of the Study 4 back up these recommendations as well. For the dis-engaged manager, NPS is an even stronger predictor of sales. For a more engaged manager who utilizes the reporting system, the effects of NPS are still strong and significant, but relatively lower as the managerial action and commitment to customer relations replaces some of the predictive power of NPS.

Ideally, managers are looking at this measure, because they are customer-oriented and want to ensure that their customers are willing to recommend them given their experience. This customer orientation ideally would focus on all aspects of a firm prioritizing their customers' desires (Donavan, Brown, and Mowen 2004) and would focus on the attitudinal nature of customer orientation in setting it as a priority for a firm. The results indicate that highly customer-oriented managers are able to dominate the value of the NPS scores alone, by supplementing these scores with other customer-oriented behaviors. Managers should attempt to better understand information they are provided by not just viewing dashboards of their NPS metrics, but to instead track other, more predictive measures to increase sales.

Theoretical Implications

This research extends our understanding of NPS and satisfaction metrics and their ability to predict sales. With respect to satisfaction, the results extend prior research that demonstrate higher sales can be predicted from satisfaction scores, by demonstrating that a similar pattern can hold looking at either retailer or product satisfaction. In terms of the NPS to sales link, this research is the first that has examined contingency factors to better understand the value of customer-oriented behaviors in predicting the validity of NPS scores.

High scores on firm satisfaction have been demonstrated previously to lead to higher revenues (Bolton 1998; Fornell 1992). Previous literature has also compared the effects of NPS on sales and its differential impact compared to typical satisfaction metrics (Morgan and Rego 2006; Van Doorn, Leeflang, and Tijs 2013; Keiningham et al. 2007a), yet they have stopped short of demonstrating why specifically the NPS is not as predictive as satisfaction metrics. This research shows the decomposition of the raw NPS responses and provides empirical evidence that the transformation of the metric is where NPS suffers. This is the first article to the author's knowledge that has demonstrated empirical evidence of this flaw.

In addition, this research examines the contingency factors predicting the success of the NPS on sales link previously unexamined in the literature. Specifically, customer-oriented behaviors are shown to at least slightly overcome the power of the NPS scores predictive validity. These results are right in line with literature espousing the values of customer-oriented firms (Fornell 1992; Aaker and Jacobson 1994). These retailers are willing to do right by their customers, and this is valued above and beyond the NPS scores alone. This is an important finding, as the intuitive appeal of NPS is one of its greatest claims (Reichheld 2003), as it gives managers one number to truly rally around.

Additionally, no meta-analysis has been previously conducted to summarize the literature in this area. This article and its meta-analytic estimates in addition to its own novel contributions can be used as a starting point for further research on the topic. Hopefully, the field will continue to try to better understand how a marketing metric as popular as NPS can be improved to help marketing managers track the success of their customer loyalty.

Limitations

Overall, no investigation is perfect or without flaws. First, and foremost, meta-analyses have several strengths, but they also contain inherent limitations. First, the constructs I include are constrained to variables for which sufficient primary data is available. Thus, this framework should be interpreted not as an exhaustive list, but as a summary of some of the most commonly studied firm growth variables and their relationship with the Net Promoter Score. This area has not been studied in great depth previously, so the Meta-Analytic Effect Size estimates reported in this article are a summary of a limited amount of literature. Hopefully, this is seen as a strength of this article in trying to invigorate a discussion on the value of this metric.

Additionally, with regards to the secondary data analysis, although the effects were tested across over 2,000 retailers, all of the retailers were a part of the same parent distribution network. Given the evidence presented in the meta-analysis that NPS has differential effects dependent upon the industry studied, different findings could be possible if the firm studied was in a different industry, or if multiple firms were examined across industries. Although a flaw, that was the rationale behind including both the meta-analytic estimates as well as the secondary data analysis to complement each other. Still, despite the quarterly aggregation of the data in these analyses, data sparseness remains.

Future Research Directions

Future research could expand upon these findings in key ways. First, subsequent studies could examine the non-linear effects inherent in these results and weight the scores of 10s more heavily. There is room to examine the variance in these scores, as well as other potential transformations, despite the information loss. Broader managerial actions could be investigated to find what other actions can subsume the NPS measure's predictive ability. Scholars might consider the potential total effect of satisfaction as an antecedent of NPS, in line with ACSI theorizing (Fornell 1992). Future research could also combat data sparseness by either expanding either to larger time buckets or seeking out industries with higher response frequencies. Finally, future research could investigate the relevant time lags in these relationships to understand when the effects of higher or lower NPS scores actually end up impacting firm revenue or profitability.

CONCLUSION

This article is focused on understanding the value of the Net Promoter Scores to firms, showing is outperformed in determining firm sales by traditional satisfaction metrics. I also provide evidence that the inherent flaw in the metric is the transformation. The likelihood to recommend question in itself is predictive of firm sales, but the NPS's transformation is problematic. The article provides further credence to the benefits of a firm's customer orientation. Customer-oriented behaviors can subsume some of the predictive validity of the NPS scores. As currently conceptualized, this article provides evidence that NPS is not truly "the one number you need to grow" (Reichheld 2003), yet points out which factors can make it a success. Across four studies, I have summarized the current literature, and expanded it into previously unstudied domains. This project will hopefully be seen as novel and important to marketing executives and academics alike.

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ARTICLE 2
PREDICTING RETENTION IN B2B RELATIONSHIPS: THE DIFFERENTIAL EFFECTS OF PROACTIVE VERSUS REACTIVE ENGAGEMENTS

ABSTRACT

The nature of B2B provider-customer meetings have changed due to advances in data management. Now vendors have a better conceptualization than ever before of how B2B customers use products and engage with vendor solutions, and they pass this knowledge onto the customers to increase the value realized from the solutions. Yet, decreased customer commitment to providers from subscription-based relationships has persisted. To provide a baseline understanding of the new norm of engagement within these B2B relationships, this article relies on the relationship marketing literature. The relationship marketing literature describes how business relationships are dependent upon trust and commitment (Morgan and Hunt 1994). The literature has even progressed to an understanding of which relationship antecedents and strategies are most effective generally (Palmatier et al. 2006), and with regards to across relationship stages (Zhang et al. 2016). A unique dataset with over 15 months of data across over 1,500 client firms within one vendor solution is utilized to understand the benefits of the new engagement strategies. Overall, the findings demonstrate that proactive attention to customers driven by insights gleaned from product usage is rewarded with higher retention. Alternatively, when the engagements are reactive to correct issues that arise, negative effects are shown on retention. These effects are suppressed by high product dependence, and explained by client growth mindsets.

INTRODUCTION

B2B vendor-customer meetings have become more important than ever. Advances in data have led this change in that it drives knowledge about how B2B customers use products, and allows for vendor solutions that better cater to customer needs. Yet, many industries are still experiencing decreased customer commitment given the increase in subscription-based relationships. In response, the B2B relationship marketing literature has transitioned to provide a better understanding of the dynamic nature of these buyer-seller partnerships. Originally, B2B relationships were categorized by broad relational states characterized as relatively static (Dwyer, Schurr, and Oh 1987). Then, the literature shifted its focus to develop a better understanding of which relationship marketing antecedents and strategies were most effective in generating strong relationships (Palmatier et al. 2006). Now, relationships have been investigated as dynamic, moving either toward or away from positive relational states based on the effectiveness of relationship marketing strategies, and the importance of meetings between the two parties (Zhang et al. 2016). These meetings have progressed beyond traditional touchpoints to include a large emphasis on proactive attention placed to customers, as well as reactive responses when customer relationships are in jeopardy. Specifically, this research will refer to these individual proactive and reactive meetings as moments of truth. Moments of truth are chosen as the focal construct of interest, as they describe how each time a client interacts with a firm, they form an overall judgement as to the quality of the firm and their willingness to do business with it in the future (Bitner 1995). The objective of this research is to establish the value of these moments of truth for retention, and to investigate which customer characteristics impact the efficacy of these meetings.

Relationship management has progressed to an understanding that each touchpoint between a firm and a client is important to the success of a relationship. The literature has moved beyond hoping that existing barriers, such as high switching costs or the length of the relationship alone create, sufficient inertia for the relationship to continue, to the new belief that each relationship encounter is critical (Harmeling et al. 2015). This portends the trend in industry practice to invest new resources to retain customers and may combat negative migration to weaker business relationships. Successful business relationships are predicated on the following of norms and expected behaviors (Jap and Anderson 2007). When these patterns of behavior are broken, then the relationship suffers and frequently will cease (Harmeling et al. 2015). As relationships are categorized by these relationship norms, each touchpoint between the firms is critically important for the client to be retained. Specifically, the research focuses on the differential value arising from proactive moments of truth, which have been established as the norm within B2B relationships versus reactive moments of truth on retention. Proactive moments of truth are interactions where the vendor provides unique insights into specific manners in which the client can best capitalize on the relationship to meet their goals. Reactive moments of truth occur when problems exist that may hinder the client's attainment of goals, which prompts the vendor to initiate an interaction to investigate and address the situation. The customer clearly plays a role in dictating the success of moments of truth, and differential effects of these critical meetings have been found to be dependent upon client industries (Hollman et al. 2015), their own situations (Gustafsson, Johnson, and Roos 2005; Roos, Edvardsson, and Gustafsson 2004), and their views of the provider firm's actions (Voorhees et al. 2014). Yet, many topics still remain unexplored regarding these moments of truth and their impact on retention, and specifically the differential effects of proactive versus reactive moments of truth.

Despite some related research, little is known about how B2B moments of truth impact retention and what factors affect this relationship. Retention is recognized as critical to the sustainability of B2B sales practice, as the cost of acquiring a new customer well outpaces the cost of maintaining a current relationship (Reichheld and Sasser 1990). Still, there is an under explored area with regards to specific strategies to implement and create positive and lasting relationships. Prior services literature has investigated the impact of reactive moments of truth to overcome issues (e.g., Bitner, Booms, and Tetreault 1990; Hollmann, Jarvis, and Bitner 2015), yet the literature is relatively deficient in investigating the impact of proactive moments of truth. Some factors may impact the outcomes of proactive and reactive moments of truth, for example a customer's growth mindset or the role of a customer's product dependence (Väänänen 2021), yet these factors have been underexplored in the literature. The growth mindset of the customer firms has not been connected to these topics before, and the belief that these firms have in their ability to grow, could certainly impact whether they want to remain in a business relationship. Finally, the impact of product dependence on B2B relationships has been examined in the literature (e.g., Hewett and Bearden 2001), but none specific to B2B moments of truth. Given the lack of research on how moments of truth and customer factors impact retention, I address three main questions. 1) B2B meetings are presumably important, but what role do proactive and reactive meetings play in retaining customers? 2) The customer also plays a large role in the outcomes of these moments of truth, as such, how does their attitude toward growth (i.e., growth mindset) impact downstream retention? 3)What is the role of "stickiness" (i.e., product dependence) of a vendor's product on the effectiveness of B2B interactions with customers?

The effects presented in this article are derived from a theoretical lens and supported by empirical results to arrive at a better understanding of the differential impacts of both reactive

and proactive moments of truth. Social Exchange Theory, which describes how business relationships follow agreed upon norms (Cropanzano and Mitchell 2005), provides a theoretical lens to understand these effects. The new norm that has been established in many business settings, including the one examined in this article, is that the establishment of proactive moments of truth as the basis of the customer relationship, which helps the client derive value from the provider's offerings, but the downstream effects of this new norm on retention have yet to be studied.

To address this gap from an empirical perspective, a unique data source with information on relationship management of B2B relationships for over 1,600 customer firms across 15 months of data is utilized. Specifically, a moderated mediation logistic regression model is tested. The initial results indicate that proactive engagements have beneficial impacts on retention, but reactive engagements have negative impacts on retention. These findings alone are not necessarily new to managers, as most good marketing practitioners know the value of providing proactive maintenance of customer relationships, and frequently attempt to implement these strategies to the best of their abilities (Kumar 1996). Yet, the nature of these proactive engagements has changed, and the expectation for these engagements has increased.

Still, in reality, a number of these engagements with clients may be reactive, as customers may have concerns that are not addressed by the proactive approach. The interesting nuances of this investigation come with the addition of viewing the effects of product dependence and growth mindsets on these relationships. Product dependence is found to buffer the negative effects of reactive moments of truth, and the positive effects of proactive moments of truth. Customer firm growth mindsets are found to be a mediating force that explains these effects, as firms with greater growth mindsets are more willing to learn the best ways to utilize the product.

This article establishes that the new norm of proactive maintenance of these relationships leads to higher client retention.

The contributions of this article are threefold. First, this investigation addresses the effectiveness of new proactive marketing strategies in B2B relationships and develops a framework that empirically investigates the effectiveness of proactive and reactive moments of truth to drive retention. Additionally, this article investigates the mechanism by which these effects work, by examining the impact of firm growth mindsets and a moderating factor (product dependence) that impacts their effectiveness. This advances research on the notion that B2B relationships mature across life-cycle stages (Jap and Anderson 2007), and that customers migrate across different relationship states (Zhang et al. 2016). Thus, this article provides further credence, that no single individual strategy can be universally applied across all customers. Finally, my findings provide relevant guidance for managers on how to effectively manage these distinct moments of truth, by paying greater attention to the client firm's unique goals and issues. The managers must use the vast amount of data on their customers' product usage at their disposal to best steer clients in the correct direction to recognize value. This allows for greater tailoring of messaging to their clients, which leads to greater retention.

CONCEPTUAL BACKGROUND

Social Exchange Theory, Relationship Marketing, and Customer Retention

Social exchange theory provides a theoretical foundation to understand the impacts of moments of truth. Social Exchange Theory illustrates how the relationships between two or more parties can evolve over time to become trusting, loyal, and mutual commitments. In essence, relationships are theorized to be characterized by two or more parties abiding by certain rules of exchange (Cropanzano and Mitchell 2005). Although rarely explicitly delineated, these rules of

exchange and norms become established over the tenure of a relationship and act as guidelines for how both parties should act. Social Exchange provides an effective theory basis for the study of moments of truth, because the effectiveness of these moments is dependent upon the ability of both parties to communicate their agreement or disagreement with the actions of the other party.

Social exchange theory pairs well with the relationship marketing literature. Relationship marketing is an enduring foundation in customer-based literature that explains how value drives loyalty. Explicitly defined as "all marketing activities directed toward establishing, developing, and maintaining successful relational exchanges" (Morgan and Hunt 1994, p. 22), relationship marketing has been shown to positively influence key variables such as sales growth, share, and profits (Crosby, Evans, and Cowles 1990). The key driver of relationship marketing is relationship quality, which measures the overall assessment of the strength of the relationship and has been demonstrated as a key to firm performance (Palmatier et al. 2006). The literature has undergone a progression from focusing on transactional relationships to better understanding how relationships can be cultivated and grown even after a successful sale. These post-sales relationships are specific in that they require special attention to both confirm current value and generate future value for clients.

Social exchange theory has been applied across a number of different contexts as a theoretical lens to understand the underpinnings of relationship marketing (Nagel et al. 2021; Wetzel, Hammerschmidt, and Zablah 2014). The binding of the two literature streams of relationship marketing and social exchange theory comes from the inclusion of relational norms in understanding these relationships. In essence, the parties rely on these norms as governance mechanisms, which form psychological contracts to help dictate future actions. Counter to legal contracts, which are associated with more transactional forms of governance (Rosseau and

Tijoriwala 1998), these psychological contracts help to inform behavior of both the provider and client firms, by providing heuristics for how actions will be perceived by the opposite party. To establish these relational norms, it is of paramount importance that communication is frequent and in-depth. Not only does this communication allow for the norms to be explicitly or implicitly stipulated, but it also provides an opportunity for the partners to gauge to what degree the relationship partner is adhering to the norms. If one of the relationship partners believes that relationship norms are not being followed, then this communication affords the parties an opportunity to resolve their issues satisfactorily.

The end goal of these relationship marketing efforts, explained by social exchange theory, is to maintain or increase revenues, which is facilitated via retaining customer relationships (i.e., customer retention). Customer retention is an important variable for any firm to track to understand the percentage of their current customers that are staying with their firm, versus the percentage of those that are leaving the firm, and the reasons behind either action (Gustafsson, Johnson, and Roos 2005). The notion of customer retention is implied in concepts found in the B2C literature, such as customer loyalty, repurchase behavior, and commitment. The genesis of these research studies that focus on retaining customers is centered around the concept of market orientation within firms (Kohli and Jaworski 1990).

Market orientation is defined as "organization-wide generation of market intelligence pertaining to current and future needs of customers, dissemination of intelligence horizontally and vertically within the organization, and organization-wide action or responsiveness to market intelligence" (Kohli, Jaworski, and Kumar 1993, p. 467). This measure has been shown to drive outcomes related to successful customer experience (Lemon and Verhoef 2016), product innovation (Han, Kim, and Srivastava 1998), and organizational performance (Baker and Sinkula

1999). Market orientation, when correctly applied, allows for a firm to have a greater understanding of their customers, their needs, and how to properly serve them. Clearly the goal of market orientation, and marketing in general, is to drive customer ongoing business.

At the broadest level, the value of a market orientation is customer retention, which allows the potential for future growth and long-term relationships with customers. In B2B firms, a focus on retention is critically important, as even firms with customer contracts, can experience annual churn (i.e., non-retention of customers) rates of 24% (Campbell 2017). This suggests firms would have to completely replace their customer base every four years. Additionally, it is estimated that it costs five times (5x) as much to acquire a new customer as opposed to retaining one (Gallo 2014). Increasing retention, even by just a few percentage points has been found to be positive, as literature investigating the increase in profits following just a 5% decrease in customer defections resulted in increased profits anywhere from 25% to 85% dependent upon the industry examined (Reichheld and Sasser 1990). Overall, the positive benefits of higher client retention underscore the reasoning behind firms collecting vast amounts of data via relational dashboards and the importance of firms correctly classifying relationship quality and setting up meetings to address these results accordingly through two-way communication with their clients. Moving beyond the broad theoretical lens, in the next section I turn to more of an explicit focus on the individual transactions dictating the success of these relationships.

Moments of Truth

This investigation will rely on previous literature, which stipulates that the most important meetings to determine the success or failure of B2B relationships can be considered *moments of truth*. These moments of truth are the touchpoints between client firms and provider firms and are critical in determining relationship quality and future consumption behavior

(Voorhees et al. 2017). The marketing literature has taken a few different directions when investigating these critical business encounters. The services literature has been the main body of work investigating this phenomenon with the terms critical incidents (Bitner, Booms, and Tetreault 1990; Keaveny 1995), triggers (Gustafsson, Johnson, and Roos 2005; Ross, Edvardsson, and Gustafsson 2004), and finally moments of truth (Voorhees et al. 2014; Voorhees et al. 2017; Bitner 1995). Although the constructs differ slightly, the essence of all of the constructs is the thought process that customers only have so many touchpoints with a firm, and that these touchpoints are of critical importance in customers evaluating their relationships with firms. In the services setting, this is certainly the case as the customers may only interact with a company a handful of times across different services settings and employees.

In B2B relationships however, the meetings between clients and firms are generally more frequent and complex. Harmeling et al. (2015) has investigated the influence of these transformational relationship events in predicting retention, and found that strong relationships help product disconfirmations, but harm relational disconfirmations. The effects of these meetings differ due to the tenure and life-cycle stage of the relationships (Jap and Anderson 2007). Yet, the literature has progressed beyond the hope that inertia created through tenure alone would suffice to continue a relationship. Particularly in newer B2B models, evidence suggests that these relationship states are more dynamic, and vendors must tailor strategies and communications to avoid negative migration toward weaker relational states (Zhang et al. 2016).

In an effort to foster more positive relational states while avoiding negative relational states, industry practice and academic literature have espoused the values of the new role of relationship manager, which allows for a proactive management of relationships. B2B relationship managers are tasked with moving beyond traditional sales and service roles to

ensure that customers are achieving their desired outcomes from the use of the provider firm's offering (Eggert, Ulaga, and Gehring 2020). To ensure that the desired outcomes are being met, these relationship managers leverage CRM software to guide goal, stakeholder, and learning management (Hilton et al. 2020). The goal of using product data is to identify ways to help customers utilize products better (i.e., be proactive) and to note where problems may be developing (i.e., reactive) that can be communicated via moments of truth. Overall, this role provides value to customers via ongoing success with solutions (Hochstein et al. 2021). Table 1 below references some of the critical literature investigating these relationships.

A few key gaps in the literature are identified in Table 2. First is the dearth of literature that investigates both reactive and proactive strategies to maintaining successful relationships. The services literature has a few papers that have investigated the impact of reactive strategies to mitigating the harm that comes from service failures. In particular, the literature reviewed has mentioned the service recovery paradox, which is the phenomenon in which a successful service recovery in reaction to a service failure can lead to more satisfied customers (Voorhees et al. 2014; Voorhees et al. 2017; Bitner, Booms, and Tetreault 1990; Hollmann, Jarvis, and Bitner 2015). These papers only examine reactive strategies, as opposed to proactive strategies that can improve relationships in service contexts. A notable exception to this trend that investigates both proactive and reactive strategies is Harmeling et al. (2015). However, in their model, proactive strategies center around exchange communication in response to these transformational relationship events. In the current study, proactive and reactive engagements are moments of truth or "transformational relationship events" themselves.

Table 1: Literature Review on Moments of Truth

Authors	Context	Definition	Method	Key Findings
Harmeling et al. (2015) *JM*	B2C and B2B	Transformational relationship event is an encounter between exchange partners that significantly disconfirms relational expectations (positively or negatively) and results in dramatic, discontinuous change to the relationship's trajectory (p. 39)	2 field studies and a lab experiment	Strong relationships benefit product disconfirmations but harm relational disconfirmations.
Bitner (1995) *JAMS*	Services	"Moments of truth" – customers receive a snapshot of the organization's quality, and each encounter contributes to the customer's overall satisfaction and willingness to do business with the organization in the future (p. 248)	N/A – Commentary	Investigates the value that customers derive from staying in service relationships.
Bitner, Booms, and Tetreault (1990) *JM*	Services	Service encounter as "the dyadic interaction between a customer and service provider" (Supremant and Solomon 1987)	Critical Incident Technique	Provides a generalizable classification system for sources of dis/satisfaction across industries.
Voorhees et al. (2017) *JBR*	Services	Moments of truth are described as critical encounters between customers and firms that significantly impact customers' impressions of the firm and consumption (p. 270)	N/A – Review Paper	The authors provide a framework of service experience research which stems across 1) pre-service encounters, 2) core service encounters and 3) post-service encounters and argue that researchers need to consider all periods in their research.
Voorhees et al. (2014) *MSI Working Paper*	Services	Moments of truth are described as critical encounters between customers and firms that significantly impact customers' impressions of the firm and consumption experience (p. 3)	Longitudinal field experiment and simulated service experiment	Acknowledgement of positive feedback from satisfied customers provides an opportunity for firms to create new moments of truth and repeat patronage.
Löfgren (2005) *MSQ*	B2C	The service encounter is a moment of truth because the customer's experience of the encounter is the main contribution to his or her perception of the total service quality (p. 105)	Interviews with managers	Consumers evaluate quality both when purchasing and consuming a product or service. The first moment of truth is about obtaining customers' attention and the second is about providing the tools the customer needs to experience the benefits.
Bitner (1990) *JM*	Services	Service encounter as "a period of time during which a consumer directly interacts with a service" (Shostack 1985, p. 243, cited p. 70)	Experiment	A model is tested experimentally which shows the effects of physical environments and employee responses on attributions and satisfaction in service failure contexts.
Jap and Anderson (2007)	B2B	Cooperative relationships require that norms or expected patterns of behavior develop. A key to establishing these norms is goal congruence (p. 262)	Primary data from resellers of a firm	This life-cycle theory of B2B relationships is proposed and tested which shows that relationship properties change throughout stages of a

Management Science				relationship. Additionally, individual sales representatives play a critical role in successful relationships.
Hollmann, Jarvis, and Bitner (2015) *JAMS*	B2B	Relational Internal Events (RIE) – events that occur within the realm of the supplier and/or customer's roles, actions, and interaction arising from the focal supply of goods and services (p. 264)	Depth interviews	B2B defection decisions are developed over time, and the decisions can be influenced by events outside the core product or service delivery process.
Van Doorn and Verhoef (2008) *JM*	B2B	Negative critical incidents can be defined as out-of-the-ordinary events during an interaction that customers perceive or recall as unusually negative (Roos 2002)	Survey	Critical incidents in B2B relationships make customers reconsider relationships and move beyond "business as usual."
Gustafsson, Johnson, and Roos (2005) *JM*	B2C	In general, a trigger is a factor or event that changes the basis of a relationship (Roos, Edvardsson, and Gustafsson 2004) Reactional triggers – those critical incidents of deterioration in perceived performance (p. 211)	Survey	Customer satisfaction, calculative commitment and prior churn predict retention. Situational and relational triggers did not moderate these relationships.
Roos, Edvardsson, and Gustafsson (2004) *JSR*	Services	Situational triggers are defined as changes in a customers' own lives, not necessarily related to the service provider at all. Influential triggers are factors related to the completive situation, such as competitors' efforts to increase market share. Reactional triggers are of immediate relevance to service provider and critical incidents are interactions between customers and providers and are typical reactional triggers	Reanalyze previously published studies with switch path mapping using SPAT	The authors differentiate between internal switching within a provider to external switching to a different provider. The changing behavior stemmed from higher energy levels even in noncompetitive industries.
Bolton (1998) *Marketing Science*	B2C	Facilitating transactions occur when the customer seeks out an encounter with the organization, typically to obtain information about existing service, purchase additional product, ask about his/her bill, and so forth (p. 49)	Longitudinal survey of cell phone customers	Customer satisfaction ratings are positively related to the duration of the relationship. Customers with longer tenures weigh prior satisfaction more heavily and new information less heavily.
Keaveney (1995) *JM*	Services	Critical incidents were defined as any event, combination of events, or series of events between the customer and one or more service firms that caused the customer to switch service providers (p. 72)	Critical Incident Technique	Interviews allow for a classification of switching behavior into 8 different categories.

Table 2: Literature Gaps Identified

Authors	Proactive Engagements	Reactive Engagements	Retention	Growth Mindset	Product Dependence
Harmeling et al. (2015) *JM*	✓	✓			No – but talks about maturity phases
Bitner (1995) *JAMS*			Conceptual		
Bitner, Booms, and Tetreault (1990) *JM*		✓			
Voorhees et al. (2017) *JBR*		✓	Conceptual		
Voorhees et al. (2014) *MSI Paper*		Giving gratitude for filling out a survey	✓		
Löfgren (2005) *MSQ*	✓	Purchase decision and consumption			
Bitner (1990) *JM*		✓			
Jap and Anderson (2007) *Management Science*			Implied	Risk, trust, goals	✓
Hollmann, Jarvis, and Bitner (2015) *JAMS*		✓	✓	✓	
Van Doorn and Verhoef (2008) *JM*	✓		✓		
Gustafsson, Johnson, and Roos (2005) *JM*			✓		Situational triggers
Roos, Edvardsson, and Gustafsson (2004) *JSR*			✓		Situational triggers
Bolton (1998) *Marketing Science*			✓		Tenure of relationship
Keaveney (1995) *JM*			✓		
This study	✓	✓	✓	✓	✓

The literature on moments of truth does not offer much guidance on factors that impact their effectiveness. Variables that describe the customer firm itself, independent of the relationship with the provider, are rarely included in these studies. A few papers have included data about the nature of the relationship between the vendor and client, such as a customer firm's satisfaction with the provider (Bolton 1998) or their level of commitment to a provider (Gustafsson, Johnson, and Roos 2005). Prior investigations, however, have only included variables regarding the strength of the relationship between the two parties, as opposed to the strength of the client business itself. While the interdependence of the two firms is important from a social exchange theoretical perspective (Molm 1994), it is important to include a measure of interdependence in this study, which is represented by product dependence in the model. This allows for a further probing of the benefits of a strong relationship measure, while also building upon the literature's investigations into similar topics such as situational triggers and tenure of the relationship. Still, the product dependence portion of the model is only capturing a client firm's situation with regards to the provider, as opposed to a measure capturing the client's broader situation. Therefore, a client firm's growth mindset will also be investigated in this study. This moves beyond literature that examine the goals of a client within a B2B relationship (Jap and Anderson 2007) to an understanding of the client's goals for their business more broadly irrespective of the provider. To the author's knowledge, this is the first B2B investigation in the marketing literature that includes a growth mindset firm level variable.

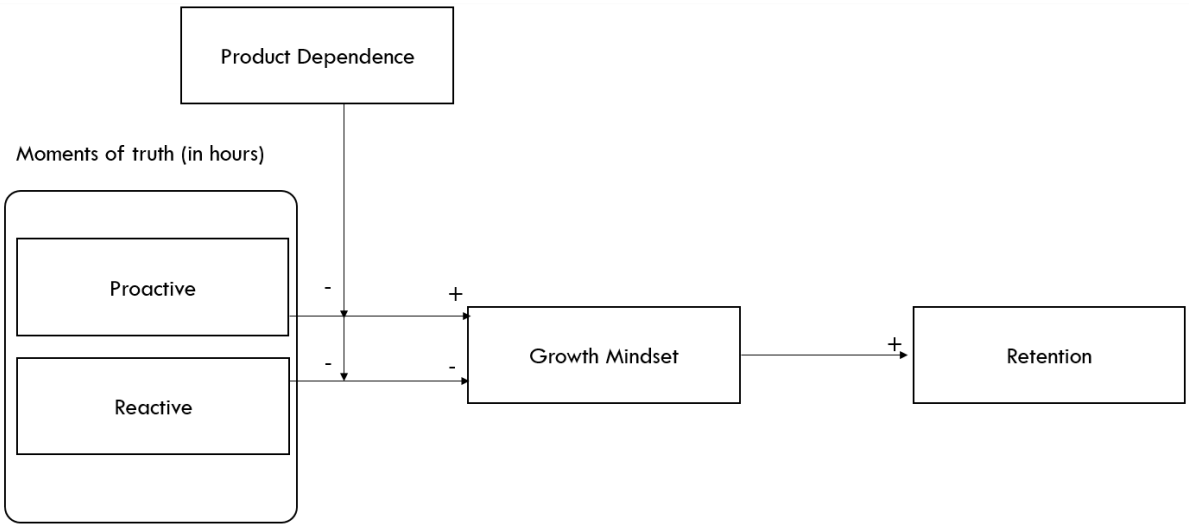
HYPOTHESIS DEVELOPMENT

Conceptual Model

B2B relationships are generally managed by some sort of boundary spanning employee. In the past, sales used to be the function tasked with this responsibility, or in some service

industries, customer service representatives. Today, it is clear that relationship marketing needs to go beyond a customer service representative that provides only reactive efforts. Similarly, traditional salespeople, providing proactive efforts to maintain a relationship, can be hampered by competing goal foci, and job demands. As mentioned previously, this role has been demonstrated to provide value to customers (Hochstein et al. 2021), yet the specific effects of the new engagement norms have not been empirically established. The following sections develop my hypotheses that fit my conceptual model depicted in Figure 1. This includes 1) proactive moments of truth and 2) reactive moments of truth direct effects' on retention and growth mindsets, 3) the mediating impact of customer firms' growth mindsets, and 4) the moderating effect of product dependence on these effects.

Figure 1: Conceptual Model



Moments of Truth

Proactive moments of truth

This research will focus on two distinct moments of truth, one being reactive and one being proactive. From the beginning of the relationship, the norm is established that meetings will be set proactively. The proactive moments of truth from the firm rely on relationship

managers engaging with clients in customer education-based meetings proactively. The provider firm combines analytics and product use data to assist the customers in finding new value that can be derived from changing internal processes and procedures to use the emerging technology more efficiently. Thus, the vendor is presenting information based on the customer's usage that the customer themselves do not realize, as that norm has been established that the clients expect the vendors to track their usage and set these meetings to proactively maximize value for the clients.

This focus on the communicated value of products to customers stems from the reality that customer inertia alone was not sufficient to ensuring high retention rates for provider firms. Although inertia has been found to be a driver of retention (e.g., Homburg, Koschate, and Hoyer 2005; Jap and Anderson 2003) there is evidence that particularly in B2B subscription models, that these relationship states are much more dynamic, and inertia alone is not enough to avoid negative migration toward weaker relational states (Zhang et al. 2016). Thus, relationship managers and marketing academics have espoused the values of communicating with clients. Specifically, communication has been found to both promote migration to positive relationship states to allow revenue and value to grow and to reduce migration to negative states which can lead to churn (Palmatier et al. 2006). In general, this is related to the relationship marketing literature's construct of information exchange. The goal of information exchange is for providers to assess a customer's level of knowledge and to add to it (Gilliam and Flaherty 2015). These meetings move beyond just simple information exchange however, as they are not solely focused on the features of the product, but on the various benefits of the product's potential to address specific customer needs. This is in parallel with the academic insistence on the role of relationship managers acting in a proactive as opposed to reactive manner to adequately discuss

the potential for future issues, and the steps that can be taken in the current moment to alleviate those concerns (Hochstein et al. 2021). As such, proactive moments of truth are expected to have positive effects on retention, as they are evidence of the vendor following the norms of the relationship, and allow for the clients to realize greater value from the vendor's solutions.

H1: *The positive effect of proactive moments of truth lead to higher client retention.*

Reactive moments of truth

In contrast, reactive moments of truth refer to meetings in which a client projects behaviors or complains that indicate migration toward more negative relationship states. The relationship manager will work cross-functionally with individuals from service, technology support, and/or finance/accounting departments to identify the root cause of the issues and to correct them. In general, literature suggests that reactive meetings lead to negative downstream effects when compared to proactive meetings (Hochstein et al. 2021). This is due to reactive moments of truth going against the norms established in the beginning of the relationship for these meetings to be set proactively by the vendor to avoid as much as possible the need for reactive meetings to correct issues. Yet, I certainly do not advocate that these meetings should be ignored, as that would lead to potentially even further downstream negative effects. This is related to the service literature's concept of the service recovery paradox. Stated simply, the service recovery paradox suggests that customers that have issues which are adequately resolved by a provider firm, end up more satisfied than customers that had no issues with the service, and this effect has been empirically demonstrated to consistently emerge with regards to satisfaction (De Matos, Henrique, and Alberto Vargas Rossi 2007). Therefore, there is quite a bit of evidence that even these reactive meetings can strengthen relationships. Still, that is assuming that the reactive meetings always end up leading to a satisfactory solution, which is not always the case.

Overall, I expect that the reactive moments of truth will lead to negative effects on retention. The reasoning behind this hypothesis is that reactive moments of truth are characterized by a B2B vendor setting the norm for proactive meetings, and customers expect it, then these recurring reactive meetings challenge the norms and have a negative impact. Ideally, the goal/norm is for zero reactive moments of truth to occur. However, when these reactive moments of truth do occur, they arise after issues, and will lead to lower downstream retention.

H2: *The negative effect of reactive moments of truth lead to lower client retention.*

Growth Mindset

The literature differentiates between two different mindsets along a continuum that an individual can possess. Along this continuum, individuals can possess a mindset that is either classified as "fixed" or stable in which they believe that people cannot change over time, versus a "growth" mindset in which they believe that talents and abilities are malleable (Dweck 1999). These mindsets are have been shown to shape goals, perceptions, and reactions in intergroup contexts (Rattan and Georgeac 2017), and have been adopted by many firms to organize their teams around diverse viewpoints. Particularly, a growth mindset has been found to increase engagement in organizational settings (Emerson and Murphy 2015), thus indicating why organizations have tried to adopt top-down growth mindsets. More specifically within organizations, it is of paramount importance that the firms reward not just effort, but learning and progress that yield results, such as trying new things, asking for help, and learning from failures (Dweck 2016). As such, with careful enough cultivation and dedication, firms themselves can adopt these mindsets.

Growth mindsets in this model stem from proactive actions through a reciprocity norm. This reciprocity norm is defined as a norm in which one party feels obligated to respond in an

equal manner to actions from the other party (Blau 1964). This norm frequently appears in studies that examine relationship that can be characterized as interdependent exchanges. Interestingly however, this reciprocity norm is not always found to have beneficial effects. In fact, the literature differentiates between positive and negative reciprocity orientations (Cropanzano and Mitchell 2005). Positive reciprocity orientations involve the tendency to return positive treatment for positive treatment, whereas negative reciprocity orientations involve the tendency to return negative treatment for negative treatment. One of the prevailing thoughts in the literature is that this reciprocity norm is frequently the catalyst for action from both the provider and customer firms. Growth mindsets can be viewed as a norm in which reciprocity for proactive attention is rewarded. There is a dearth of literature however, on how specifically certain meetings between the exchange partners can help create and foster an environment governed by reciprocity norms.

As there is evidence that these growth mindsets can be adopted from firms, I hypothesize in this setting that the greater the client growth mindset, the higher client retention. This pattern is expected to hold, as the firms with the highest desire to grow, will continue on in the relationship. This is because of their learning orientations and their ability to handle tougher criticism and view as an opportunity to learn, as opposed to the fixed mindset firms which are only motivated by the outcomes. The norm in these relationships is for engagements to be set up proactively to address how best a customer can utilize the product. If the customer does not indicate a desire and willingness to learn (i.e., exhibit a fixed mindset) then the norms of the relationship have been compromised, and these meetings will not be as impactful on retention. Specifically, proactive moments of truth will lead to higher growth mindsets, while reactive

moments of truth, will lead to lower growth mindsets. The greater the growth mindset, the greater the probability of retention. Thus, I propose:

H3a: *Proactive moments of truth lead to greater client growth mindsets.*

H3b: *Reactive moments of truth lead to lower client growth mindsets.*

H4a: *The positive effect of proactive moments of truth on client retention will be mediated by the client firm's growth mindset.*

H4b: *The negative effect of reactive moments of truth on client retention will be mediated by the client firm's growth mindset.*

Product Dependence

This investigation would be incomplete without considering both how proactive meetings' positive effects can be amplified, and how reactive meetings' negative effects can be suppressed. The next focus of the current study is centered on the customer firm's level of usage of the provider firm's product. This relates to the customer dependence construct from the relationship marketing literature, in that it captures evaluations of structural constraints with the exchange partner (Zhang et al. 2016). The customer has some level of use and dependence based on their product relationship and whether there is a weak or strong link. Within this literature, a prevailing belief is that "reciprocal exchange" is not classified by explicit bargaining, but rather by understanding that one party's actions are contingent on the other's behavior (Molm et al. 2000). Specifically, this interdependence is found to reduce risk and encourage cooperation (Molm 1994). This relates to the benefits product dependence has been found to drive within these relationships, as the more embedded within a provider firm that a customer finds himself or herself, the more they rely on cooperation. In essence this allows for the relationship manager to

make some assessment of the relationship quality. Meetings can then proceed with the goal of increasing a growth mindset, and understanding the product dependence's effects.

This product dependence has an effect on the relationship in two ways. First, the more dependent the customer is on the product, in general the more revenue they can recognize from the solution. Additionally, the higher the level of product dependence, the harder and costlier it will be for a customer to cease the relationship. This is due to the concept of customer inertia, which is found to increase throughout the build-up and maturity phases of a relationship (Mullins et al. 2014), and is defined as the habitual repurchase with little information search or alternative evaluation (Voss, Godfrey, and Seiders 2010). Overall, the more reliant on the product the customer firm, this product dependence buffers the effects of these moments of truth, given the power differential between the firms (Kumar, Scheer, and Steenkamp 1998). However, for firms with low product dependence, these meetings are more critical. Reactive moments of truth are expected to be found to have less of an impact on retention for the client firms that are highly product dependent, as these firms are highly reliant on the provider, and thus are motivated to make the relationship work.

The positive benefits of proactive moments of truth are also expected to be muted by high product dependence, as these firms have less room to grow in the relationship in terms of embeddedness. Presumably, the clients that are highly product dependent have experienced the positive benefits from these proactive moments of truth, and the norm has been established and upheld that these meetings occur with regularity. Thus, many of the positive benefits from the following of these norms have already been experienced, and the incremental value of each additional proactive engagement will be smaller.

H5: *The effects of positive (negative) proactive (reactive) moments of truth to growth mindset path will be moderated by product dependence, to the extent that effects from both proactive moments of truth (H4a) and reactive moments of truth (H4b) are reduced as product dependence decreases.*

RESEARCH METHOD

Data Overview

The author is partnering with a large SaaS (software as a service) firm to answer these research questions and test the hypotheses. Specifically, I leverage a diverse set of data including relational data from the CRM system, accounting information, contracting, customer survey, product usage, and relationship manager survey data across 1,600 customer firms nested within 50 post-sale relationship managers. Data are provided monthly for a 15-month period starting in September 2020, with customers ranging from over 120 countries. The model will be estimated on the dependent variable of interest of retention to understand the impacts of proactive and reactive moments of truth.

Table 3: Coverage of Measures

Variable	Definition/Measurement	Representative Citation
Retention	Binary dependent variable, simply coded as 1 for retained, and 0 for churned for the focal month	Gustafsson, Johnson, and Roos (2005)
Proactive Moments of Truth	Number of hours spent on proactive moments of truth in a focal month	Unique to this study
Reactive Moments of Truth	Number of hours spent on reactive moments of truth in a focal month	Maxham and Netemeyer (2002)
Product Dependence	Subjective measure from the relationship manager capturing the level of reliance of the customer on the	Hewett and Bearden (2001)

	provider firm's offering, scored from 0–10	
Growth Mindset	Subjective measure from the relationship manager capturing the level of potential and desire for the customer firm to grow, scored from 0–10	Murphy and Dweck (2016)
Relationship Length	Relationship Length in Months	Verhoef (2003)
Out of Contract Percentage	Percent of time period out of contract	Contract Specificity (Mooi and Ghosh 2010)

Table 4: Means, Standard Deviations, and Correlations

	Variable	Mean	SD	1	2	3	4	5	6	7
1	Retention	0.93	0.25							
2	Proactive MOT	2.32	4.01	0.10*						
3	Reactive MOT	0.10	0.38	-.02	.16*					
4	Product Dependence	7.02	2.60	.15*	.04*	-.01				
5	Growth Mindset	5.68	1.28	.20*	.10*	-.03	.23*			
6	Relationship Length	16.60	13.80	-.01	-.06*	-.03	.04	-.04		
7	Out of Contract	0.25	0.39	-.04	-.01	.00	.04	-.05*	.72*	

Proposed Method

Logistic regression is particularly useful for binary dependent variables, such as retention in the current study. This proposed research design will not utilize the longitudinal aspect of the data, as the number of churn incidents is too infrequent to be studied longitudinally. Thus, the data is collapsed by client firms, to understand the impact of the variables and their significance on retention likelihood at any point in time in the dataset. However, the model will still utilize logistic regression with a moderated mediation model containing the growth mindset as the mediator, and product dependence as the moderator.

Results

To test the hypothesized effects, MPLUS was used to estimate models in line with the approach proposed by MODEL 8 PROCESS. MPLUS is preferred as it allows for the simultaneous estimation of multiple independent variables and interactions to the mediator from these IVs, which is not currently handled within PROCESS (Stride et al. 2015; Hayes 2017).

MPLUS specifically was used to estimate a conditional process model with Cadence Hours and Escalation Hours as the independent variables, Retention as the dependent variable, Product Dependence as a moderating variable, and Growth Mindset as a mediating variable.

Effects on growth mindset

With respect to main effects, proactive moments of truth had a positive and significant direct effect on growth mindset (b = .030, se = .007, $t = 4.183$, $p < .01$), while reactive moments of truth (b = -0.174 se = 0.077, $t = -2.268$, $p < .05$) had a negative and significant direct effect on growth mindset. In addition, product dependence also had a significant, positive effect on growth mindset (b = 0.102, se = 0.011, $t = 9.041$, $p < .01$). In addition, both interaction terms had significant effects on growth mindset. Specifically, the interaction between proactive moments of

truth and product dependence was negative and significant (b = -0.005, se = 0.003, t = -2.103, p < .05) on growth mindset, which suggests that the effect of positive moments of truth is weakened as product dependence increases. Meanwhile, the interaction between negative moments of truth and product dependence was positive and significant (b = 0.086, se = 0.029, t = 2.927, p < .01) on growth mindset, which suggests that the negative effects of reactive moments of truth are decreased as product dependence increases. A follow-up calculation of simple slopes effects confirmed this relationship. Specifically, at low levels of product dependence (-1 SD), proactive moments of truth had a positive and significant effect on growth mindset (b = 0.044, se = 0.008, t = 5.342, p < .01) and this effect was weaker and became insignificant when product dependence was high (+1 SD; b = 0.016, se = 0.011, t = 1.461, p < .01). The simple slopes for the reactive moments of truth revealed that at low levels of product dependence (-1SD), reactive moments of truth had a negative and significant effect on growth mindset (b = -0.397, se = 0.126, t = -3.157, p < .01), and this effect was weaker and became insignificant when product dependence was high (b = 0.048, se = 0.087 t = 0.555, p >.05). Finally, the covariates did not significantly affect growth mindset. Altogether, the variables explained 6.8% of the variance in growth mindset.

Effects on retention

With respect to main effects, both proactive moments of truth (b = 0.359, se = 0.071, t = 5.076, p < .01) and reactive moments of truth (b = -0.392, se = 0.211, t = -1.860, p < .05) had significant direct effects on retention. In addition, product dependence (b = 0.111, se = 0.042, t = 2.657, p < .01) and growth mindset (b = 0.405, se = 0.078, t = 5.213, p < .01) also had significant, positive effects on retention. Finally, the covariates did not significantly affect retention. With regards to the odds-ratios, the impact of a one-unit increase in growth mindset is

associated with a 50% higher likelihood that the customer will be retained. Each additional hour in a focal month of proactive moments of truth is associated with a 43.2% increase in odds of retention as indicated by the odds-ratio. However, the odds ratio of the reactive moments of truth indicate that each additional hour results in a 32.4% decrease in the odds of retention. Additionally, the impact of a one-unit increase in product dependence is associated with an 11.7% increase in the likelihood for the customer to be maintained. Finally, as indicated in the prior statistics, the covariates had relatively minor impacts as demonstrated by the odds ratios, as the relationship length increasing by one month only increased the odds of retention by 0.8% and the out-of-contract percentage increasing by one percent is associated with a 5.8% decrease in the odds to retain. The pseudo R-square statistic suggested that the variables explained 47.7% of the variance in retention.

Indirect effects

To formally test mediation, I calculated indirect effects from each independent variable on retention via growth mindset. The results revealed that both indirect effects were significant. Proactive moments of truth had a positive and significant indirect effect on retention via growth mindset (b = 0.146, se = 0.039, $t = 3.747$, $p < .01$) and reactive moments of truth had a negative and significant indirect effect (b = -0.159, se = 0.089, $t = -1.790$, $p < .05$). Taken together with the tests of direct effects, these results show evidence of partial mediation via growth mindset. Finally, I also tested the extent to which these indirect effects were contingent on product dependence by calculating the index of moderated mediation. These results demonstrated that the indirect effect was significantly moderated for both proactive moments of truth (index of moderated mediation, b = -0.002, se = 0.001, t = -1.950, p < 0.05) and reactive moments of truth (index of moderated mediation, b = 0.035, se = 0.014, t = 2.552, p < 0.05) (Hayes 2015).

Table 5: Moderated Mediation Results

Direct Paths to Mediator	**Effect**	**S.E.**	***t***	***p*-value**
Constant	5.710	0.047	121.592	0.000
Proactive MOT	0.030	0.007	4.183	0.000
Reactive MOT	-0.174	0.077	-2.268	0.023
Product Dependence	0.102	0.011	9.041	0.000
Proactive MOT x Dependence	-0.005	0.003	-2.103	0.036
Reactive MOT x Dependence	0.086	0.029	2.927	0.003
Relationship Length	-0.003	0.003	-1.133	0.257
Out of Contract	-0.020	0.099	-0.202	0.840
Direct Paths to DV	**Effect**	**S.E.**	***z***	***p*-value**
Constant	-0.713	0.466	-1.533	0.125
Growth Mindset	0.405	0.078	5.213	0.000
Proactive MOT	0.359	0.071	5.076	0.000
Reactive MOT	-0.392	0.211	-1.860	0.063
Product Dependence	0.111	0.042	2.657	0.008
Relationship Length	0.007	0.010	0.717	0.473
Out of Contract	-0.060	0.335	-0.180	0.857
Simple Slopes – Proact MOT	**Effect**	**S.E.**	***z***	***p*-value**
-1SD PD → Growth	0.044	0.008	5.342	0.000
+1SD PD → Growth	0.016	0.011	1.461	0.144
Simple Slopes – React MOT	**Effect**	**S.E.**	***z***	***p*-value**
-1SD PD → Growth	-0.397	0.126	-3.157	0.002
+1SD PD → Growth	0.048	0.087	0.555	0.579
Index of Moderated Mediation	**Effect**	**S.E.**	***z***	***p*-value**
Proactive MOT	-0.002	0.001	-1.950	0.051
Reactive MOT	0.035	0.014	2.552	0.011

Discussion of Results

This analysis reveals support for the proactive moments of truth having a positive impact on retention, and reactive moments of truth having negative impacts on retention. Thus, the first two hypotheses are supported. Additionally, support is provided for Hypothesis 3 in that proactive moments of truth lead to higher growth mindsets and reactive moments of truth lead to lower growth mindsets. The model also provides support that clients' growth mindsets have significant effects on retention, and provides evidence of partial mediation, supporting

Hypothesis 4. Finally, product dependence is found to act as a buffer for these effects, as the proactive moments of truth are more positive at lower levels of dependence, and reactive moments of truth are more negative at lower levels of dependence, supporting H5a and H5b, respectively. Thus, this model provides support for each of the five hypotheses. This indicates that the clients that continue on in the business relationship, in general, are more likely to do so, when they believe in their ability for their firm to grow and that product dependence can significantly buffer the effects of both proactive and reactive moments of truth.

IMPLICATIONS

Theoretical Implications

Proactive versus reactive moments of truth

This article advances the relationship marketing literature in a few critical directions. First, this research provides evidence that proactive moments of truth are helpful for retention, while reactive engagements hurt retention. Proactive moments of truth have the effect of proactively avoiding issues before they occur and helping confirm value, while the reactive moments of truth are intended to correct issues that have occurred. This is the new norm that has been established within these settings, in that the vendor will help the client optimize their value realized from the solution. Theoretically, these results are driven by the adherence to the reciprocity norm (Blau 1964), in that clients understand the value that the vendor is providing for them through these proactive moments of truth, and are more willing to continue in the relationship through this positive reciprocity orientation.

The opposite effect holds for the impact of reactive moments of truth. Reactive moments of truth are found to decrease the odds of retention, as they only occur after a problem is apparent. This breaks the relationship norm for these meetings to be engaged in proactively, and

leads to these negative downstream effects. As such, this article contradicts the service recovery paradox literature that clients end up more satisfied after the successful recovery of a service failure than if there had been no service failure (De Matos, Henrique, and Alberto Vargas Rossi 2007). There is no evidence that clients have a higher likelihood to stay with the firm after these reactive moments of truth.

This article also provides evidence that the proactive moments of truth that occur *before* an issue arise, with a purpose of addressing needs before they are voiced, are critically important. Previous literature has investigated proactive responses to transformational relationship events in B2B relationships (Harmeling et al. 2015), yet these proactive responses only occurred after the meeting had taken place as opposed to addressing customer needs before they voiced them. Taken together with the service recovery paradox literature (Bitner, Booms, and Tetreault 1990; Hollmann, Jarvis, and Bitner 2015), this article demonstrates the proactively adding value.

Overall, this article lends credence to previous forays into the value of moments of truth. These moments of truth describe how each time a client interacts with a firm, they form an overall judgement as to the quality of the firm and their willingness to do business with it in the future (Bitner 1995). This article finds evidence that each touchpoint between a client and a firm can be critical to the success of the relationship. It is an important distinction that this article finds the positive benefits from the proactive moments of truth, and negative effects from the reactive moments of truth, as it establishes that it is better when these touchpoints are set up and driven by the firm to confirm current value and establish potential avenues for further value.

Growth mindsets

This article also empirically demonstrates the value of fostering growth mindsets among customer firms. Although this variable is generally recognized as an individual, as opposed to a

firm level trait, this investigation provides evidence that the growth mindset at the firm level is important. Specifically, firm growth mindsets explain why the proactive moments of truth have positive effects, and the reactive moments of truth have negative impacts. Simply stated, firms that desire to grow, and that adopt these mindsets, are interested in proactively managing problems so that they can avoid bigger issues down the line once the business scales up further. This is due to firms with growth mindsets having more of a learning as opposed to an outcome orientation (Murphy and Dweck 2016). Firms with these growth mindsets are willing to be criticized and hear what they are doing wrong and how to improve, while those with more fixed mindsets want to hear reassurances that they are operating well (Blackwell et al. 2007).

The firms that exhibit more of a fixed mindset, generally want to avoid hearing about the problems and this hampers their ability to grow. The demonstration of this fixed mindset alone is a deviation from the relationship norm to engage in communications proactively to drive value. These clients are not fully appreciating the guidance and resources that the vendors can provide to create value from the solution. These clients end up being more complacent in allowing problems to be addressed as they come, and thus are less likely to recognize the inherent value in addressing problems before they arise. Overall, this leads to these firms not truly appreciating the value of a provider's offering, and therefore, they are more likely to cease the relationship.

Product dependence as a buffer

Finally, the positive effects and negative effects of proactive and reactive moments of truth, respectively, are buffered by the product dependence of the client firm. These moments of truth have weaker effects in both directions when the client is already extremely reliant on the provider firm. This relates to the relationship marketing's understanding of the importance of commitment. Commitment within relationship marketing is defined as "an enduring desire to

maintain a valued relationship" (Moorman, Zaltman, and Deshpande 1992). This level of commitment is determined by the amount of effort that the parties display in order to maintain the relationship indefinitely (Morgan and Hunt 1994), and it has been found to be a key determinant of relationship success (Palmatier et al. 2006). This commitment is frequently determined by the level of interdependence between these firms. Greater interdependence has previously been found to encourage cooperation and reduce risk (Molm 1994), which can explain why the negative effects of reactive moments of truth are muted in these relationships by greater product dependence, as the customer firm is more willing to cooperate as they are heavily reliant on the supplier. The positive effects of proactive moments of truth are buffered however by the higher product dependence as well, presumably because there are so embedded in these relationships, that there are fewer additional products or services that they utilize.

Yet, the main effects of both proactive and reactive moments of truth are significant in the model as well, indicating that even highly product dependent customers cannot be ignored. Thus, these results lend further credence to the notion that customer inertia, or product dependence, is no longer sufficient to maintain a relationship (Mullins et al. 2014). While it is an important factor that needs to be monitored, it is not the factor that predominantly explains the relationships found in this article. Therefore, relationship managers should certainly tailor their messages dependent upon the level of product dependence, but not at the sake of ignoring the other factors these relationships are contingent upon.

Managerial Implications

Importance of resolving issues before they occur

This article establishes the benefit of provider firms adding value before customers realize their needs. The relationship is then able to prosper as the client is not having to

constantly call for specific issues when they come up, but rather are led in a positive direction. This is shown to foster a greater desire among these firms to grow, which in turn makes them more willing to continue on in the business relationship. Importantly, the results of the analysis did not demonstrate full mediation, and suggested that the positive value of these proactive meetings are significant in their own right. The new norms being established in these relationships for the vendor to utilize their resources and data on client product usage is confirmed to be valuable. These customer success teams are not easy to manage, but the value is clear.

The value of these proactive meetings stems from the value of communication with clients more broadly. The goal of these meetings is to progress beyond simple information exchange in which the provider simply increases customers' level of knowledge of the products/services (Gilliam and Flaherty 2015) to being specifically tailored toward customer needs and issues. With greater tailoring of the messages, meetings no longer take the shape of high-level status reports, but rather are opportunities for the vendor to educate the customer toward positive growth. Proactive maintenance is possible through increased communication and essentially helps solve issues before they arise. In a similar manner to the service recovery literature indicating the value of correcting a wrong *after* it has occurred (Bitner, Booms, and Tetreault 1990; Hollmann, Jarvis, and Bitner 2015), this article takes the natural next step in empirically demonstrating the value of correcting a wrong *before* it has occurred.

Overall, it is demonstrated that relationship managers that meet with their customers proactively can enjoy higher retention rates. Thus, relationship managers should ensure that they are meeting with their clients on a regular cadence that works for both sides, whether that be monthly, quarterly, or as frequently as the schedules allow. This allows more opportunities for

these proactive moments of truth to have their beneficial impacts, and more opportunities for the client firm to develop positive impressions of the provider.

Importance of dependence

For relationship managers to do their jobs well, it is beneficial if they can serve their customers so well, that the client feels that their business could not survive without the provider's offering. Managers must create as highly embedded customers as possible, as this weakens the negative effects of the reactive moments of truth. To do so, managers should push their clients to use as many services or features of a provider's offering as possible. Not only does this create higher perceived switching costs, but it also creates more touchpoints in the relationship, thus allowing for more proactive engagements.

Managers should still be mindful of only pushing products or services that they truly believe will derive value for their clients. If clients that do not truly find value in purchases, there will presumably be more reactive moments of truth, for the client to voice their displeasure and oftentimes cease the relationship. Therefore, the proactive moments of truth should be used to truly best understand the current state of the client's business, and their unique needs and desires. Only after these needs are considered, and the client usage data is viewed, should the relationship managers proceed with suggesting further features or services.

Measuring and fostering growth mindsets

Arguably the main contribution to relationship management practice, however is the importance of fostering a growth mindset among customers. The client firms that have more of a growth mindset, as opposed to a fixed mindset are shown to better understand the value of engagements with the provider to enhance their firm's success. Firms that engage in these

subscription-based services need to begin measuring and monitoring clients' growth mindsets and to train their relationship managers to determine their approach dependent upon these traits.

From a practical perspective, there are potentially a few ways that relationship managers can foster growth mindsets. Relationship managers should attempt to view their meetings with their clients as learning opportunities, and to use similar verbiage when interacting with their clients. Open mindedness from the provider firm can foster greater open mindedness among the customer firm, and allows for greater opportunities for the provider firm to truly understand their customers' needs (Buss 2022). Importantly, ways in which the relationship manager can create an environment conducive to learning is important as it sets the stage not only for learning to occur, but for these meetings to be viewed through a learning as opposed to outcome driven lens.

Limitations and Future Research Directions

Further research could investigate the content covered in meetings, as the data in this article allowed only for the observation of whether a moment of truth occurred either proactively or reactively. What are the actual words that should to be said, or which specific strategies need to be employed to foster a positive impression in the customer firms' minds? Greater investigation into the specific content covered would be a fruitful area for future research.

Additionally, the reactive moments of truth are found to have negative impacts on retention, yet the resolution from these meetings are not known. Specifically, the data does not demonstrate which of these meetings led to satisfactory solutions, and as such cannot be viewed as disproving the service recovery paradox. This is a key limitation of this study, and future researchers should investigate the specific content covered in these meetings and their outcomes.

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OVERALL CONCLUSION

This dissertation falls broadly under the realm of marketing strategy with a specific focus on relationship marketing, as it evaluates commonly used metrics and strategies among practitioners and academics in the prediction of two extremely important outcomes in revenue and retention.

The first article attempts to resolve contradictions in the marketing literature as to the usefulness of Net Promoter Scores. While some papers claim their unbelievable effectiveness (Reichheld 2003), others provide some doubts (Keiningham et al. 2007). Therefore, the first part of this article provides a meta-analysis of the current literature to arrive at a conclusion of where the current knowledge lies. Then, I rely on a secondary data analysis to better understand why I found the effects in the meta-analysis. Specifically, the article provides an examination of the transformation of the metric, and its crippling ability on the effectiveness of NPS to measure firm growth. Beyond providing evidence of the negative effects of the transformation, I also find that the metric's usefulness can be improved through the customer orientation of a firm. Given that NPS is tracked through the majority of Fortune 500 firms, and that these systems are costly to implement, this article is of great importance to marketing managers, while also clarifying contradictions in the literature.

Article 2 provides an extension of Article 1 to better understand another important context in which NPS is frequently investigated. Specifically, Article 2 relies on data across over 1,600 customer firms across 18 months from a B2B Software as a Service firm to better understand retention. This article combines this rich dataset with managerial actions to

investigate the impact of both proactive and reactive moments of truth on retention. This is the first investigation in the relationship marketing literature to look at the impact of post-sales managers have on evaluating the client-firm relationships, to better understand proactive measures firms can enact to improve retention.

Overall, through a multi-method design, the two articles focus on better understanding the value of marketing metrics on firm performance. This dissertation extends the streams of literature focused on Net Promoter Scores as well as retention, with relationship marketing literature as a theoretical underpinning explaining the results. This dissertation aims to provide value to both marketing managers and academics alike, by investigating metrics that are viewed on a daily basis in industry and their impact on focal variables of great interest in revenue and retention.

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