



Engaging in customer citizenship behaviours to predict customer lifetime value

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Abstract

The aim of this study is to analyse the research gap of the relationship between customer citizenship behaviour (CCB) and customer lifetime value (CLV) in the customer engagement framework (CE). We discuss how marketing analytics gains information from the digital environment related to data, metrics, and online aspects to predict business performance through motivational drivers and engagement. We divide an entire data sample (306 observations) of telecom service customers using prediction-oriented segmentation to test the hypothesis and evaluate the predictive quality of our second-order partial least squares (PLS) model. Results show that brand attitude–attachment, social value, and benevolence are precursors of these voluntary, discretionary, and extra-role customer behaviours called CCBs, and that intentional loyalty plays an essential mediating role in achieving future financial firm performance (CLV). This research analyses from a theoretical and empirical perspective the impact of the customer engagement formation from customer citizenship behaviour on customer lifetime value.

Keywords PLS · Prediction-oriented segmentation · Customer lifetime value · Customer citizenship behaviour · Customer engagement

Introduction

Contemporary customer research stresses that relationships between customers and brands are built on engagement and reciprocity, not just basic transactions and the usage of the brand. Firms and marketers can gain valuable insights from customer-engaged content that will help them to improve their products and services as well as their customer relationship management practices. Customers may engage in a variety of behaviours towards a specific firm. Discretionary, voluntary, and/or extra-role manifestations that define customer citizenship behaviours (CCBs) are also behavioural stances induced by motivation drivers to express customer engagement (CE) with a firm or brand beyond the purchase (Paulssen et al., 2019). CCBs are therefore not necessary for successful value creation but can enhance value for firms, their employees, customers, and potential

customers (Assiouras et al., 2019). Marketing literature also recognises CE's positive (e.g. helping) versus negative (e.g. harming) valence. For this value-based effect, CCBs reflect the focal customer's positive brand engagement (Clark et al., 2020).

Thus, research should identify CCBs that benefit firms financially. These phenomena have been predicted previously, albeit rarely. Therefore, the aim of this study is to analyse the relationship between CCB and customer lifetime value (CLV) in the CE framework.

CE goes beyond purchasing, creating a relationship through value exchange between firm and customer while assessing the customer's psychological state from participating in different firm initiatives (Lemon and Verhoef, 2016). Customers are engaged in firm activities when brand-related content connects with their aspirations and increases their sense of purpose (Malthouse et al. 2019). For this reason, conventional marketing analysis methods based on transactions may not be that relevant for customer engagement contexts, such as online brand communities or social networking sites. In this sense, marketing analytics gains information from the digital environment related

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to data, metrics, and online aspects to predict business performance through motivational drivers and engagement.

Increasingly, customers find that the brand helps them to interact with others to express themselves. They feel proud of themselves for interacting with their preferred providers through social media posts; this positively enhances their engagement. People compare their opinions, abilities, and emotions with those of others for self-improvement or to feel good about themselves (Festinger, 1954). This internal self-assessment is a social comparison with other people (or customers), who they believe are or feel the same, better, or worse (lateral, ascending, or descending comparisons). The process helps them to evaluate themselves more accurately. Citizenship behaviours improve the customer's positive self-image by showing other people (employees and other customers) their engagement and/or prosocial behaviour (Dang and Arndt, 2017). The digital environment favours opinions, emotions, and all kinds of interactions that enable customers to compare their self-images through the prestige of the leading brands of telecom service providers that they use (not low-cost brands from the competition). Customers can also make lateral comparisons between the top three telecom service provider brands in our study.

Taking the above aspects into consideration, our study makes several important contributions to the CE literature, particularly to the CCB field. First, this research contributes to the current predictive analytic models debate about whether both direct/transactional and indirect/non-transactional behaviours can be considered in CE literature. Previous research has explored CCB as a form of engagement, but how CCB affects CLV has not received attention by other researchers (Gong and Yi, 2021), as far as we know. Accordingly, our research addresses this gap in the literature by analysing the relationship between CCB (non-transactional) and CLV (transactional), as well as intentional loyalty mediates between CCB and CLV. Second, we show that the existence of motivational drivers is positively associated with engaging in CCBs. The literature has identified three drivers or equities in order to maximise CLV: value, brand, and relationship (Seyedin et al., 2021). We review the prior literature on CCB to design and propose a model, which incorporates three antecedents of CCB for each of the equities of CLV (value, brand, and relationship). Thus, we contribute to the current body of literature on CE based on motivational drivers and CCB by providing new evidence in the drivers of the CLV model. Third, this study provides a new research stream by using PLS prediction-oriented segmentation (Becker et al., 2013) to form two homogenous groups of observations (customers) for further data analysis (entire and two-segmented sample) over a coefficient path model estimation. To the best of our knowledge, this has not yet been examined in the drivers of the CLV model. We test

these hypotheses using the PLS-POS technique and assess the predictive power, capacity, and relevance of the model by evaluating a holdout sample to cross-validate the final sample (Shmueli et al., 2019).

Theoretical background

Marketing analytics in the customer engagement literature

In customer value management, a customer's value is generally linked to direct customer outcomes such as current and future transactions with the firm. Most analytical "traditional" models that have been developed focus on customer transactions (Bijmolt et al., 2010). For instance, not considering customers' future value or whether they exhibit a pattern of likely attrition or switching to a competitor in the original segmentation models makes it challenging to segment customers for further strategic and personalised campaigns (Kanchanapoom and Chongwatpol, 2022). Moreover, firms can evaluate the effectiveness of their loyalty programmes using the integration CLV and customer migration model to improve customer segmentation and increase profitability (Yoo et al., 2020). In contrast, customer engagement (additionally) includes customer behavioural manifestations that indirectly impact firm performance. Despite this rather narrow perspective, these more "traditional" models that provide knowledge and modelling approaches from the transaction area may be leveraged for model building in a customer engagement context.

In their effort to better understand customer behaviour, new approaches focus on predictive model evaluation, which conforms to PLS-SEM's causal-predictive nature. In this sense, latent class methods developed by marketing researchers, such as PLS prediction-oriented segmentation (PLS-POS), have been shown to have a superior performance in recovering segment-specific model estimates (Sarstedt and Cheah, 2019). Marketing analytics are used to predict customer behavioural patterns. Engagement initiatives are designed to drive sales by assisting and engaging customers, unlike "traditional" marketing interventions designed to create and execute advertising campaigns in addition to prompting sales (Gill et al. 2017). For example, Malthouse et al. (2019) described a model predicting engagement levels for only those dimensions found to affect sales. Furthermore, metrics alignment could be performed between engagement and CLV for description, diagnosis, prediction, and personalised prescription of customer lifetime experience management towards marketing performance (Lemon and Verhoef, 2016). Overall, firms can use analytics to identify and retain profitable engaged customers and get more from each category or segment (Iacobucci et al., 2019).



With the development of engagement theory, indirect/non-transactional behaviours are expanded due to the system and actor-network perspective. Customers are viewed as actors determining their engagement behaviours, and individual and network factors moderate this relationship (Li et al., 2019). Engagement theory encompasses the relationship formation process preceding the process of engaging. The marketing analytics literature offers little guidance on how digital marketing analytics tools should be selected and leveraged to support the firm's overall strategy (Vollrath and Villegas, 2022). Firms should provide mobile application resources and technologies to access the customer and their engagement process (Rodriguez and Boyer, 2020). Nowadays, social media has become a new avenue for firms to engage with their customers and expand their businesses. However, firms who have designed their market space emphasising functionality over the fun element may need to motivate customers to engage (Singh and Kumar, 2021). Thereby, firms should also consider customers' motivations to download branded apps to increase engagement, in addition to the experiential value added to the user when introducing new features to their apps (Llorens and Hernández, 2021).

Customer citizenship behaviour in the customer engagement literature

In telecom service industry, the prevalence of high-involvement products makes it easy to elicit customer interactions and engagement behaviours because of firms promote it in social media platforms. For instance, the top three telecom service providers in Spain provide added value to their customers and distinguish themselves from low-cost firms by offering so-called convergent packages that combine land-line and mobile connections and include paid audio-visual services. Moreover, they conduct giveaways and contests, such as raffles of high-end terminals, as social media posts of this type elicit high levels of interaction and engagement. They also generate content related to new 5G technology or augmented reality products, offer reference content related to their sports programmes, hold events that include open questions to users or encourage participation through emojis, and post humorous or creative content that users can identify with. In fact, the top three telecom service providers in Spain lead all firms and sectors in publishing social network content on promotions, service offers, and customer service (IAB, 2021).

However, CEB can be initiated by a firm's stance or customer. When customers engage cognitively and affectively with a brand, they are more willing to behave favourably towards it by purchasing its products/services, promoting it, influencing others on social media platforms, and providing valuable feedback to the brand (Bozkurt et al.,

2021). Consequently, firms expect that their investments in new technologies and platforms will encourage CE, as well as CCB, and ultimately produce positive financial returns. Online brand communities are used to support customers when they encounter product problems because some customers who receive good social support exhibit CCB. The characteristics of in-store technology can also be moderated by customer education, which increases CCB in retail stores. In this sense, Gong et al. (2022) provide evidence that perceived complexity and perceived risk lead to customer exhaustion, resulting in decreasing CCB. In contrast, perceived advantage and perceived compatibility lead to CE, resulting in increasing CCB. Furthermore, many individual characteristics of customers can influence cognitive processes and decision-making in predictable ways that affect behaviours. The role of customers' traits (friendliness, extraversion, prosocial, and proactive personality) have been studied as predictors of CCB (Choi and Hwang, 2019). Recently, homophily was studied as a motivational driver that can actively induce extra-role behaviours like CCB (Mandl and Hogreve, 2020).

CE behaviours (CEBs) are manifestations that go beyond transactions with a brand or firm that result from motivational drivers (van Doorn et al., 2010). Engagement is a motivational state that occurs by virtue of an individual's focal interactive experiences with a particular object (brand) or agent (firm). Dessart et al. (2017) demonstrate that customer–firm identification, self-enhancement goals, and social integration are associated with engagement. Choi and Lotz (2016) provide evidence that self-enhancement is one of the driving factors in CCB. According to social comparison theory and Festinger's studies (1954), individuals have a drive for self-improvement that leads them to compare themselves with others who are seemingly better off. The fulfilment of this psychological need leads to a connection between customers and brands because 'people are motivated to create a favourable and consistent self-identity' (Escalas and Bettman, 2003, p. 340). A related theory, social identity theory, has broader implications. It relates the individual to reference groups such as virtual communities and clubs, whereas social comparison theory focuses on the way individuals compare themselves with others to improve themselves and achieve a social identity. People possess an internal drive to compare their opinions and abilities with those of others, and the process of social interaction satisfies this social need (Festinger, 1954). When customers perceive greater value, they will be more motivated to help a firm in return through a desire for reciprocity. If an individual cannot access his or her own self to make comparisons, the positive image of the interaction partner is used as a motivation driver for self-enhancement. Social exchange theory posits that internal comparisons are used to compare rewards with an individual's expectations of reward (Dang and Arndt,



2017). Consequently, motivational drivers are particularly crucial for voluntary behaviours in CCB and CE (Burnham et al., 2021; Choi and Lotz, 2016; van Doorn et al., 2010).

The CCB literature accepts the firm–customer relationship not only as a specific form of social exchange (Bowen, 1990), and an outcome of commitment and trust in the buyer–seller relationship (Gruen, 1995), but also as a form of CE (Groth, 2005). Thus, CCB strengthens the customer–brand relationship and reduces service costs, providing great value to marketers (Groth, 2005). Firms' value co-creation is also associated with manifestations of customer intention to engage in citizenship behaviour (Assiouras et al., 2019). Mitrega et al., (2022) propose that CCB be defined as the voluntary, extra-role, and non-monetary customer behaviours that help a firm create value. According to Mitrega et al. (2022), CCB relates to concepts such as CE (van Doorn et al. 2010), customer participation (Dong and Sivakumar, 2017), and value co-creation (Yi and Gong, 2013). Scholars distinguish between two key customer behavioural roles: in-role and extra-role behaviours. Customer participation contributes to the service experience: individuals' participation may benefit both themselves and other customers (Dong and Sivakumar, 2017). Customer in-role behaviours involve financial transactions, and customer participation is required to obtain a service (Yi and Gong, 2013). In contrast, customer extra-role behaviours do not involve financial transactions and are not required for the service, although they do add value to the firm (Paulssen et al., 2019).

Scholars recognise that CCB is a positive, non-monetary, extra-role consumer action in favour of a firm, but they continue to dispute its dimensions (Mitrega et al., 2022). Groth (2005) categorises CCBs into three types of behavioural manifestations: a) those oriented towards the organisation providing feedback, b) those oriented towards helping other customers, and c) those oriented towards making recommendations. The three dimensions proposed by Groth (2005) are recognised in the CCB literature and have been revised by Yi and Gong (2013) into four dimensions: feedback, advocacy, helping, and tolerance. They complement the core CCB structure developed by Groth (2005). A recent review by Gong and Yi (2021) summarised the CCB dimensions in the value creation process as making recommendations, providing feedback to the organisation, helping other customers, displaying relationship affiliations, participating in the firm's activities, benevolently facilitating service, and being flexible. Mitrega et al. (2022) identified the dimensions of CCB somewhat differently, listing feedback, tolerance, advocacy, helping others, displaying affiliations, courtesy, rituals, and mitigating others. Yet the individual facets of CCB and their effects have not been clearly defined. Overall, the literature treats CCB as a one-dimensional behaviour

that customers may engage in and that has antecedents and consequences.

Hypotheses

Increasingly, firms promote strong emotional connections to their brands to achieve CE. Brand attachment refers to the emotional connections that consumers develop with brands that reflect their self-images (Japutra et al., 2018). The brands rely on hedonic and social values to create an emotional bond with the customer (Barari et al., 2020). The effects of actual and ideal self-image congruence on emotional brand attachment are stronger for high-status brands. Recent findings depend on motives such as self-esteem or social approval in an emerging in an Islamic country (Klabi, 2020). Social comparison theory also supports the notion that such an experience can be an emotional process (Festinger, 1954). Previous studies have found that brand attachment does not have a direct effect on CCB but only a mediation effect through perceived value (Cheng et al., 2016). Although previous studies have shown that there is no direct effect of brand attachment on CCB, the theoretical framework supports the existence of a direct relationship.

H1. Brand attitude/brand attachment positively influences CCB.

Firms promote CE with functional and experiential initiatives. According to Park et al. (2021), engagement is greatly enhanced by perceived functional value, followed by personal value and social value. Hsiao (2021) recognise the importance of socialise with people to make purchases through commerce activities and social utility of social media use. Social value is mostly realised through status and self-esteem enhancement related to social self-concept. It means that Social value has a significant effect on behavioural intention to social commerce and it derived from the utility to enhance social self-concept. This dimension makes it easier for individuals to compare themselves to others through the social image of the brands they buy or use. A brand's positive reputation is part of its perceived quality in a social context and can increase favourable customer behaviours towards it. Therefore, what customers think of a firm affects CCB and loyalty (Bartikowski and Walsh, 2011). Abdelmoety et al. (2022) indicated that value relevance and ethical standards are key drivers of retailer commitment to CSR (viewed as firm's reputation), which in turns lead to CCB.

H2. Social value positively influences CCB.

To participate in long-lasting, engaging relationships that involve an exchange of benefits, customers need



to trust a firm. Benevolence is a component of trust in relationships; therefore, firms are willing to try and avoid any behaviour that could be detrimental to building partnerships with consumers. Mal et al. (2018) show that customers associate benevolence with the organisation that owns a brand rather than the product or service that is branded. Therefore, they highlight the provider's ability to continue to meet customers' expectations in the future. Caring improves the belief in benevolence and is a basis for building and transferring trust. Caring is a cognitive process that reduces the dissonance associated with holding divergent beliefs about parties perceived to be associated with oneself (Festinger, 1954). Bove et al. (2009) observed a positive association between the perceived benevolence of service workers and CCB. Chan et al. (2019) consider benevolent acts of service facilitation (for instance, cooperating with a service employee) the result of an organisation's discretionary preferential treatment of customers. Ghomi et al. (2022) found that suppliers' benevolence towards customers enhanced customer flexibility towards the suppliers. Customer flexibility permits suppliers to adjust their service or product offerings and increases customers' willingness to accept products or services with less desirable attributes.

H3. Benevolence positively influences CCB.

Kim et al. (2019) argued that a holistic concept of perceived innovativeness in restaurants was the key predictor of customers' value co-creation behaviour. Such behaviour is composed of two subdimensions: customer participation behaviour and CCB. Both subdimensions lead to customer satisfaction and loyalty. Efficiency-centred and novelty-centred business models that are designed from the customer's perceptual perspective can directly affect customer loyalty and indirectly affect it through the mediating role of CCB. Therefore, CCB has a significant and positive impact on customer loyalty (Hu et al., 2020). Revilla-Camacho et al. (2017) examined the customer-related antecedents of the customer's intention to switch firms. They found that CCB was a key antecedent of satisfaction, trust, and attitudinal loyalty in users of beauty-care service firms in five countries. In turn, satisfaction and trust were correlated with customers' intentions to abandon relationships with their service providers, whereas attitudinal loyalty was not related to the intention to switch.

H4. CCB positively influences intentional loyalty.

'Good' consumers are evaluated on financial metrics such as sales volume, revenue, profit, or CLV. Silveira et al. (2017) claim that a static model of CLV can be equivalent to a dynamic model to achieve these commonly accepted financial metrics for CLV. The marketing literature recognises that both types of models are good proxies for

the market value of firms. Incorporating a measure of the market value is key to relating marketing effort to customers, market valuation, and firms' financial success. Segarra-Moliner and Moliner-Tena (2016) find evidence for the relationship between intentional loyalty and CLV. Yoo et al. (2020) observe that the implementation of differentiated segmentation for Casino loyal customers produce positive CLV.

H5. Intentional loyalty positively influences CLV.

Some scholars have suggested examining the effect of CCB on components of firms' financial performance, such as profitability or CLV (Bove et al., 2009), market share, return on equity, sales, Tobin's q (Yi and Gong, 2013) and profits (Paulssen et al., 2019). However, these proposed CCB investigations have not yet been performed, although researchers have studied the impact of CCB on performance outcomes (Groth, 2005; Bove et al., 2009). We found studies of the relationship between CCB and sales performance in the business-to-business literature. Gong (2019) recently reported that CCB is positively related to sales volumes through employee satisfaction and performance. The customer's decision to stay or leave can be determined by the perceived benefits (or loss of benefits) received from the customer experience delivered by the current provider (Temerak and El-Manstrly, 2019). The more citizenship behaviour creates a pleasant social context, the more likely customers are to enjoy and gain from the service experience. However, there is a gap in the literature: researchers have not focused on the role of CCB as an economic metric or predictor of firms' financial performance.

H6. CCB positively influences firms' financial performance (CLV).

Measures, sample, and telecom service providers in Spain

Brand attitude–attachment, social value, and benevolence are antecedents of CCB in the model developed. We measure brand attitude–attachment, social value and benevolence using the same measurement scale as Segarra-Moliner and Moliner-Tena (2016). We encompass three subdimensions of CCB. We use the measurement scale developed by Bartikowski and Walsh (2011), based on Groth (2005), to measure helping customers (three items) and provide feedback (three items), as well as two items of Groth's (2005) original scale to measure recommendations (one item detached, see Annex). The consequences of CCB in the developed model are Intentional loyalty and CLV. We measure Intentional loyalty using the same measurement scale as Segarra-Moliner and Moliner-Tena (2016) and



calculate CLV based on Silveira et al. (2017) and Segarra-Moliner and Moliner-Tena (2016).

The items of these composites: brand attitude–attachment, social value, benevolence, and intentional loyalty are evaluated on a scale of 1 to 5, where 5 is very high and 1 very low. CCB also includes the indicators on a Likert scale of 1 to 5 points, ranging from 1 (0–20%) to 5 (80–100%). The questions are preceded by the following question: ‘Based on your past experience with this firm, how likely are you to ...?’. Silveira et al. (2017) describe a continuous scale in the formula $CLV = (m * r) / (1 + i - r)$. Two items define the composite of CLV, where the variable ‘margin’ is the only one calculated differently to achieve two reflective indicators. The margin (m) or the income from the customer is multiplied by 12 months and calculated from personal monthly spending. It is also calculated from household monthly spending divided by the number of household members. The remaining parameters of the equation are the same. The retention rate (r) is measured in the same way as Silveira et al. (2017) in the static model. That is, for the CLV, over n periods, the margin is assumed to be fixed over time (as in cell phone contracts, for instance). To apply the formula, we obtain the retention rate (r) from question 12 of our questionnaire for each observation: ‘What is the probability that you will continue with this firm/brand when you review your contract? Indicate a value between 0 (not at all likely) and 100 (entirely likely)’. In this study, we apply the discount rate or weighted average cost of capital calculated by the CNMC (National Commission on Markets and Competition) in 2019 for operators in the telecom service industry in Spain.

The population of the study consists of persons of legal age living in Spain who contract a telecom service (mobile line, internet access, and pay TV at home). Over 50 million telecom contracts outstrip the number of Spanish citizens (over 47 million). The convenience sample is appropriate because these are services used by everyone and can produce extra-role or CCBs (Alves et al., 2016). The sample error of the population is 5.6% for a confidence level of 95% for the least favourable case ($p = q = 50\%$). The data were collected in an online form (Google docs) and the fieldwork took place in July 2019. The result was a total of 306 valid online questionnaires from the telecom industry with all data correctly completed (92 observations from Firm A, 109 from Firm B, and 105 from Firm C).

The Spain retailer telecom service industry (telecom service providers) in 2018 and 2019 was highly competitive. In recent years, competitive dynamics have involved segmentation of the offer: (i) basic and quality-price adjusted offers, from both new incoming brands and the top three brands through second brands, and (ii) the trend in offers designed to satisfy all the communication needs of the home was also maintained, the pay television service being a

differentiating element, marketed only by the leaders or main brands (Movistar, Orange, and Vodafone). These leaders or main telecom service providers in Spain account for 76.8% of total mobile lines, although they suffered market share losses in 2019. The high levels of portability (or switch of telecom service provider) reflect the competition and are very close to those registered in a record year like 2018. Specifically, there were more than 9.5 million brand switches between mobile and fixed numbers, slightly below the 9.8 million in 2018 (CNMC, 2020). As Table 1 shows, despite the global circumstance of COVID-19, the percentage of sector retail revenue was also maintained in 2020 (CNMC, 2021).

Results

SmartPLS 3.0 consider two models (measurement and structural) to perform a statistical analysis focusing on variance (PLS). PLS path models also have different ways of measuring construction: factor models or composite models (Henseler et al., 2015). We apply reflective indicators in a composite model, since the composite model does not impose any limitations on the covariances between the indicators of the same construct. It relaxes the assumption that all the covariation between a block of indicators is explained by a common factor. In our research, we propose that CCB is a second-order composite made up of three dimensions: word-of-mouth (WOM), helping other customers, and helping firms. In the first stage, we estimate the aggregate scores of the first-order dimensions and, in a second, we use these aggregate scores to model the second-order composite. The rest of the dimensions of the developed model are first-order composites. Moreover, we use PLS prediction-oriented segmentation or POS (Becker et al., 2013), which is a distance-based segmentation method. It uses a specific objective criterion to form homogenous groups of observations with increased predictive power (R^2 endogenous variables) of the group-specific path model estimates. In this way, our empirical research begins with a PLS model that divides the sample obtained in two segments oriented to one ratio (R^2) of predictive quality.

Table 1 Percentage of telecom service providers revenue. Source: CNMC

Firms	2016	2017	2018	2019	2020
Movistar	42.7	41.6	41.8	42.3	41.9
Vodafone	19	18.6	17.9	16.6	16.4
Orange	17.1	17.8	17.8	17.3	16.9
<i>Total 3 firms</i>	78.8	78	77.5	76.2	75.2
Others (low-cost)	21.2	22	22.5	23.8	24.8



To evaluate the measurement model of this empirical research, we performed four tests: a) individual reliability from items/indicators and b) composite reliability, convergent validity, and discriminant validity from composites. We also performed test multicollinearity on items/indicators by the variance inflation factor (VIF). We considered that a high collinearity between indicators of the construct leads to unstable estimates, because the distinctive effect of each indicator is difficult to differentiate. First, we checked individual reliability (IR) through item/indicator loading. The criterion was at least 0.707 (Hair et al., 2019) and other authors point out that $VIF > 3.3$ indicates collinearity (Hair et al., 2019). Table 2 shows fulfilment of these parameters (IR and VIF). Second, we checked internal consistency through composite reliability (CR). The criterion was at least 0.6 (Hair et al., 2019). Third, we checked convergent validity through average variance extracted (AVE). The criterion was at least 0.5 (Hair et al., 2019). Four, we checked discriminant validity through heterotrait–monotrait (HTMT). The criterion was not higher than 0.9 (Henseler et al., 2015). Table 3 shows fulfilment of these parameters (CR, AVE, and HTMT).

To check the structural model, we performed a nonparametric bootstrap resampling procedure (5000 samples). We tested the hypotheses for the study (direct effect) using the PLS technique of the structural model. We also undertook a mediation test (Indirect effect). In both tests, path coefficients are statistically significant at 95% when confidence intervals (lower and upper) do not include the value zero (Henseler et al., 2015). Table 4 shows fulfilment of all our research hypotheses and mediation tests.

Our model with the entire sample confirms the acceptance (not rejection) of the research hypotheses, and the predictive quality is satisfied. Of the three equities or CCB antecedents, brand attitude–attachment is the main precursor of CCB with a direct effect coefficient (0.41), while the combined coefficients of social value (0.21) and benevolence (0.15) do not exceed it. The direct effect of CCB on CLV does not give a high coefficient (0.13), but when the indirect impact by mediation (0.46) is added, we find an important impact on CLV (0.59). CCB on intentional loyalty is the highest direct effect coefficient (0.72), and intentional loyalty on CLV is the following highest direct effect coefficient (0.64). The predictive quality in both segments over the entire sample is similar, after R^2 , Q^2 , and q^2_{predict} indicators have been considered. Analysing the main indicator in the entire sample, q^2_{predict} , we obtained a moderate effect of CLV and a significant effect of CCB and intentional loyalty.

We tested the predictive quality of the model with SmartPLS based on three ratios: power (R^2), capacity (q^2), and relevance (q^2_{predict}). First, R^2 indicates the amount of variance of a construct that is explained by the predictor variables of said endogenous construct in the model; the

values of R^2 range from 0 to 1. In predictive models based on PLS, the structural model has more predictive power (R^2 ratio) for each composite, the higher the value. The values are substantial in each composite if the value obtained is higher than 0.67, moderate if between 0.33 and 0.66, and poor if between 0.19 and 0.32 (Hair et al., 2019). Second, the predictive capacity test (Q^2 ratio) follows a blindfolding procedure, where part of the data for a certain construct are omitted using the mean and the parameters of the estimated model (Hair et al., 2019). We evaluate the predictive capability through Stone–Geisser's Q or Q^2 (Hair et al., 2019) using the cross-validation (redundancy) of each endogenous composite. The values obtained in each composite must be higher than 0. Hair et al. (2019) recognise this ratio can be evaluated in each composite by three levels: $Q^2 > 0$ (low), $Q^2 > 0.25$ (medium), and $Q^2 > 0.5$ (high). Third, we measure the predictive relevance (or predictive validity) of the PLS model (q^2_{predict} indicator) using a holdout sample. The antecedent variables of an endogenous variable can be used to predict it, and its indicators, in separate samples from the initial data set used to test the theoretical research model. PLS predict uses values of the holdout sample (out-of-sample data) of the indicators of the independent constructs to generate predictions of the indicators of the dependent constructs. That is, we apply the estimates of the model parameters obtained from the total number of observations called 'training sample'. This ratio q^2_{predict} is tested in each composite by three levels: small effect is $0.02 \leq q^2 < 0.15$, moderate effect is $0.15 \leq q^2 < 0.35$, and large effect is $q^2 \geq 0.35$. Table 5 shows the predictive validity of our model.

The models estimated by prediction-oriented segmentation (Becker et al., 2013) provide information on the values of the trajectory or path coefficients that improve or worsen with respect to the entire sample (306 observations from three firms–brands). In the entire sample, the chain of effects is that brand attitude–attachment, social value, and benevolence impact on CCB directly, and loyalty mediates between CCB and CLV. Segment 2 contains 135 observations and shows that all the hypotheses are accepted (not rejected). Thus, the chain of effects is the same, but the path coefficients are higher than the entire sample, except for two cases: the path social value on CCB and the path value from intentional loyalty on CLV. It suggests that, in this segment 2, firms–brands achieve a firm's financial performance in long-term customers (CLV) through brand attitude–attachment and benevolence, because they directly increase the path value of CCB on intentional loyalty. However, we find in segment 1 (171 observations) that CCB does not influence CLV directly, only indirectly. This indirect effect coefficient of segment 1 is 0.52, somewhat higher than the entire sample (0.46). Moreover, we also obtain that benevolence does not directly influence CCB. This suggests that when there is no benevolence in CCB,



Table 2 Measurement Model by SmartPLS: IR and VIF

COMPOSITE	ITEM <- COMPOSITE	IR		VIF	
		ENTIRE	SEG1	ENTIRE	SEG1
Brand Attitudinal Attachment	I would think of owning this brand	0.80	0.81	1.93	1.98
	This brand is very special to me	0.83	0.83	2.22	2.24
	I have a very good impression of this brand	0.86	0.85	1.86	1.68
	Using this brand makes me feel very happy	0.85	0.81	2.11	1.93
	The people I know believe it's all right to participate in this company	0.80	0.84	1.53	1.76
Social Value	Participating in the services of this company has a good image	0.90	0.90	2.21	2.32
	I think the people involved in the service company have a certain category	0.83	0.84	1.82	1.89
Benevolence	The staff were concerned for my well-being at all times	0.90	0.88	2.31	2.08
	They have always been concerned about my problems	0.86	0.84	2.03	1.90
	I am sure they always want the best for me	0.90	0.91	2.52	2.48
Intentional Loyalty	I intend to continue doing business with this company in the future	0.91	0.89	2.79	2.22
	As long as the present service continues, I doubt that I would switch firms	0.86	0.84	2.07	1.92
CLV	I will choose this company the next time I need this service	0.93	0.91	3.10	2.57
	ln_clv1b <- CLV_	0.97	0.97	4.22	4.62
CCB (Second order, Annex*)	ln_clv2b <- CLV_	0.97	0.97	4.22	4.62
	WOM <- CCB	0.86	0.79	1.23	1.19
	CCB1 <- CCB	0.75	0.80	1.68	1.68
	CCB2 <- CCB	0.76	0.78	1.72	1.66



Table 3 Measurement Model by SmartPLS: CR, AVE, and HTMT

COMPOSITE	ENTIRE	CR	AVE	HTMT					
				BEN	BRA	CCB	CLV	INT	SOV
BEN-Benevolence		0.92	0.79						
BRA-Brand		0.90	0.70	0.65					
CCB		0.83	0.62	0.58	0.67				
CLV_		0.97	0.94	0.44	0.54	0.64			
INT-Intentional		0.93	0.81	0.49	0.66	0.79	0.80		
SOV-Social_value		0.88	0.71	0.57	0.62	0.60	0.52	0.58	
	SEG1			BEN	BRA	CCB	CLV	INT	SOV
BEN-Benevolence		0.91	0.77						
BRA-Brand		0.90	0.68	0.72					
CCB		0.83	0.62	0.60	0.70				
CLV_		0.97	0.94	0.54	0.54	0.79			
INT-Intentional		0.91	0.78	0.59	0.63	0.90	0.89		
SOV-Social_value		0.90	0.74	0.63	0.57	0.70	0.49	0.52	
	SEG2			BEN	BRA	CCB	CLV	INT	SOV
BEN-Benevolence		0.93	0.81						
BRA-Brand		0.91	0.71	0.57					
CCB		0.82	0.60	0.56	0.65				
CLV_		0.96	0.93	0.33	0.53	0.45			
INT-Intentional		0.94	0.84	0.41	0.68	0.69	0.72		
SOV-Social_value		0.86	0.67	0.49	0.70	0.47	0.58	0.66	

Table 4 Fulfilment hypothesis and mediation test of the structural model by SmartPLS

PATH DIRECT EFFECT	ENTIRE			SEG1			SEG2		
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
Benevolence→CCB	0.15	0.05	0.26	0.08	<i>- 0.07</i>	0.23	0.19	0.04	0.34
Brand→CCB	0.41	0.30	0.51	0.40	0.27	0.54	0.46	0.28	0.61
CCB→CLV_	0.13	0.01	0.24	0.13	<i>- 0.02</i>	0.26	0.23	0.03	0.49
CCB→Intentional	0.72	0.67	0.77	0.73	0.66	0.81	0.76	0.69	0.83
Intentional→CLV_	0.64	0.54	0.73	0.70	0.60	0.82	0.49	0.26	0.65
Social_value→CCB	0.21	0.12	0.30	0.30	0.17	0.42	0.15	0.01	0.31
PATH INDIRECT EFFECT	ENTIRE			SEG1			SEG2		
	Beta	2.5%	97.5%	Beta	2.5%	97.5%	Beta	2.5%	97.5%
CCB→Intentional→CLV_	0.46	0.38	0.54	0.52	0.42	0.63	0.37	0.20	0.51

The values marked in italics indicate that confidence intervals include zero in PLS

there is no CCB in CLV. As a result, if the benevolence of the employee is not perceived by the customer, there is no direct firm’s financial performance impact from the customer’s extra-role and voluntary behaviours. Therefore, in segment 1, or for most of the sample, the chain of effects is different because brand attitude–attachment and social value impact on CCB directly, and intentional loyalty mediates between CCB and CLV. The predictive quality in both segments over the entire

sample is similar, after R2, Q2, and q2_predict indicators have been considered. By analysing the main indicator in two segments, q2_predict, we obtain a moderate effect of CLV and a significant effect of CCB and intentional loyalty.



Table 5 Predictive validity of SmartPLS model

COMPOSITE	R2			Q2			Q2_PREDICT		
	ENTIRE	SEG1	SEG2	ENTIRE	SEG1	SEG2	ENTIRE	SEG1	SEG2
	CCB	0.43	0.44	0.45	0.23	0.25	0.22	0.41	0.42
CLV_	0.54	0.65	0.46	0.50	0.60	0.42	0.27	0.29	0.26
Intentional	0.52	0.54	0.57	0.42	0.41	0.47	0.37	0.35	0.39

Discussion and managerial implications

Theoretical contributions

The aim of this study is to analyse the relationship between CCB and CLV based on the theoretical framework of CE. First, this research contributes to the current predictive analytic models debate about whether both direct/transactional and indirect/non-transactional behaviours can be considered in CE literature. Previous research has explored CCB as a form of engagement. However, as far as we know, how CCB affects CLV has not received attention by other researchers (Bove et al. 2009; Gong and Yi, 2021). Accordingly, our research addresses this gap in the literature by analysing the relationship between CCB (non-transactional) and CLV (transactional), as well as intentional loyalty mediates between CCB and CLV. According to the literature, engagement is a motivational state, and CCB actions lead to the customer perceiving benefits from the service such as self-awareness, self-efficacy, self-determination, self-enhancement, and well-being (Gong and Yi, 2021). In turn, the findings obtained up to this point reveal that engaging in CCB also leads to future financial firm benefits through loyalty and CLV, due to the economic exchange continues as long as the customers and firms mutually benefit. These findings summarise the main contribution of this study. Engaging in CCB arises through exchanges and relationships encouraged by motivational drivers. Moreover, we should compare the entire data sample and two-segmented samples of customers in order to generalise the research findings. In the light of the above, our study makes two further contributions.

A second relevant academic contribution is the antecedents or three motivational drivers of our study. Firms can use analytics to identify and retain profitable customers, deriving more from each category or segment. Furthermore, they can assess the customer's psychological state in terms of motivational drivers and engagement. New technologies have empowered customers. They can interact with firm touchpoints to develop a relationship with the firm and strengthen their engagement with the firm's brand. Social comparisons and social exchanges are motivational drivers that encourage customers to engage in CCBs with firms or brands. Brand, and more specifically, the brand attitude-attachment customer is the main precursor of CCB. Previous studies maintain that brand attachment does not have a direct effect on CCB, only a mediation effect through perceived value (Cheng et al., 2016). Customers also engage in CCBs with brands to compare their opinions, abilities and emotions with those of others through social media posts for self-enhancement or the desire to feel good about themselves.



Their experiences generate increasingly strong bonds that firms hope will further the brand attachment.

Brand is not the only motivational drive that activates these discretionary, voluntary, and extra-role customer behaviours. In addition, customers tend to consider the most relevant brands as a symbol of social status and identity; hence, a perceived social value is implicit. This symbolic benefit or independent dimension of the total value acts on how customers want to be seen and/or how they want to see themselves (Dang and Arndt, 2017; Gong and Yi, 2021). Social exchanges arise in the service purchase process and can reappear in the post-purchase or subsequent digital interactions. Thus, customers enhance both their feeling of self-esteem and social acceptance through their use of these brands. Finally, as a third motivational driver, we emphasise the important role of supplier's benevolence. Supplier's benevolence develops closer customer benefit through friendship to engage in social exchanges as a sense of approval and social support. Supplier's benevolence aims to produce subsequent reciprocal behaviours by customers based on a feeling of obligation from the behaviour of previous experiences.

The third contribution of this study is prediction-oriented research using PLS modelling in four issues. The first is the use of the CLV metric through a composite based on these two continuous variables specified as reflective indicators. PLS models both discrete variables based on the Likert scale and continuous variables. In this study, we used a combination of both. The second is the multidimensionality of CCB (recommendations, helping other clients, and helping the firm) proposed by Groth (2005) through a second-order composite. PLS uses the scores obtained from the indicators of the first-order model to define a multidimensional second-order composite. Thus, we can analyse the concept of CCB as unidimensional rather than the effect of subdimension by subdimension. This is naturally attuned to CCB as a form of engagement driven by motivational drivers. The third is to calculate CLV and estimate prediction-oriented segmentation, which means that the firm can design better strategies focused on its value proposition, classify different types of customers based on motivational drivers, or review the employee–customer interaction. Finally, prediction quality is performed using three indices (power, capacity, and relevance), which use holdout samples to verify our entire data and segmented model. Using these indices in the field of prediction-oriented models represents a scientific development in this kind of research that focuses on exploring phenomena, even with less information or data, and relying on theoretical approaches without the need to demonstrate them again.

Managerial recommendations

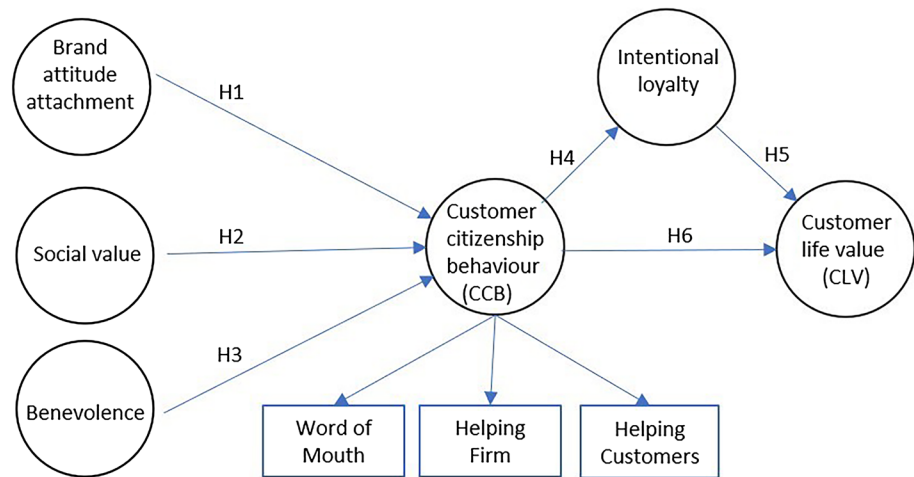
From a management point of view, the service provided to customers who contracted telecom in 2019 can also be increased in intensity to favour non-transactional behaviours such as CCB. To lead interaction with customers and followers on social networks in Spain, the main telecom service providers boost the publication of content in relation to the launch of promotions, offer of services, and customer service. The three main brands of telecom service providers in 2019, and in 2018, adopted similar business practices of providing added value to the customer through so-called convergent packages, unlike low-cost firms. These convergent packages include successive price increases for improvements in the benefits of the services marketed that combine landline and mobile connections, including paid audio-visual services. Telecom service providers are therefore online audio-visual content providers (Movistar+, Vodafone TV, and Orange TV), which indicates a second level of competition with firms like Netflix, Amazon Prime, and HBO. It drives to a revaluation of the offer by the customer and allows for the future value of retained customers to be predicted based on their loyalty and non-transactional behaviours (CCBs). This quality of prediction is even more valuable after foreseeing a greater use of electronic communications services (calls, all modalities of video calls, internet access, content streaming, etc.) and an increase in data traffic after the outbreak of the coronavirus pandemic in 2020, which led to changes in lifestyle during lockdown, severe limitations to economic activity, and the temporary widespread introduction of teleworking. In this sense, we recommend that the role of the marketing manager not be reduced to investment portfolio management, in which the economic value of the client or CLV is found in the dilemma of acquisition and retention costs or on the revenue expected over the customer's lifetime. CLV should be used as a predictive measure of customer valuation from loyal customer purchases throughout their lifetime, as well as the extent of benefits from active customer engagement.

Limitations and future lines of research

A first limitation of this study involves the scope of the sample, which is country- and service-industry-specific. We therefore suggest that it be extended to other countries and industries. A second limitation refers to the CLV metric, because we consider margins such as the customer's monthly income. We uphold the retention rate as the probability of repurchase, which remains constant over time. We do not include new customers or acquisition costs in the calculation. However, the basic CLV model



Fig. 1 Hypotheses and variables of the PLS model



proposed is simple to apply and a good indicator of the value of the firm to the service industry. A third and final limitation is the setting of the three equities to only three antecedents of CCB, and the impact on firm's financial performance (CLV) in a prediction-oriented model of customer retention. Although it is relevant to CCB research, we believe it is only one step towards future knowledge of other new antecedents and consequences of CCB not yet analysed (Fig. 1).

Annex

(*) CCB. Based on your past experience with this firm, how likely are you to...?

WOM: recommendations.

...Recommend the business to your family.

...Recommend the business to people interested in the business' products/services.

CCB1: providing feedback.

...provide information when surveyed by the business.

...provide helpful feedback to customer service.

...inform the firm about the service provided by this employee.

CCB2: helping customers.

...teach someone how to use the service correctly.

...help other customers when they don't know how to use this service.

...explain to other customers how to use the service correctly.

Data availability The dataset generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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