An Exploratory Study Towards Understanding Communication Preferences of Banking Customers

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Abstract: Banks and service companies in general are facing problems with multi-channel management, especially in the context of outbound communication. Problems are the high costs of the multi-channel systems, unsatisfied customers, and low amounts of customers who interact with companies. Personalization of the selection of communication channel to reach a customer is seen a solution to these problems. However, a complication is that currently no insight exists in what factors can explain channel preferences of customers. These factors are required for estimating the channel preferences of customer. In order to identify these factors a survey has been used to collect channel preferences of banking customers in the context of outbound contact. Furthermore, hypotheses about what factors are expected to explain channel preferences were constructed. These hypotheses have been tested through multinomial logistic regression models. Multiple relations between channel preference and predictors were found. To assess the impact of the findings on the presented problems, it is recommended to start pilots in which the selection of a channel to reach a customer is based on the identified predictors.

Keywords: Multi-channel management, channel preferences, multinomial logistic regression, outbound communication, financial sector

1 Introduction

Intense competition, technical developments and changing customer demands forced service companies to develop an interaction strategy with its customers that really enables to differentiate from competitors (Payne & Frow, 2004; Rosenbloom, 2007; Verhoef & Donkers, 2005). The resulting interaction strategies strongly contributed to the development of the multi-channel management field (Reis, Amorim, & Melao, 2015). The field of multi-channel management can be described as “the design, deployment, coordination, and evaluation of channels through which firms and customers interact” (Neslin et al., 2006). The financial sector has always been an early adapter and innovator in the field of multi-channel management and is therefore a key player for understanding developments in multi-channel management (Cortiñas, Chocarro, & Villanueva, 2010; Reis et al., 2015).

The objective of this article is to improve the understanding of channel preferences of banking customers in the context of outbound communication. First a brief overview of the struggles in the overlapping area of multi-channel management and outbound communication is provided. Based semi-structured interview with customer interaction experts at a large bank and based on multi-channel management and channel choice literature, a conceptual model is proposed. This conceptual model visualizes hypothesized associations between independent variables and channel preference. To test these hypothesized associations a separate multinomial logistic regression (MLR) model is estimated for each communication channel that is in scope of this article. The channel preferences of customers are collected through a survey. The values of independent variables, belonging to the customers who participated in the survey, are collected from a customer database of a large bank. The outbound communication channels that are in scope of this study are: landline, mobile phone, e-mail, mobile app, internet banking. The first three channels are strait forward, the last two are briefly discussed. The mobile app is an application on a smart phone that can be used to organize transactions. Internet banking is similar to the mobile app but is not restricted to a smart phone. Furthermore, it allows the organization of more complex products compared to the mobile app. Both channels can receive messages and are provided by almost all banks.

1.1 Multi-channel management and outbound communication

It is not a coincidence that multi-channel management strategies are especially of great importance in the service industry. The main reason for this is that customers perceive services as more risky than tangible goods (Murray, 1991). The intangible nature of services makes the design and implementation of interaction strategies with customers crucial for service providers. This may even hold stronger when customers themselves perform the service task in-home in absence of the service provider, which is the case for many banking services. Therefore, effective communication between service companies and customers becomes crucial as it can be considered as a requirement to successful customer relationships management (Birgelen, Dellaert, & Ruyter, 2012). From this perspective multi-channel management should be regarded as a concept which provides great opportunities for gaining better understanding of customers and strengthening relations with them (Payne & Frow, 2004).

Rosenbloom (2007) reviewed large amounts of multi-channel management research and identified multiple issues concerning multi-channel management: multi-channel management does not increase the amount of customers who interact with companies, high costs of multi-channel systems, multi-channel management systems causes customers to be unsatisfied. Personalizing the outbound communication strategy is acknowledged as key in solving the identified problems (Godfrey, Seiders, & Voss, 2011). This article only focusses on outbound communication channels. Outbound communication is initiated by a bank. This means that a bank has a specific reason for contacting a customer. Examples of outbound communication by a bank could be: a bank observed that a customer possesses a substantial amount of savings and believes that this customer can receive a higher interest rate with another financial product. In that case the bank want to get in contact with this customer. Another example could be that a bank observes that a customer established his own company and the bank wants to inform the customer about financing opportunities. In both situations a communication channel to reach these customers need to be selected.

When the outbound communication strategy is personalized, customers are only contacted through their preferred communication channel. Firstly, this should lead to a reduction of the number of customers who cannot be reached through outbound communication. Secondly, it should lead to improved customer satisfaction about outbound contact with banks since customers are served according to their preferences. For implementing personalization of the outbound communication process, knowledge about the channel preferences of customers is required. This knowledge is required since the preferred communication channel of a customer needs to be selected. The main barrier in personalizing the outbound communication strategy is a lack of insight in which factors explain communication channel preferences of bank customers (Coelho & Easingwood, 2003). The challenge is to identify factors that explain the channel preferences of customers for outbound contact. Currently no insights in these factors exist within banks. Banks do therefore not know the drivers which determine the preferred communication channel of their customers. This has the effect that banks use communication channels which are not preferred by customers (Wilson, Street, & Bruce, 2008). Furthermore, no prior research to outbound communication preferences have been found during extensive literature research.

Therefore, service industries are looking to the world of online and offline shopping in which extensive research have been performed on channel choice. However, within the field of channel choice, focus has been on the characteristics of channels and how these channel characteristics explain channel preferences of customers (Birgelen et al., 2012; Konus, Verhoef, & Neslin, 2008; Reis et al., 2015). To gain insight in how customer characteristics can explain channel preference a conceptual model is proposed. This model is based on channel choice and customer behaviour literature and visualizes how channel preference is explained by customer related characteristics. The conceptual model is discussed in the next section.

2 Conceptual model and hypotheses

Five drivers for *channel preference for outbound contact* are identified. The identified drivers are: *perceived complexity of contact, value of time, technological skills, activity* and *loyalty.* Additionally, some moderating effects are expected to explain *channel preference for outbound contact.* This conceptual model forms the basis for hypotheses about what factors explain channel preference for outbound contact. As in most multi-channel research a distinction between offline channels (landline and mobile phone) and online channels (E-mail, Internet banking and Mobile app) has been made in the hypotheses.

2.1 Perceived complexity of contact

Service complexity has been found to explain channel choice in a comparison between online and offline shopping (Simon & Usunier, 2007). It is expected that complexity can also explain channel preferences for outbound contact. The main reasoning for this expectation is that the substantive complexity of contact between a customer and a firm is not the same for each situation and that this influences channel preference. Birgelen, Jong, and Ruyter (2006) for example stated that channel preferences are dynamic since routine situations involve standardized procedures with relatively simple decisions, whereas more complex situations require higher involvement and knowledge intensive communication. It is therefore reasoned that customers may have different channel preferences for different situations (Dijk, Minocha, & Laing, 2007; Patricio, Fisk, & Cunha, 2003). Pieterson and Dijk (2007) even observed that citizens tend to prefer face-to-face communication channels for communication with municipal institutions when the perceived complexity of contact increases. Based on the presented arguments it seems likely that a higher perceived complexity of contact increases the chance that a customer prefers an offline communication channel. This is even more likely if the logic of Birgelen et al. (2006) is considered: "the delivery of non-routine financial services, such as mortgage and investment consulting, is more likely to lead to a positive customer evaluation through a face-to-face contact than routine services, such as credit applications, for which customers increasingly use internet banking". The arguments discussed lead to the following hypothesis:

H1: Perceived contact complexity is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

Operationalization

Complexity is operationalized in three levels: high, medium and low. This is common way for measuring complexity in channel management (IntelliResponse & Oracle, 2011). However, just operationalizing complexity by asking *'To what extent do you prefer being contacted through communication channel A in a low/medium/high complex situation'* will not provide reliable data because people will interpret complexity differently. Alexander and Becker (1978) described ambiguity as a major problem in public opinion and survey research. They identified abstract and limited information in questions as the main cause of perceived ambiguity of questions among respondents. To overcome these issues the use of vignettes is proposed. "Vignettes help to standardize the social stimulus across respondents and at the same time makes decision-making situations more real" (Alexander & Becker, 1978). In this study two vignettes per level of complexity (low, medium and high) are used to make complexity concrete and collect channel preferences for different levels of complexity. Each vignette deals with a situation about a financial product. For the construction of the vignettes 25 experts where consulted to help assigning financial products to the complexity levels. The financial products that are selected for the vignettes are: Insight in spending & income and savings account for low complexity, Insurance portfolio and mortgage for medium complexity, retirement related products and investments account for high complexity.

2.2 Value of time

Value of time (VoT) is the monetary value that a person assigns to a unit of time (Dijst, Rietveld, & Steg, 2009). VoT is commonly used in transportation to explain the monetary value of travel and is mainly determined by the money a person could have earned in the time he/she was traveling. Research in the transportation field showed that travellers use the VoT to select a preferred mode of transportation in which travellers with a high VoT select the transportation mode with the lowest travel time to minimize the lost earnings (Dijst et al., 2009; Schoemaker, 2002). It is expected that the same logic accounts for the relation between channel preference and VoT. This means that customers with a high VoT would like to minimize the time spent on interaction with the bank and therefore prefer communication channels with low interaction time. Offline communication usually requires more interaction time and are harder to postpone to a moment when the VoT is lower. The minimization of interaction time by customers with a high VoT has been observed in the comparison between offline and online shopping behaviour of Bitner, Brown, and Meuter (2000); Verhoef and Langerak (2001) where shoppers with a high VoT preferred the online channel. The arguments discussed lead to the following hypothesis:

H2: Value of time is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization
VoT is commonly operationalized by someone's salary (Dijst et al., 2009; Schoemaker, 2002). The VoT is therefore operationalized by the monthly salary that a customer receives on his/her checking account.

2.3 Technological skills

The role of habits in human behaviour has been widely researched in the social sciences. And there is strong evidence that habits influence future behaviour (Aarts & Dijksterhuis, 2000; Birgelen et al., 2012). It is expected that previous behaviour in the context of channel usage also influences preferences for future channel use. Since previous behaviour in the context of channel preference is based on channel choices (for inbound contact) of customers made in the past, the assumption has been made that channel preference for inbound contact is similar to the preference for outbound contact. The logic of this reasoning is that when people use a particular communication channel more often, they are apparently satisfied with the channel. This higher satisfaction with a channel reduces the perceived risk of using this channel (Venkatesan, Kumar, & Ravishanker, 2007). This low perceived risk of channel usage makes it more likely that a customer will use or prefers to use that channel in future interaction with a firm. In the same way does a lack of familiarity with a communication channel and dissatisfying experiences increase the perceived risk of using a channel (Valentini, Montaguti, & Neslin, 2011). The increased perceived risk will reduce the chance that a customer will use or prefer a channel in future interaction with a firm. It is expected that previous usage of online communication channels makes it more likely that an online communication channel is preferred for future interaction. The same accounts for previous usage of offline communication channels. The arguments discussed lead to the following hypotheses:

H3: Inbound usage of online communication channels is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

H4: Inbound usage of offline communication channels is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization
Technological skills in multi-channel literature are commonly measured by the usage of applications to use a channel (Carlson & Zmud, 1999). A remark is that only data available at the ING database can be used. Usage of online communication channels is measured by the number of *logins to internet banking* and *logins to the mobile app* over a period of 3 months. Usage of offline communication channels is measured by the *usage of bank offices* and *usage of the call centre* of a bank over a period of 12 months. A longer period for these channels is used since they are used less frequently than the online channels.

2.4 Activity

Insights from the semi-structured interviews (Expert, 2015) and internal customer behaviour databases of a bank show that customers that are actively using financial products, make less use of offline communication channels compared to customers that are less actively using their financial products. It is expected that this logic also accounts for the channel preference for outbound contact. Reason for this expectation is two folded. The first reason is that customers who are actively using their financial products are online oriented (Gensler, Leeflang, & Skiera, 2012). The online orientation can be explained by the fact that active usage of financial products is mainly facilitated by the rise of online banking services (Payne & Frow, 2004). The second reason is that customers who are actively using financial products understand these products better than customers who do not use their financial products frequently (Birgelen et al., 2012). Consequently, this better understanding of financial products makes it less likely that active customers prefer offline communication for outbound contact. The arguments discussed lead to the following hypotheses:

H5: Activity is negatively associated with the preference for landline and mobile phone, and positively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

Financial activity is regularly measured by the number of transactions performed by a customer (Dholakia, Zhao, & Dholakia, 2005; Gensler et al., 2012). Here the *total number of transactions* over a period of 12 months is measured.

2.5 Loyalty

Loyalty is a phenomenon which develops slowly and is not solely limited to interaction moments between customer and a firm (Lemke, Clark, & Wilson, 2011). Since loyalty is build up during a long period, customers that are long-time customers can be regarded as loyal to a bank. Client data of a large bank shows that loyal customers appear to make more use of offline communication channels compared to less loyal customers. An explanation of this could be that at the time more loyal customers became client, online communication channels were almost not available. Therefore, they are used to using offline communication channels (Valentini et al., 2011). This makes that it is expected that more loyal customers prefer offline communication channels for outbound contact. A second reason for the expectation is that more loyal customers expect a more personal treatment since they are long-time customers, stored large amount of money at the bank and have multiple financial products of the bank (Expert, 2015). Offline communication channels can fulfil this expected treatment. The arguments discussed lead to the following hypotheses:

H6: Loyalty is positively associated with the preference landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound contact.

Operationalization

In multi-channel research loyalty is commonly measured by the *length of relationship* between the customer and a firm (Birgelen et al., 2006). For this reason loyalty is measured by the *length of relationship* between a customer and the bank.

2.6 Moderating effects

Moderating effects that are commonly recognised in the area of multi-channel management and channel choice are included in this conceptual framework. The moderating effects that are included are: *age, education, habitat* and *customer type* (Cortiñas et al., 2010; Dholakia et al., 2005; Pieterson & Dijk, 2007; Strebel, Erdem, & Swait, 2004). Based on the semi-structured interviews some additional moderating variables are included: *number of financial products* a customer possesses, the summation of *the average amount of savings and investments* over a period of 3 months, *possession of Internet* *banking*, and *possession of mobile app*. Special attention goes to the age variable since it has been found to be a major predictor of channel preferences for inbound contact, where age was positively associated with offline communication channels (Birgelen et al., 2012; Simon & Usunier, 2007). For the other moderating variables no specific hypotheses are drawn. This leads to the last hypothesis:

H7: Age is positively associated with the preference for landline and mobile phone, and negatively associated with the preference for e-mail, internet banking and the mobile app in the context of outbound communication.

3 Research method

This section discusses the methods that were used to test the hypothesized conceptual model. First the identified factors of the conceptual model need to be operationalized. The operationalization of these factors has been discussed in the previous section. A complication in the operationalization was that the operationalized variables must be measurable in databases. This is required to predict the channel preferences of customers in the future, without having to collect new data from customers. Next step is to measure channel preferences of banking customers. The third step is to retrieve customer data from databases. These are the attribute values of operationalized factors from step 1. The last step is to perform the data analysis. The measurement of channel preferences and data analysis are discussed in more detail, the measurement of independent variables from a customer database is not discussed since this is a straightforward process.

3.1 Measuring channel preferences: Survey design and respondents sampling

The survey design was strongly influenced by insights which the survey should provide. The required insights which this survey should provide were split into two components: *contact complexity* and *channel preference*. *Channel preference* was measured by asking respondents to rate channels on a scale from 1 to 5. Section 2.1 described that *contact complexity* was measured by vignettes. Two vignettes per level of contact complexity (high, medium & low) were used to measure channel preferences for different levels of complexity. Respondents were not forced to rate the communication channels, since this would have provided biased channel preferences. To avoid biased channel ratings a respondent was first asked whether he/she wants to be contacted for a situation in a vignette. If the respondent did not want to be contacted, no rating had to be provided. High value banking customers (5.500 customers) with an equity of >75,000€ were invited to participate in the survey, 419 responded and 300 of them finished the survey.

3.2 Regression analysis

The dependent variables were measured by a Likert type scale. Consequence of the Likert type scale of the dependent variables was that dependent variables were assumed to have an ordinal or nominal scale. The exploration of dependent variables further showed that respondents either strongly preferred or strongly not preferred the channels landline, mobile and e-mail. The variability in these dependent variables was therefore limited, potentially making it harder to find relations with the independent variables. The assumed ordinal or nominal scale of the dependent variables had large effects on the possible regression techniques that could be used. The easy interpretable technique of linear regression for example does only allow a dependent variable to have an interval or ratio scale (Baarda & Goede, 2006) and was therefore not suitable in this study. Issues with dependent variables with an ordinal or nominal scale have been researched by many authors since the 80' of the previous century. McCullagh (1980) and Engel (1988) strongly contributed to the development of alternative regression techniques for dependent variables with ordinal and nominal scales. This resulted in the Ordinal Logistic Regression (OLR) technique and the Multinomial Logistic Regression (MLR) technique. The OLR models do assume that the dependent variables have an ordinal scale and therefore use cumulative probabilities to relate independent variables to dependent variables. The MLR models do not assume any order in the different levels of the nominal variables. For this reason can MLR be regarded as a combination of multiple binary logistic regression models in which each level of the nominal dependent variable is compared to the one level of the nominal dependent variable, the reference level. Due to the multiple models that are created by the MLR models, interpretation of MLR models is hard. The assumptions of MLR models are however less restrictive than the assumptions of the OLR models (Williams, 2008). Since the important parallel lines assumption of the OLR model was violated, only MLR models were estimated.

Specification of Multinomial Logistic Regression Model.
Ordinal regression assumes the existence of a latent continuous variable of which the observed response variable is a coarse approximation. Multinomial logistic regression does not assume the existence of a latent continuous variable. It does not require such an assumption since it assumes no ordinal scale of the response categories (Bender & Grouven, 1997). Since no ordinal scale of the dependent variable is assumed, the multinomial logistic regression (MLR) model does not use the cumulative probabilities but instead performs multiple binary logistic regressions. It is supposed that the nominal scale response variable (Y) has k response categories. To avoid performing multiple binary logistic regressions the MLR creates *generalized logits* in which response category k is selected as a reference category. In the *generalized logits* the probability π_j, with $j = 1, \ldots, k-1$, is described as the probability of belonging to response category *j* compared to the reference category k. The π_j depends on the value of a vector of independent variables *x* through regression parameters (Armstrong & Sloan, 1989). The *generalized odds* are defined by:

$$\pi_j = \frac{P(Y = j)}{P(Y = k)} \qquad (j = 1 \ldots .. k - 1)$$

The *generalized logits* are with *m* independent variables is defined by:

$$logit(\pi_j) = \ln\left(\frac{\pi_j}{\pi_k}\right) = \alpha_j + \beta_{j1} * x_1 + \ldots + \beta_{jm} * x_m \qquad (j = 1 \ldots .. k - 1)$$

Since the proportional odds assumptions is not applicable for MLR, the MLR model is given by *k -1* equations. This has the effect that each level *k* of the response variable *Y* has its own parameters. So the effect having less strict assumptions is that interpretation becomes harder.

$$\begin{aligned} logit(\pi_j) = \alpha_j &+ \beta_{j1} * Complexity + \beta_{j2} * Education + \beta_{j3} * Gender + \beta_{j4} \\ &* Urbanity + \beta_{j5} * Possession\ ING\ app + \beta_{j6} * Age + \beta_{j7} \\ &* Duration\ relation + \beta_{j8} * Salary + \beta_{j9} * Transactions \\ &+ \beta_{j10} * Login\ Mijn\ ING + \beta_{j11} * Login\ ING\ app + \beta_{j12} \\ &* Office\ visit + \beta_{j13} * Inbound\ call + \beta_{j14} \\ &* Number\ of\ products + \beta_{j15} \\ &* Average\ savings\ \&\ investments \end{aligned}$$

$$with \quad (j = 1, \ldots, 4)$$

When actually calculating the probabilities of belonging to a response category or lower, the logit function describes the following function (Stock & Watson, 2007):

$$\pi_j = \frac{e^{(\alpha_j + \beta_{j1} * x_1 + \ldots + \beta_{jm} * x_m)}}{1 + e^{(\alpha_1 + \beta_{11} * x_1 + \ldots + \beta_{1m} * x_m)} + \ldots + e^{(\alpha_k + \beta_{k1} * x_1 + \ldots + \beta_{km} * x_m)}}$$

4 Multinomial logistic regression results

This section discusses the model diagnostics of the MLR models and results of the hypotheses tests.

4.1 Multinomial logistic regression models diagnostics

The advantage of multinomial logistic regression is that it does not make many assumptions. MLR does not make any assumptions of normality, linearity, and homogeneity of variance for the independent variables. The assumptions for MLR are: the dependent variable should have a nominal scale, no multicollinearity and independent variables should not be able to predict the dependent variable perfectly. When the dependent variables can be predicted perfectly, unrealistic coefficients will be estimated. The dependent variables are assumed to have a nominal scale here and no multicollinearity was detected. For the mobile phone and mobile app models the independent variable *education* caused perfect predictions. This variable has three levels: high, medium and low education. The low education group is very small (only 5% of respondents) and caused the perfect predictions. The problem was resolved by merging the medium and low education categories for both models.

Table 1 shows that all models are significantly better in predicting the dependent variable compared to an intercept-only model. The goodness of fit of the models is only statistically significant (at a 95% confidence level) for the landline model. Meaning that only the landline model fits the data well and the other models do not fit the data well. The outcomes of the goodness of fit tests should be interpreted with great care since the Chi-Square test statistic is very sensitive to independent variables with a ratio level (Allison, 2014; McCullagh, 1980). The reason for this sensitivity to independent variables with ratio levels is that these variables strongly increase the number of potential profiles of cases with identical values. This makes it less likely that the expected distribution of profiles, based on the model, is similar to the observed distribution of profiles the dataset. Consequence is that the Chi-square values are significant for most models, indicating that data does not fit models. An alternative goodness of fit test for multinomial logistic regression models is the accuracy of predictions made by the models (Hoetker, 2007). Hoetker (2007) shows that MLR models can be regarded to have a

Table 1. Diagnostic information of multinomial logistic regression models (*:α=0.05, **α=0.01)

Channel	**Significant model? (Chi-square df=84)**	**Goodness of fit (Pearson chi-square df-3492)**	**Nagelkerke pseudo R-squared**
Landline	357,766**	3373,108	0,348
Mobile	217,390**	3662,363*	0,236
E-mail	281,933**	3756,007**	0,294
Mobile app	416,691**	4794,412**	0,393
Internet banking	332,433**	3769,568**	0,326

good fit when their overall accuracy rate is significantly better than the proportional chance criterion (PCC). The PCC represents a random classification of samples to groups in proportion to group sizes (McGarigal, Cushman, & Stafford, 2000). The PCC can then be computed by:

$$\textit{Proportional by chance criterion} = \boldsymbol{p_1}^2 + \boldsymbol{p_2}^2 + \boldsymbol{p_3}^2 + \boldsymbol{p_4}^2 + \boldsymbol{p_5}^2$$

Where $\boldsymbol{p_1}$ is the proportion of cases in the first group (response category 1) and $\boldsymbol{p_2}$ is the proportion of cases in the second group (response category 2), etc.. The difference between the PCC and the accuracy rate for the predictions in the training sample are standardized in a z-score and tested for significance by a right sided z-table (Marcoulides & Hershberger, 1997). Negative z values indicated that the model performed worse than the PCC and was not fitting the data. As can be seen in **Table 2** all models had significant z-values and therefore all MLR models can be assumed to have a good fit with the data. Combined with the diagnostics of the MLR models in **Table 1** it was concluded that all MLR models were statistically valid.

Table 2. Goodness of fit test with predictive value of models

Channel	**Proportional by chance criterion (PCC)**	**Accuracy of predictions**	**Z-value (if negative model invalid)**	**P-value (α=0,05)**	**Goodness of fit?**
Landline	27%	49%	15,08	0,000**	Yes
Mobile	39%	60%	12,95	0,000**	Yes
E-mail	36%	57%	7,76	0,000**	Yes
Mobile app	26%	53%	18,16	0,000**	Yes
Internet banking	23%	43%	14,10	0,000**	Yes

4.2 Multinomial logistic regression model results

In MLR each independent variable has *k-1* separate coefficient for *k* response categories. This means that for this study 96 coefficients were estimated per channel ((intercept + 14 ratio scale predictors+ 2 categorical scales predictors with in total 9 levels) * *4)*. For all models in total, 480 coefficients were estimated. This was too much information to present in one table. For that reason only the conclusions on hypotheses are presented in this paper. The separate tables with coefficients (odds) are presented in the attached appendix at the end of this article. If an independent variable had a significant relation with the dependent variable the odds values were presented. If there was no significant relation, no odds values were presented. If the presented odds values significantly contributed to distinguishing between response categories *(95%) or **(99%) were used to indicate significance levels.

The results of the MLR models led to accepting about 50% of the hypotheses about the relation between factors from the conceptual model and channel preference for outbound contact. **Table 3** provides an overview of the accepted and rejected hypotheses per communication channel. **Table 3** showed two remarkable patterns which were not expected:

- No association between perceived contact complexity and channel preference was detected for any channel (hypothesis 1).
- Almost all hypotheses were rejected in the MLR model for the mobile channel. This was mainly caused by large differences in the proportions of scores (1,2,3,4 or 5), limiting the ability of the MLR model to find relations in the data.

Table 3. Overview of results from hypotheses tests (a red ‘indicates a rejection of the hypothesis, a green checkmark indicates acceptance of the hypothesis, conclusions were drawn at a 95% confidence interval).

	Landline	**Mobile**	**E-mail**	**Mobile app**	**Internet banking**
H1 (complexity)	✗	✗	✗	✗	✗
H2 (VoT)	✗	✗	✓	✓	✓
H3 (use of online channels)	✓	✗	✗	✗	✗
H4 (use of offline channels)	✓	✗	✓	✓	✓
H5 (active)	✓	✓	✗	✗	✗
H6 (loyal)	✓	✗	✗	✗	✓
H7 (age)	✓	✗	✓	✓	✓

5 Discussion, conclusions, and limitations

Translating the results from the hypotheses test to associations between independent variables and preferences for offline and online channels resulted in **Table 4**. This table shows the significant associations between independent variables and channel preferences that were identified in this study. To enhance interpretability the channels e-mail, mobile app and internet banking were grouped into online channels. The landline channel represents offline channels. The mobile channel was excluded from this table since the ability of this model to detect relations was strongly reduced due to a large proportion negative preference scores. For example, when age increases, the preference for an offline channel (landline) increases. At the same time does the preference for online channels decrease when age increases. It can be seen in **Table 4** that variables which are positively associated with the preference for offline channels, are negatively associated with online channels, which is according to the hypotheses. For the variables which are negatively associated with the preferences for offline channels, no opposite effect was detected at the preference for online channels.

The associations between moderating variables and channel preference were not included in the table but are shortly described: when the level of education increases, the preference for landline decreases and the preference for online channels increases. The results do furthermore show that living in an urban area is negatively associated with the preference for landline and positively associated with the preference for e-mail. Lastly, results indicate that woman prefer landline more than man and have lower preferences for mobile, e-mail, and Mobile app. To assess the expected impact of using channel preference predictions on the required effort to reach customers satisfaction, it is recommended to start pilots in which the identified factors in this article are used to select a communication channel to reach a customer.

Table 4. Associations (at a 95% confidence level) between independent variables and preference for online and offline channels. The channel mobile was excluded from this table.

	Preference for offline channel (landline)	**Preference for online channel** (e-mail, Mobile app, Internet banking)
Positive association	• Use of offline channels • Loyalty • Age	• Value of time
Negative association	• Use of online channels • Activity	• Use of offline channels • Loyalty* • Age

*Only applicable for the channel Internet banking

For the interpretation of the results of this study, limitations of this study should be noted. The most important note is about non-response bias. A check for non-response bias found that there is a risk for biased results since it was likely that on average older men who are actively using Internet banking did respond to the survey. When non-response bias was not avoided it is possible to correct for the non-response bias. The Heckman correction model can be used for assessing and correcting the non-response bias (Sales, Plomondon, Magid, Spertus, & Rumsfeld, 2004). For two reasons it was decided not to apply the Heckman correction model. First reason is that it is not possible to evaluate the effect of the Heckman correction model. This not possible since the channel preference s of customers that did not respond to the survey are unknown. Therefore it is not possible to assess if the effect of the Heckman correction would be valid. The second reason for not applying the Heckman correction model is related to the first reason. It would require substantial amounts of time and funds to perform the correction and collect channel preferences of customers who did not respond to the survey. These time and funds were not available. It should be noted that the Heckman correction model could also help to correct for the sampling bias which was caused by only inviting customers of whom the e-mail address was known for participation in the survey. Since no corrections for non-response bias was performed, results from this study should be interpreted with the caution that the data included an overrepresentation of older men which frequently use Internet banking. For future research it is recommended to apply the Heckman correction model improve the generalizability of the research findings.

Second potential limitation is that the contact complexity hypothesis (H1) was rejected for all communication channels. Meaning that no relationship between contact complexity and channel preference was found in the dataset. Based on section 2.1, which describes that many authors found a relation between contact complexity and channel preferences, the outcome of the hypothesis tests was not expected. This increases the likelihood that not finding a relation between contact complexity and channel preference can be attributed to the operationalization of contact complexity, compared to the likelihood that there is no relation between contact complexity and channel preference. Complexity was operationalized by using financial products in vignettes. The financial products were categorized into three levels of complexity (low, medium, and high) with the help from experts. The usage of vignettes is an accepted technique in surveys (Alexander & Becker, 1978). However, the categorization of financial products into different levels of complexity might have limited the measurement of complexity. An indication of this is that when asked, respondents appeared to perceive the expected contact complexity regarding financial products in the vignettes less complex than the experts. With the consequence that only a limited range of contact complexity is measured and finding a relation becomes harder. To increase confidence in the operationalization of contact complexity, and attitude based factors in general, in future research towards channel preferences of customers, it is recommended to validate the operationalization through the use of surveys or interviews with customers. In this way results based on the operationalization can be used with more confidence.

Third potential limitation is that a considerable amount of coefficients was not found to be significant. Reasons for non-significance could be non-existence of relationships between the independent variables and dependent variables, too many parameters to be estimated compared to the number of observations, or a low signal to noise ratio in the dataset. Noise in the dataset and too much parameters increase the possibility that (weak) relations between independent variables and the dependent variables were not detected, potentially threatening conclusion validity. Reducing the scale of the dependent variables from a five point scale to a three point can be a solution for using the data more efficiently for detecting relationships. Since it will reduce the number of parameters to be estimated and potentially reduces noise in the data, allowing the model to use data more efficiently for detecting relations. It is recommended to replicate this research with dependent variables which have a scale with less levels, preferably three.

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Appendix.

H1: Perceived contact complexity is positively associated with the preference for landline (a) and mobile phone (b), and negatively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound communication.

Table 5. Hypothesis test conclusions for hypothesis 1. X represent a rejection of the hypothesis at a 95% confidence interval. No relation bestween complexity and channel prference was detected for in any model.

Landline	Mobile	E-mail	Mobile app	Internet banking
✘	✘	✘	✘	✘

H2: Value of time is negatively associated with the preference for landline (a) and mobile phone (b), and positively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound contact.

Table 6. Hypothesis 2: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval)

		Landline	Mobile	E-mail	Mobile app	Internet banking
Salary (per €1000)	Response score 1	-	-	-	,912**	,920**
	Response score 2	-	-	-	,942*	-
	Response score 3	,940*	-	-	,949**	,932**
	Response score 4	,937*	-	,910*	,934**	,950**
	Response score 5	0	0	0	0	0
Conclusion		✘	✘	✓	✓	✓

H3: Inbound usage of online communication channels is negatively associated with the preference for landline (a) and mobile phone (b), and positively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound contact.

Table 7. Hypothesis 3: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval)

		Landline	Mobile	E-mail	Mobile app	Internet banking
Login internet banking	Response score 1	1,013*	-	-	1,023*	,993*
	Response score 2	-	,987*	1,011*	1,036*	1,015**
	Response score 3	-	-	-	1.019*	,989**
	Response score 4	-	-	-	1.019*	-
	Response score 5	0	0	0	0	0
Login mobile app	Response score 1	1,028*	-	,964*	,990*	-
	Response score 2	-	-	-	0,964*	-
	Response score 3	1,027*	-	-	-	-
	Response score 4	1,024*			1,006*	
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✗	✗	✗

H4: Inbound usage of offline communication channels is positively associated with the preference for landline (a) and mobile phone (b), and negatively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound contact.

Table 8. ; Hypothesis 4: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval)

		Landline	**Mobile**	**E-mail**	**Mobile app**	**Internet bakking**
Office visits	Response score 1	,742**	-	1,290*	-	-
	Response score 2	-	-	-	-	1,495**
	Response score 3	-	-	-	-	1,200*
	Response score 4	-	-	-	-	-
	Response score 5	0	0	0	0	0
Inbound calls	Response score 1	-	-	-	-	1,145*
	Response score 2	.748*	-	1,355*	-	-
	Response score 3	-	-	1,197*	1,195*	1,230**
	Response score 4	-	-	1,229*	-	1,272**
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✓	✓	✓

H5: Activity is negatively associated with the preference for landline (a) and mobile phone (b), and positively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound contact.

Table 9. Hypothesis 5: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval). In Mobile app and Internet banking relation was not significant.

		Landline	Mobile	E-mail	Mobile app	Internet banking
Trans-actions in 12 months (per 10 trans-actions)	Response score 1	-	-	-	-	-
	Response score 2	1,013*	-	-	-	-
	Response score 3	-	-	-	-	-
	Response score 4	1,017*	1,012*	1,007*	-	-
	Response score 5	0	0	0	0	0
Conclusion		✓	✓	✗	✗	✗

H6: Loyalty is positively associated with the preference landline (a) and mobile phone (b), and negatively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound contact.

Table 10. Hypothesis 6: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval)

		Landline	Mobile	E-mail	Mobile app	Internet banking
Duration relation (per month)	Response score 1	,998*	-	-	-	-
	Response score 2	-	-	-	-	-
	Response score 3	-	-	-	-	1,003*
	Response score 4	,996**	-	-	-	1,002*
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✗	✗	✓

H7: Age is positively associated with the preference for landline (a) and mobile phone (b), and negatively associated with the preference for e-mail (c), Internet banking (d) and the Mobile app (e) in the context of outbound communication.

Table 11. Hypothesis 7: Odds of voting a response score compared to scoring a 5 (preferring a channel very much) ; (* sig. at 95% confidence interval;** sig. at 99% confidence interval)

		Landline	Mobile	E-mail	Mobile app	Internet banking
Age	Response score 1	,909**	-	1,057*	1,036*	1,047**
	Response score 2	,895**	-	-	-	-
	Response score 3	,931**	-	1,039*	-	1,034*
	Response score 4	-	-	-	-	-
	Response score 5	0	0	0	0	0
Conclusion		✓	✗	✓	✓	✓