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Customer Analysis as a Driver of Financial Performance in the Polish Insurance Industry

Abstract: The paper outlines the outcomes of an empirical investigation of the links between involvement of insurance firms in customer analysis and their financial performance. The data were collected through a CAWI survey of independent insurance agents in Poland (n=590). Statistical methods included exploratory factor analysis and structural equation modeling. In keeping with the customer lifetime value model and loyalty management theory the concept of customer analysis was operationalized as a second-order reflective construct, expressed through five first order subconstructs. Financial performance was measured with an index of five self-reported metrics. The findings lend support to the hypothesis of a positive association between engaging in customer analysis and financial performance.
Key words: customer analysis, customer research, customer lifetime value, financial performance, insurance industry, Poland.

Theoretical background

Customer analysis (CA), encompassing customer data collection, profitability measurement and lifetime value estimation, is a crucial component of several well-known

marketing concepts, such as customer relationship management [Reinartz et al. 2004], customer lifetime value management [Doligalski & Tomczyk 2014; Tomczyk 2014; Akroush et al. 2011] customer equity management [Bruhn et al. 2008] and interaction orientation [Ramani & Kumar 2008]. As such, CA components often appear in marketing studies as elements of other constructs or conceptual systems, but comprehensive research that centers on how companies' involvement in CA is linked with financial performance (FP) is scarce. Among a few quantitative studies that addressed this topic, mild positive effects were reported by Akroush et al. [2011], who found that collecting information about key customers by banks and insurance firms had a weak but statistically significant association with financial performance. According to another study, collecting and processing data about customer profitability was a crucial component of how the utility of CRM systems was viewed by managers [Bruhn et al. 2008]; there, the CRM value was strongly dependent on perceived benefits from the use of the system, with the amount of generated profits figuring prominently among said benefits. In contrast, various aspects of CA were found to have only negligible or no effects on earnings in research by Ramani and Kumar [2008].

The role of metrics in performance systems is dependent – among other things – on the type of strategic orientation adopted by the company. In companies with dominant customer orientation, compared to those following product or market orientation, customer-related metrics will play a more important role in systems for evaluating marketing performance. Sheth et al. [2000] list business marketing, direct marketing and services marketing as being at the forefront of customer-centric marketing. As such, metrics of customer profitability and customer lifetime value may be of great benefit since they allow to segment customer portfolio, and to take actions aimed at increasing the value of customer segments. The value of customer portfolio is also an important indicator of a company's valuation [Gupta & Lehman 2002]. The rationale for conducting customer analysis stems from the relationship between customer orientation and sales performance. According to Homburg et al [2011] the effect of customer orientation is similar to an inverted U-shaped curve. Customer analysis should therefore help determine the optimal extent of the investment in a given customer relationship.

On the whole, it seems that the problem of links between CA and FP is not sufficiently investigated, as evidenced by the ambiguity of findings, and the lack of works that take a systematic and complete view of CA. Thus, it can be argued that the current study makes a meaningful contribution to address this gap in marketing theory.

Characteristic of the Polish insurance market

At the time of this research, Polish insurance market was the 14th insurance market in Europe with gross written premiums of 13,9 billion EUR in 2012, which amounted to 1,2% of the European market (Polish Insurance Association, 2013a). In total, 60 insurance companies are authorized to conduct insurance business in Poland (Polish Financial Supervision Authority, 2013). Among them there was a single dominant player – PZU with a market share of around 30% (Polish Insurance Association, 2013a). In regard to market dynamics, the compound growth of the gross value of premiums in the years 2009–2012 amounted to 11% in Section I (life insurance), and 16% in Section II (other personal insurance and property insurance). At the same time, the claims, administrative costs and acquisition costs decreased (Polish Insurance Association, 2013b).

Consumers in the Polish insurance market have had relatively low knowledge of the insurance offer. Perhaps for this reason, they expected access to all relevant information and an intensive contact with the seller to minimize the risk of making a wrong purchase decision [Nowotarska-Romaniak 2014]. The choice of an insurer was mostly determined by a compensation level, an insurer's trustworthiness and fast loss compensation. There was also a country-of-origin effect occurring. Consumers tended to declare the highest level of trust in Polish companies (35%), followed by German (17%) and English ones (14%) [Nowotarska-Romaniak 2014].

By the end of 2012, there were 34,300 intermediaries registered. The number of intermediaries declined slightly from 36,800 in 2007 [Polish Financial Supervision Authority 2013]. This fall can be partially explained by the growing role of sales through direct channels, such as phone and Internet. Despite their dynamic growth, direct channels were still in early stages of development, accounting for only a small fraction of total sales (e.g. 6,5% of sales in vehicle insurance, which may be perceived as a product of small complexity and therefore easy to purchase online). Agents perceived these channels as complementary rather than competitive, since many of their customers expected direct services. Insurance companies attempted to support their agents with information systems handling first contacts, assistance and selling [KPMG 2013]. In general, the role of the intermediaries seemed to be unthreatened by direct channels, especially for more sophisticated services requiring personal assistance during the purchasing process.

Conceptual model

In the current study[1], following guidelines from the marketing and consumer behavior literature, as well as our own observations, we conceptualize CA as a second order reflective construct with five dimensions, each corresponding to a different area of information about customers. Statistically, the dimension attributes were assumed to be first order latent variables measured by a set of Likert-scale items each. This understanding of CA is congruent with the customer lifetime value model and loyalty management theory.

To identify CA dimensions, we looked at several prominent marketing theories, most notably the above-noted customer lifetime value (CLV). CA represents a key element in the measurement of CLV, serving as a method for estimating a current amount of net benefits gained by a company over the length of its relationship with a customer [Doligalski 2015; Borle et al. 2008]. Here, the key value streams are represented by cash flows [Gupta & Lehmann 2003], meaning a discounted difference between revenues and marketing costs incurred to maintain the relationship with a customer [Berger & Nasr 1998]. The need for measuring financial costs and benefits gave rise to the first two CA components of **Customer Costs (COS)** and **Revenues and Earnings (REV)**. Establishing CLV, based on expected costs and earnings, enables firms to differentiate homogeneous customer groups, which is considered an advanced and effective marketing practice. To account for it in our CA dimensions, we came up with **Customer Segmentation (SEG)** as another component of the CA construct.

The above financial metrics, even though critical for effective management, do not provide the full picture of a customer-firm relationship. What is missing are less quantifiable but still very relevant benefits from maintain an individual as a customer [Bauer et al. 2003; Bauer & Hammerschmidt 2005]. CLV is, inter alia, a function of loyalty [Keane & Wang 1995]. Loyalty management calls for information about customer behavior, preferences and referrals, as well as estimation of non-monetary values of key streams delivered to the company during its relationship with the customer (e.g. recommendations, image benefits, behavioral patterns and other insights gained

1. This is a revised and extended version of the paper originally presented at the 6th Regional Conference of European Marketing Association in Vienna, September 16-18, 2015. The major changes include the extension to the literature review and the discussion section, as well as the addition of a characteristic of the Polish insurance market. The same data file was used in a paper published in the Journal of Business Research [Tomczyk et al. 2016], where we took a broader view to evaluate a larger number of antecedents of financial performance. In contrast, this current paper is centred on the role of customer analysis in enhancing profits.

from customers). Thus, we embedded in our model a subconstruct labeled **Intangible Benefits and Customer Behavior (INT).**

Quantifiable benefits and knowledge of intangible customer benefits and behavior are still not sufficient to fully assess the CLV potential. To complement their customer records, companies need to look at prospective clients in terms of characteristics of desired products and services [Doligalski 2015], likelihood of purchasing [Dwyer 1989] and future benefits from customer retention [Rosset et al. 2003]. These future-oriented aspects of CA were operationalized as the final dimension of our measurement model termed **Prospective Customers (PRO).** The specific content of the Likert items used for measuring each of the five subconstructs were given in Table 1 in the results section.

Research objectives and method

The study aims to explore the relationship between the involvement of insurance service providers in customer analysis and their performance. Following on from the presented literature review we proposed that **higher levels of customer analysis would correspond with better financial outcomes**. By the same token, **low levels of customer analysis would characterize relatively underperforming firms**.

To test this hypothesis of **a positive link between customer analysis and financial performance** we collected data from insurance salespersons who operated as independent intermediaries. These were micro-entrepreneurs, catering to both B2B and B2C markets, selling a wide range of popular insurance policies (life and non-life). On the whole, 590 questionnaires with complete response sets were collected through the CAWI method in October and November 2012. The sample was obtained from a comprehensive register that comprised insurance providers from across the whole country. The wide scope and large number of records made the database a fitting representation of this segment of the Polish insurance industry.

The questionnaire included 18 Likert scale items designed to serve as indicators of the observable manifestations of the CA dimensions. The particular statements were informed by extant research on similar topics and partially modified by the authors to be applicable to small-sized insurance intermediaries.

The two main techniques used in statistical analysis were exploratory factor analysis (EFA) and structural equation modeling (SEM), available in SPSS 22 and AMOS 22.

Research Outcomes

The first step in statistical analysis involved an EFA with the maximum likelihood estimation method and an oblique rotation of the factor matrix. The EFA solution confirmed our initial theory-driven assumptions that the employed Likert scale items were appropriate proxy variables for the five distinct hidden variables that represented different focus areas of customer analysis (we chose not to provide detailed outputs of the EFA due to space constraints in the paper). The specific meaning of each hidden variable can be interpreted from Table 1 by looking at its associated items. The pattern of latent and proxy variables displayed in Table 1 was used as a measurement model of CA in the subsequent SEM analysis to test the hypothesis of a positive relationship between customer analysis and financial performance. All Likert items could take values from 1 to 5, where 1 was labeled "strongly disagree" and 5 "strongly agree".

Table 1. Operationalization of Customer Analysis in the study

Focus areas (subconstructs) of Customer Analysis	Item designation	Item content
Customer Costs (COS)	COS1	We collect information about costs of acquiring each customer
	COS2	We collect information about costs of servicing each customer
	COS3	We estimate acquisition costs of each customer
	COS4	We estimate future costs of servicing each customer
Revenues and Earnings (REV)	REV1	We gather information about revenues from providing service to each customer
	REV2	We estimate future revenues from selling to each customer
	REV3	We estimate expected profits from each customer
Intangible Benefits and Customer Behavior (INT)	INT1	We collect information about referrals and recommendations from each customer
	INT2	We collect information about preferences of each customer
	INT3	We try to learn behavioral patterns of our customers
	INT4	We assess the value of information provided by customers
	INT5	We identify the value of image gains from selling to a given customer

	SEG1	We categorize our customers according to estimated future benefits from cooperation
Customer Segmentation (SEG)	SEG2	We make our decisions to cooperate with customers based on estimated amounts of future benefits
	SEG3	We resign from servicing those customers who fail to bring in expected benefits
	PRO1	We determine the likelihood of acquiring each customer
Prospective Customers (PRO)	PRO2	We estimate the length of likely cooperation with each customer
	PRO3	We evaluate likely benefits from cooperating with each customer

Source: own elaboration.

Fully in agreement with our previous conceptual choices, the structural equation model framed involvement in CA as a second order reflective construct expressed through five first order subconstructs (dimensions), as seen in Table 1.

To measure financial performance of insurance agents we used a composite variable formed by taking the mean of scores on the five following Likert-type items: (1) Mean earnings per customer that we have obtained this year are greater as compared to the past year; (2) We expect that the mean earnings per customer will be higher next year as compared to the present one; (3) The average monthly commission that we earned this year was greater than last year; (4) Our total profits this year were greater than the past year's profits; and (5) In the current calendar year we managed to reach our profit targets.

This method of computing is one of frequent ways of establishing values of formative constructs in structural models [Temme et al. 2014]. Financial performance was assumed to be a formative construct since its components could change to some extent independently of each other and the directionality was from indicators to the construct, which was formed by its indicators. By contrast, in reflective constructs the direction is reversed, since it is assumed that a latent variable does exist but is not directly measurable and can only be approximated by how it correlates with its indicators (hence, indicators for reflective constructs must be correlated, which is not required for formative latent variables).

In addition to the outcome and predictor variables the structural model also controls for possible extraneous variables, such as the gender of a firm's owner, the number of serviced customers and the years of work experience of the firm's owner.

The model's layout and its standardized parameters are depicted in Figure 1.

Figure 1. Structural equation model of the relationship between CA and FP *(Significant standardized regression weights and factor loadings were marked in bold)*
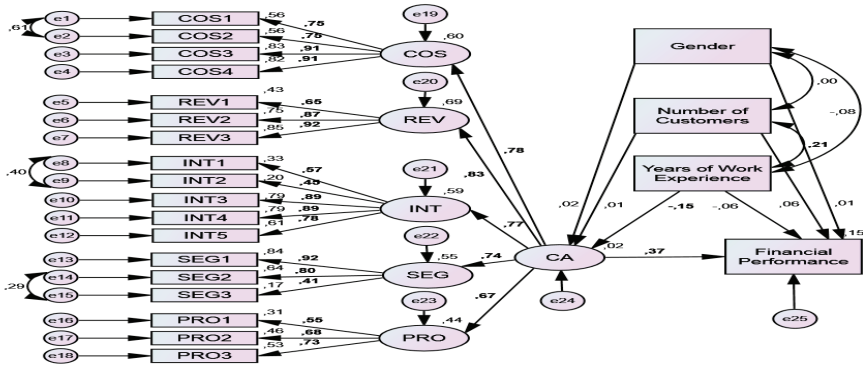
Source: own elaboration.

Before results can be discussed it is necessary to establish the model quality, or how well it fits with the empirical data. To this end, a number of typical diagnostic metrics were computed and set out in Table 2.

Table 2. General diagnostic measures for the structural model

Metric	Value	Threshold for a well-fitting model
Chi-square/df (relative chi-square)	2.942	<2 for good fit, <3 for acceptable fit
p-value for the model	<0.001	>0.05
GFI (goodness of fit index)	0.918	≥0.9
CFI (comparative fit index)	0.941	≥0.9
AGFI (adjusted goodness of fit index)	0.897	≥0.8
RMSEA (root mean square of approximation)	0.057; HI90=0.063	≤0.05 for good model fit; ≤0.08 for adequate fit; in addition, the upper 90% confidence limit (HI 90) should be no more than 0.08 for a well-fitting model

Source: own elaboration. Cutoff points based on Garson [2012].

The goodness-of-fit indices brought together in the table point to a close correspondence of the model with the empirical data. The only exception is the chi-square test, which rejects the null hypothesis of the equivalence of the observed covariance matrix with the one produced by the model. But for large sample sizes chi-square tests tend to be over-sensitive often indicating a bad fit even for apparently adequate models. For that reason, negative chi-square tests could be disregarded if other metrics imply a well-fitting solution, which was the case with the current analysis [Byrne 2010, pp. 76–77; Bowen, Guo 2012, p. 142].

Table 3 looks at individual subconstructs and offers insights into their internal reliability (Cronbach's Alpha), convergent validity (AVE, or average variance extracted) and discriminant validity (MSV, or maximum shared variance).

Table 3. Reliability and validity measures of component constructs in the structural model

Construct	Cronbach's Alpha	AVE	MSV
Costs	0,911	0,693	0,436
Revenues and Earnings	0,848	0,537	0,436
Intangible Benefits and Customer Behavior	0,854	0,544	0,423
Customer Segmentation	0,772	0,550	0,372
Prospective Customers	0,715	0,433	0,314

Source: own elaboration.

All CA dimensions have satisfactory internal validity as Cronbach's alphas exceed the threshold of 0,7 [Malhotra 2014, p. 287]. Convergent validity is deemed sufficient if a hidden variable explains at least 50% of variance it all its indicators, which is demonstrated by AVE values greater than 0,5 [Hair et al. 2010]. This requirement is missed only by Prospective Customers with its AVE at 0,433, suggesting that above half of the variance in the manifest variables under that construct was accounted for by extraneous factors, not included in the model. One such factor could be the marketing strategy followed by a company, which might be quite different to what companies do in the area of customer research, and could be more closely linked to the segments of serviced customers. When such a low value of AVE occurs it could be a justification for removing the construct from the solution. However, the construct could also be retained if there is a compelling theoretical rationale in favor, such as when collecting and processing information from would-be clients is a useful complement of the other areas of CA. In addition, the low AVE value could be a one-off

outcome due to random measurement errors. Hence, we decided to keep Prospective Customers in the model. With regard to discriminant validity, which determines if factors were explained better by their own indicators rather than the indicators for other factors, the metrics do not raise any doubts, since MSV values are less than the corresponding AVEs for each of the CA dimensions [Hair et al. 2010].

It should be noted that the path diagram has three correlated error terms, which was a means to obtain gains in the model fit. Statistics literature indicates that this practice is acceptable if the associated error terms concern indicators under the same construct [Mulaik 2009, pp. 342–345]. It is not, however, advisable to connect error terms across different constructs, not least because ensuing difficulties in interpretation.

In summary, according to the diagnostic metrics the model seems to be a sufficiently accurate representation of the empirical data and could provide a reliable basis for hypothesis tests and interpretations.

Looking at the regression weights between CA, FP and the three extraneous variables, it is clear that CA had a mild but significant influence on FP. The standardized regression weight of 0.36 implies that this factor explained about 14% of variance in financial outcomes, with the rest of variability (86%) accounted for by other determinants not subsumed within the model. In addition, it seems that the positive impact of CA was fairly independent of the salient characteristics of businesses and their owners, as only the Years of Work Experience were slightly negatively associated with CA. This suggests that there might have been some substitution of professional experience for actual research, especially among older respondents, but this does not change the general conclusion of the positive link between CA and performance. As such, **the study provides support for the hypothesis that increased involvement in customer analysis might lead to enhanced financial outcomes.**

Discussion and limitations

According to our findings, CA is positively correlated with FP. This is an important observation, as it justifies activities in the area of CA. The further research may investigate which specific practices and techniques comprising CA are the most effective at improving FP. CA allows customer segmentation, and – consequently – key customer focus [Sin 2005]. This facilitates adopting various measures aimed at customers of unsatisfactory or even negative profitability, which can include relationship termination [Pepers & Rogers 2011].

Our research ties in with the results of several previous studies. Akroush et al. study the influence of four CRM components on financial performance in Jordan's banks and insurance companies (2011). They find that CRM organization, knowledge management and technology-based CRM are positively correlated with financial performance. Interestingly, Akroush et. al did not find a significant direct link between the key customer focus and financial performance. It may suggest that in-depth analysis of customer value is more consequential for a company and its financial results than just offering higher value to key customers. The reason for this may be a large percentage of customers with negative profitability, whose costs of servicing exceed incomes that they generate to a company. Despite similar research areas, our approach was different. Akroush et al. perceive CRM components (especially CRM organization and key customer focus) more through the lens of the value for a customer, while our study concentrates on the customer lifetime value (value of a customer for a company).

Storbacka shows that in the case of traditional (not online) banking services customers with negative profitability may constitute more than half of a customer base [1997]. Such a situation may also occur in other sectors in which a major role in building a value proposition is played by customer service or by offering low margin services. This highlights the need for customer portfolio segmentation, enabling differentiation of actions aimed at specific customer groups. A segmentation-backed strategy targeting unprofitable customers should attempt to increase their value to a satisfactory level, or aim to terminate the relationship altogether. The migration to an online channel may also be a solution as it reduces the amount of customer service in the value proposition, replacing it with self-service, such as in configuring various options of an offer, or designing elements of a product. As a consequence, the value of low profitability customers may increase [Doligalski 2015].

Other types of strategic orientation may diminish the role of customer-centric measurement systems. Sheth and al. mention product and market orientation as previously popular among companies [2000]. Schindehutte et al. present two other orientations dominant at the time of their research [2008]. These are technology orientation, distinguished by prioritizing technology and innovation over the customer, and entrepreneurial orientation involving innovativeness, risk taking and proactiveness. A well designed performance measurement system should reflect the type of selected strategic orientation in order to incorporate the metrics essential for a business. Hence, in measuring the performance of certain types of companies customer-related metrics may not be at the center.

In interpreting our results one should take note of the limitations to generalizability that stem from the specific industry and the national context of the research. Sales of insurance products are characterized by diverse levels of customer service. This leads to the situation in which customers purchasing the same product can generate various levels of costs. In other sectors this kind of costs may be lower and more equally distributed among customers, which may amount to smaller benefits resulting from CA.

Although the presented model proposes that greater involvement in CA leads to FP improvements, the reverse causal relationship is also plausible due to the presence of a feedback loop [Rosenzweig 2007]. Accordingly, better FP may lead to a deeper involvement in customer relations, including an increased use of CA. In our opinion, however, the strength of such a reversed causal link is rather negligible as compared to the primary effect.

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