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Customer segmentation using unobserved heterogeneity in the perceived value-loyalty-intentions link

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Abstract:

Multiple facets of perceived value perceptions drive loyalty intentions. However, this value-loyalty link is not uniform for all customers. In fact, the present study identifies three different segments that are internally consistent and stable across different service industries, using two data sets: the wireless telecommunication industry (sample size 1,122) and the financial services industry (sample size 982). Comparing the results of a single-class solution with finite mixture results confirms the existence of unobserved customer segments. The three segments found are characterized as "rationalists", "functionalists" and "value maximizers". These results point the way for value-based segmentation in loyalty initiatives and reflect the importance of a multidimensional conceptualization of perceived value, comprising cognitive and affective components. The present results substantiate the fact that assuming a homogeneous value-loyalty link provides a misleading view of the market. The paper derives implications for marketing research and practice in terms of segmentation, positioning, loyalty programs and strategic alliances.

Keywords: customer segmentation, perceived value, unobserved heterogeneity, finite mixture modeling

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1 Introduction

The vast majority of research on perceived value assumes that value perceptions affect all buyers in a comparable manner (e.g., Babin, & Babin, 2001; Sheth, Newman, & Gross, 1991) and, therefore, buyers respond similarly in terms of outcome variables such as customer loyalty, word of mouth and willingness to pay. This assumption seems to be unrealistic in many instances of behavioral research. Indeed, some researchers argue that, for any given market offering, heterogeneous interpretations of perceived value and multiple customer segments which apply different weights to the value drivers, exist (DeSarbo, Jedidi, & Sinha, 2001). In a similar fashion, Bolton (1998) claims that a considerable amount of heterogeneity must exist because some customers perceive a higher value for a service offering than others.

Yet, only a few studies have explicitly accounted for buyer (i.e., consumer) heterogeneity in relation to perceived value (Ruiz, Castro, & Armario, 2007) and its predictive power regarding loyalty intentions. Additionally, extant research uses data from single industries only and does not investigate whether there are common patterns of the value-loyalty link across industries. This is surprising for at least two reasons: First, an aggregate analysis of perceived value and its relation to other purchase-related constructs may inappropriately combine members from heterogeneous sub-populations, resulting in parameter estimates that are misleading (DeSarbo et al., 2001). Second, heterogeneity among consumer preferences, attitudes, and perceived value is the main motivation behind customer segmentation (Olsen, Prebensen, & Larsen, 2009). Customer segmentation has become a central concept in marketing and many companies use it to better satisfy customer needs.

Against this background, this study examines unobserved customer heterogeneity regarding the perceived-value - loyalty-intentions link, for the purpose of customer segmentation. A multi-industry comparison enriches the extant knowledge by exploring how the nature of perceived value affects the intention to stay loyal to a service provider. Based on consumption value theory (Sheth et al., 1991; Sweeney & Soutar, 2001), the study uses a multidimensional perceived value conceptualization to identify different consumer segments. These segments differ regarding both their perceived value assessments and associated effects on loyalty intentions towards the service provider.

The present study focuses on continuously provided services, such as those in the telecommunications or financial services industries, in which the duration of the provider-customer relationship is closely tied to profitability. Continuously provided services are characterized by the distinctive feature that the customer typically enters into a formal relationship with the service provider and subsequently consumes the service for a stipulated period of time (Bolton, 1998). Analyzing potential heterogeneity in the customer perceived-value - loyalty-intentions link is particularly important for such services' segmentation efforts.

In order to determine the number of customer segments, the study uses regression mixture modeling. Mixture models assume homogeneous attitudes and intentions within each customer segment, and heterogeneous perceptions across segments (Wedel, & Kamakura, 2000). Additionally, individual level estimates account for individual heterogeneity[1].

This study will be of use to marketing scholars and managers. Knowledge regarding different consumer groups can help firms tailor their market offerings and communications towards each segment more efficiently. Furthermore, determining which value dimensions drive customer loyalty can help firms to develop customer loyalty programs. Since the results are stable across industries, the results can be used in building strategic alliances with companies in other industries, focusing on the same type of customer. Marketing scholars can

[1] The authors thank an anonymous reviewer for this valuable advice.

use the results to further enhance the concept of perceived value. This study also contributes to the issue of unobserved customer heterogeneity, which is still an under-researched area.

2 Conceptual background and model development

This section summarizes prior literature on consumer segmentation based on perceived value and on the empirical methods adopted for this research. Then, it briefly conceptualizes perceived value and its relationship with loyalty intentions and introduces the conceptual model.

2.1 Prior literature on perceived value as a basis for segmentation

Smith (1956) is the first author to have recognized the existence of heterogeneity in the demand for goods and services. Smith bases his assumption of market heterogeneity on the economic theory of imperfect competition. He claims that market segmentation consists of viewing a heterogeneous market as a number of smaller homogeneous markets, with differing product preferences among important market segments. In other words, heterogeneity of customer needs and preferences is the driving force behind market segmentation.

Since its introduction, market segmentation has become a central concept in both marketing theory and practice (Wedel & Kamakura, 2000). Researchers have based the segmentation of markets on various factors, including cultural, geographic, and socioeconomic variables as well as personality, life-style, user status and usage frequency. Customer segments based on these variables may be easy to understand and determine, but may not provide the best possible explanatory power (Wedel & Kamakura, 2000).

As a consequence, marketing scholars highlight the need to account for heterogeneous customer perceptions and expectations in order to develop better firm strategies (e.g., DeSarbo et al., 2001; Slater & Narver, 1998). Similarly, DeSarbo et al. (2001) propose applying perceived value segmentation, emphasizing the failure to incorporate heterogeneity in the underlying dimensions of value. Finally, authors such as Zeithaml (1988), Holbrook

(1994) and Sinha and DeSarbo (1998) agree that the sources of heterogeneity in perceptions of perceived value include differences among consumers, product classes, and consumption situations. Given the need for perceived value segmentation, it is surprising that few studies have specifically addressed this issue empirically.

Swait and Sweeney (2000) discuss an approach to modeling consumer choice behavior based on customers' value orientations and their perceptions of various product and store characteristics. Reflecting a consumer's general value orientation concerning electrical appliances (n = 1,040), they identify three segments: (a) quality-conscious, (b) value-conscious, and (c) price-conscious. The framework they propose requires the joint estimation of a latent segment membership function and a discrete choice model.

In another study, DeSarbo et al. (2001) propose a finite mixture methodology to estimate the a priori unknown number of market segments and perceived value drivers at the market level. In doing so, they find significant differences in perceptions of value for money among business-to-business customers of an electric utility company (n = 1,509).

Ruiz et al. (2007) explain market heterogeneity in terms of value perceptions in the wireless telecommunications industry (n = 877). Specifically, they explore how special treatment of the customer by the service provider, the level of customer involvement with the service, and the customer's accumulated experience with the company act as predictors of market heterogeneity. Based on regression mixture modeling, the authors find five latent segments depending on perceived value dimensions.

Wiedmann, Hennigs, and Siebels (2009) explore a multidimensional framework of luxury value to identify different types of luxury consumers according to the dimensions that influence their perceptions of value. With the application of a hierarchical clustering procedure, four value-based consumer segments emerge (n = 750): (a) the materialists, (b) the rational functionalists, (c) the extravagant prestige-seekers, and (d) the introvert hedonists.

In general, extant research that accounts for market heterogeneity conceptualizes perceived value as either unidimensional (DeSarbo et al., 2001; Swait & Sweeney, 2000; Zeithaml, 1988) or as multidimensional construct (Ruiz et al., 2007; Wiedmann et al., 2009), but without solid theoretical or substantive rationales for such conceptualizations. In contrast, this study conceptualizes perceived value based on consumption value theory (Sheth et al., 1991; Sweeney & Soutar, 2001). Hence, the study explicitly considers cognitive and affective dimensions with potential relevance for consumers' loyalty intentions.

Even more importantly, studies on customer segmentation have neglected the influence of perceived value on behavioral intentions such as loyalty. In other words, prior research has identified customer segments based on perceived value, but failed to consider potential consequences and outcomes of these evaluations. However, particularly the effects of value perceptions on loyalty intentions are of substantial worth for marketing practice in the light of the current competitive landscape of exchangeable service offerings.

2.2 Model development: the perceived-value – loyalty-intentions link

Researchers regard perceived value as one of the most powerful forces in today's marketplace (Patterson & Spreng, 1997) and an underlying source of competitive advantage (Woodruff, 1997), defining it as the customer's overall evaluation of a market offering, based on their perceptions of what they receive and what they give (Zeithaml, 1988).

Recently, researchers have conceptualized perceived value as a multidimensional construct (Babin & Babin, 2001; Holbrook, 1994; Petrick, 2002; Sweeney & Soutar, 2001). Considering functional as well as hedonic and social aspects, the multidimensional approach overcomes the excessive concentration on economic value of the traditional value conceptualization and echoes the growing relevance of emotions in consumer behavior research (Sánchez-Fernández, Iniesta-Bonillo, & Holbrook, 2009). Moreover, the approach accounts for the notion that consumption experiences usually involve more than one type of value simultaneously. Based on seminal work by Sheth et al. (1991) and Sweeney and Soutar (2001), this study adopts an extended four-dimensional conceptualization of perceived value, which comprises both cognitive and affective factors (see also Oliver, 2010). The construct reflects consumers' functional, economic, emotional, and social value perceptions.

One can view loyalty intentions as a customer's psychological disposition toward a marketing offering. Loyalty intentions reflect favorable attitudes toward the brand or firm. To explain the evolution of loyalty, the researcher must consider not only cognitive but also affective aspects (Oliver, 2010; Vogel, Evanschitzky, & Ramaseshan, 2008). As value incorporates cognitive and affective facets (Petrick, 2002; Sweeney & Soutar, 2001), the authors of this paper suggest that perceived value is the key determinant of customer loyalty intentions (Parasuraman & Grewal, 2000). Hence, higher levels of perceived value lead to higher levels of customer loyalty, which, in the long run, determines the success of an organization (Cronin, Brady, & Hult, 2000; Snoj, Korda, & Mumel, 2004; Ulaga & Chacour, 2001).

Figure 1 shows the conceptual model for this study. It reflects the abovementioned proposed link between the underlying dimensions of perceived value and loyalty intentions. The latent variable classes and dotted arrows pointing to the regression paths depict the assumption of customer heterogeneity. It is worth mentioning that this study uses age, gender and service industry as segmentation descriptors but the authors do not claim a causal effect from these variables on the potential differences in the regression paths of the latent classes.

Figure 1 here

3 Methodology

3.1 Data collection and sampling

The authors test the model shown in Figure 1 on two different service industries (wireless telecommunication and financial services), collecting data with an online questionnaire. For both industries, a randomly selected sub sample of the customer data base is contacted by the companies and asked for participating in a research study. Subsequently, the authors only contact customers who agreed on participating in the current study. For Sample 1 (wireless telecommunication service), 1,122 customers of one of the largest European mobile service providers complete the survey (66 % of the customers who initially agreed). For Sample 2 (financial service), 982 customers of one of the largest European debit card issuing companies participate in the study (62 % of the customers who initially agreed).

3.2 Measures

This study adopts a multidimensional conceptualization of value, based on Sheth et al. (1991) and Sweeney and Soutar (2001). It measures the constructs with items that are taken from previous literature (Johnson, Herrmann, & Huber, 2006; Petrick, 2002; Sweeney & Soutar, 2001) and adapted to the present context. The authors conduct two focus groups to test whether the wording of the items is appropriate and the multidimensionality of the value construct. Additionally, they conduct a pre-test with 12 respondents, using a think-aloud-technique. Each construct comprises at least three items, as suggested by Anderson and Gerbing (1988). The survey uses a likert scale ranging from 1 (strongly disagree) to 7 (strongly agree) throughout.

3.3 Assessment of measurement properties

Firstly, the authors conduct an explorative factor analysis to test the underlying theoretical factor structure. Principle component analyses reveal four eigenvalues greater than one, suggesting a four-factor solution. Web Appendix A shows that the factor loadings on the intended constructs are all well above 0.6, with no cross-loadings higher than 0.42. Item loadings lower than 0.2 are not reported in the table. The exploratory factor analysis reveals a simple factor structure for both industries. The data confirms the multidimensional conceptualization of perceived value.

Secondly, the authors run separate confirmatory factor analyses for each sample, to assess the measurement properties of the scales. For both, the measurement model yield highly satisfactory global fit indices (for the wireless telecommunication service MS: χ^2 = 953; df = 98; CFI = .919; TLI = .900; RMSEA = .088; SRMR = .087 and for the financial service DCS: MS: χ^2 = 402; df = 98; CFI = .948; TLI = .937; RMSEA = .056; SRMR = .057). All factor loadings are highly significant ($p< 0.001$) and exceed the suggested threshold of 0.5, demonstrating a high level of convergent validity. Composite reliability (CR), average variance extracted (AVE), and Cronbach alpha scores (CA) suggest a high level of internal consistency. Additionally, there is sufficient discriminate validity since the square root of the AVE is greater than the correlation of each pair of factors. Web Appendix B gives a detailed list of items and measurement properties for each sample. Web Appendix C shows the correlation matrices for each pairs of factors and the square root of the AVE's on the diagonal.

3.4 Model estimation

To estimate the proposed model, the authors selected regression mixture modeling, also called latent class regression (Fruehwirth-Schnatter, 2006; McLachlan & Peel, 2000). These models allow the researcher to account for heterogeneity that is unobservable directly, either because data are unavailable or because the reason for the heterogeneity is, in itself, latent. Research shows the technique to be superior to classic clustering methods (McDonald, 2010; Wedel & Kamakura, 2000) and thus recommends it for customer segmentation since (1) the researcher does not define the classes a priori, but derives them from the data of the segmentation bases (a priori segmentation seems unrealistic because many firms do not know how many segments can be built in advance), (2) the researcher can compare alternative models using statistical and managerial criteria, and (3) the technique groups homogeneous consumer preferences together, so that the researcher can better consider the economic boundaries of customer segmentation compared to individual-level segmentation. Given the advantages of the technique, it is not surprising that previous researchers have successfully applied regression mixture models to comparable applications in marketing (Cortinas, Chocarro, & Villanueva, 2010; DeSarbo et al., 2001; Vriens, Wedel, & Wilms, 1996).

Technically speaking, regression mixture models assume that a certain number K of unobserved segments generate the data. Each subject i (i = 1,…,n) belongs to one of them. Let (y,x) denote an observation, where y is the dependent variable and x a vector of independent variables (typically with an intercept included). Within each segment k, the relationship between y and x is governed by the segment-specific parameter vector β_k. Additional segment-specific nuisance parameters are collected in the vector σ_k'. The conditional density of y given x and $\theta_k = (\beta_k', \sigma_k)'$ in each segment is given as $f(y|x,\theta_k)$ and in our case is the density of the normal distribution with mean $x'\beta_k$ and scalar nuisance parameter σ_k^2, that is

$$f(y|\mathbf{x},\boldsymbol{\theta}_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left[-\frac{(y-\mathbf{x}'\beta_k)^2}{2\sigma_k^2}\right]. \qquad (1)$$

The finite mixture model for all K segments k is then (Leisch, 2004)

$$h(y|\mathbf{x},\boldsymbol{\phi}) = \sum_{k=1}^{K} p_k f(y|\mathbf{x},\boldsymbol{\theta}_k), \qquad (2)$$

with side conditions

$$p_k \geq 0, \quad \sum_{k=1}^{K} p_k = 1.$$

Here, p_k are the (unknown) prior probabilities (or mixing probabilities) of the k = 1,…,K segments, θ_k is as before and φ is the vector of all parameters combined, that is φ =

$(p_1,\ldots,p_k,\theta_1',\ldots,\theta_k')$. To estimate the unknown parameters $\hat{\phi}$ from n observations $\{(y_i,x_i)\}_{i=1,\ldots,n}$, one can use the EM algorithm (Dempster, Laird, & Rubin, 1977) as implemented in M-Plus (Muthén, 1998-2004). Additionally, one can define the posterior probability of (y,x) belonging to any class l,1 ≤ l ≤ K as

$$p(l|\mathbf{x},y,\phi) = \frac{p_l f(y|\mathbf{x},\boldsymbol{\theta}_l)}{\sum_k p_k f(y|\mathbf{x},\boldsymbol{\theta}_k)}. \quad (3)$$

The estimated posterior probabilities for subject i, $\hat{p}$ $(l|x_i,y_i,\phi;i)$ allow a kind of soft partitioning since each subject is assigned a posterior probability of belonging to a class k (k = 1,...,K). This can be used to classify the observation into segment k (hard partitioning) by, for example, assigning it to the class with the highest posterior probability or randomly assigning it according to $\hat{p}$ $(l|x_i,y_i,\phi;i)$.

As subsequent analyses, in this study the authors calculate individual-level predictors based on the finite mixture results. These predictors are parametric empirical Bayes estimates (Deely & Lindley, 1981; see also Kamakura & Wedel, 2004 for an improvement) and, as such, conceptually similar to best linear unbiased predictions (BLUPS) in random coefficient models. The prediction of the value subject i assigns to y (individual-level predictions) is

$$\hat{y}_i|\mathbf{x}_i,\hat{\boldsymbol{\phi}} = \sum_k \hat{p}(k|\mathbf{x}_i,y_i,\boldsymbol{\phi};i)\mathbf{x}_i'\hat{\boldsymbol{\beta}}_k. \quad (4)$$

4 Results

4.1 Determining the number of classes

The authors use Mplus6 for estimating the mixture regression models. Since the authors do not have any prior information about the number of classes, they carry out a series of mixture regression models with K=1,2,3,4 segments (we calculate model solutions with more than 4 classes, but stop since the class size became very small), on each industry separately, to explore the number of classes and class probabilities.

Consistent with current practice and scientific literature, the authors find that using a mix of criteria is best for determining the number of classes and selecting the best model (McLachlan & Peel, 2000). Tables 1 and 2 present the log likelihood values for each solution and give an overview of the indices used to determine the number of groups. Following the findings of a simulation study by Nylund, Asparouhov, and Muthén (2007), the authors particularly emphasize the results of the parametric bootstrap likelihood ratio test (BLRT) for determining the number of classes. BLRT uses bootstrap samples to estimate the distribution of the log likelihood difference test statistic. The authors apply the BLRT to the data in this study using a full set of bootstrap draws (McLachlan and Peel (2000) suggest a maximum of 100 draws) and increase the number of random starts to ascertain whether the results are sensitive to the number of random starts for the k-class model (Nylund et al., 2007).

Finally, the authors use both managerial and theoretical perspectives to select the most appropriate model.

Tables 1 & 2 here

The authors finally select the model with K=3 for the following reasons: First, the BLRT clearly favor a three-class solution. Second, for the four-class solution, class sizes are very small for some groups and the economic boundaries of customer segmentation are better considered if the class sizes are substantial. Third, interpretations of the three-class solutions are logically consistent. Moreover, results are in line with prior findings of comparable applications (Swait & Sweeney, 2000). Fourth, the path coefficients and class means do not differ significantly across some classes when K=4. Fifth and finally, convergence problems and local optimal solutions occur when using four classes. The number of random starting values and the number of iterations have to be larger to produce proper solutions.

Hence, the authors conclude that the model with K=3 is favorable for technical and managerial reasons. The complete results of all calculated models are reported in Web

Appendix D, and only the results of the three-class solution are discussed and compared with the single-class solution in the next section.

4.2 Mixture regression and single-class results

The findings shown in Table 3 indicate that the perceived value dimensions have a substantial and significant effect on loyalty intentions. The top section shows the results for the single-class solution, which assumes a homogeneous sample. The results also demonstrate that perceived functional value is the most important loyalty driver (0.45 for the wireless telecommunication service; 0.43 for the financial service). These results are in line with prior research on perceived value and provide empirical evidence in support of this paper's basic model.

The finite mixture analysis suggests three classes of customers, whose value perceptions along the various dimensions have varying impacts on their loyalty intentions towards the service provider. For example, the standardized estimate of the economic value dimension is rather low in class 3 (0.08), but slightly exceeds 0.5 in class 2 for the wireless telecommunication service. Similar discrepancies occur for the financial service provider (perceived economic value for class 2 is 0.44; for class 3, 0.23).

Next to these interclass differences within each service industry, the results are fairly stable across the industries. In other words, 'common' heterogeneity exists in the perceived value to loyalty intentions link across the two industries. Although this paper does not formulate an explicit hypothesis, the data empirically supports its assumption of customer heterogeneity.

Table 3 here

The comparison of the single-class solutions with the results of the mixture regression analysis shows substantially differences. For example, the importance of perceived functional value is significantly higher in class 1 than in the single-class solution for the wireless telecommunication service (0.45 versus 0.67). Moreover, for the financial service, the two affective (emotional and social) dimensions of perceived value in class 2 have much higher weights than the single-class solution (0.51 versus 0.21). These differences also affect the explained variance. The R^2 of classes 2 and 3 are substantially higher than that of the single-class solution. Again, these differences reflect that the assumption of a homogeneous sample does not hold when measuring the link between perceived value and loyalty intentions.

The results of the member partitioning procedure are highly satisfactory and confirm the three-class solution. The average latent class probabilities for most-likely latent class membership exceed 73% in the wireless telecommunications service sample and 80% in the financial service sample (see Table 4).

Table 4 here

4.3 Subsequent analysis and robustness test

To fully account for heterogeneity and, respectively, gauge the appropriateness of this paper's mixture model solution, the authors calculate individual-level predictors of the regression coefficients[2]. Furthermore, they compare the observed values with the values the latent class regression predicts. Figure 2 presents the histograms of the observed loyalty values for both industries. The smooth line is the density estimation (Gaussian kernel) of the individual-level predictions from the fitted mixture models.

Figure 2 here

The distributions of both industries are skewed to the left, and therefore deviate from a normal distribution. However, the density estimates show that the predicted values follow this general form satisfactorily well. Hence, the three-class solution captures deviations from the

[2] The FlexMix module of R was used for calculating the individual-level predictors.

normal distribution. A correlation between the observed and predicted values of approximately 0.95 reflects this finding. In other words, the results of the finite mixture solution largely capture the unobserved heterogeneity in the data and the remaining heterogeneity within classes is negligible.

5 General discussion and implications

5.1 General discussion

A thorough and comprehensive identification and analysis of what customers actually value is of utmost importance but falls short if it does not account for market heterogeneity. When it comes to loyalty intentions, consumers attribute different weights to the four value dimensions. The results of this paper strongly support the argument that perceived value influences behavioral intentions, but also that the effects differ in magnitude depending on the consumer segment. Hence, the basic model, assuming a homogeneous sample, provides a misleading view of consumer evaluations, with regression coefficients reflecting merely the ‘midpoints’ of given perceptions.

Based on the findings of the finite mixture analyses, the authors identify the following three classes:

Class 1 – The rationalists

Respondents of class 1 give substantially higher weight to the cognitive dimensions of perceived value compared to the single-class solution and, therefore, are called the rationalists. To gain loyalty intentions from this group, functional and economic value are more important than emotional and social value dimensions. Although the cognitive aspects are of predominant importance, in order to secure customer retention, the affective dimensions need to be satisfied on a basic level, as well. Overall, the four perceived value dimension explain more than 60% of the variance in loyalty intentions. The rationalists represent the largest class in the analysis, accounting for 69% (wireless telecommunication service) and 57% (financial service) of all customers. The proportion of female respondents is slightly higher for both wireless telecommunication services (58%) and financial services (55%). Additionally, rationalists are slightly younger than the average customer.

Class 2 – The value maximizers

For members of this group, all value dimensions are relevant in forming loyalty intentions towards the service provider. Hence, members of this class are called the value maximizers. Except for perceived economic value in relation to the wireless telecommunication service industry, value maximizers assign higher weights to all value dimensions compared to the single-class solution. With around 60% explained variance in both industries, the creation of perceived value is equally as important as it is in class 1. Considering this finding, members of this group only express loyalty if firms are able to provide value in all four dimensions. Hence, people in this segment are more likely than those in other groups to take social value aspects into account. They are concerned about other people's opinions and might want to attract attention and be accepted within their peer group. Being the smallest identified segment, the value maximizers comprise 20% of wireless telecommunications service customers and 6% of financial services customers. The proportion of female respondents is lower for both service industries (wireless telecommunications 53%; financial 49%). Additionally, value maximizers are slightly younger than the average customer.

Class 3 – The functionalists

Members of this group concentrate on the functional value dimension when evaluating the loyalty intentions towards continuously provided services and, therefore, are called the functionalists. The remaining dimensions have lower regression coefficients than functional value. Thus, firms need to offer user-friendly and reliable services. Economic, emotional, and social value dimensions are of minor importance when serving this segment. Whereas in classes 1 and 2, perceived value accounts for around 60% of variance, in class 3 only 30% of variance in loyalty is explained by perceived value perceptions. The proportion of female respondents is slightly lower for both service industries (wireless telecommunications 52%; financial 53%. Additionally, functionalists are older than the average customer.

5.2 Managerial implications

The current study contributes to prior perceived value, customer segmentation, and unobserved heterogeneity literature. The multidimensional conceptualization of customer perceived value in explaining loyalty intentions proves successful in two different service industries. Loyalty intentions in the wireless telecommunications and finance industries are not only affected by cognitive value dimensions, such as functional and economic value, but also by affective aspects, such as emotional and social value.

The results may guide future strategic decisions of marketing managers in the service industry in the following ways:

First, the findings of this study show that 'one service offering fits all' is an appropriate strategy in neither the wireless telecommunications nor the financial services industry. Given the existence of common value-based segments across service industries, companies are encouraged to develop segment-specific offerings in order to better target the needs of their customers. The rationalists are by far the biggest group. Hence, from an economic business perspective, it absolutely makes sense to cater for customers in this segment first. However, big companies may not be interested in smaller segments, such as value maximizers or functionalists. This theory implies that specialized companies may be able to run a successful niche strategy to satisfy the needs of these smaller segments. Currently, service providers predominantly engage in efforts relating to price (economic) and quality (functional value). Although companies should provide high performance in these domains for the entire customer base, they might also use value-added services to satisfy segment-specific needs for affective value elements. In the case of both wireless telecommunications and financial services, such add-ons might be tangent to the core service but might also entail product-related elements, for example providing emotional and social signaling value via an attractive, bundled cell phone or specially designed credit card.

Second and related to the previous implications, questions of positioning and service differentiation arise when firms aim to satisfy heterogeneous customer needs. Therefore, some companies have employed different positioning and multi-brand strategies in the past, according to the preferences of their target group. For example, the success of Visa cards is based on its world-wide acceptance (functional value) and its fees, which are affordable to many customers (economic value). On the other hand, Diners Club clearly runs a premium strategy, offering a wide range of value-added services (e.g. airport lounges) at higher costs. Similar examples of different positioning and service differentiations can be found in the wireless telecommunication and airline industries.

Third, companies in the wireless telecommunication and financial service industries should incorporate this paper’s findings into their efforts to achieve customer loyalty. A recent development in the loyalty and reward program literature suggests a differentiation of hard rewards (more cognitively toned, e.g., additional functional or economic added value) from soft rewards (more affectively-toned facets) for loyal customers (Wirtz, Mattila, & Lwin, 2007). Given the differences in the impacts of value assessments on loyalty intentions between segments, the present results recommend offering hard benefits (e.g., price deductions) to rational functionalists, and soft rewards (e.g., VIP tickets for concerts) to value maximizers, who place a high importance on affective value dimensions.

Fourth and finally, segmenting based on the multidimensional value to loyalty intentions link smooths the way for establishing strategic alliances. For instance, functionalists and rationalists may value prepaid wireless services offered at a discount grocery store, whereas those customers seeking multiple value dimensions might prefer the wireless service or financial service provider to engage in a strategic alliance with the leisure industry, thus covering their affective consumption needs. In this case, both industries can benefit from a positive halo effect as the consumers perceive the value dimensions they gain to be sound and cohesive. This might strengthen the perceived brand image and ensure loyalty intentions.

6 Limitations and outlook

Despite the strengths of this study, there are some limitations. First, the authors used data from current users of wireless telecommunication services and financial services. This limits the findings of the study as follows: (a) The authors cannot draw conclusions regarding potential customers and related acquisition strategies. (b) Since service providers are diverse, ranging from medical to financial services, the generalization of the findings to other services may be risky. Inter-industry or even inter-market segmentation is an interesting topic for future research (see Ko, Taylor, Sung, Lee, Wagner, Navarro, & Wang, 2011 for a global application of this concept). The current data set, including only two industries, does not allow for a study about perceived value typology across service industries. (c) The number of industries also limits the pool of analysis techniques. Random coefficient models, which are another promising means of accounting for customer heterogeneity, require nested data. If one uses service industry as a reference variable, one requires a sufficient number of sub-industries to fulfill the statistical requirements of such models.

Second, the data sets consist of survey data only and the study does not consider moderators. Linkages between survey and transaction data may increase the predictive power of customer segmentation. Unfortunately, transaction data are difficult to obtain due to privacy issues and the inclusion of these kinds of data has the drawback that model estimation becomes very complex. This study does not model or empirically test moderating variables, such as trust, commitment, or involvement, which could provide further insights.

Third and finally, research on perceived value assumes linear relationships between the respective variables. Yet, non-linear causal relationships or neuronal networks between perceived value and related constructs are also conceivable (Wiedmann et al., 2009).

Despite these limitations, the authors are heavily convinced that the results are trustworthy and valuable for marketing scholars and managers. Nevertheless, the authors explicitly encourage other scholars to replicate the findings in different industries using the various techniques available for dealing with unobserved customer heterogeneity.

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Figure 1: Conceptual model

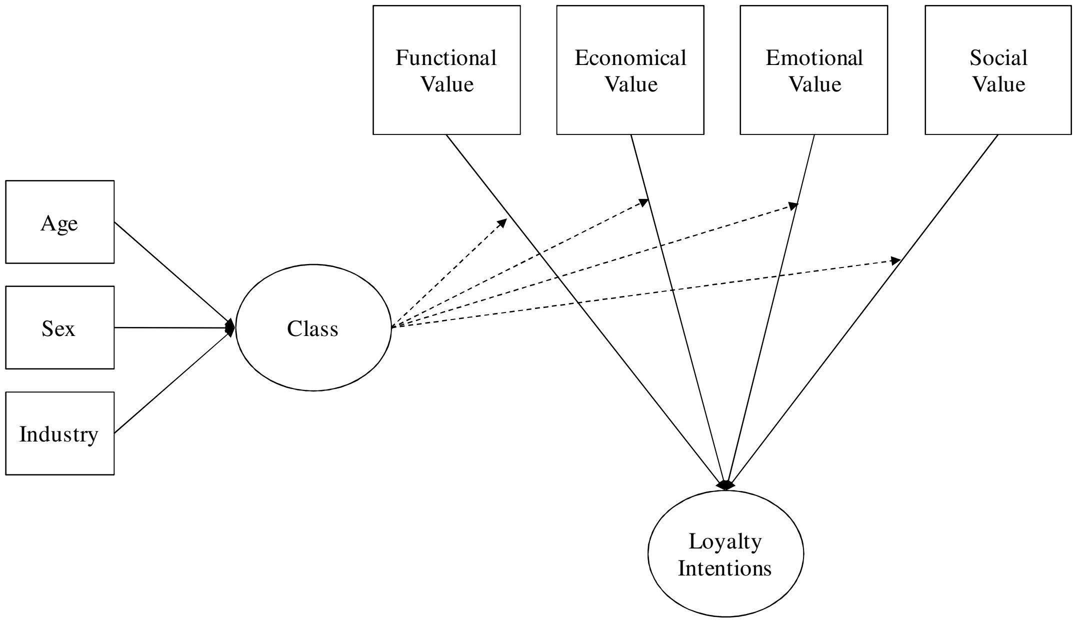
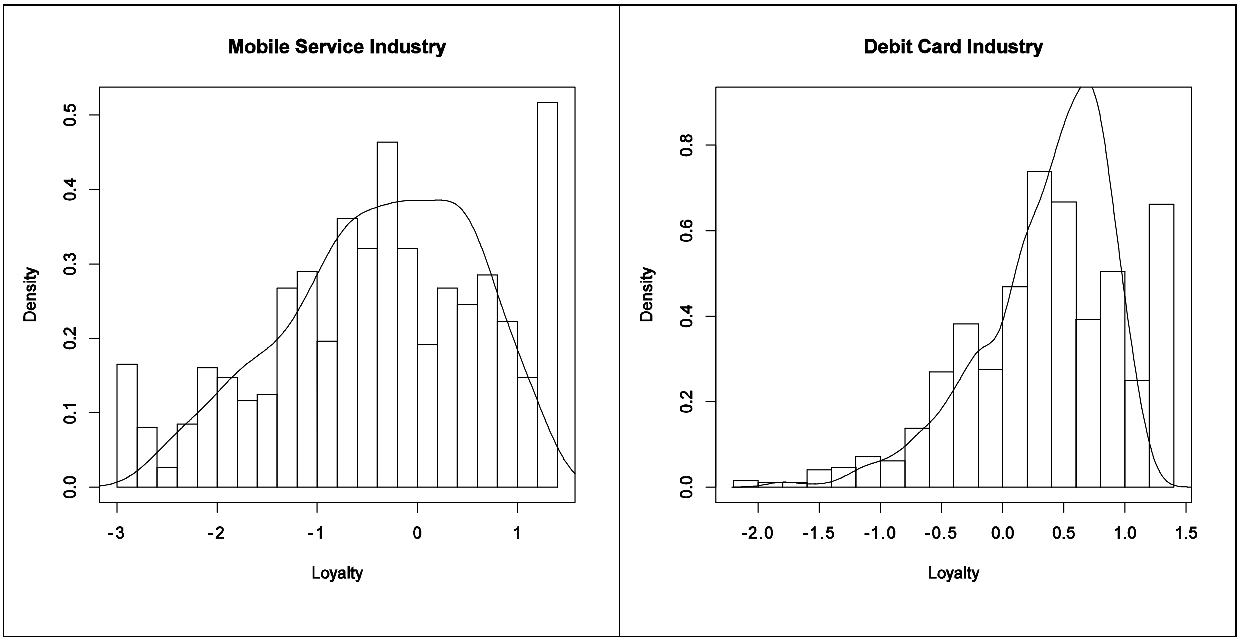


Figure 2: Histograms



Note: Factor scores of loyalty intentions are shown on the horizontal axis.

Table 1: Comparison of fit indices for models with K =2,3,4 classes (Wireless Telecommunication Service)

Model	*LL*	*AIC*	*BIC*	*ABIC*	*ENT*	*LMRT*	*BLRT*
2Class	-1402	2828	2888	2850	.34	.004	.004
3Class	-1372	2781	2872	2814	.47	.001	.001
4Class	-1355	2759	2880	2804	.61	.068	.065

Note: LL = Log Likelihood; AIC = Akaike Information criteria; BIC = Bayesian Information Criteria; ABIC = Adjusted Bayesian Information Criteria; ENT = Entropy, LMRT = Lo-Mendell-Rubin-Adjusted-Likelihood-Ratio-Test; BLRT = Parametric Bootstrap Likelihood Ratio Test

Table 2: Comparison of fit indices for models with K =2,3,4 classes (Financial Service)

Model	*LL*	*AIC*	*BIC*	*ABIC*	*ENT*	*LMRT*	*BLRT*
2Class	-818	1661	1720	1682	.26	.30	.31
3Class	-794	1625	1713	1656	.60	.01	.01
4Class	-779	1606	1723	1647	.48	.26	.27

Note: LL = Log Likelihood; AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; ABIC = Adjusted Bayesian Information Criteria; ENT = Entropy; LMRT = Lo-Mendell-Rubin-Adjusted-Likelihood-Ratio-Test; BLRT = Parametric Bootstrap Likelihood Ratio Test

Table 3: Mixture regression and single-class results

	Wireless Telecommunication Service							Financial Service						
	coeff.	*sig.*	*R^2*	*counts*	*counts %*	*average age*	*females %*	*coeff.*	*prob.*	*R^2*	*counts*	*counts %*	*age*	*females %*
	Basic Model (Single-Class Solution)							*Basic Model (Single-Class Solution)*						
Loyalty /Functional Value	.45	.00						.43	.00					
Loyalty / Economic Value	.32	.00						.29	.00					
Loyalty / Emotional Value	.27	.00						.29	.00					
Loyalty / Social Value	.21	.00						.21	.00					
Total			.41	1122	100	29	56			.28	982	100	28	54
	3-Class Solution							*3-Class Solution*						
Class 1														
Loyalty /Functional Value	.67	.00						.57	.00					
Loyalty / Economic Value	.33	.00						.49	.00					
Loyalty / Emotional Value	.31	.00						.41	.00					
Loyalty / Social Value	.20	.00	.69	775	69	28	58	.30	.00	.60	566	57	28	55
Class 2														
Loyalty /Functional Value	.24	.01						.47	.00					
Loyalty / Economic Value	.52	.00						.44	.00					
Loyalty / Emotional Value	.37	.00						.44	.00					
Loyalty / Social Value	.46	.00	.65	221	20	28	53	.51	.00	.62	61	6	27	49
Class 3														
Loyalty /Functional Value	.50	.00						.47	.00					
Loyalty / Economic Value	.08	.36						.23	.02					
Loyalty / Emotional Value	.22	.01						.28	.00					
Loyalty / Social Value	.09	.20	.31	126	11	30	52	.25	.00	.30	355	36	29	53

Note: coeff. = coefficient; sig. = significance value; R^2 = explained variance of loyalty; ALCP = Average latent class probability
All reported coefficients are standardized parameter estimates

Table 4: Average latent class probabilities

Wireless Telecommunication Service				Financial Service			
Class	*1*	*2*	*3*	*Class*	*1*	*2*	*3*
1	**.73**	.13	.14	1	**.80**	.00	.20
2	.20	**.80**	.01	2	.00	**.82**	.18
3	.24	.01	**.75**	3	.16	.03	**.81**