MASTER THESIS

Using Customer Interactions to understand the Customer Engagement Value

A predictive study in the B2B insurance industry

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Abstract

Aim. The popularity of data drive marketing strategies is rising nowadays, also in the B2B insurance industry. Based on the interaction data of the business holders, different theoretical and practical implications regarding interaction between insurer and customers can be provided. In fact, the Customer Engagement Value can be predicted or even increased through interaction. Therefore, the aim of this is study is to test the effect of interactions on the evolution of the Customer Engagement Value factor. Next, the effects of the kind of interaction, the effects of the type of the interaction channel and the effects of the combination in the use of interaction channels on the Customer Engagement Value are tested.

Method. To test the hypotheses, explanatory research has been executed. Firstly, data from a time period of 7 years were pre-procced and cleaned, a new dependent variable was created and data was manipulated. Then, a correlation matrix and stepwise linear regression models were performed. Due to the low variance in the data, the data was transformed into binary variable tablets. Subsequently, stepwise logistic regression models were performed. Within the research, 1,842 various points of interactions from 1,345 business policyholders were used.

Findings. The result of this study indicates that interactions do have a positive influence on the evolution of the Customer Engagement Value factor. The result of this study indicates that interactions do have a positive influence on the evolution of the Customer Engagement Value factor. In fact, it appears that adding one interaction increases the chance of a positive evolution of the CEV factor by 28.8%. In the case of single interactions, interactions via the interaction channels telephone and direct communication have the most significant contribution. For a series of interactions, an interaction strategy combining the above interaction channels increases the chance of a positive evolution of the Customer Engagement Value by 14.5%.

Conclusion. The more interactions, the greater the chance of a positive evolution of the Customer Engagement Value. When looking at on the use of the kinds of interaction channels, a combination of telephone and direct commination will be the most effective to gain more customer loyalty. However, marketers and call center employees should be aware that excessive interaction can lead to irritation. In addition, the sentiment of the interactions has not been studied, which requires further research. Furthermore, further research should imply the number of interactions in terms of overkill and irritation.

Keywords: Customer Interactions, Customer Engagement Value, Loyalty, Customer Interactions Journey, the B2B insurance industry.

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1. Introduction

The rise of the interest in data-driven marketing strategies is unprecedented. Since more and more marketing departments within companies as well as digital marketing agencies experience the use of data, several questions come to light. In addition to the rise of big data, other developments in the marketing field can be observed. Whereas in the past years the focus was mainly focused on higher up the customer purchase intention, a new objective of a marketing department or marketing agency is to create and even increase Customer Engagement Value (CEV) for companies (Kumar et al., 2013). Especially when looking at service marketing, specific insurance companies, the value of retaining customers starts to become more important over the past years. Due to the fact that insurance contracts aren't contemporary purchases, but often contain a longer period of time, extending this contract period is even more important. Mainly since a premium has to be paid every month. The focus shifts partially from increasing the purchase intention to engaging customers in a way of customer loyalty and extending the value of the customer in a way of contract length in years. When focusing on the Dutch insurance industry, a tendency can be seen. In recent decades, the focus was mainly on challenging the price, being the cheapest. While these days there is mainly a focus on maintaining an increased Customer Engagement Value, which partly depends on attracting purchasing power (Lee, 2018; Shaw-Ching Liu, Petruzzi, & Sudharshan, 2007).

By focusing on the marketing field in a broader spectrum, another quick digital development can be observed; the presence and use of Big Data. According to the Marketing Science Institute (2018), the analysis of Big Data, and applying Big Data in various marketing strategies can be seen as the future of the fast-developing marketing field. Currently, the value of data is insurance increasing, as a result of a rapidly increasing amount of data. Data is everywhere, especially in industries there is data about consumer behavior, gathered by the use of various tracking applications. The data is called Big Data and is characterized by the following characteristics: Volume, Variety, Velocity, Veracity, and Value (McAfee, & Brynjolfsson, 2012; Villars et al., 2011).

To specify and move this new field in a certain direction, nowadays, academic literature cannot provide clear answers to practical questions as: "How do you design the digital and physical offerings and messages of an insurance company to optimally reach and engage customers at every touchpoint? How do you interact and engage and adapt in a continuous manner across the customer journey?" As stated by Kumar et al., 2013, the CEV is gaining popularity within the insurance industry, so it is important to know the effects of interaction on the evolution of the level of the CEV. The novelty of this study lies in the exploration of the effects of interaction on the level of the CEV. It tries to demonstrate that insurance organizations have to interact with customers in order to increase the level of CEV. Further, it will give practical impactions regarding the number of interactions and choice in use of interaction channels.

In order to create and maintain a decent Customer Engagement Value, data can play an important role. Especially, by using several data mining models combining the analysis of customer journeys (Bolton et al., 2000; Donkers et al., 2007). These data can be used to predict whether a consumer is prone to brand switching or not, and at which points of the customer journey the customer is the most sensitive to information and persuasive messages (Aggarwal, 2011). Based on this, data can predict the main customer interactions within a customer journey in order to understand the CEV, in particular in a business insurance contract context.

There has been researching done to several CEV loops, especially focused on service-orientated organizations. The CEV is used as a metric that measures, analysis, and measures the net success of several marketing investments (Gupta et al., 2006). The CEV is a predicting concept and states that only the most valuable customers are profitable and focuses on the predicted customer activity in the future and the likelihoods that the customer will positively return to the company, in order to become even more valuable (Kumar, 2007; Kumar, 2008). Mostly the CEV is computed over a three-year customer-company relationship (Kumar, 2010). However, in practice, the customer-company relationship is longer in length of years (P. Zwikker, personal communication, April 22, 2019).

Within a CEV loop, there are several points of interaction that have to be analyzed in order the investigate and determine the usefulness of interaction. By understanding the CEV of a business' customers, several opportunities and benefits can be explored (Castaño, 2017; Chiang, & Yang, 2018). However, it isn't yet clear what the effect of the interactions on the CEV factor are. Based on this, a theoretical framework has to be established in order to answer the following research question:

RQ: *What are the effects of Customer Interactions on the evolution of the Customer Engagement Value in a B2B insurance context?*

Based on the data, points of interaction within a customer journey can be analyzed. By researching the components of the CEV, value can be assigned to interactions. Both previous research and new research into the components of the CEV should bring these predictors to light. The final step of the research is to link the interaction points to the CEV tactics, in order to generate implications in how, where and when an organization should interact with its target group.

2. Theoretical framework

The Marketing Science Institute (2018) indicated that increasing and stabilizing the CEV is the main focus of marketing departments within insurance companies. According their preliminary study, interaction will play a major role in this. Barwitz, Körs, and Ramezani (2017) demonstrated that the level of interaction with the customers is even more important than the insurance company's brand. Furthermore, Barwitz, Körs, and Ramezani (2017) found that customers are even more willing to pay more for additional interaction opportunities. Interacting with customers will make positive contribution to consumer's decision making when renewing an insurance contract. However, research should which points of interaction within a digital customer journey are the most critical, especially within the insurance B2B context.

2.1. Customer Engagement Value

The Customer Engagement Value (CEV) is a clarification of the creation of business value by customers. In addition, the CEV metric is built from a business perspective and aimed at binding existing business customers, provided that these customers have a positive CEV. The CEV can be measured not only on the basis of the premiums paid by a customer, but it includes behavioral characteristics as well.

For insurance companies, the CEV becomes more significant (Kumar et al., 2010). Gupta et al. (2006) states that the metric can measure, analyze and manage the success of marketing investments and the value per customer in the future. Currently, most of the common metrics focusing on the past, the CEV focuses on the future and is more predictive (Gupta et al., 2006). The CEV metric is becoming increasingly important as a concept for companies because the need for companies to justify marketing investments is desirable. Metrics such as brand awareness, attitudes, or even sales and share are not solid enough to indicate a return on marketing investments. Even worse, marketing actions that improve sales or share can actually harm the long-run profitability of a brand (Yoo, & Hanssens, 2005). The CEV was developed to meet the desire to be able to steer at the customer level. That is why CEV provides insights into the expected future value of a client, or more specifically per product, and into the expected duration of a customer relationship (Hollebeek, 2013). Within insurance companies, the aim of the CEV is to increase the value of the customer for the insurance by means of targeted implications, both within the acquisition and with existing customers (P. Zwikker, personal communication, March 22, 2019).

Based on literature research and sound from the service marketing field, it can be concluded that the metric of Customer Engagement Value is hailed as a powerful marketing metric: *"organizations are increasingly seeking customer engagement and participation with their* *brands”* or *“CEV is suggested to generate enhanced organizational performance”,* are often quoted statements (Hollebeek, pp. 17, 2013). The CEV is therefore seen as a strategic steering method, but not as an accountability model. A solid CEV will increase the revenue growth, the overall profitability and the overall increased competitive advantage (Brodie, Hollebeek, Jurić, & Illić, 2011). A growing number of marketing research reports state that an improved CEV will result in growth and organizational overall success (Kumar et al., 2010).

The value of the CEV cannot be underestimated. However, more information about the metric is needed in order to fully understand its practical implications. Kumar et al. (2010) stated that the Customer Engagement Value consists of several customer-organization-orientated metrics. First, the researchers found that Customer Lifetime Value (CLV) is one of these metrics. This metric focusses on the customer transactional behavior towards the organization. Next, they stated that the CEV includes both value of transactional and non-transactional behavior. Kumar et al. (2010) therefore introduced the Customer Influencer Value (CIV), or the extent to which a customer becomes a brand-advocate, and the Customer Referral Value (CRV), which relates to the referral of new customers. Finally, they introduced Customer Knowledge Value (CKV), which is in relation to the number of feedbacks a customer will translate to the organization. However, both Blattberg and Deighton (1996) as well as Venkatesan and Kumar (2004) stated the CLV lends itself as the main predictor of the CEV. For organizations, particularly in the field of service marketing such as insurance, the focus will be on the CLV as the main predictor of the CEV, as a result of the cashflow focus of CEOs. It is then stated that the influence of Worth-of-Mouth will be greater within service marketing compared to are more product marketing approach (Luo, 2009; Trusov, Bucklin, & Pauwels, 2009). Even Verhoef, Reinartz, and Krafft (2010) introduced the CEV as an overarching principle of overarching customer value metrics. They also paid attention to the transactional and non- transactional customer behavior. However, their research stated that organizations’ focus will be on improving the CLV in order to improve the total CEV.

Based on the literature, the concrete insurance CEV model consists of net margin times the engagement factor (See paragraph 2.2.2.). The aim of this research will be on giving insights to the relationship between interactions and the level of the CEV. In addition, by analyzing customer journey loops, ways are explored to manipulate the level of CEV are explored.

2.2. Components of the Customer Engagement Value

In order to measure the CEV during the various customer journeys, it has to be clear which CEV components need to be analyzed, as the measured data consists of many different components. It is therefore necessary to define which components affect the CEV and can be found in the literature. Gupta et al. (2008) indicated that the probability of customer retention, customer acquisition, and customer expansion will play a role with respect to the CEV. According to Singh and Jain (2013), measuring the customer retention rate, the customer acquisition rate, and the customer expansion rate alone are not good enough. According to their research, the CEV can be measured by churn rate, purchases, returns, a company's marketing activities, a firm's network and the discount rate of its products. However, one clear model is not given. On the other hand, an organization must keep an eye on the cost of customer retention, acquisition, and expansion.

Subsequently, in order to measure the abstract factors above, the context of the CEV will play a play a role (Borle, Singh, & Jain, 2008; Fader, Hardie, & Lee, 2006; Venkatesan, & Kumar, 2004). Within this research, the context of the CEV will be a contractual context since there is a relationship between an insurance company and a client, governed by a contract or a membership. In this case, the client's is directly linked to the duration of their membership. On this basis, an insurance company focuses on maintaining a long customer-company relationship. In this context, customer engagement, inter-purchase time and spending are factors that are directly linked to the CEV, while the inter-purchase time can be seen as costs of a membership. Thus, the focus on the customer engagement has to be prior in a contractual context (Singh, & Jain, 2013).

2.2.1. Computing the CEV

A more detailed analysis of the currently used insurer's CEV model reveals that the CEV value is composed of the net margin times the engagement factor. The basis of the net margin is the paid premium (*P*i) in a particular period, mainly per month. For the calculation of the net margin per business customer, the paid premium is deducted by the expected damage (*D*i), the allocated (*A*i) and capital costs (*C*i) per customer. To calculate the overall CEV per customer over a given period, the margin is multiplied by the CEV factor (*F*). The CEV factor determines the loyalty of the customer relationship in years and is made up of several components. Therefore, the CEV factor can quickly increase the total CEV, provided there is a positive net margin, otherwise a negative marge is multiplied by a multiplication factor.

$$\text{CEV} = \sum_{i=1}^{n} F(P_i - D_i - A_i - C_i)$$

Concerning academic literature, different models can be used when modelling the CEV in a contractual context: The Basic Structural Model of CEV (Jain & Singh, 2002; Berger, & Nasr, 1998), RFM-models (Donkers, Verhoef, & de Jong, 2007) and the Hazard Rate Models (Borle, Singh, & Jain, 2008). The Basic Structural Model of CEV can be used in a B2B context, focuses on the future and is linked the period of cash flow from the customer transaction, where i = the period of cash flow from customer transaction; *Ri* = revenue from the customer in period *i*; *Ci* = total cost of generating the revenue *Ri* in period *i*; *n* = the total number of periods of projected life of the customer under consideration. However, the length of the subscription per customer is not measured using the basic model. To determine the CEV value per customer, the margin must be multiplied by the CEV factor (*F*). The CEV factor is computed by several components that will be discussed later (section 2.2.2.) (Borle, Singh, & Jain, 2008).

$$\text{CEV} = \sum_{i=1}^{n} F \frac{(R_i \ - \ C_i)}{(1+d)^{i-.05}}$$

The Basic Structural Model of CEV assumed that the CEV will be calculated at the end of a period. The calculated CEV identifies the future cash flow from customers and assumes a certain time of the cashflow. They apply only to customers who are doing business with the firm, they ignore both past and potential customers, they ignore acquisition costs, they do not consider a number of important factors such as the stochastic nature of the purchase process and timing of cash flows, and they are very simple and therefore easy to use. Next, the Basic Structural Model is developed from a more business perspective, linking a certain CEV value to a certain turnover (Jain, & Singh, 2002). From the perspective of this research, the Basic Structural Model of CEV can be used in a proper way.

However, RFM-models more focuses on timeliness of past purchases, the frequency of past purchases and the monetary value of the past purchases. In any case, the last model predicts the CEV on the hand of hazard rate models in marketing. The hazard of an event means the risk of an event, H here, the event is customer defection or purchases. Based on these findings, RFM-models, as well as Hazard Rate Models, are not suitable within this research. (Singh, & Jain, 2013).

2.2.2. Computing the CEV factor

Several ways of interaction produce affinity or create a bond (De Valck, Van Bruggen, & Wieringa, 2009). Brodie, Ilić, Jurić, and Hollebeek (2013) stated that customer engagement can be improved by actively interacting with customers. Mainly using the internet as an interaction platform will improve the CEV factor (Sawhne, Verona, & Prandelli, 2005). As mentioned earlier, within this research the concentration will be on improving the CEV factor in contract years. In order to improve the engagement factor interactions with the customers, or maybe potential customers are needed. J. Leijdekker – Duin (personal communication, April 15, 2019) explained that within the service-orientated marketing field, especially within the insurance industry, other factors influence, such as a number of insured products, the nature of business policyholder, the type of organization, and previous claims. Data analysts have noted that interaction does affect the engagement, even within insurance companies.

Table 1

Components of the Customer Engagement Value Factor

Current component variables	**Description of the components**
Premium	Yearly total premium
Age	Age of the customer
Gender	Gender of the customer
Partner	Do the customer also have a policy in the company
Discount	Discount program (Y/N)
Policies	Type of insurance policy, insured products
Type of Company	Small company, SME, Corporation, SA
Claim history	Claims in the past. Claims paid out (Y/N)
Expected new component variable	**Description of the new component**
Interaction	Kind of and number of interactions in the past

Within the Basic Structural Model of CEV, described in section 2.2.1., a CEV factor can be found: *i = the period of cash flow from customer transaction*. The longer this period, the higher the value of the CEV. Regarding the main research question, it is important to find components that can increase this period and raise the level of churn (Sing, & Jain, 2013; Wong, 2011). Günther, Tvete, Aas, Sandnes, and Borgan (2011) found *Premium, Age, Gender, Partner, Discount, Policies* and *Lifetime* as components of the Customer Engagement Value Factor. On the basis of a specific combination of these factors, are certain curve can be composed, which is represented by the CEV factor. However, the found components by Günther et al. (2011) mainly focusing on the B2C context. Nevertheless, Vafeiadis, Diamantaras, Sarigiannidis, and Chatzisavvas (2015) found that most of these factors also can be applied to the B2B context, provided that the type of the company and the claim history is also taken into account. It has to be said that they indicated that age, gender and partner do not have that much impact in a B2B context. For the sake of completeness, they are included (table 1).

Tikkanen et al. (2009) found that interaction can influence the CEV factor. They argued that social interaction with customers via the internet can improve customer engagement, and thus the overall CEV. In addition, interaction can create business value. Customer-organization interaction allows sales reps to better engage customers in understanding their business, and in this way, customers become more attached to the brand and contract renewals become more likely (Prahalad & Ramaswamy, 2004; Sashi, 2012). Subsequently, it appears that conversation with business customers will positively influence the CEV factor (Tuzovic & Brooks, 2013). Holt (2004), and Pansari, and Kumar (2016) also argued that the customer-interaction contributes to more engaged customers, provided that the manner of interacting is related to the motives of interaction. According to the academic literature, interaction can be seen as a component of the CEV factor. For this reason, interaction is added as a component in table 1.

2.3. Customer Interactions

As described in the section above, the research is aimed at increasing the Customer Engagement Value (CEV). Customer Insurance Interactions is a collection of customer-company interactions relating to one case per customer. Multiple Customer Insurance Interactions or cases per customer together form a Customer Interaction Journey. Research into these Customer Interaction Journeys can determine when and where it has to interact with its customers. Based on this, the single interactions, Customer Insurance Interactions, and Customer Interaction Journeys will play a role in the research. According to Castaño (2017), there are various metrics to measure the value of interaction points or even a complete journey. In most cases, the Conversion Rate (CR) is seen as the most valuable metric, because it represents the revenue out of a customer journey. However, the emphasis in this study will be on increasing the CEV, which is seen as another metric.

In short, by comparing the data of this study with the academic literature, various components of the CEV factor have been found. These components indirectly influence the CEV. There are several components that influence the CEV factor, but based on literature interaction certainly does have an influence. First, the data analysis has to classify interaction as component for the CEV factor. Next, the data analysis should focus on measuring the most discriminating interactions with respect to influence on CEV. Based on this, the following hypothesis has been formulated:

H1 *Customer Interactions contributes to the evolution of Customer Engagement Value in a B2B contractual context.*

2.3.1. Single Customer Interactions

Within the insurance industry, Cebulsky, Günther, Heidkamp, and Brinkmann (2018) argued that the focus on offline interactions, like consultancy, agents, will shift to a more online multi-channel environment. Based on this fact, online interaction should be explored to maintain the current level or even increase the CEV level. The experience of the customer with the company or the relationship with a company will evolve each time a customer comes into contact with the organization. A sum of these interaction points determines the customer's opinion of a company or its service (Clatworthy, 2011). Fortini-Cambell (2003) describes interaction points as being*: "in a more complex consumer experience ... there may be literally hundreds of small elements" (p.63).*

The points of interaction in the insurance industry, or in a contractual context, differ from the type of interaction in a non-contractual context (Singh, & Jain, 2013). Different interactions may arise in the contractual context, which focuses on trigger, review, purchase decision, engagement, relationship management and renewal (table 2) (Cupman, & Hoffman, 2017). These points of interaction are not only connected when a client is in contact with a company, but can also arise in the stadium before a contract is concluded with a company. In this context, the insurer's marketing department indicates that it mainly uses the telephone, post, mail, booklet and direct communication as channels for interaction. The insurer therefore has access to this data.

Especially in the trigger and review phase, the customer will use other tools, websites or companies to create a division. Together, these points of interaction will generate Customer Insurance

Interactions (Maechler, Naher, & Park 2016). Based on this, it is expected that the interaction channels individually will influence the evolution of the CEV. The following hypotheses can be drawn up:

H1a *Interaction via telephone contributes to the evolution of Customer Engagement Value.*
H1b *Interaction via email contributes to the evolution of Customer Engagement Value.*
H1c *Interaction contributes to the evolution of Customer Engagement Value.*
H1d *Direct interaction contributes to the evolution of Customer Engagement Value.*
H1e *Interaction via booklets contributes to the evolution of Customer Engagement Value.*

2.3.2. Customer Insurance Interactions

Within the current research, customer journey data of a Dutch insurance company are analyzed. For this research, P. Zwikker (personal communication, March 22, 2019) proposed an insurance-orientated customer journey. In general, this journey is divided into three parts: *acquisition, development,* and *retention*. During this customer journey, there are various interactions, divided over the marketing instruments: *price, place, promotion,* and *product.* It is expected that several separate interaction points together will result in an increase of the CEV factor conversion. To achieve such an increase, multiple channels will be used together, which is called multi-channel interaction (Kent, Vianello, Cano, & Helberger, 2016).

Within the B2B contractual context, the online multi-channel interaction approach is used by several customers. The types of single interactions may differ per customer and per case or goal (Carrol, & Guzmán, 2016). Within this research, the multi-channel interaction approach is also called Customer Insurance Interactions. A B2B multi-channel customer journey is defined by De Baere (2015) (figure 1). Within this customer journey, both offline and online single interactions are given, dived over six stages. NITT Technologies has found a more insurance-based multi-channel model (figure 2). As can been seen, most of online channels can be found in both of the models. As indicated earlier, a combination of several of these single interactions will be used to observe a positive evolution (Carrol, & Guzmán, 2016). Li and Kannan illustrated a model that provides Customer Insurance Interactions in a B2B context (table 2). In addition to the single interactions and Customer Insurance Interaction, there will be a deeper interaction level; Customer Interaction Journey that

Table 2

Single Interactions in a contractual B2B context

	Stages					
	Trigger	***Review***	***Purchase decision***	***Engagement***	***Relationship management***	***Renewal***
Channel of interaction	Email Social Media Website Chat	Website Remarketing	Website Calling Email Remarketing	Chat Email Website	Chat Call Website Email	Email Calling Chat

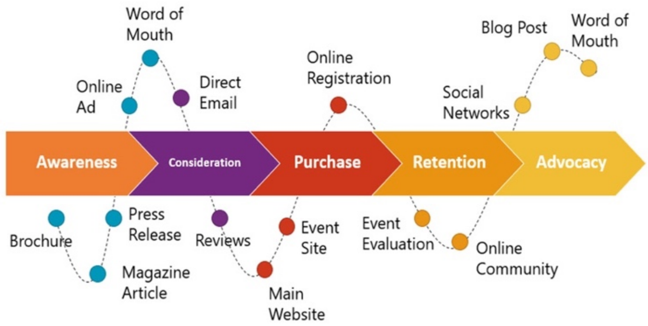

Figure 1. *Multi-channel B2B Customer Journey*

Figure 2. *Multi-channel B2B Insurance Customer Journey*

focusses on multiple sets of Customer Insurance Interactions in order to achieve multiple goals over a particular period of time. In the course of this research, however, it cannot be excluded that analyzing the single interactions and Customer Insurance Interactions will result in noticing 'new' single interactions or sets of these interactions.

2.3.3. Customer Interaction Journey

As mentioned earlier, within this research, the deepest layer in terms of B2B customer interactions will focus on the Customer Interaction Journey. Customer Interaction Journey can be described as the sum of the Customer Insurance Interactions in order to achieve multiple goals, such as claiming damages and renewing a business insurance contract. Like single interactions and Customer Insurance Interactions, the Customer Interaction Journey will vary by business customer (Carrol, & Guzmán, 2016). In order to track and uncover the Customer Interaction Journey, which does affect the CEV, data analysis is required to identify the interaction patterns (NICE, 2018). Lemon and Verhoef (2016) describe these Customer Interaction Journeys as all the interactions over time, during different purchasing cycles, and across single points of interactions between a customer and an organization. In fact, a customer journey includes all customer experiences that a customer has with an organization. Increasing customer loyalty or improving the CEV is inextricably linked to the focus on the customer to find the interaction.

With regard to measuring the CEV, the value of every Customer Interaction Journey is not the same. The purpose of this research is to filter out several Customer Interaction Journeys that do influence the level of the CEV. Because of the possibilities of data analytics and data analytics software, it becomes possible to indicate these points of interaction (Straker, Wrigley, & Rosemann, 2015). Based on the research of Lemon and Verhoef (2016), paying attention to the customer through interaction will have an effect on the positive evolution of the CEV factor. The following hypothesis is therefore proposed:

H2 *Customer Interaction Journeys with the more interactions bring contribute more to the evolution of the Customer Engagement Value.*

2.3.4. Attributing Value to Interactions

In addition to analyzing the different interaction points, it is even important to assign the conversion value to the correct interaction points. In the past, the value was mainly assigned to the last interaction, because these points resulted in a lead or conversion. In practice, this is not correct, because marketers start from a customer journey, where different interactions lead to a common goal: a conversion in this case improved engagement through interaction. The latter interaction model would thus give a distorted picture, since previous interaction points within the entire customer journey are not attributed to a certain conversion value. Attribution models provide insight in assigning the right value to the right interaction points and the interaction channel during the customer journey (Zhang, Wei, & Ren, 2014).

Basically, five different types of attribution models can be distinguished, including the last interaction, first interaction, time lapse, linear and position-based attribution models. According to the attribution model for the last interaction, the conversion value is assigned to the last interaction channel used between customer and organization. However, the first interaction attribution is more of a growth-oriented attribution model, which assigns all conversion value to the first interaction channel used by the customer and the organization. The focus of these two types of attribution models separately contradicts each model. Therefore, according to the academic literature, three different models can be observed between both outliers. First, the time decay attribution model. This attribution model assigns the conversion value to the interaction channels closest to the conversion. Final, linear, and position-based attribution modeling. The attribution of the value in a linear way refers to giving the same value to each channel. Next, the position-based attribution will assign both 40% of the total value to the first and last channel and the other 20% to the remaining channels (Zhang, Wei, & Ren, 2014).

However, Bouman (2018) found that using data-driven attribution models will make more sense because these models predict the value per interaction on real interaction data. They used real-time analytical data to develop a specific attribution model, but these models will differ per case and organization (Shao, & Li, 2011). Within this research, the nature of the attribution value of a certain point of interaction is important, because it will give direct implications. However, the data analysis should make clear which type of attribution model will be used to correctly assign value to interaction points, especially in a B2B insurance context. In order to obtain these insights and to give practical implications, the following hypothesis is drawn up:

H3 *The first interaction brings the most contribution to the evolution of the Customer Engagement Value.*

2.4. Sequence of interaction channels

Besides exploring and analyzing the components of the CEV factor and the Customer Interaction Journey patterns, with respect to measuring the Customer Engagement Value, the findings need to be correlated to each other to answer the main research question. As mentioned earlier, several questions are emerging in the field of big data and marketing, one of which is: "*How do you as business company interact, engage and adapt in a continuous manner across the customer journey in order to increase the customer engagement?"*. According to the Marketing Science Institute (2018), this is one of the most prior questions regarding the enforcement of the CEV. These rising questions consist of two parts: the interaction with customers and the customer journey. By translating these parts into this research, the following points of attention can be defined: the maintenance, or even expansion, of the CEV and the interaction points of the customer journey.

As the Marketing Science Institute (2018) indicates, it is important to seek interaction with a company's target group at the right time in terms of time and days. An important part of these interaction moments is the right choice of an interaction channel. Following the research of Samp (2017), Face-to-Face (FtF) and communication technology mediated communication (TMC), as telephone contact, must nowadays challenge the complete digital media communication (CMC), as WhatsApp or e-mail. The increase in the use of CMC tools can be observed in the younger generation (generation Z). Godfrey, Seinders & Voss (2011) also stated that telephone interaction can be described as a personal TMC way of communicating, in addition to e-mail. It has to be said that e-mail is a more CMC means of communication, compared to TMC. However, when it comes to sensitive or personal subjects, FtF communication and TMC channels are preferred, even under this generation Z, to discuss these matters (Samp, 2017). Barwitz, Körs and Ramezani (2017) indicate that taking out insurances are personal and important matters for individuals. It can be concluded that telephone, as part of TMC, and FtF communication can be seen as a channel to discuss personal matters, such as concluding, extending or renewing insurances.

As a result, the hypothesis below has been drawn up to test whether a combination of telephone and direct communication has the most contribution on the development of the CEV compared to other channels:

H4 *A combination in interaction via telephone and direct interaction contributes the most to the evolution of the Customer Engagement Value.*

2.5. Customer Engagement Value Evolution Models

As described in the earlier phase of this report, several research models are described. Section 2.1. and 2.2. described the Customer Engagement Value, which is used by various insures in order to predict the current and future value of a customer. In this case, the customer is in a particular business market. The formula used in section 2.2.1. gives the CEV's structure from a business perspective, with a particular focus on extending the contract length. Section 2.2.2. gives an overview of components that influence the contract length. When it comes to customer interactions, section 2.3. first assumes that customer interactions influence the factor CEV. In more detail, it is stated that characteristics of customer interactions, such as the type and number of interactions, influence the CEV factor in certain directions. In particular, assigning the right conversion value to the right interaction gives practical applicable implications. Finally, it is stated that models with FtF-channels have more influence on the CEV factor than non-FtF channels.

In short, the theories explain the extent to which the use of interaction can influence the CEV factor in years. Based on this literature review and existing information, Customer Engagement Value Models are drawn up. Each model justifies a layer within the study. The first model establishes a more general way of thinking; interactions do influence the CEV factor.

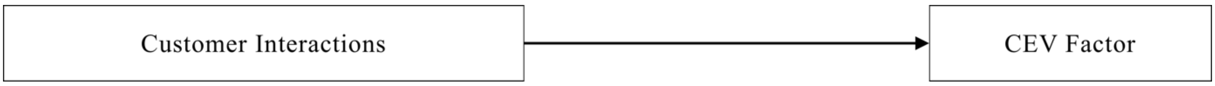

Figure 3a. *Customer Engagement Value Evolution Model*

The following model captures the second layer within the research: a more in-depth study of the characteristics of Customer Interactions:

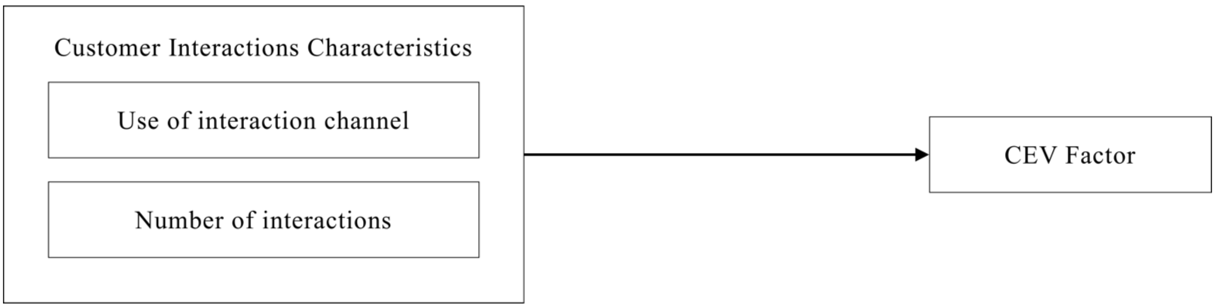

Figure 3b. *Customer Interaction Characteristics Engagement Evolution Model*

Finally, the third model represents the deepest layer within the research. It states that models with a certain sequence of interaction channels more to the CEV factor. Furthermore, it indicates that certain interactions within the sequence will give more force to evolution than others:

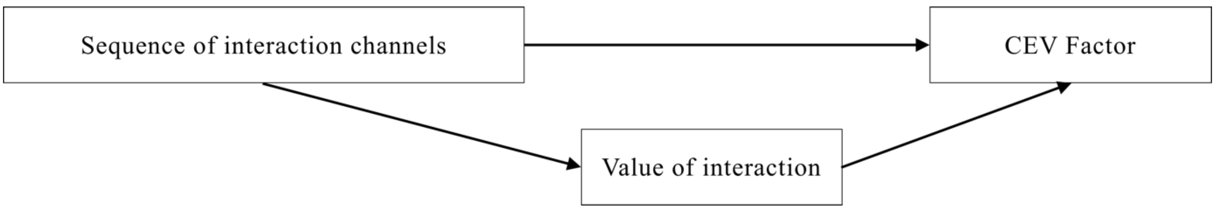

Figure 3c. *Customer Interaction Sequence Engagement Evolution Model*

3. Methodology

This part defines the general experimental design of this thesis. First, the general datasets and the way in which these data are collected are illustrated. Next, the procedure of data cleaning is described, even as the classifiers used to analyze the data. At the end of this chapter, a descriptive analysis of the data used is given.

In short, the way in which the research was executed. It had to be clear in order to be able to test hypotheses. While analyzing the data, the data analysis software used provided insight into the customer journey and the associated interaction points between business customers and the insurance company. These insights contributed to test the hypotheses and to answer the research question. The data was selected, pre-processed, cleansed and analyzed using RStudio; an open-source data analysis software.

3.1. The CEV datasets

In order to investigate and track patterns in the customer journey of the insurance company's customers, real and up-to-date data were needed. Together with a Dutch insurance company, several CEV datasets were compiled. The insurer provided both business and personal insurances for various objects or products. However, regarding to this thesis project, only data of business policyholders are analyzed.

A unique dataset is used within the research. Unique in several respects: the used data relate to a specific part of the insurance sector, namely the Dutch B2B insurance market. Furthermore, no research has ever been done with this specific type of data in this specific context. The findings of this research will therefore have the necessary practical implications for both the marketing department and other marketers active in the insurance market. In addition, this dataset, the general research method and the findings will provide new insights and can serve as starting points for new data research within the B2B insurance industry.

This key data concerned values of the CEV during the customer journey. In addition, it contains the customer data related to B2B customers, which currently have business insurance contracts with the insurance company. These business insurance policies related to mobility car insurance, where most of the insured customers had one current insurance policy. This data covered all interactions, which can be separated by the customer numbers, and the channels used, as well as the frequency of interaction per channel. Interaction channels analyzed were telephone, booklets, e-mail, mail and direct interaction.

Within this research only the outbound interactions are measured, because these are the interactions that can be manipulated to get a more positive evolution with respect to the CEV (Ruta, Kazienko, & Brodka, 2009). Zwikker (personal communication, 13 June 2019) indicates that these outgoing interactions can be better influenced, as opposed to the inbound interactions. *"The marketing department of our insurance company can check the outgoing interactions based on the results, but the* *incoming interactions are difficult to predict or manipulate"*. In short, by analyzing only the outgoing interactions, this study can provide both valid theoretical and practical implications. Valid implications, because the outgoing interactions can easily be manipulated. Manipulating incoming interactions is more difficult because it involves a more customer-oriented approach, which is not tested in this study. Selecting the outgoing interactions was the first step in data selecting and cleaning (P. Zwikker, personal communication, June 13, 2019).

3.2. Data analysis procedure

The data obtained were unstructured and not suitable for direct analysis. The first step in the analysis of this data consists of preprocessing and cleaning the data (Gandomi, & Haider, 2015). By preprocessing the data, the missing values, outliers, etc. are replaced or removed in order to obtain a structured data set that is easier to analyze. In addition, data from different marketing communication channels are merged. The different datasets are thus merged and combined with all the company's datasets to create one large dataset, which is used as a starting point for the analysis. At a later stage of the research, the raw dataset will be divided into separate datasets per interaction channel. In this way, independent effects of the different interaction channels could be tested. A more detailed description of the data selection and cleaning is given in section 3.3.

First, a descriptive analysis is executed, in which calculations of the mean and the standard deviation are given in order to better understand the data. Next, correlation analyses are performed to observe general correlations between variables within the datasets. Furthermore, both linear and logistic regressions are performed. By performing a linear and logistic regression different models are tested to test the hypotheses (Bloomfield, 2014). These regressions indicate the best model to test these hypotheses. Furthermore, several stepwise regressions are performed to see which models represent the best sequence and combinations in the use of the interaction channels. In general, the calculation of R^2 reveals the most important significant models. Simultaneously, the Akaike's Information Criterion (AIC) is calculated. The AIC is a value of the model that depends on the probability and the number of model parameters. The lower the number, the better model. Finally, statistical algorithms and data are converted into graphs and diagrams to display the customer journey and valuable interactions.

3.3. Data selection and cleaning

The dataset obtained by the insurance company consists of the monthly CEV value per customer per specific month, from January 2012 to January 2019. In total, the dataset consists of data of 20,033 business policyholders over 7 years. The distribution of the business policyholders per branch are displayed table 3. However, data relating to customer interactions could only be obtained for the months of June 2017, April 2018 and January 2019.

Table 3
Number of policyholders per kind of branch before data selection and cleaning

	Trade, Industry & Service	Real Estate & Construction	Automotive & Transport	Government, Health & Education
No. of policyholders	12,926	5141	740	1226

3.3.1. Customer Interactions

The first step of the selection procedure was to select the CEV values within the months of April 2017 and January 2019, as only the interactions within this data range were available and could be related to the known CEV values. As a result, only data over 3 years were analyzed, instead of 7 years. This led to a loss of a lot of available data. Without data on the interactions, however, no proper research can be done. Subsequently, only the outbound interactions are selected, based on the arguments described in section 3.1. Another reason to use the outbound interactions is the fact that it is difficult to predict when and through which channel a business policyholder will contact the insurer. In fact, it is better to anticipate than to respond to questions, remarks and comments from customers. In short, the outbound interactions are easier to monitor (Ruta, Kazienko, & Brodka, 2009). Good regulation of these outbound interactions will lead to a more positive development of the CEV and fewer complaints via customer service (P. Zwikker, personal communication, 23 April 2019).

Finally, the duplicated and missing values were removed. Research shows that removing duplicates will increase the validity and reliability of the study in a positive way. In this way, the value of, for example, an extremely loyal customer is not counted twice. On the other hand, negative values do not count twice either (Furusjö, Svenson, Rahmberg, & Anderesson, 2006). There were 1,842 different interactions between the insurer and business policyholders. All these interactions take place via various channels, including the Internet, booklets, telephone, e-mail and direct interaction. After selection of the data, the data of only 1,345 business policyholders could be used, a large reduction of the data originally available. In order to obtain a more structured dataset, additional data such as premium costs, founding dates, descriptions, addresses and contact details were removed.

3.3.2. Evolution of the CEV

The main research question within the project concerns the evolution of the CEV value, based on the number and nature of the interactions in the period June 2017 to January 2019. To test the described evolution in the CEV value, data manipulation is needed. The first manipulation: adding a new variable representing the evolution of the CEV value to the data set. The value of the evolution is calculated by subtracting the first known CEV value from the last available CEV value. In most cases, a slight positive evolution is constructed (an increase between 0 and 4 in the CEV factor). However, a small number of policyholders showed an enormous positive evolution (more than 10 to 14 in the CEV factor). These small numbers of outliers have been removed to maintain the reliability of the study (Furusjö, et al., 2006). This created variable has an indispensable function, since the evolution in the CEV variable is the dependent variable within the study. The testing of constructs, correlations and models will depend on the evolution of this variable.

3.3.3. Interaction, whether or not?

In the last part of the study, manipulation of the data took place. In order to test whether the more interactions lead to an improved probability in the evolution of the CEV, a new data frame with new binary variables is drawn up. It was necessary to use binary data, because the variance in the original analyzed data was little or too little (figure 4). A linear regression assumes that a dependent variable is continuous in nature. This is not the case in this study (Lammers, 2007). In short, the evolutions in the value of the factor CEV were too low to test the effects of the number of interactions used. In order to be able to test, the data within the data frame were converted into binary data, when customers become more loyal, a 1 was noted (positive evolution), a 0 for a negative or unchanged evolution.

To test whether the more interactions contributes more to a positive evolution of the CEV factor, a binary logistic regression model with logit link should be performed. A binary logistic regression was performed to test whether the independent variables together (interaction via all interaction channels), and separately (interaction via a separate interaction channel) have a significant effect on the evolution on the CEV. A binary logistic regression analysis is suitable in this case, because the analysis is powerful to test the amount of data in a fast and clear way. The results can then be used in a simple way to test subsequent models (Carey, Zeger, Diggle, & 1993). The binary logistic regression is thus used to test whether the more interactions lead to an improved chance of the evolution of the CEV and to see which combination of interaction channels contributes the most to the chance of the evolution of the CEV, in an effective way.

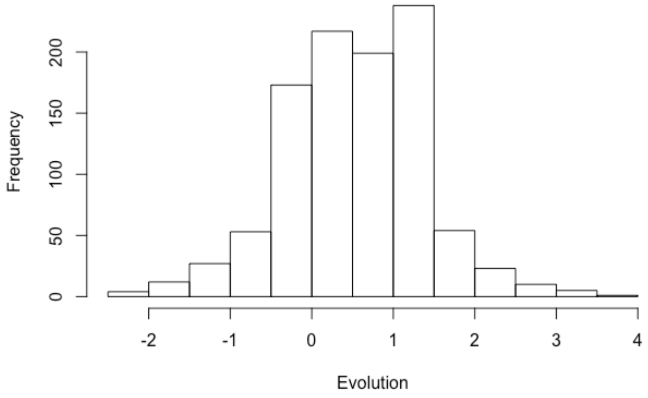

Figure 4. *Variance in the evolution of the CEV factor.*

3.4. Pre-processed data

Within the research the data of 1,345 business policyholders were analyzed. All these policyholders did have a function within a small and medium sized organization. These policyholders accounted the several kinds of branches. A segmentation divided the organizations into different branches. The majority of the organizations could be classified to the Trade, Industry & Service sector (63.5%).

Table 4
Number of policyholders per kind of branch after data selection and cleaning

	Trade, Industry & Service	Real Estate & Construction	Automotive & Transport	Government, Health & Education
No. of policyholders	854	345	51	95

4. Results

This chapter explains the main results of the data analysis. First, descriptive statistics and general correlations are given. Next, different models are shown with which the different hypotheses are tested.

4.1. Descriptive analysis

On average, there were almost two interactions per Customer Interaction Journey (M=1.82, SD=1.8). Most of the measured interactions took place via telephone (M=.42, SD=0.51), post letters (M=.37, SD=.84). and direct communication (M=.44, SD=.52), as shown in table 5. In addition, the average evolution of the CEV was positive (M=.52, SD=.85). In general, therefore, the level in the CEV has increased; customers have become more loyal in most cases.

Table 5
Descriptive statistics

	N	Mean	SD
Interaction via telephone	319	.42	.51
Interaction via post	285	.37	.84
Interaction via booklet	18	.02	.15
Interaction via direct communication	334	.44	.52
Interaction via e-mail	60	.08	.31
Interaction via all channels	1842	1.82	1.8
Evolution of the CEV Factor	1343	.52	.85

Table 6 presents us a correlation matrix of the independent variables separately and together *(interactions via all channels)* between the independent variables. Next, it gives the correlation between de variables of the research models.

Table 6
Correlation between interaction channels and the evolution in CEV (Pearson Correlation)

	Telephone	Post	Booklet	Direct	E-mail	All channels	Evolution CEV
Interaction via telephone	-	**-.422*****	**-.096****	**-.473*****	**-.170*****	**-.096****	**.087***
Interaction via post		-	**-.084****	**-.437*****	**-.156*****	**.200*****	.005
Interaction via booklet			-	**-.094****	**-.034**	-.0192	**-.085***
Interaction via direct communication				-	**.175*****	**-.099****	-.037
Interaction via e-mail					-	.0167	.011
Interaction via all channels						-	.054
Evolution in CEV Factor							-

***. Correlation is significant at the 0.001 level (2-tailed)
**. Correlation is significant at the 0.01 level (2-tailed)
*. Correlation is significant at the 0.05 level (2-tailed)

First, a significant correlation between interaction by telephone ($r = .087$, $p < 0.05$) and by booklet ($r = -.085$, $p < 0.05$) on the evolution of the CEV can be observed. The number of interactions via telephone is positively correlated with the evolution of the CEV factor. The same factuality can be observed for interactions via booklets. Further, the independent variables present multicollinearity, most of the them showing significant correlations: mainly the direct interaction variable, which is correlated with interaction by telephone ($r = -.473$, $p < 0.001$), post ($r = -.156$, $p < 0.001$), booklet ($r = -.094$, $p < 0.01$), and e-mail ($r = .175$, $p < 0.001$) very strongly. When direct communication takes place, it may also depend on other interaction channels. Therefore, it is logical that direct interaction also correlates significantly with a combination of all interactions ($r = -.099$, $p < 0.01$). Within the study the presence of multicollinearity has been indicated, yet no values will be removed or merged within the dataset. This is because the r-value before that is not very high (max -.473).

4.2. The effect of Customer Interactions

In order to test the effect of the customer interaction on the evolution of the engagement value, a correlation analysis, simple linear, multiple linear and logistical regression analyses were performed executed. Within these analyses the interaction channels telephone, post, direct, e-mail, and booklet were the independent variables. Subsequently, all the conducted interactions together were tested. These interactions account all the interactions in the period January 2017 till January 2019.

The hypothesized relation between the interactions and the evolution of the Customer Engagement Value were tested. To test the main effects of the interactions, first a Stepwise Multiple Linear Regression Analysis was executed. Later, a Stepwise Multiple Logistic Regression Analysis was performed.

4.2.1. Linear Regression

First, the first hypothesis assumed that interacting with customers will contribute to a positive evolution of the CEV. To test this relation, a linear regression analysis is executed. A single linear regression analysis is a statistical model to test the relationship between two variables; in this case, the interaction between the evolution of the CEV. Results indicates that there is a significant relation between interacting and the evolution of the engagement factor ($\beta = .03$, $t = 1.56$, $p = .045$). Based on this result, the first hypothesis is supported.

As described in chapters 2 and 3 of this study, the study will go deeper into analyzed results. Since the first hypothesis is supported, it is interesting to test the contribution of each interaction channel on the evolution of the CEV factor. A stepwise multiple linear regression is executed.

Table 7
Linear Regression Analysis Results

	β	t	*p*
Overall model			
Intercept	.49	13.62	**.000**
Interaction via all channels	.03	1.56	**.045**

The dependent variable is Evolution in CEV

Stepwise regression is a way to build a model by adding or removing predictive variables. The analysis is first used to determine the different relationships between the interaction channels and the engagement factor. Next, it is tested which combination of interaction channels contributes the most to the evolution of the CEV.

Results show that a linear regression model, containing all the interaction channels as independent variables, has no significant effect on the evolution of the CEV ($R^2 = .03$, $F(1,1014) = 2{,}970$, $p = .08$). In addition, no significant relationship between individual interaction channels and evolution can be observed. In principle, a model with a combination of all interactions cannot explain the evolution in the CEV factor significantly. Using the stepwise multiple linear regression analysis, a significant model was composed ($R^2 = .010$, $F(4,1011) = 2.404$, $p < .05$). This model includes interaction via telephone, mail, direct and e-mail as independent variables and has a significant effect on the dependent variable. However, both the R^2 and the p-value of the multiple linear regression outcomes indicate that the relationship between the independent and the dependent variable is not very strong. By adding one or more interactions per interaction channel, the evolution of CEV can be explained. Furthermore, the linear regression analysis indicates that each of the independent variables within this significant model individually has a significant contribution to the evolution of the CEV. In short, the channels telephone, mail, direct communication, and e-mail have a significant relationship with evolution. The equation for the linear model is: Evolution in CEV = .06 + .55*(Telephone) + .47*(Post) + .43*(Direct Communication) + .50*(E-mail). Analysis show a strongly significant effect of interacting by telephone ($\beta = .55$, $t = 2.71$, $p < .001$). By adding one call, the evolution of the CEV will increase by a value of .55. It seems that interaction over the telephone does have the most effect on the evolution of the CEV, compared to other interactions.

Table 8
Stepwise Multiple Linear Regression Analysis Results (Backward)

	β	t	*p*	*F*	*p*	R^2
Step 1						
Overall model				2.970	.08	.003
Intercept	.49	10.52	**.000**			
Interactions via telephone	.12	1.93	.054			
Interactions via post	.04	.67	.500			
Interactions via direct communication	-.07	-.62	.534			
Interactions via e-mail	.08	.69	.432			
Interactions via booklet	-.43	-2.09	.370			

Dependent variable is Evolution in CEV

	β	t	p	F	p	R^2
Step 2						
Overall model				2.404	.04	.010
Intercept	.06	.30	**.763**			
Interactions via telephone	.55	2.71	**.001**			
Interactions via post	.47	2.30	**.022**			
Interactions via direct communication	.43	2.20	**.028**			
Interactions via e-mail	.50	2.10	**.037**			

The dependent variable is Evolution in CEV

The first model 8 *(Model - Step 1)* shows that the presence of interactions via booklets do not have a significant relation with the evolution in CEV (β = -.43, t = -2.09, p = .370). In fact, by adding one interaction via booklets, the evolution of the CEV will drop down with a value of 0.43. An explanation for this non-significant relation may be that booklets are perceived as more impersonal. Based on this, the variable booklet will not be included in further analyses. More extensive tables can be found in Appendix A. Based on the outcomes of the stepwise multiple linear regression analysis hypotheses 1A, 1B, 1C, and 1D are supported, but hypothesis 1E is not.

4.2.2. Logistic Regression

In addition to testing channel type relationships on the evolution of the CEV, it is also interesting to test the frequency level of interaction; does more interaction result in a higher CEV? However, to test the frequency of interaction, the condition is that single interactions should a significant contribution to the evolution of the CEV factor. As described in chapter 3 of this study, the variance in the original data of this study was too less to test the hypothesis. Many evolutionary values were around 0 or 1, which gave few insights for these hypotheses. A linear regression analysis assumes that a variable is continuous, which was not the case in this study (Lammers, 2007). As a result, the low variance has led to margin significance in the relationship between dependent and independent variables. In addition, the models tested showed little predictive (R^2value as well). Therefore, a stepwise multiple logistic regression analysis was constructed to test whether interaction, the choice of the interaction channel and the frequency of the interactions influence the evolution of the CEV.

The statistical model tests the relationship between the number of interaction and the engagement factor. A binary logistics linear model with a logit-link has been used for this. Within this test it is predicted whether more interaction leads to an increased chance that an evolution of the CEV will be positive or will lead to a decrease or remain stationary. This converted data into binary numbers: 0 (for a decrease or no difference in CEV) and 1 (for an increase in CEV). The logistic model is based on odds, or rather on chance ratios: odds. The odds of an increase or decrease in evolution based on more interaction.

The first step was to check whether adding interactions, regardless of the kind, does have an influence on the evolution and to what extent. The binary logistic linear model contains interaction via all channels as a predictor of the evolution in CEV. Results show that the chance of positive evolution of the CEV by adding one interaction, regardless of the channel, increases by 28.8%

Table 9
Stepwise Multiple Logistic Regression Analysis Results (Backward)

	β	*p*	Exp(B)
Intercept	.61	**.000**	1.832
Interaction via all channels	.25	**.001**	1.288

Dependent variable is Evolution in CEV
AIC = 1161.2

	β	*p*	Exp(B)
Step 1			
Intercept	.45	.350	1.571
Interactions via telephone	.72	.147	2.070
Interactions via post	.52	.296	1.688
Interactions via direct communication	.02	.224	1.023
Interactions via e-mail	.61	.966	1.835

Dependent variable is Evolution in CEV
AIC = 1177.4

	β	*p*	Exp(B)
Step 2			
Intercept	.47	**.043**	1.600
Interactions via telephone	.71	**.008**	2.033
Interactions via post	.51	*.059*	1.658
Interactions via direct communication	.59	**.026**	1.802

The dependent variable is Evolution in CEV
AIC = 1175.5

(*exp*(.25)=1.288, p<0.001). The model goodness-of-fit was assessed with Akaike's information criterion coefficient (AIC = 1161.2). The higher the AIC value indicates a low model fit to complexity ratio, indicating that the model might not include all the predictors for explaining the changes in the response variable. However, the AIC is not evaluative, but should be compared with the AIC value of other models. In this case no variable can be removed and no improved model can be created. More extensive tables can be found in Appendix A. In conclusion, we again found support for the first hypothesis: Interacting contributes to a positive evolution of the CEV.

Subsequently, a stepwise multiple logistic regression analysis was executed to further investigate the influence of interaction through separate channels and the effect of use in a combination of interaction channels on the evolution of the CEV. Analysis, mainly based on the Akaike's information and criterion coefficient (AIC), indicates that a logistic model with the interaction channels telephone, post, direct contributes the most to a positive evolution of the CEV (*AIC* = 1175.5); a lower AIC value represents a more parsimonious model. Therefore, adding one interaction via one of the channels described will therefore increase the chance of a positive evolution of the CEV.

As can be seen, both telephone (*exp*(.71)=2.070, p<0.01) and direct interaction (*exp*(.59)=1.969, p<0.05) contribute significantly to a positive evolution of the CEV. Based on the results, it can be indicated that if the insurer will call a customer, this increases the chance of a positive development of the CEV by 103%. However, it should be noted that a random call is not expected to contribute directly. Further research into the sentiment of these calls have to be conducted to get a better implication of the results. In addition, the results reveal that adding a direct moment of interaction will increase the chance of a positive evolution by 80%. Again, the sentiment of the conversation requires further research. It is assumed, e.g. that a greeting will not be enough. However, the interaction channel post ($exp(.51)=1.658$, $p=0.059$) is not significant at .05 significance level. Still, the contribution of interaction via this interaction channel can be considered significant; the significance level is close to .05 and the effect is significant at the .1 significance level. For a significance level of .1 it is assumed that in 1 out of 10 scenarios the zero hypotheses will be wrongly rejected; interaction via mail has a significant effect whereas this is not the case (Type 1 error) (Kim & Choi, 2019). In addition, this Type 1 fault is not so impulsive, the incorrect estimation of the CEV value will not result in direct consequences - in 1 out of 10 cases attention can be given to customers who turn out to be less loyal.

In conclusion, the effects of the different interaction channels, with the exception of booklets, have been reaffirmed. In addition, it has been shown that more interactions will result in a significantly increased chance of a positive evolution of the CEV with 28.8%. To see all the effects of the separate interaction channels on the chance of positive evolution of the CEV, table 9 can be used.

4.3. The effect of the Customer Interaction Journey

4.3.1. Attribution Modeling

Due to missing values regarding time and day data, testing which interaction within a set of interactions contributes most to the positive evolution of the CEV factor was not possible. Unfortunately, there was no day or time to link to the various interactions in the dataset. As a result, the order of the interactions could not be determined and no value could be attributed to specific interactions within a dataset. Therefore, the third hypothesis could not be tested.

4.3.2. Combination of interaction channels

Finally, the contributions of the combinations of interaction channels to the evolution of the CEV were tested. In order to test whether a combination of the interaction channels telephone and direct communication brings the most contribution to the evolution of the CEV, several combinations of interaction channels were tested as models and compared with each other. As can be seen in table 2, the interaction channel which were used most are the channel telephone ($N = 319$, $M = 0.42$, $SD = 0.51$) and direct interaction ($N = 334$, $M = 0.44$, $SD = 0.52$). In nearly half of all Customer Interaction Journeys, interaction occurred through these channels.

Various models are constructed to test combinations of interaction channels. First, linear regression models are conducted to test whether a combination affects the evolution of the CEV. The following models have been tested: a combination of telephone and direct interaction (R^2 = .007, F(1,820) = 6.89, p < .01), a combination of telephone, direct interaction and post (R^2 = .003, F(1,820) = 3.91, p < .05), a combination of telephone, direct interaction, post, and email (R^2 = .001, F(4,820) = 0.09, p = .76) (Appendix A). Results indicate that a combination in interaction via telephone and direct interaction significantly contributes to the CEV factor's evolution. In addition, comparing the models indicates that a model with this combination gives the most predictive value to a positive evolution. As already indicated, the predictive value of the linear regression models are low. The low variance in the data may be a justification for this. Consequently, logistic regressions are set up to test whether the CEV is more prone to a positive evolution, as a result of a certain combination in interaction channels.

Similar to previous findings in this study, logistic regression models generally provide the same results as logistic regression models: a combination of telephone and direct interaction (*exp*(.14)=1.147, *p*=.363, *AIC* = 912), a combination of telephone, direct interaction and post (*exp*(.08)=1.091, *p*=.554, *AIC* = 912.48), a combination of telephone, direct interaction, post, and email (*exp*(.02)=1.026, *p*=.794, *AIC* = 912.76). A more detailed explanation of the models is given in Appendix A. However, the three models do not differ from each other, again it can be proven that a combination of telephone and direct interaction increases the probability of a positive evolution of the CEV by 14% (figure 5). Again, the sentiment of the interaction needs to be further explored.

In addition, the contribution of the combination of interaction via telephone and direct interaction is not surprising, since interactions via these channels correlate strongly (r = -.473, p <

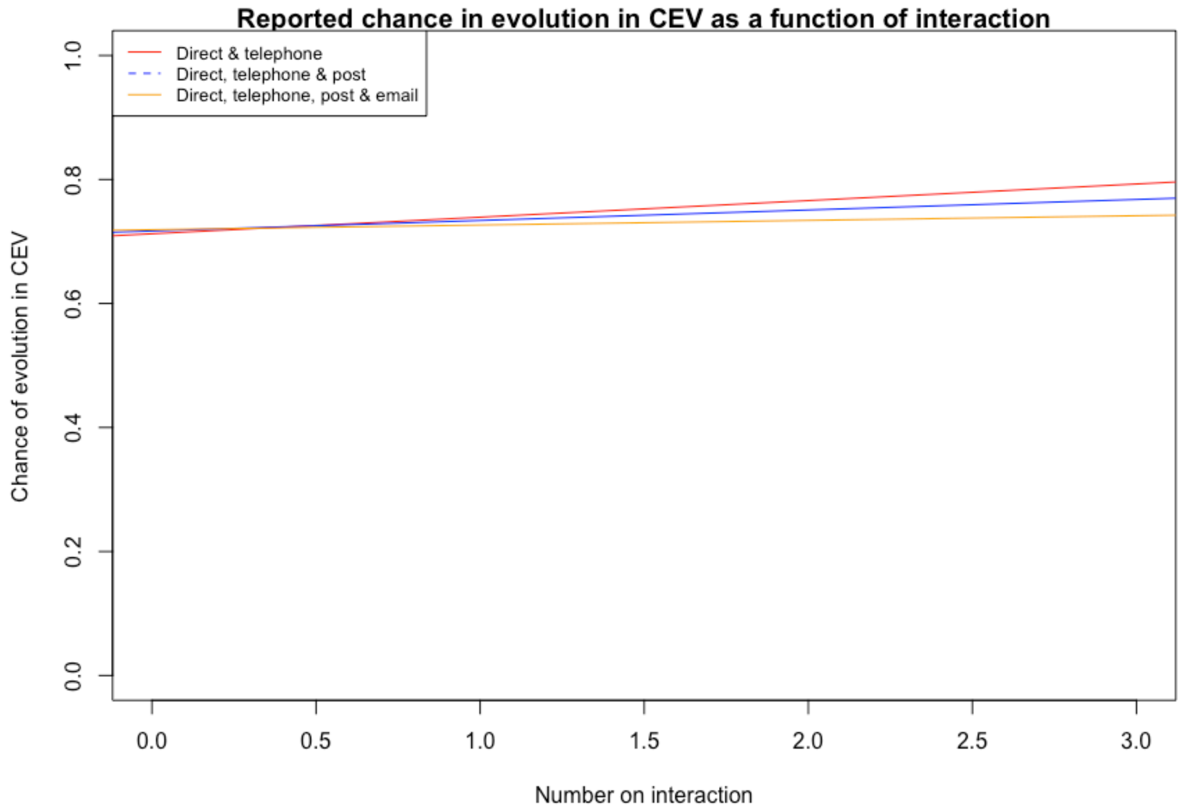

Figure 5. Logistic regression with interaction channel combinations on the evolution in CEV.

0.001) (Table 2). Based on the findings, it was demonstrated that interactions via a combination of telephone and direct interaction increase the chance of positive evolution by 14.5%. Other combinations result in a lower chance of increase. Therefore, the fourth hypothesis is supported.

4.4. Hypotheses testing

On the basis of the results, the hypotheses can be tested. A summary of both the substantiated and unsupported hypotheses is given in table 10. In the next chapter of this research, implications of these hypotheses will be discussed in more detail. The links between the constructs used in the main research, together with the associated hypothesis, are shown in figure 6.

Table 10
Supported and unsupported hypotheses

Hypotheses		Supported?
H1	*Customer Interactions contributes to the evolution of Customer Engagement Value in a B2B contractual context.*	Yes
H1a	*Interaction via telephone contributes to the evolution of Customer Engagement Value.*	Yes
H1b	*Interaction via email contributes to on the evolution of Customer Engagement Value.*	Yes
H1c	*Interaction via post contributes to on the evolution of Customer Engagement Value.*	Yes
H1d	*Direct interaction contributes to on the evolution of Customer Engagement Value.*	Yes
H1e	*Interaction via booklets contributes to on the evolution of Customer Engagement Value.*	No
H2	*Customer Interaction Journeys with the more interactions bring contribute more to the evolution of the Customer Engagement Value.*	Yes
H3	*The first interaction brings the most contribution to the evolution of the Customer Engagement Value.*	Not tested
H4	*A combination in interaction via telephone and direct interaction contributes the most to the evolution of the Customer Engagement Value.*	Yes

First, this model shows that there is a significant of interaction on the chance of positive evolution of the CEV, as well as the significant effect per interaction channel. In addition, the study demonstrates that the combination of telephone interaction and direct interaction results in an increased contribution to the evolution of the CEV, when compared to other combinations. In general, it can be concluded that interactions contribute to an increased chance of a positive evolution of the CEV. In single interactions this is 28.8%, for a combination of telephone interactions and direct interactions this is 14.5%.

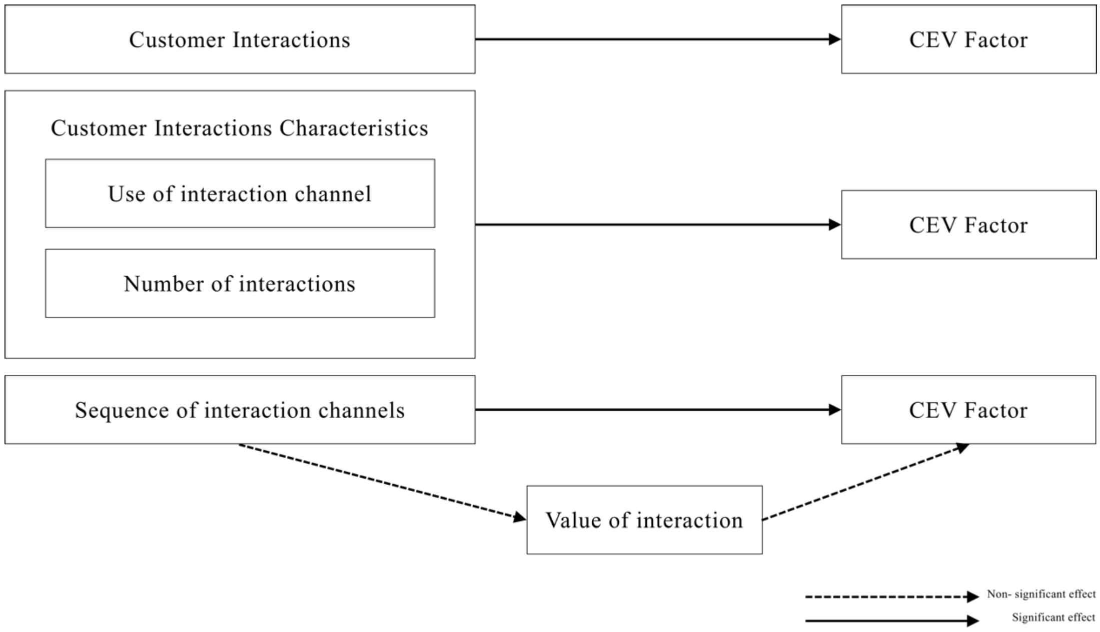

Figure 6. Overview of hypothesized relations between the theoretical constructs.

5. Discussion

The aim of this study was to investigate the effects of the level of interaction, the effect of the interaction per interaction channel, the effect of the use of combinations in interaction channels and the effect of the sequence of use of combinations in interaction channels on the evolution of the Customer Engagement Value Factor. This CEV factor reflects the business value of corporate policyholders at a large Dutch insurer. It was assumed that the independent variables, both individual and interaction variables, do contribute to the evolution of the CEV factor. In addition, it was assumed that the combination of the interaction channels and the sequence of interactions contributes as well. Although not all the hypotheses formulated have been supported, a number of interesting results have been found.

5.1. Discussion of the results

First, the study found that interaction in general does have a significant contribution to the evolution of the CEV in a positive sense. Regardless of the number of interactions and the type of interaction channels, it appears that interaction with a company policyholder will positively increase the chance of a positive evolution in the CEV factor. Adding one moment of interacting will increase this chance with 28.8%, which is not surprising. Although other previous research did not give actual figures, the first main finding of the current research is in line with the findings within earlier research of e.g. Brodie et al. (2013). They found that the level of Customer Engagement Value can be increased by actively interacting with a business' customers. In addition, the current research provides even more insights into the effect of interactions on Customer Engagement Value in the field of a tangible percentage. However, the findings within this research are contradicted with the findings of Sawhne, Verona, and Prandelli (2005). They proved that mainly interaction via the internet will have an effect. This study, however, shows contradictory findings; in particular telephone interaction and direct interaction contribute substantially to the evolution. An explanation for the fact that this effect is not found in the study may because of the fact that the conclusion, renewal or renewal of an insurance contract is still a personal matter. Samp (2017) stated that these personal matters prefer personal, offline interaction. In general, it is found that interacting will positively contribute to the evolution of the Customer Engagement Value.

In the period that a business policyholder has a contract, or during the period that a customer wants to conclude, renew or extend a contract, there are several interactions between the insurer and the potential policyholder. These single interactions together form the Customer Interaction Journey. To go deeper, it was expected that all these separate interactions have separate contributions to the evolution of the CEV factor, regardless of the interaction channel. In general, this expectation is confirmed. However, focusing on the interaction channel indicates that booklet-based interactions will have a negative effect on the evolution of CEV. Interaction via other channels, such as telephone, mail, e-mail or direct interaction (FtF) do have a significant influence on the evolution of the CEV factor. These findings are marginally consistent with the findings of Cebulsky et al (2018), which stated that offline interactions, such as booklets, will shift more to online, multi-channel interactions. However, the significant contribution of direct interaction (FtF) on the CEV factor differ from the findings by Cebulsky et al (2018). A possible explanation for this finding is given by Eckhardt and Räthke-Döppner (2010), who stated that the most effective way to conclude a contract is through direct communication, regardless of whether the policyholder is exclusive or not. The effect of direct (FtF) interaction on the evolution of the CEV factor is an interesting observation, since both the theories and the marketing department of the insurer stated that important interaction will mainly shift from an offline to an online multichannel means of communication.

Third, in line with the first main conclusion, it was expected that more interactions would contribute significantly more to the evolution of Customer Engagement Value, compared to fewer interactions. As concluded in the first part of this discussion, the probability of a positive increase in the evolution of the CEV factor is 28.8% by adding a single interaction in the set of interactions. However, it must be mentioned that the sentiment of the interaction does call for further research. These findings are in line with the research of Lemon and Verhoef (2016) which stated that increasing customer loyalty, or CEV, is coherent with adding up the number of interactions. Next, to go further on the findings of Lemon and Verhoef, the current research focused on the effect of the interaction separately as well. A binary regression is conducted, which measures success (positive evolution) or failure (no or negative evolution). It is found that the effect of interaction via telephone, email, post and direct communication does have a strongly significant effect on the positive evolution of the factor CEV. In other words, by adding up one interaction via one of these channels, the chance of positive evolution of the CEV factor is respectively 103% for interaction via telephone, 80% for interaction via direct communication, and 65% for interaction via post. It must be said that the actual value of the positive evolution in numbers is not clear. A slight evolution of the CEV can be classified as a success, although the change does not necessarily have to do with interaction. However, these high percentages give interesting findings in addition to those of e.g. Lemon and Verhoef, especially for research on B2B insurance industries.

Following the line of reasoning that interaction via the channels telephone, email, post and via direct communication bring a significantly contribution to the evolution of the CEV factor, this brings us to the following expectation. Based on the study by Godfrey, Seinders & Voss (2011) and Barwitz, Körs and Ramezani (2017) it was expected that interactions via a combination of interaction channels do have more effect on the CEV factor evolution than interaction via channels separately. According to the reasoning of these studies carried out, the combination of the use of the telephone as an interaction channel and the interaction via direct communication will contribute most to the evolution of the CEV factor. Binary logistic regression models indicate that a model with telephone and direct communication actually contribute the most to an increased chance of a positive evolution. The theory of Samp (2017) provides an explanation for this: The research stated that personal matters prefer personal, offline interaction. Earlier, Godfrey, Seiders & Voss have previously argued that the phone and direct interaction can be described as personal, partly offline interaction channels. The contribution of a combination of telephone and direct interaction can, at least in an insurance context, extend the findings of the previous studies.

This research was not able to test the value of the several interactions with a Customer Interaction Journey, by means of giving more value to particular interactions. Due to the lack of data, no significant results could be found.

Essentially, interacting with business policyholder does have a direct contribution to the evolution of the CEV factor. Indirect, this CEV factor determines the overall CEV. It can be concluded that interaction contributes to the loyalty of business policyholders. However, clear choices must be made regarding the choice and manner of communication. This research showed that interaction via booklets does have a contrary contribution to the CEV factor evolution. Communication with customers is most effective through telephone interactions and via direct interactions, in other words: Face-to-face interaction. Further, research indicates that the more interaction will result to a higher evolution in the CEV factor. In general, the more interacting with business policyholders, the higher the chance of a positive CEV factor evolution. Therefore, marketers or call centers employees need to interact with customers. Based on this research a maximum of 14 interactions via telephone and direct communication do not directly cause irritation or overkill. However, this study did not study the sentiment of the interactions. It is expected that the sentiment has an important influence on the evolution. The sentiment needs further research, as well as the maximum interactions given irritation or overkill.

5.2. Limitations

Although this study contributed to the theoretical and practical findings, some limitations have been identified. Firstly, the lack of data. Due to this lack it was not possible to relate the different points of the interaction to the correct date and time of the interaction. It was therefore not possible to determine the sequence used by policyholders. Difference in the value per interaction could not be demonstrated. Subsequently, due to the lack of the CEV factor values in the period before 2017, it was not possible to use all 20,033 interactions within the analysis. In addition, only less than 20% of all obtained data could be used, which makes the value of the study lower than if more data could have been used (Rothman, 2007).

Subsequently, the interaction points before policyholders conclude a contract, as well as the data on the sentiment of the interactions, in general, were not obtained within this study. Analysing these data can provide different insights into the way in which the B2B insurer interacts, because these data can provide an explanation of the correct way in which content is used within i.e. telephone calls or direct information. These findings will be very useful and applicable for marketeers or other departments. Furthermore, data in the pre-contractual phase can provide other insights into customer acquisition. The insurer currently focuses mainly on the internet, while both this and other research indicates that personal, often offline, communication is most effective in this context (Eckhardt & Räthke-Döppner, 2010).

As mentioned above, the study shows that personal communication still has a strong significant contribution to the evolution of the CEV factor. However, since the beginning of 2017, the insurer has been using a new communication program relating to customer interaction. This program focuses mainly on the internet as a platform for interaction. The roll-out of this platform was done in the timeframe of the data obtained. Based on this, it may be that the evolution of the CEV factor will be more positive by using the channels that are more focused on the internet when conducting the research at the time of writing this thesis. Subsequently, it is likely that errors were made during the rollout of the platform. These errors may have had a negative impact on the CEV factor in general, or on the channels aimed at the internet (P. Zwikker, personal communication, 16 February 2020).

5.3. Future research

During the current research, new directions of research into the effect of interaction on Customer Engagement Value have been observed. Firstly, due to the lack of data, new research is coming to light. It is expected that the influence of website and app usage, as part of the new communication platform, will play a role in the process of closing, renewing or expanding a B2B policy. Future research should indicate the effect of these channels on the evolution of the CEV factor. Subsequently, the findings of the research can provide insight into the process of concluding, renewing or expanding a B2B policy. This will have practical consequences for various departments of insurers.

Furthermore, based on the findings of this study, the effect of use in interaction channels, as well as the number of interactions, also needs to be tested in the B2C context. If the same finding occurs, the insurer can develop one large interaction strategy for B2B and B2C context. It seems that B2C needs a different approach, but based on the findings in this study, personal communication is very important. The role of booklets in the B2C context should also be tested.

In order to give more value to the findings of this project, the willingness of a (potential) customer to conclude, renew or extend a contract must be made clear. It is expected that when the insurer is dealing with a customer who is not or minimally orientated, the insurer should not 'spam' this customer with information. If the insurer is dealing with a customer who is much more willing to conclude or extend a contract, the insurer must provide the customer with information. This provides new insights into the use of interaction channels.

These indications for future research will provide both the insurer and others with an insight into how to deal with policyholders, especially those with more business value, in order to increase their loyalty.

6. Conclusion

Concluding, the main research question prepared for this study can be answered:

"What is the effect of Customer Interactions on the evolution of the Customer Engagement Value in a B2B insurance context?"

It can significantly be said that interacting with policyholders affects the evolution of the CEV factor in a positive way. In other words, policyholders become more loyal to the insurer by interacting with them. However, interaction have to be in the right way: the more interactions, the more contribution to the evolution in the CEV factor, interacting via the interaction channels telephone and via direct communication will bring the most contribution to the evolution, and by the search for a combination in interaction channels, both channels have to be used. The right sequence of the channels could not be explained.

It can be concluded that this study underlines the importance of the right way of interacting with customers in order to let them become more loyal. Furthermore, this study has contributed to the provision of information in the field of B2B interactions in an insurance context and has provided new insights into this field, both theoretically and practically. Follow-up studies could shed additional light on the role of sentiment and the use of the internet in the way of communicating.

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Appendix

Appendix A: Additional tables and results for the main study

Table A1
Stepwise Multiple Linear Regression Analysis Results (Backward)

	Unstandardized Coefficients		Standardized Coefficient					
	β	SE	Beta	t	Sig.	*F*	*p*	*adj. R^2*
Step 1								
Overall model						2.970	.08	.003
Intercept	.49	.05	.56	10.52	.000			
Interactions via telephone	.12	.07	.05	1.93	.054			
Interactions via post	.04	.20	-.03	.67	.500			
Interactions via direct communication	-.07	.11	-.07	-.62	.534			
Interactions via e-mail	.08	.18	.09	.69	.432			
Interactions via booklet	-.43	.20	-.50	-2.09	.370			

Dependent variable is Evolution in CEV
AIC = -343.43

	β	SE	Beta	t	Sig.	*F*	*p*	*adj. R^2*
Step 2								
Overall model						2.404	.04	.010
Intercept	.06	.20	.06	.30	.763			
Telephone	.55	.20	.55	2.71	.001			
Post	.47	.20	.47	2.30	.022			
Direct	.43	.23	.50	2.20	.028			
E-mail	.50	.20	.44	2.10	.037			

Dependent variable is Evolution in CEV
AIC = -349.02

Table A2
Stepwise Multiple Logistic Regression Analysis Results (Backward)

	β	SE	Wald X^2	Sig.	Exp(B)
Intercept	.61	.14	4.380	.000	1.832
All interactions	.25	.08	10.632	.001	1.288

Dependent variable is Evolution in CEV
AIC = 1161.2

	β	SE	Wald X^2	Sig.	Exp(B)
Step 1					
Intercept	.45	.48	.940	.350	1.571
Interactions via telephone	.72	.50	2.108	.147	2.070
Interactions via post	.52	.50	1.092	.296	1.688
Interactions via direct communication	.02	.55	1.148	.224	1.023
Interactions via e-mail	.61	.50	.001	.966	1.835

Dependent variable is Evolution in CEV
AIC = 1177.4

	β	SE	Wald X^2	Sig.	Exp(B)
Step 2					
Intercept	.47	.23	2.020	.043	1.600

Interactions via telephone	.71	.27	7.034	.008	2.033
Interactions via post	.51	.27	3.565	.059	1.658
Interactions via direct communication	.59	.26	4.969	.026	1.802

Dependent variable is Evolution in CEV
AIC = 1175.5

Table A3

Linear Regression Analysis Results of channel combinations

	Unstandardized Coefficients						
	β	SE	t	Sig.	*F*	*p*	*adj.* R^2
Overall model					1.820	0.010	0.07
Intercept	.45	.04	10.81	.000			
Telephone + Direct	.16	.06	2.62	.008			

Table A4

Linear Regression Analysis Results of channel combinations

	Unstandardized Coefficients						
	β	SE	t	Sig.	*F*	*p*	*adj.* R^2
Overall model					1.820	0.050	0.03
Intercept	.47	.05	10.43	.000			
Telephone + Direct + Post	.12	.06	1.98	.048			

Table A5

Linear Regression Analysis Results of channel combinations

	Unstandardized Coefficients						
	β	SE	t	Sig.	*F*	*p*	*adj.* R^2
Overall model					1.820	0.090	0.01
Intercept	.55	.05	11.48	.000			
Telephone + Direct + Post + Email	.01	.04	.30	.762			

Table A6

Logistic Regression Analysis Results of channel combinations

	β	SE	Sig.	Exp(B)
Intercept	.90	.10	.000	2.476
Telephone + Direct	.12	.15	.004	1.145

Dependent variable is Evolution in CEV

AIC = 912

Table A7

Logistic Regression Analysis Results of channel combinations

	β	SE	Sig.	Exp(B)
Intercept	.92	.11	.000	2.532
Telephone + Direct + Post	.09	.14	.542	1.091

Dependent variable is Evolution in CEV

AIC = 912.48

Table A8

Logistic Regression Analysis Results of channel combinations

	β	SE	Sig.	Exp(B)
Intercept	.95	.12	.000	2.589
Telephone + Direct + Post + Email	.02	.09	.791	1.026

Dependent variable is Evolution in CEV

AIC = 912.76