Mapping dimensions of customer experience using big data analytics to enhance customer relationship management strategies: a case study in the B2B context

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Stijn Oosterholt

Examiner(s): D.Sc., Olli Kuivalainen

D.Sc., Stéphanie van den Berg

D.Sc., Raymond Loohuis

ABSTRACT

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Keywords: CLV, Customer Loyalty, Customer Relationship Management, Referral Intention, NPS, Customer Emotion, Repurchase Behavior

This paper investigates the role of customer emotions in predicting referral intention and repurchase behavior. A combined qualitative and quantitative research approach was implemented to extract sentiment from written customer reviews that serve as input for the regression analysis.

The results show that a combination of qualitative and quantitative customer data might reveal underlying dimensions of customer satisfaction in contrast with the usage of uni-dimensional constructs like Net Promoter Score to measure customer satisfaction.

Furthermore, the outcomes show that combining customer relationship management strategies with the implementation of a customer-centric culture can be beneficial for strengthening customer relationships, increased firm performance and reduced churn rates.

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1. Introduction

Customer Relationship Management (CRM) remains an important factor in the digital and online marketing paradigms. Companies grow ever more customer centric to stay ahead of competition in a marketing field that is more and more digitalizing and growing more customer-oriented. There is a clear trend that is showing a need from companies to build and strengthen customer relationships and to keep track of their wants and needs in the market. To gain and maintain a sustained competitive advantage, adoption of proper CRM strategies is needed (Saha et al., 2021).

CRM has been approached by scholars from both a technological and a strategic perspective. Both CRM tools and strategies are aimed at customer acquisition and retention. Retained customers are referred to as loyal customers in the marketing literature. Loyal customers are *“customers who purchase from the same service provider whenever possible, and who continue to recommend or maintain a positive attitude towards the service provider”* (Kandampully & Suhartanto, 2000, p.346). Customer loyalty has been widely accepted as one of the most important indicators for sustained growth and profitability and with an online market that is growing ever-more customer-centric, an essential competitive asset for any business (Chen, 2012; Nyadzayo & Khajehzadeh, 2016; Rai & Srivastava, 2012; Gulati & Oldroyd, 2005), resulting in higher market shares and lower operational and marketing costs. Because of a higher likelihood for positive word of mouth from loyal customers to potential prospects, marketing costs are reduced (Ladhari et al., 2011).

The necessity to implement successful CRM strategies is even higher for B2B firms, compared to B2C firms, according to former research (Kumar et al., 2012; Saini et al., 2010). A relatively smaller market space compared to B2C markets leads to a greater interdependence between buyers and sellers and higher transaction values. Therefore, it is more important for B2B firms to build trusting customer relationships and deliver extraordinary customer experiences to gain sufficient market territory.

The availability of new marketing technologies allows companies to increase the connectivity with their customers exponentially. Developments in data technologies together with an increase in interconnected devices through the Internet of Things enables firms to *"create actionable insights for delivering sustained value, measuring performance and establishing competitive advantage"* (Bertello et al., 2021). Different to traditional CRM literature that is mainly focusing on the usability of quantitative and structured data metrics to capture the customer experience, such as the NPS score, recent research outcomes from the IT paradigm suggest marketers to implement new data techniques to gain better understanding of the overall customer experience (Lemon & Verhoef, 2016; Wetzels & Wetzels, 2023). The rise of big data analytics (BDA) enables companies to gain more customer insights from data that was difficult to measure before, for example data from texts, images, webpages, audio and video (Adronie et al., 2019). Literature on usability of big data analytics in CRM is scarce. Recent research has started to discover linkages between customer experience management and customer loyalty outcomes, and suggests that more research is needed on combining qualitative, unstructured data and quantitative, structured data to gain more insights in the total customer experience at multiple touchpoints throughout the customer journey (Wetzels & Wetzels, 2023; Lemon & Verhoef, 2016).

Although the attention on BDA seems to increase, research on the implementation of BDA in CRM is on the low side (Batistič & Van der Laken, 2019). Moreover, there is a call to action from customer experience researchers to dive deeper into data collection and analysis techniques to capture and analyze various components of customer experience (Lemon & Verhoef, 2016; Wetzels & Wetzels, 2023). There is more big data available on customer experience than there was before, so this might lead to new insights on customer behavior. The main research question of this paper is formulated as follows:

“How can BDA provide valuable insights for CRM enhancement in B2B firm-customer relationships?”

2. Theory

2.1 Resource-based view

The resource-based view (RBV) is a strategic framework that links sustainable competitive advantage to the internal resources of a firm and its capabilities to manage these resources. (Barney, 1991). Resources are all assets and capabilities or competences under control of the firm that contribute to product or service creation which in turn creates value for customers. Competitive advantage is gained by the firm best capable of bundling the resources and competences within the same sector as its nearest competitors. One of the outcomes of RBV is that same-sector firms show higher performance differences between them compared to differences between firms in different sectors (Rumelt, 1984).

2.1.1 Resources

Firms capable of exploiting market resources gain competitive advantage over competitors. An important resource in the modern age, where the Internet of Things is an incubator of market and customer knowledge, is to implement effective market orientation principles. This principle dates back to the ‘80s, and its main premise is for firms to be able to extract and integrate knowledge on customers and competitors, and subsequently transform and use this knowledge within the own firm (Drucker, 1985). Lin and Wu (2014) extend this theory and find that valuable market knowledge combined with customer knowledge management instigates product innovation. Barney (1991) distinguishes four resource characteristics, valuable, rare, inimitable and organization.

According to the VRIO framework, firms that are able to exploit and integrate resources consisting of a combination of these characteristics are more likely to create competitive advantage within their respective markets. Within the context of this thesis, data on customer experience with the firm’s products and/or services can be seen as an idiosyncratic and valuable asset to a firm. This can be data on purchase behavior, knowledge behavior, referral behavior or influential behavior (Lemon & Verhoef, 2016).

2.1.2 Dynamic capabilities

Although possession of resources that are valuable, rare, inimitable and non-substitutable are important, if a firm lacks the ability to successfully exploit and integrate these resources, a sustained competitive advantage cannot be reached. These dynamic capabilities turn resources into firm assets that result into the creation of valuable products and services for customers (Teece, 2007).

IT studies researching BDA have already linked BDA to the resource-based view and have concluded that BDA contributes to organizational performance and can be seen as both a valuable firm resource as a firm capability (Batistič & Van der Laken, 2019). It enables firms to be more future proof, and when incorporated successfully, decreases acquisition costs and increase revenue, because more data-driven decision-making leads to more effective and efficient business operations.

Zhang et al (2020) have also linked big data analytics intelligence to firm performance, though their research suggests the linkage to be indirect. The researchers state that the access to valuable insights and information extracted from big data resources, does not lead to an increase in firm performance directly. Through a various set of interviews the researchers discovered that implementing a higher degree of big data analytics intelligence within the firm leads directly to the development of new firm capabilities that in turn could lead to an increased firm performance. An important consequence of BDAI assimilation the researchers describe is the capability to mass-customize products and services for individual customers. For an organization to successfully incorporate mass-customization capabilities, it has to embody a data-driven culture.

2.2 Towards customer centricity: service-dominant logic

2.2.1 Value co-creation

Different from RBV, which take an internal, firm-based scope when it comes to management of resources, S-D logic argues that resources can only come into existence through interaction with network partners operating within the external environment of the firm (Vargo and Lusch, 2008). Value can only be created when there is an exchange of services, both parties involved become so-called resource integrators who provide value propositions to one another. The value that is co-create with both parties involved is the value-in-use. With this logic, it is detrimental for companies to develop the skills and knowledge to co-create value together with its customers. Moreover, the customer experience can be approached as a valuable resource to firms and the firm has to enable customers to express the experience they have with the firm's products and services. This provides valuable knowledge and insights that in turn, enable the company to adapt their products and services more efficiently and effectively to the customers' needs. B2B value co-creation activities have been found to have a positive impact on customer satisfaction in the South-East Asia manufacturing industry (Firend & Langroudi, 2016).

BDA serves as a facilitator in the value co-creation process (Xie et al., 2016). The customer as co-creator of value, can take on four different roles in providing big data for companies. First, a customer is a buyer, and provides transactional big data that companies can use to analyze purchasing behavior. Second, customers can be ideators, who generate communication big data. This data is more unstructured and results from direct communication between customers and firms. Examples of communication big data are digital records of phone calls to customer service, online customer reviews or new product trial reports (Xie et al., 2016). Third, customers can be designers who generate participative big data. This data is generated by customers who actively co-participate in developing new services and/or products together with the company. Finally, customers can be intermediaries who generate transboundary big data.

To summarize, the service-dominant logic moves away from the resource-based view by shifting the scope of value. Value is no longer created solely by the firm through resource allocation, rather it is created through interaction between firm and customer both providing resources that results in value-in-use. It is an iterative process that happens at every touchpoint within the customer journey, and it is necessary to develop opportunities for customers to contribute to the value co-creative process.

This current thesis takes a service-dominant scope and is taking a deep-dive in the operant resources a customer provides in the value co-creative process that organizations can harvest and turn into profitable value propositions.

2.3 Customer journey and customer experience

The lifetime relationship with a firm or customer relationship, consists of a series of interactions and experiences with a firm. These interactions might take place with a firm's website, offline sales business unit, customer care or by directly using the firm's products and/or services. These firm-customer points of interaction are so-called touchpoints, and the sum of all touchpoints is defined as the customer journey. Lemon and Verhoef (2016) divide the customer journey in three distinct phases, the pre-purchase phase, the purchase phase and the post-purchase phase. Each phase has its distinct touchpoints where interaction between firm and customer takes place. Each interaction triggers an internal subjective response for the customer, that could be either positive or negative. In literature this response is defined as the customer experience (Japutra et al., 2021). This thesis focuses on the third or post-purchase phase of the customer journey, since in this phase the actual consumption of goods and services takes place (Lemon & Verhoef, 2016).

2.3.1 Touchpoints

Throughout the customer journey, there are many moments of interaction between customer and firm. These touchpoints are separate interactions a customer faces during a series of experiences with the company's or brand's products and services. This series of interactive events forms the customer journey, from initialization until the post-purchase stage, can be either direct or indirect. Often touchpoints can be affected by different channels. Together these touchpoints make up one holistic customer experience that scholars have studied from the customers' perspective (Lemon & Verhoef, 2016).

Interactions with customers can take place in either of three separate customer journey stages, the pre-purchase stage, purchase stage and post-purchase stage, and may be categorized into four types, depending on the touchpoint ownership.

Lemon and Verhoef (2016) distinguish brand-owned touchpoints, partner-owned touchpoints, customer-owned touchpoints and social/external touchpoints.

Brand-owned touchpoints are within control and designed by the firm itself. The touchpoints include marketing advertisements, the firm’s website and a combination of marketing mix features such as packaging, pricing, customer service, and sales and loyalty programs. Partner-owned touchpoints are designed and controlled by the firms in cooperation with its’ partners. Partners can operate as marketing agencies, distributors or as communication channel partners. An example of a partner-owned touchpoint could be the Google Play Store, which functions as a communication channel partner for a firm that develops a smartphone application for its customers to use.

Customer-owned touchpoints are customer actions that neither the firm nor the partners can control. An example of customer-owned touchpoints is the product or service consideration during the pre-purchase stage. In the post-purchase stage the actual consumption and usage of the product or service is also considered a customer-owned touchpoint. Customer-owned touchpoints can contain valuable insights for a firm that can serve as input for value co-creation. Examples of customer-owned touchpoints that serve as input for co-creation with the firm are usage and assembly videos shared by the customers in different channels. Firms can utilize these videos to either create more attention for a specific product or service, or can look at these videos as customer feedback. Customer feedback, direct or indirect, might also provide an important resource for value co-creation. Firms might detect unmet needs or product improvements. Last but not least, independent touchpoints are controlled by other customers, influencers, or information sources apart from the organisation that influence decision-making during the whole customer journey. Examples of independent or external touchpoints are third-party review sites that might influence customer journeys, or the opinion of other customers or peers.

In the past, the only source of information for customers was brand-owned, completely designed and controlled by the firm. Because the world has become more digitalized, customers can be listened to in real time during the whole customer journey. By collecting real time consumer data, this provides valuable insights that can assist in allocating resources between different touchpoints efficiently. Firms should evaluate and renew customer experience constantly by mapping, designing, monitoring, prioritising and adapting touchpoints within the customer journey. Customer preferences tend to change over time due to internal or external stimuli. Thus, customer journeys have to be re-evaluated constantly to meet customer needs and to build trusting customer relationships. Furthermore, touchpoints should be relevant, consistent and connected with each other. By optimising the customer journey, gaps can be uncovered, as well as unmet customer needs detected. Furthermore, futile, ineffective touchpoints can be discovered by categorising them as satisfying, dissatisfying or neutral.

In order to be able to categorise touchpoints, it is required to map all touchpoints throughout the customer journey and analyse them through the customer's point of view. By using either survey or interviews, the customer experience along all touchpoints can be mapped out. Most customer-owned touchpoints can be found within the post-purchase phase of the customer journey. These touchpoints are outside of the firm's or its partners' control or influence (Lemon & Verhoef, 2016). Within the context of the current thesis, the role of customer feedback as an important customer-owned touchpoint that can serve as value proposition within the SD-logic, is explored (Vargo & Lusch, 2008).

2.3.2 Smooth journey model

According to Court et al. (2009), the customer journey is an iterative process that consists of four distinct phases (*Figure 1*): 1) the initial consideration, which consists of the perceptions a customer already has towards an initial set of brands and recent touch points with those brands, 2) active evaluation which consists of information gathering and comparing possible outcomes of purchase, 3) the actual purchase and 4) the post-purchase experience.

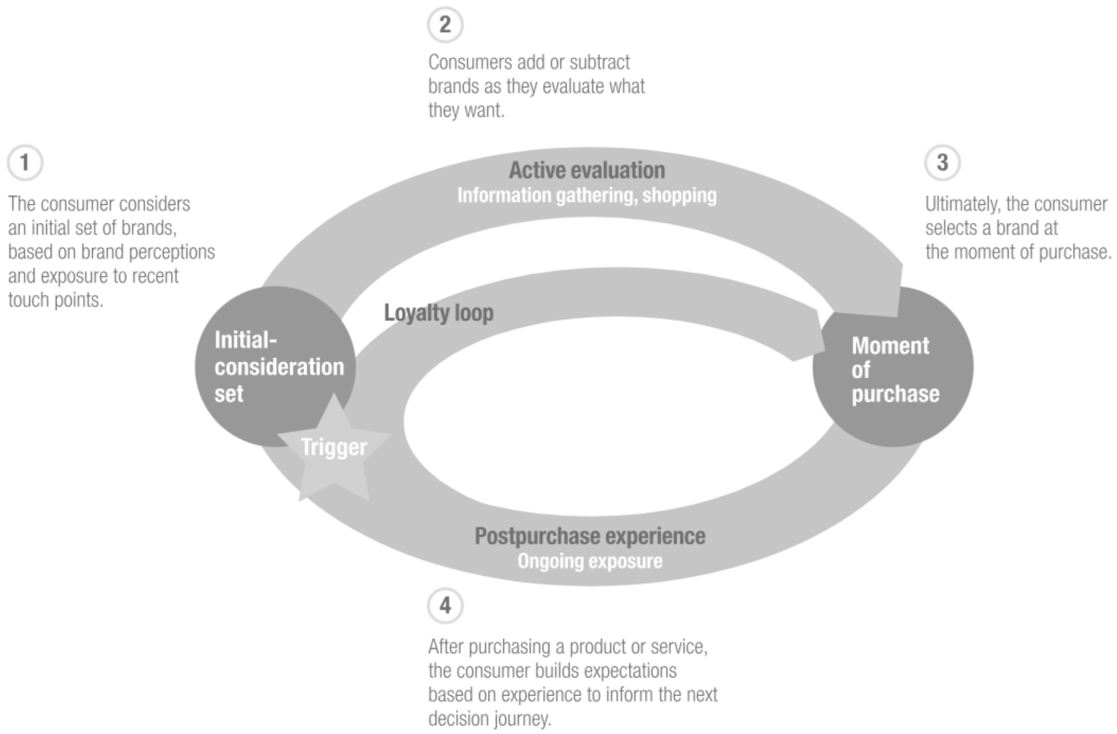

Figure 1 Loyalty Loop (Court et al., 2009)

These results imply that a customer becomes a loyal customer when the post-purchase experience exceeds his pre-purchase expectations.

Recent studies suggest a change in scope away from *"short-term customer experience of a single service cycle towards long-term journey patterns across multiple service cycles"* (Siebert et al., 2020, p. 46). Being able to build predictable customer experiences across all service cycles leads to smooth customer experience journeys. To be able to streamline customer journeys, firms have to provide decision support to customers along all four distinct phases of the customer journey (Siebert et al., 2020). In the consideration phase, firms have to provide sufficient brand advertising and content marketing to create awareness, in the active evaluation phase, firms have to provide interactive website tools for customers to be able to get familiar with all the service offerings and be able to communicate with the brand to gather enough information. At the moment of purchase, firms should offer sufficient in-store advertising and special offers to push the customer to the actual first purchase and during the consumption phase, firms have to provide sufficient informative packaging and service updates to increase the customer experience.

Although the body of literature on customer experience is quite expansive, little research has focused on B2B relationships. Most customer experience research has focused on B2C relationships and has a scope in the instrumental services industry, such as banking, pharmacies and transport. The current study focuses on the post-purchase phase of B2B customers in the wholesale industry in the Netherlands.

H1: *BDA facilitates decision support capabilities to enhance the customer experience at the post-purchase stage.*

2.4 Customer satisfaction

Customer satisfaction has been identified as a state of ‘pleasurable fulfilment’ (Oliver et al., 1997). As one of the founders of the expectancy-disconfirmation theory, Oliver et al. (1997) state that satisfaction is the outcome of a customer experience that exceeds the expectations prior to the experience. The same is applicable to customer dissatisfaction, which occurs when the customer experience is inferior to the expectations. Customer satisfaction is a cognitive or emotional response with a specific focus. It is aimed towards either the product, customer expectations or consumption and it arises at a specific time, post-purchase at the consumption phase of the customer journey. It is also the accumulation of previous purchase cycles (Giese & Cote, 2000). A significant body of literature comprises the antecedents and outcomes of customer satisfaction. Customer satisfaction leads to favorable firm outcomes, such as positive word-of-mouth and repurchase behavior (Swan & Oliver, 1989; Han & Hyun, 2018), whereas customer dissatisfaction instigates negative word-of-mouth behavior, switching behavior and negative attitude towards a service provider which can harm brand reputation (Bachleda & Berrada-Fathi, 2016).

Reichheld (2003) introduced the NPS or Net Promoter Score to measure customer satisfaction rates. This scale-based metric is used to divide customers into three distinct segments: 1) promoters, who’s experience with the service provider exceeds their expectations, resulting in positive word-of-mouth behavior and a higher likelihood to repurchase, 2) passives, who’s experience with a brand or service provider matches their expectations and 3) detractors, who’s experience with the service vender does not meet their expectations. The last group of customers has a higher likelihood to display negative word-of-mouth behavior, which may harm brand reputation.

It is detrimental for companies to measure customer satisfaction at all touchpoints within the customer journey. At all touchpoints, customers can experience feelings of pleasure or displeasure which can lead to a certain behavioral outcome. To develop the necessary skills and knowledge to measure customer satisfaction at every step in the customer journey can present firms with opportunities for service and product improvement. As a result, firms can pick up early signs of customer dissatisfaction and act accordingly to counter the negative behavioral outcomes of customer dissatisfaction and increase customer satisfaction levels. In the current study, a BDA approach is taken to explore the aspects of customer satisfaction and dissatisfaction within the wholesale industry.

2.5 Customer emotion

Customer owned resources in value co-creative process can be both operand or operant in nature. Operand resources are tangible in nature, like economic resources such as money and time. These resources are objectively measurable. Operant resources, such as tacit knowledge and experience, are important resources that can provide firms with insights into customers' needs and wants.

Customer emotions research has roots within the psychology literature (Izard & Izard, 1977; Plutchik, 1980), where emotional state of individuals was already researched based on emotional affect (positive or negative) and valence (the strength of the emotional response). Other research focused on distinct emotions such as joy, anger and sadness and its antecedents and outcomes (Laros & Steenkamp, 2005). Holbrook and Hirschman (1982) underline the importance of evoked emotions during the experience with a brand or product. Customer emotions have been identified as an important predictor of outcome-based metrics such as retention, customer satisfaction and loyalty behaviors (Laros & Steenkamp, 2005).

Most recent BDA studies on customer experience have focused on capturing customer sentiment in unstructured, textual data to identify important dimensions of product quality within the tourism and hospitality industry (Ordenes et al., 2014; Pang et al., 2008). The current research aims at identifying important dimensions of customer experience within the wholesale industry from a B2B perspective. Because customer satisfaction has been linked to loyalty behaviors such as positive word-of-mouth and repurchase behavior and since connections have been found between customer emotions and customer satisfaction, the following two hypotheses are formulated:

H2: *There is a relation between customer emotion and referral intention.*

H3: *There is a relation between customer emotions and repurchase behavior.*

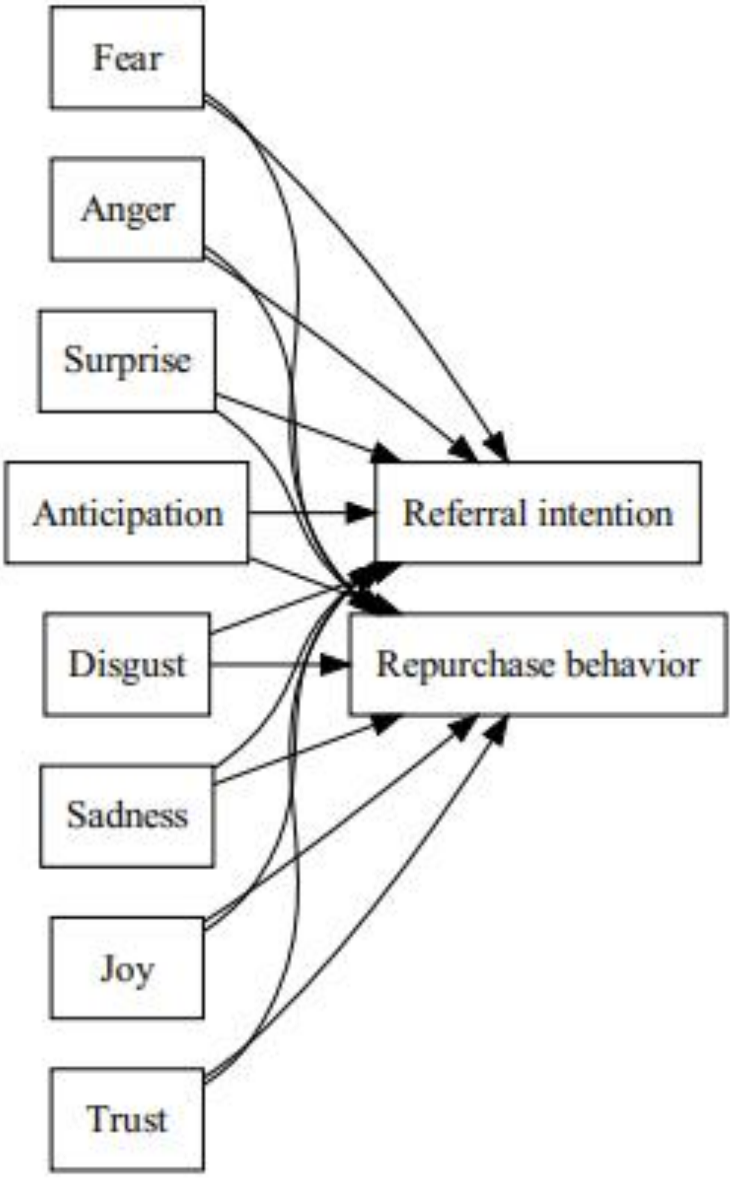

Figure 2 Conceptual Framework

3. Method

3.1 Research design and data collection

The current study comprised a survey research combined with secondary data to be able to 1) categorize customers into different segments based on their respective purchase behavioral patterns and to 2) measure the relations between evoked customer emotions during the post-purchase customer experience and the post-purchase outcome variables recommendation intention and repurchase behavior. The proposed research method followed a three-step approach. First, survey data and secondary data were independently obtained, cleaned and transformed. Second, transactional data and customer experience data were merged, cleaned and transformed, resulting in a final data set containing all variables. Last, the formulated hypotheses were tested following a regression analysis. The data preparation, data cleaning, data transformation and data analysis were performed using a variety of R packages. Survey data was collected using a case sample approach, utilizing a customer database of a Dutch operating firm within the school supplies wholesaling industry. The case firm is a medium-sized supplier with 200 employees and is offering a variety of school supplies to primary schools and day-care facilities in the Netherlands. Among other supplies, the firm offers:

- Furniture and equipment for primary education institutions and daycare facilities.
- Professional courses for teachers in primary education.
- Hardware and software solutions for e-learning purposes in classrooms.
- Learning methods for children in various age groups.
- Remote and on-location IT support.

The case firm is suitable for the current study, while it is maintaining a large electronic customer database containing transactional data and marketing performance data. Furthermore, the firm can provide a unique customer ID that is simultaneously being send out together with the survey to serve as unique customer key variable to connect different data sources.

Questionnaires were sent out to approximately 30.000 individual customers through a link in two company newsletters in early June 2022. The total amount of respondents after two weeks of data collection amounted to 317. The survey consisted of three questions, of which two close-ended and one open-ended question. Of the 317 respondents that reacted to the survey, 119 respondents completed the survey in its entirety.

Subsequently, transactional data was collected through the firm's sales database, which comprised order history data of 16.699 individual customers. This resulted in a dataset containing 320.482 individual orders placed in the time period 2017-2021. The dataset comprised three variables important for RFM modelling, namely customer ID, order date and order amount in Euros. The survey dataset and secondary dataset were then merged via joint customer ID number. The final dataset comprised 119 observations of 20 variables. Customer ID numbers were then converted into random numbers to ensure data anonymization. Lastly, linear regression analysis was implemented to measure the relations between the constructs.

3.2 Measurements

To measure repurchase behavior, a customer segmentation method known as RFM was used to measure individual scores for each customer for respectively recency of purchase (R), frequency of purchase (F) and monetary value (M) (Dogan et al., 2018; Maryani & Riana, 2017). Recency of purchase stands for the number of days since a customer made their last purchase at the case firm, counted from the day the survey data collected was terminated (June 17th, 2022). Frequency of purchase is the total number of purchases made by an individual customer and the monetary value is the total expenses of each customer at the company (in euros). Each customer received a score between 1 and 5 for all three aforementioned metrics. The lowest 20% received a score of 1 and the highest 20% a score of 5. Total RFM scores were calculated by taking average values of recency, frequency and monetary value, resulting in an RFM score with a scale between 1 and 5.

Customer segmentation is used to divide customers into homogeneous groups. Each segment comprises of a combination of transactional metrics, the recency, frequency and monetary value of customer purchases. This data-driven segmentation technique allows marketers to apply different targeting strategies across all calculated segments. It allows for more personalized and differentiated strategies. Targeting based on user behavior allows for more user engagement with the brand content and higher retention rates (Makhija, 2018).

The resulting segments depict the actions marketers have to take to keep customers invested in the brand, and provides guidelines for communication strategies to raise value for every segment. Now the most important customer segments are described in means of spending behavior, the frequency, recency and monetary value of purchases.

The first customer segment is the **champions** segment: This group consists of a company's top-tier customers. On average, this group spends the highest amount in terms of monetary value, it is also the group with most frequent buyers and the most recent buyers.

In the second segment we find the **loyal customers**. Loyal customers do not spend as frequent as the most loyal customers, the champions. However, the customers within this customer segments generate a high amount of revenue compared to the lower-tier customer segments. Therefore, it is suggested to reactivate customers within this segment on a regular basis with retargeting campaigns.

In the third segment we find the **potential loyalists**. The potential loyalists where an average frequency pattern can be discovered. Next to that, they are not the top spenders like the champions segment, still they spend above average in comparison to lower-tier customer segments.

In the fourth customer group we find the **new customers**. New customers are the most recent customers, customers who bought the fewest amount of days ago compared to present day. These customers are not yet as engaged to the firm as higher-tier customer segments. It is important to start engaging with this group as early as possible to build opportunities for cross- and upselling. If successful, customers from this group could potentially move to higher-tier customer segments and become more loyal customers.

The fifth customer group consists of customers that have purchased quite recently, but not much in terms of revenue. This group of **promising customers** might be susceptible to cross- and upsell strategies to keep their attention and to trigger repurchase opportunities.

The sixth customer segment resemble a higher-tier customer segments containing customer that **need attention**. This group has above average recency, frequency and monetary value metrics. Customers within this group spend higher amounts of money on a regular basis, and need to be reactivated on a regular basis as well. By reactivating with regular newsletters for example, these customers are triggered to repurchase. Because these customers buy on a regular basis, they can also be approached to opt-in for a loyalty program.

The seventh customer segment contains customers that have below average values when it comes to recency, frequency and monetary value metrics. Because these customers haven’t bought for a while and may be **about to sleep**, these customers might need an extra nudge to repurchase, for example a discount coupon that serves as trigger to repurchase.

The same can be applied for the eighth customer segment, or the customers that are **at risk**. The only difference with the previous group is the average spent that is slightly higher. Because this group contains more big spenders, the firm’s marketing focus might be slightly more aimed at this group to keep them coming back, since keeping these customers are more cost-efficient than acquiring new customers with the same level of spending.

The ninth customer segment is very similar to the former customer group, but customers within this group have purchased a longer time ago, and have a higher average spent that the eighth customer segment. This group is labeled as customers that **can’t be lost**. Because customers within this group have purchased a long time ago, it might be hard to reactivate them. An extra incentive such as a higher discount or free shipping might persuade these customers to come back.

The last two segments, the **hibernating** and **lost** customer segments, might contribute to a higher profit by allocating less marketing spent to these groups. These customer segments have the lowest average values when it comes to recency, frequency and monetary value levels. That is why it can be more cost-efficient to spend less on trying to retarget customers within these segments, because these customers are not very valuable to your business in the first place and trying to retarget these customer might have no effect at all.

Table 1 RFM Segments (Makhija, 2018)

Segment	Description	Recency Score	Frequency Score	Monetary Score
Champions	Bought recently, buy often and spend the most.	4 - 5	4 - 5	4 - 5
Loyal Customers	Spend good money. Responsive to promotions.	2 - 4	3 - 4	4 - 5
Potential Loyalists	Recent customers, spent good amount, bought more than once	3 - 5	1 - 3	1 - 3
New Customers	Bought more recently but not often	4 - 5	< 2	< 2
Promising	Recent shoppers but haven't spent much	3 - 4	< 2	< 2
Need Attention	Above average recency, frequency & monetary values	3 - 4	3 - 4	3 - 4
About to Sleep	Below average recency, frequency & monetary values	2 - 3	< 3	< 3
At Risk	Spent big money, purchased often but long time ago	< 3	2 - 5	2 - 5
Can't Lose Them	Made big purchases and often but long time ago	< 2	4 - 5	4 - 5
Hibernating	Low spenders, low frequency and purchased long time ago	2 - 3	2 - 3	2 - 3
Lost	Lowest recency, frequency & monetary values	< 2	< 2	< 2

Table 2 Calculated RFM Segments

segment	Mean_Freq	SD_Freq	Mean_Rec	SD_Rec	Mean_Mon	SD_Mon	Number
About To Sleep	1.136204	0.3431557	907.34183	169.49169	218.7129	223.5942	1138
At Risk	5.038371	13.8075419	1388.73140	244.19858	6194.9004	27786.0923	1277
Champions	68.864706	74.6514295	85.46551	45.80974	63842.6039	80094.0745	3740
Lost	1.082340	0.2749568	1552.01788	201.14660	226.0401	215.4856	1846
Loyal Customers	10.397664	15.3361730	409.98734	311.14265	11553.6717	24424.1972	4109
Need Attention	2.792208	1.0806214	874.49784	171.14538	819.8094	630.4747	693
Others	2.371580	2.7023359	808.70786	564.67462	6562.2838	13619.0093	1133
Potential Loyalist	2.119797	1.3754529	260.97394	161.26044	549.4563	622.9751	2763

The dataset holds sales records of the entire customer database of the case company in the time period 2017-2021. After cleaning the dataset, the following customer segments can be distinguished (Gül & Şen, 2022).

The biggest customer segment within the customer database of the case company is the **loyal customer** segment. The spending behavior is above average, and the customers within this segment also purchase regularly. However, they are not the top buyers in terms of purchasing power. Compared to this customer segment group, the **champions** customer segment has the highest purchasing power with an average order value of € 63.842,60. Next to that, customers who are in this segment have the highest average frequency and lowest recency rate, meaning that on average they come back the most often to do new purchases and have also purchased a product at the firm the shortest while ago in terms of days from the present day. The champions and loyal customers together are 47% of the total customer database. This particularly high percentage can be explained through the lens of B2B relationships, where the strength of firm relationships developed over time and buyers often return to the same supplier.

On the other side of the spectrum we find the **lost** customer segment. This is the customer segment that represents customers of which the last time they bought a product from the case company was the longest time ago, compared with the other customer segments, with an average of 1552 days or 4,25 years ago. Customers within this segment also score lowest on average order value and average purchase frequency.

Just above the lost segment there are those customers who have been spending a decent amount and have come back multiple times to repurchase, however customers that fall within the **at-risk** segment have made their last purchase a long time ago.

To measure referral intention, a unidimensional concept measuring the intention to recommend a product and/or service to other people was derived from Anderson (1998) and Reichheld (2003). The scale for this question is between 0 (“would not recommend at all”) to 10 (“would definitely recommend”). This resulted in a so-called Net Promoter Score or NPS.

To measure customer emotion, an open-ended survey question was used to make the respondents clarify their answer to the referral intention survey question. This way the retrieved answer was a personal customer review of the firm's products and/or services. An end-to-end text mining process was used to create a text corpus for sentiment analysis using RStudio (Gallagher et al., 2019). Textual data was tokenized, or in other words, spaces between words were recognized as boundaries to create a bag-of-words. Subsequently stop words were removed, which resulted in a bag-of-words usable for sentiment analysis.

To analyze sentiment within the created text corpus, the NRC Word-Emotion Association Lexicon (aka EmoLex) was used (Mohammad & Turney, 2013). The NRC EmoLex is a dataset containing 14.182 words in the English language and their respective sentiment score (positive/negative). It also contains 8 discrete emotions that are associated with words within the dataset, namely joy, sadness, trust, anticipation, anger, fear, disgust and surprise. If a word is associated with any of the discrete emotions an association score of 1 is appointed. By joining the EmoLex with the text corpus created from our raw textual data, it is possible to analyze word-emotion associations within the customer reviews.

Figure 3 in *Appendix A* shows the word-emotion association frequencies, that is, how words used in the customer reviews are appointed to their associated discrete emotions, according to the EmoLex. As an example, 'good', 'pleasant' and 'friendly' are the most frequently occurring words within the customer reviews associated with the emotion joy. The implicit emotion score within the dataset is the number of occurrences of words associated with a specific discrete emotion in a customer review, for example the number of words associated with joy per customer review, ranging from 0 (no occurrences) to 7 (maximum number of occurrences within a review).

To validate the sentiment analysis from qualitative customer feedback data, an additional survey question was used to measure the extent to which respondents had experienced certain emotions during their time as customer of the case firm. The emotions that were explicitly questioned in the survey were taken from Mohammad and Turney (2013) and Plutchik (1980). 8-point scales were adopted from Laros and Steenkamp (2005), with 0 being “not experienced at all” and 7 being “experienced to a great extent”.

To unravel the aspects of customer satisfaction and dissatisfaction hidden within the textual data, word correlations were calculated and visualized using word correlation networks. These networks are composed of three elements: nodes, edges and text. Using this method allows companies to find communalities between customers. In Appendix C the n-gram networks of word correlations are displayed for promoters and detractors.

Table 3 shows the final dataset containing respectively the number of observations and the mean, standard deviation, minimum and maximum values of the research variables. Observed variables are RFM Score, NPS Score, discrete *explicit* emotions measured from the quantitative survey question, and word-emotion association scores extracted from the customer reviews, hereinafter referred to as *implicit emotions.*

Table 3 Descriptive statistics

Statistic	N	Mean	St. Dev.	Min	Max
RFM_Score	119	4.39	0.95	1.33	5.00
NPS_Score	119	7.81	1.34	3	10
JoyExpl	119	4.41	1.98	0	7
SadnessExpl	119	1.00	1.63	0	7
TrustExpl	119	5.32	1.77	0	7
DisgustExpl	119	0.50	1.21	0	6
FearExpl	119	0.29	0.94	0	6
AngerExpl	119	0.50	1.36	0	7
AnticipExpl	119	3.85	2.59	0	7
SurprExpl	119	2.35	2.47	0	7
AngerImpl	119	0.06	0.24	0	1
AnticipImpl	119	0.82	0.98	0	4
DisgustImpl	119	0.04	0.20	0	1
FearImpl	119	0.15	0.40	0	2
JoyImpl	119	0.61	0.68	0	3
SadnessImpl	119	0.18	0.44	0	2
SurprImpl	119	0.46	0.59	0	2
TrustImpl	119	1.06	1.00	0	6
NegativeImpl	119	0.32	0.70	0	4
PositiveImpl	119	1.22	1.03	0	4

4. Results

4.1 Hypotheses

Table 3 (*Appendix B*) shows the Pearson correlations between NPS Score, RFM Score and explicit emotions. Positive correlations were found between NPS Score and explicit emotions with positive emotional affect joy (r (109) = .32, p < .05) and trust (r (109) = .38, p < .01). Negative correlations were found between NPS Score and explicit emotions with negative emotional affect sadness (r (109) = -.39, p < .01), disgust (r (109) = -.48, p < .01), fear (r (109) = -.24, p < .01) and anger (r (109) = -.27, p < .01). Furthermore, there was a negative correlation found between RFM Score and explicit emotion surprise (r (109) = -.23, p < .05).

Subsequently, correlations between explicit emotions asked in the survey and implicit emotions extracted from the customer reviews were calculated to see if the words used by the survey respondents reflect the same sentiment as the emotions that respondents explicitly experienced. In *Figure 2* below the correlations are displayed between the word-emotion association scores (implicit emotions) and their explicit counterparts. Most emotions measured from the textual data correlate weak to moderately with their explicit counterpart. For example, FearExpl (explicit emotion fear) correlates with FearImpl (r = .20), which means that there is a weak to moderate correlation between respondents explicitly stating they have experienced fear and the words they are using within the written customer review that are associated with fear according to the NRC EmoLex.

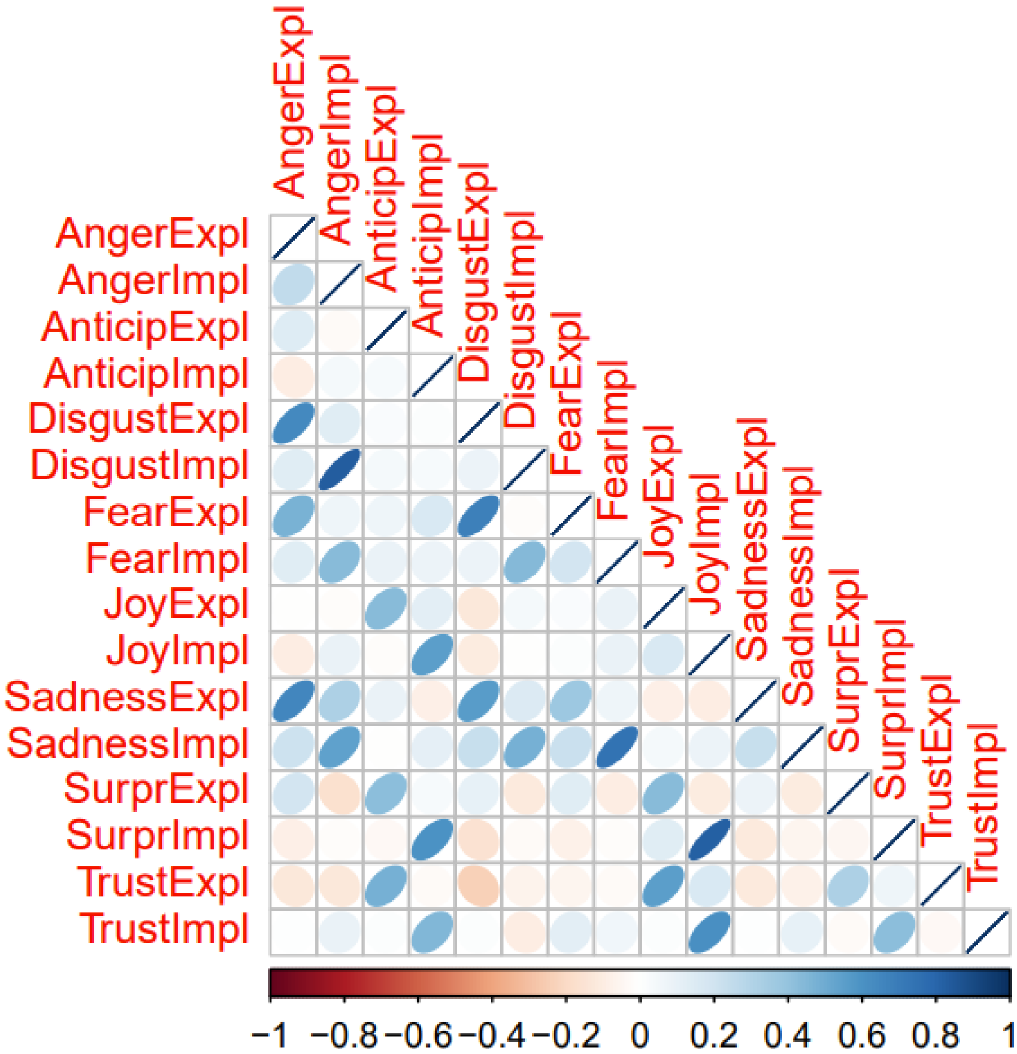

Figure 3 Correlations explicit and implicit emotions

Table 4 Regression analysis results

	Dependent variable:	
	NPS_Score	RFM_Score
	(1)	(2)
JoyImpl	0.953** (0.377)	−0.028 (0.281)
SadnessImpl	−0.272 (0.441)	−0.226 (0.329)
TrustImpl	−0.139 (0.166)	0.012 (0.124)
DisgustImpl	0.588 (1.181)	−0.765 (0.879)
FearImpl	−0.026 (0.449)	0.611* (0.335)
AngerImpl	−1.601 (1.027)	0.410 (0.765)
AnticipImpl	−0.198 (0.162)	0.005 (0.120)
SurprImpl	−0.339 (0.405)	−0.134 (0.302)
Constant	7.810*** (0.187)	4.407*** (0.139)
Observations	119	119
R^2	0.136	0.045
Adjusted R^2	0.073	−0.025
Residual Std. Error (df = 110)	1.292	0.963
F Statistic (df = 8; 110)	2.159**	0.647
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 2 shows the regression results. Hypothesis 2 stated a direct effect between customer emotions and referral intention. A significant positive effect was found in the relation between joy and NPS (B = .953, $p < .05$). No significant relations were found between the other implicit emotions and referral intention. Hypothesis 3 stated a direct effect between customer emotions and repurchase behaviour. No significant relations were found between any of the implicit emotions and RFM.

The main hypothesis of this paper states that BDA acts as a facilitator for decision support capabilities to enhance customer experience.at the post-purchase stage of the customer journey. The results of the thesis show that BDA aid in marketing support in two ways. First, BDA supports customer segmentation, identifying the most profitable customer groups within a company's customer base. It allows for companies to focus more on making their most loyal customers more profitable, saving marketing spent by focusing less on less profitable customer segments. Second, BDA allows for finding hidden patterns in data which was previously immeasurable, like image, video and textual data. The results of this paper show that a combination of text mining and sentiment analysis contributes to distinguish customer groups based on their sentiment towards the company. This enables companies to detect customer dissatisfaction at an early stage and act accordingly to counter the negative effects of customer dissatisfaction, like negative reviews and damage to corporate image. Next to countering the negative effects of customer dissatisfaction, this also enables companies to adapt their service offerings more to the customers' wants and need to enhance customer loyalty behaviors. Last, BDA allows for finding underlying dimensions of customer satisfaction. Looking at the word correlation networks (*Appendix C*), we can distinguish several underlying dimensions for both detractors and promoters. For promoters, responsiveness, product quality, delivery time and communication seem to be the most important dimensions of customer satisfaction. For detractors, price and delivery time seem to be the most important dimensions of customer dissatisfaction.

4.2 Towards customer centricity

The results of this thesis show the importance of companies to adapt a customer-focused culture that aims at customer centricity. This is in line with research done by Gulati and Oldroyd (2005), who proposed a four-stage path to adopt a customer-focused culture. In this section a brief description is given on how the adoption of a customer-focused culture interlocks with the current literature on service-dominant logic, customer journey and customer relationship management. Moreover, implications for BDA as a facilitator for the customer-focused culture are described.

The fist stage is described as communal collaboration, which involves identifying customer's past behavior and creating a centralized database to store customer data. BDA can help to extract, clean and store data from various sources to disseminate this data to other business units. This dissemination process happens in the second adaption stage, which is described as serial coordination. At this stage, a central analytics team is responsible for data analysis and furthering the results and to the right business units where the insights are used to act upon. For

CRM, this stage entails the customer segmentation process, where transactional data and other customer data is analyzed to classify customers into target groups according to their buying behavior. Marketers can then decide on the right marketing incentive to approach different customer groups. For example, sending less marketing communication to loyal customers who have already been buying at a particular brand for a long time, and do not need extra incentives to repurchase. For the SD-logic this means that value is created through a combination of both customer-owned touchpoints and firm-owned touchpoints. The customer provides the transactional and attitudinal data that can be used to create new value propositions for these customers.

The firm-owned touchpoints in this sense are the capabilities to extract, clean, store, analyze and disseminate the data to create new insights and improve products and services to increase customer profitability. In the third stage, which is described as the stage of symbiotic coordination, new hypotheses are developed together with the business experts of each business unit to not only retain the current customer base, but to also expand it. In this stage the collected data on customer past behavior is used as input to predict customer future behavior. These models are then used as input for new campaigns or other alterations within the customer journey in attempts to alter customer behavior. Results of these experiments are used as input to adjust the predictive models and to formulate new hypotheses.

All these experiments together contribute to the optimization of trigger events that lead to new loyalty loops, which is in line with the smooth customer journey model proposed by Court et al (2009). In the last stage (integral coordination), all the new developed knowledge on the firm’s customer base is translated into the day-to-day activities of the firm, to literally function as the eyes and ears for their customers. At this stage BDA does not only serve as a facilitator for decision support, it can actually contribute to automated decision-making. For instance, when a customer sends a negative review, BDA will automatically detect an anomaly in the textual data sent by the customer, will link this data through a data warehouse to the customer’s transactional history with the firm and will alert the right business unit about the dissatisfaction a loyal customer has with the company. This alert will be sent directly to customer support, who can act accordingly in real-time by offering the customer the right incentive to counter the experience that led to dissatisfaction.

5. Practical implications

The current thesis shows the potential for B2B firms to develop the dynamic capabilities to sense and seize opportunities to measure customer experience throughout the customer journey. Using the power of big data, firms can facilitate customer experience enhancement by enabling customers to express how they feel and think about the service provider at the post-purchase phase.

To gain competitive advantage over competitors, the extraction of customer-owned big data is not sufficient in itself. The right dynamic capabilities need to be adopted by firms to streamline data extraction, storage, transformation and dissemination processes towards the corresponding department. This is detrimental in turning data insights into value propositions to create value-in-use for customers. In other words, customer feedback data should not only be extracted and analyzed properly, it should also be stored and transferred to customer service to act accordingly towards satisfied and dissatisfied customers. In combining transactions and communication big data, marketers can quickly distinguish satisfaction rates of high and low value key accounts within their customer database and set appropriate measure in place to act accordingly when high value key accounts experience either satisfaction or dissatisfaction.

For marketers, the current findings might also lead to the develop of new customer experience measurement metrics. Looking at the word correlations in *Appendix C*, it becomes quite clear that the detractors are most dissatisfied with long delivery times and promoters on the other hand value fast delivery times. For firms in the wholesale industry this could mean that delivery time is important to their customers, and so it is only logical to develop metrics like the average delivery time that should also be measured along with other customer satisfaction metrics to enhance customer experience.

Next to the development of new customer experience measurement metrics, the findings of this research also show that RFM modeling is still an effective and easy-to-implement tool to quickly gain insight into customer buying behavior and to apply customer segmentation techniques to create homogeneous customer groups for differentiated marketing strategies. Churn rates might be countered by identifying customers in lower ranked customer segments and using personalized offers to reactivate customers that have not been in touch with your brand for a while. On the other hand, marketing spent could be saved by sending less marketing communication and personalized offers to customers that fall within the champions segments.

The probability of these customers returning to your firm to repurchase is higher than other segments, so these customers do not need that extra nudge to reactivate them. These customers need a different targeting approach than customers that are lost or at risk. For example, champions might be early adopters of new products, so providing early access to these products might be a fitting marketing strategy. Next to this, benefits could be offered to champions like a loyalty bonus or free shipping on all orders, since these customers are your biggest spenders and are most likely to repurchase. On the other hand you marketers can try to reactivate hibernating or at risk customers by offering personalized offers or a one-time discount on a next purchase to stimulate repurchase behavior.

Customer relationship management is about understanding your customers. Implementing BDA strategies across the entire customer journey creates customization and personalization opportunities to adapt service offerings to the changing wants and needs of customers through every service cycle. The results of this research show that it is important to analyze the post-purchase phase of the customer journey to foster CRM strategies that maximize loyalty behavior and counter churn.

6. Theoretical implications

This paper adds to literature in multiple ways. First, it adds to customer experience literature by applying a BDA approach to gain more knowledge on the underlying dimensions of customer experience within the wholesale industry in the Netherlands. Customer experience triggers an emotional and behavioral response, and utilizing BDA strategies enables the extraction and analysis of these responses and transforming them into valuable firm assets. This is also in line with the expectancy-disconfirmation theory (Oliver, 1997), which means that BDA techniques can be used to measure if products and services exceed customer expectations or are not meeting customer expectations.

Secondly, this paper adds to SD-logic literature. The firm and the customer are important resource integrators who bring operant and operand resources to the value co-creative process. BDA acts as a facilitator in the value co-creative process because it enables transforming customer experience as a crucial operant resource into valuable knowledge and insights for the firm to, in turn, develop new value propositions.

Thirdly, this paper adds to the CRM literature. In B2B markets it is even more important than in B2C markets to build and strengthen firm-customer relationships. By implementing BDA strategies guides in strengthening customer relationships in multiple ways. First, it helps in identifying behavioral patterns that enable segmentation purposes. By applying segmentation into multiple customer groups, high value key accounts can be identified that are most important in terms of revenue. This allows for more efficient marketing resource allocation, because firms can focus on delivering upsell and cross-sell opportunities to key accounts that are more likely to return. Second, BDA can help identify underlying dimensions of customer satisfaction and dissatisfaction. This enables companies to pick up on early signs of customer dissatisfaction and allows marketers to act accordingly to counter the negative behavioral outcomes of customer dissatisfaction and increase customer satisfaction across all touchpoints of the customer journey.

7. Limitations and future research

This research has some limitations. First, to measure the effect of implicit emotions on referral intention and repurchase behaviour required a lot of textual data. The relatively limited sample size of 119 lowers the explanatory power of the regression model. The initial sample group was a customer base of a single company in the Dutch B2B wholesale industry comprised of 30.000 customers. A sample size of only 119 respondents might impact the external validity of the research results in a negative way. It could be that taking a different sample of 119 respondents at another company within the same industry might result in different results. Second, the implicit emotions are solely based on word-emotion association scores, which means that individual words in a sentence are appointed a score based on emotional affect. This means that a review such as “not bad” is seen as negative, because both words are associated with negative emotional affect.

Future research should aim at combining sentiment analysis with word-association models to measure sentiment more effectively from individual words and words in context to other words within a sentence. For instance, word clustering can be implemented to identify word groups that have a higher occurrence rate for loyal customers compared to new customers. Another limitation lies in the fact that there are only weak correlations found between the implicit emotions measured from the customer feedback text and the explicit emotions measured in an additional survey question. This could be explained by the nature of both questions asked in the survey, whereas the question where customers were asked to write feedback was about the last interaction the customers had with the firm, and the question where customers were asked to explicitly mention the emotions they experienced during their customer journey was about the whole time period respondents had been customer of the case company. For future research, it is important to validate the sentiment analysis with a follow-up question that measures a construct that is on the same level as the construct that is being validated.

Moreover, the current research solely focused on capturing the customer experience at the post-purchase phase of the customer journey. Future research should aim at developing frameworks that capture the most important dimensions and metrics of customer experience at every stage of the customer journey, from customer acquisition to customer retention.

This paper aims to step away from traditional studies on customer satisfaction and loyalty within the B2B context, that measure behavioural intention in a unidimensional fashion with quantitative data sources only. What this research has aimed to achieve is to take a combined approach of qualitative and quantitative data sources to better understand underlying dimensions of the customer experience. With the increase of data available and a rise of data tools to analyse big data derived from multiple sources, more research that aims to investigate interrelations between attitudinal loyalty and behavioural loyalty is to be expected in the near future. This paper opens the doorway to a new research paradigm on the intersection between relational marketing, digital marketing and data science, exploring new techniques to apply and combine machine learning and artificial intelligence in developing CRM strategies with an ever-growing customer-centric perspective

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APPENDIX A

Figure 4 NRC word-emotion association frequencies

APPENDIX B

Table 5 Correlation matrix

Variable	M	SD	1	2	3	4	5	6	7	8	9
1. NPS_Score	7.81	1.34									
2. RFM_Score	4.39	0.95	.19* [.01, .36]								
3. JoyExpl	4.41	1.98	.32** [.14, .47]	.08 [-.10, .26]							
4. SadnessExpl	1.00	1.63	-.39** [-.53, -.22]	.02 [-.16, .20]	-.08 [-.26, .10]						
5. TrustExpl	5.32	1.77	.38** [.21, .52]	.05 [-.13, .23]	.56** [.42, .67]	-.12 [-.29, .06]					
6. DisgustExpl	0.50	1.21	-.48** [-.61, -.33]	-.00 [-.18, .18]	-.13 [-.30, .05]	.56** [.43, .68]	-.24** [-.40, -.06]				
7. FearExpl	0.29	0.94	-.24** [-.41, -.07]	.15 [-.03, .32]	.03 [-.15, .21]	.38** [.21, .52]	-.05 [-.23, .13]	.68** [.57, .77]			
8. AngerExpl	0.50	1.36	-.27** [-.43, -.10]	.05 [-.13, .23]	-.01 [-.19, .17]	.66** [.54, .75]	-.12 [-.30, .06]	.65** [.53, .74]	.47** [.32, .60]		
9. AnticipExpl	3.85	2.59	.10 [-.08, .27]	-.01 [-.19, .17]	.44** [.28, .57]	.10 [-.09, .27]	.48** [.33, .61]	.03 [-.15, .21]	.07 [-.11, .25]	.14 [-.04, .32]	
10. SurprExpl	2.35	2.47	.08 [-.10, .26]	-.23* [-.39, -.05]	.44** [.28, .57]	.08 [-.10, .26]	.33** [.16, .48]	.10 [-.08, .28]	.13 [-.05, .30]	.19* [.01, .36]	.43** [.27, .56]

Note. Note. M and SD are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * indicates $p < .05$. ** indicates $p < .01$.

APPENDIX C

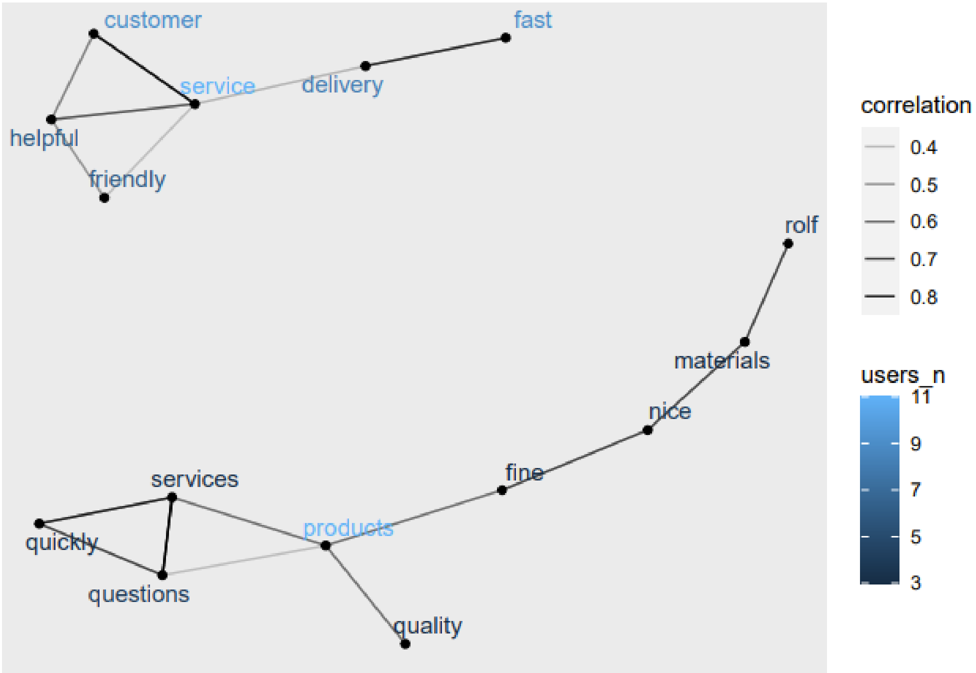

Figure 5 Word correlations for promoters

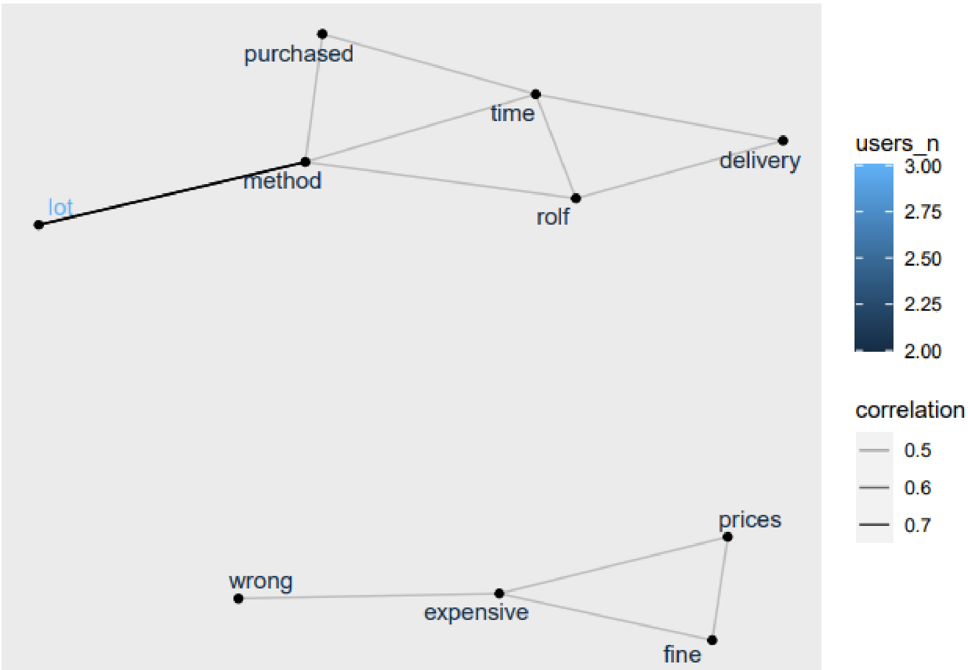

Figure 6 Word correlations for detractors

APPENDIX D

Survey ‘Effect of Customer Emotion on Loyalty Behavior

Q1. Based on your customer experience with the Rolf group, to what extent would you recommend its products and services to friends and colleagues? [scale question with 0 = ‘most unlikely’ and 10 = ‘most likely’]
Q2. We’d happily invite you to describe in a couple of sentences below how you experience products and services from the Rolf group, based on past experience with the company. Your feedback is important to better adjust future products and services to your want and need, and is therefore very appreciated. [open-ended textual question]
Q3. Under the following statement you will find 8 different emotions. Describe to what extent, during your interactions with the brand and/or organization *de Rolf groep* you have experienced the following emotions [scale 0-7]: *Joy, sadness, trust, disgust, fear, anger, anticipation, surprise*