Journal of Strategic Marketing

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rjsm20

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To cite this article: Paul Williams, Nicholas J. Ashill & Earl Naumann (04 Oct 2023): Drivers of contract renewal over time: a framework of analysis in B2B services, Journal of Strategic Marketing, DOI: 10.1080/0965254X.2023.2257704

To link to this article: https://doi.org/10.1080/0965254X.2023.2257704

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Published online: 04 Oct 2023.

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JOURNAL OF STRATEGIC MARKETING
https://doi.org/10.1080/0965254X.2023.2257704

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Drivers of contract renewal over time: a framework of analysis in B2B services

Paul Williams[a], Nicholas J. Ashill[b] and Earl Naumann

[a]Department of Digital and Data-Driven Marketing, University of Southampton, Southampton, United Kingdom; [b]School of Marketing and International Business, Rutherford House, Wellington, New Zealand

ABSTRACT
Despite the wealth of research into Business-to-Business customer relationships, there are a number of gaps in the literature, where most studies have used cross-sectional research designs. In this study, we explored customer relationships over a three-year period, using data from a large Fortune 100 industrial services provider. Our longitudinal research design compared the drivers of customer satisfaction and contract renewal decisions over time, and provides a holistic framework for viewing customer relationship drivers and their effects at an aggregate level. While some drivers were quite stable, others changed significantly between quarters. The main implications of this study are that firms should closely manage their supplier–customer relationships by tracking the drivers over time to enable service responsiveness to changing customer needs. From a theoretical perspective, the data also indicate that researchers should be cautious in drawing concrete conclusions from cross-sectional studies, as many drivers are dynamic over time. Future researchers are encouraged to develop more longitudinal research designs.

ARTICLE HISTORY
Received 18 October 2022
Accepted 6 September 2023

KEYWORDS
Stability; customer attitudes; longitudinal; B2B services

Introduction and background to the study

The importance of building strong relationships between buyers and sellers in B2B markets is paramount to maintaining long-term profitability of the firm (Murphy & Sashi, 2018; Rauyruen & Kenneth, 2007). The strong link between relationships, customer loyalty and profitability has been widely acknowledged in many B2B markets, particularly with regards to on-going contract renewals, or system upgrade decisions (Williams et al., 2017; Ruiz-Martinez et al., 2019). Previous literature has investigated the nature and drivers of long-term B2B relationships from two contrasting perspectives. The first considers B2B buyer–seller relationships as relatively stable, and temporally homogeneous phenomena (La Rocca, 2020;) where buyers respond in similar ways to relationship marketing initiatives (Zhang et al., 2016). In mature industrial markets, B2B relationships and their respective drivers are seen as relatively stable, mainly because change in such markets is slow and insignificant, and there is generally minimal impact on the supplier–

CONTACT Paul Williams paul.williams@soton.ac.uk

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customer relationship (La Rocca, 2020). Additionally, the relatively small and stable customer base (Dotzel & Shankar, 2019) results in increased social capital between buyer and seller, creating another switching cost.

The second perspective considers relationships in B2B markets as more dynamic (Cova & Salle, 2008; Lemon & Verhoef, 2016), where firms are affected by globalization, communication technologies, economic recession, competitive pressures, and other political–legal changes (Forkmann et al., 2018). This changing environment results in relatively unstable relationships requiring dynamic collaboration between suppliers and customers (Forkmann et al., 2018; Weirsema, 2013). The changing nature of B2B relationships has also been highlighted through the theoretical lens of 'dynamic capabilities' (Stefano et al., 2014; Teece et al., 1997).

Against this backdrop, the goal of our study is to investigate the evolution and dynamism of several B2B relationship drivers on customer loyalty over a three-year period. We test a customer loyalty model that explores the relative impact of a firm's business relationship capabilities on customer satisfaction and contract renewal intentions over time. Our study offers several contributions to marketing theory and practice. First, we unravel some of the complexity of business relationships, and examine if, and how they change over time. This approach enables firms to see which relationship drivers influence loyalty consistently, and which ones are more dynamic over time. Previous studies have not provided a complete view of the dynamism of B2B relationships over multiple time periods. This is surprising given the importance of interpersonal interactions in B2B services for building long-term relationships (Hohenschwert & Geiger, 2015).

Our second contribution is the use of a repeated cross-sectional (RCS) research design as a framework of analysis that enables scholars and practitioners to better understand the complex nature of B2B buyer–seller relationships over time. In the literature, cross-sectional research designs predominate (Chang et al., 2021; Rindfleisch et al., 2008) largely due to the expense of capturing longitudinal data and the logistical difficulties of tracking identical samples and panels over longer time periods where there is often respondent attrition and survey fatigue (Cummings, 2018; Spector, 2019). Although relatively inexpensive, they lack generalizability due to their snap-shot nature (Wang et al., 2020). They also focus on explanatory power rather than testing predictability.

In response to these weaknesses, a number of longitudinal studies have emerged that examine B2B relationships over time (see Table 1). Panel research and RCS designs are the two main forms of longitudinal research (Menard, 2002). Panel research makes use of the same respondents at different time points whereas RCS designs survey respondents based on some form of probability sampling (Doering et al., 2020; Lebo & Weber, 2015), where data is collected at two or more time points from different samples of the same population. RCS designs have been shown to be successful at detecting changes in attitudes and behaviours over time and are common in disciplines such as political science, population studies, health behaviours, media polls, opinion surveys, and television ratings (Cummings, 2018; Moretti, 2004; Walley et al., 2009). They often provide a better representation of changing populations than panel designs and can be used to examine change at the aggregate level. Steel (2008) notes that maintaining good sample representation to produce unbiased estimates for each time period can be achieved without following the same

Table 1. Longitudinal studies of B2B relationships.

Author(s)	Study	Research Approach	Model Estimation and Evaluation Focus
Mittal et al. (1999)	Longitudinal study of relationships between attribute-level performance, satisfaction, and behavioural intention	Survey of 5206 car owners at 3 different time points. Same respondents at each time point.	Explanatory power
Eggert et al. (2006)	Longitudinal study of the effects of different stages of the relationship cycle on the relative importance of value-creation dimensions	Survey of purchasing managers in large B2B firms (chemical, mechanical, and electrical industries) using a quasi-longitudinal research design. Data collected at one point in time. Relationships classified by phase and data used for quasi-longitudinal analysis.	Explanatory power
Palmatier et al. (2007)	Longitudinal study of business-to-business relationships between a major Fortune 500 company and local distributors	Survey of 396 distributor managers across 3 years. Same respondents at each time point.	Explanatory power
Román and Martín (2008)	Longitudinal study of the effects of sales call frequency on the supplier-customer relationship	Survey of customers of 1 industrial supplier over a 2-year period. Same customer-relationship examined at each time point but no explanation if the same respondents were survey at each time point.	Explanatory power
Autry and Golicic (2010)	Longitudinal study of the effects of interorganisational relationships on firm performance	Secondary objective data (no key informant data)	Explanatory power
Williams and Naumann (2011)	Longitudinal study of the effects of customer satisfaction on firm-level company performance metrics	Survey of B2B customers of a Fortune 500 firm over a 5-year period. Repeated cross-sectional longitudinal research design.	Explanatory power
Palmatier et al. (2013)	Longitudinal study of the effects of relational constructs (commitment velocity, relationship commitment level) on firm performance	Survey of 433 seller-customer relationships over 6 years. Same seller-customer relationship examined but no explanation if the same respondents were surveyed at each time point.	Explanatory power
Zhang et al. (2016)	Longitudinal study of the effects of relationship marketing strategies across different customer relationship states	Survey of 522 B2B channel relationships maintained by a Fortune 500 firm over a 4–6 year period. Same channel relationships examined but no explanation if the same respondents were surveyed at each time point.	Explanatory power
Ha (2020)	Longitudinal study of the effects of trust on firm performance during the development of B2B relationships	Survey of 467 channel relationships at four time points (T1, T2, T3, and T4), each separated by a six-month time lag. Same channel relationships examined but no explanation if the same respondents were surveyed at each time point.	Explanatory power

respondents over time. In addition, RCS designs are not affected by respondent attrition, and are less prone to learning and conditioning effects (Lebo & Weber, 2015). RCS designs also increase variances in independent variables (Steel, 2008).

With the exception of Williams and Naumann (2011), the majority of studies examining B2B relationships identified in Table 1 report a pure longitudinal design where the same customer relationship is examined, although in some studies it is not clear if the same respondents were surveyed. However, as noted by Eggert et al. (2006), gathering longitudinal data on B2B relationships is problematic because collecting data about the same set of relationships with the same respondents over multiple periods of time is virtually impossible. In the current study, participants were assured of anonymity which meant that it did not match responses across different time points. Polit et al. (2003) also suggest that a RCS design makes sense when there is logical reasoning or theory indicating that one variable precedes the other, conditions that exisit in our study of B2B relationships over time.

Our third contribution is the use Partial-Least Squares (PLS) modelling. Roemer (2016) suggests that PLS modeling is highly appropriate to use to analyze change in constructs in longitudinal studies because of two methodological characteristics. First, constructs such as satisfaction and loyalty (in our research contract renewal intentions) often need to be predicted, and PLS allows researchers to predict constructs (Hair et al., 2011). Second, model complexity increases when change is analyzed in longitudinal studies. In our study, we measure seven constructs and their effects at different points in time. PLS is highly suitable to deal with complex models (Roemer, 2016). PLS models can also be replicated and then contrasted across several sample sets using holdout samples (Hair et al., 2017; Sharma et al., 2021). Carrión et al. (2016) and Shmueli et al. (2019) recommend the use of out-of-sample prediction to indicate a model's ability to predict, which involves estimating a model on a training sample and evaluating its predictive performance on a holdout sample. The holdout sample is separated from the total sample before executing the initial analysis on the training sample data, so it includes data that is not used in the model estimation. PLS thus provides more predictive accuracy (Shmueli et al., 2016) which is crucial for enhancing practical and managerial implications (Sharma et al., 2022; Shmueli & Otto, 2011). Following Sarstedt and Danks (2022), we argue that making statements about managerial implications requires a prediction focus on model estimation and evaluation which PLS can deliver.

Model development

Several studies have empirically examined the main antecedents and consequences of satisfaction and loyalty for B2B firms (Hinterhuber et al., 2021; Williams & Naumann, 2011). These studies have shown that various dimensions of service performance, product quality, and price perceptions are key drivers of satisfaction and loyalty. Grounded in these scholarly works, we discuss the main literature of these predictive variables in more detail to frame our model. Viewed holistically, the findings from prior research suggest that service performance (Tiexiera et al., 2020), product quality (Brax & Visintin, 2017) and price competitiveness (Hinterhuber, Snelgrove & Stensson, 2021) represent the main drivers of customer satisfaction and loyalty.

Service performance

In the B2B context of this study, we expected that the quality of a customer's service experiences over the term of an annual service contract would be an influential customer metric, particularly for contract renewal and contract upgrade decisions (Bolton et al., 2008; Lee et al., 2019). The main premise being that poor service performance leads to less likelihood of contract renewal. Various authors have empirically tested service quality perceptions and consistently found them to have a direct and positive impact on outcomes such as customer satisfaction, retention, behavioural loyalty and positive word-of-mouth recommendations (Tiexiera et al. 2020). Most of this research has been conducted in B2C markets, although a number of studies in recent years have looked at B2B markets (Lee et al., 2019).

In order to create a customized B2B service solution, there must be an increased understanding of the customer's needs through relational exchange (Tzemplelikos, 2020; Rajamma et al., 2011). Collectively, dyadic supplier–customer interactions shape the customer's attitude towards service performance, and, therefore, the nature of their relationship with the supplier. The multiple points of personal contact imply that the 'service provider-customer' relationship is a network with numerous participants (Tiexiera et al. 2020; Palmatier, 2008). These service delivery contact points usually interact with the facilities manager from the customer organisation and influence their attitudes towards satisfaction (Tiexiera et al. 2020; Hinterhuber et al., 2021). We differentiate between the three main service relationship contact points: account representatives, technicians, and call center personnel, and hypothesize that each contact point would predict satisfaction.

Product quality

It is well documented that many B2B services, particularly maintenance, and support services, have a tangible product component (Brax & Visintin, 2017). Similarly, Ulaga and Reinartz (2011) coined the term 'hybrid services' to describe the integrated product and service offering in a B2B context, and this developed into the literature around 'servitization' in B2B markets (Rabetino et al., 2018, 2021). The literature reveals product quality perceptions are common drivers of customer satisfaction in general, but with even more importance when product quality is viewed in a services context (Rabetino et al., 2021; Tuli et al., 2007). In our context, product quality includes a tangible computerized building management system, that monitors the heating, ventilation, air-conditioning (HVAC) accurately, consistently and reliably. We therefore hypothesize that customer attitudes towards product quality would predict satisfaction.

Customer satisfaction and contract renewal intentions

In the academic literature, customer satisfaction has been consistently shown as a strong driver of customer loyalty, represented by variables such as repurchase intentions, positive word of mouth recommendations, contract renewals or actual customer loyalty behaviours (Tiexiera et al. 2020; Williams et al., 2011). For example, van Doorn and Verhoef (2008) demonstrated that satisfaction has a positive effect on both the intention to renew contracts and the likelihood of actually renewing contracts in the B2B context of logistics services. In our study, we did not measure actual customer loyalty but instead used contract renewal intention as a surrogate of actual customer behaviour. Jones and Suh (2000) define contract renewal intentions as the intention to purchase products or services from the same providers again. These intentions are equivalent to a psychological commitment that the customers express toward the product/service provider.

Price competitiveness and contract renewal decisions

Several studies suggest that customer satisfaction does not override price perceptions in predicting behaviour (Williams et al., 2011; Martín-Consuegra, Molina, and Esteban 2007). Recent literature has continued to emphasize the importance of price competitiveness in driving loyalty in B2B markets. For instance, a study by Hinterhuber, Snelgrove, and Stensson (2021) examined the effect of perceived value on the relationship between price satisfaction and loyalty. The study found that perceived value significantly mediates the relationship between price satisfaction and loyalty, indicating the importance of providing value-added services that justify higher prices. B2B customers are considered rational decision-makers when evaluating value propositions (Hinterhuber et al., 2021). Moreover, recent research by Naumann et al. (2010) has highlighted the importance of customer expectations in shaping the relationship between price competitiveness and loyalty in B2B markets. The authors found that when customer expectations are high, price competitiveness has a negative effect on loyalty, while when expectations are low, price competitiveness has a positive effect. For our study, price competitiveness was considered to be an important driver of contract renewal intentions, because of the necessary presence of a 'value' ingredient during customer's evaluation of the purchase.

Our proposed model is shown in Figure 1. In testing these relationships, our objectives were threefold. First, we sought to examine the stability of the PLS model over time by analyzing the measurement model indicators across 10 quarters of data. Comparisons can be misleading unless researchers establish the invariance of their measures. Second, we sought to derive a more holistic view of customer–supplier relationships by examining the relative impact of each predictor variable over time to identify changes between quarters. Our third objective was to analyze the effect and predictive capacity of three main service relationship contact points and product

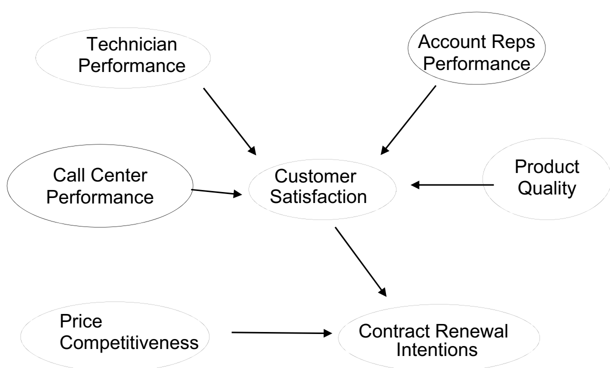

Figure 1. A priori model of expected relationships.

quality on customer satisfaction, and also customer satisfaction and price competitiveness on contract renewal intentions in a B2B services context. There have been increasing calls that marketing researchers should complement their explanation-oriented analyses with prediction-orientation as is common in the natural sciences (Hofman et al., 2017).

Context of the study

Our firm was a Fortune 100 company in the building services industry delivering large-scale project installations and on-going maintenance. The firm had over 25,000 annual contracts for the maintenance and upkeep of the HVAC systems in large commercial buildings across the USA, with an average contract value of $18,000.00 USD per annum. The mean length of relationship between the supplier and customer organisations was around 15 years suggesting that most of the customers had likely achieved a high level of relationship maturity with the firm. This supplier/customer relationship has continually evolved through emergent learning and experiential knowledge transfer (Davies et al., 2016) and therefore serves as an excellent focal firm for our study into the relative stability of attitudes. Like other B2B services suppliers, the firm provided both a product and service component, or 'hybrid services' (Rabetino et al., 2021; Tuli et al., 2007). In addition, the capital-intensive nature of the building management systems meant it is difficult to change suppliers quickly or willingly. The on-going nature of personal interaction between the customer and supplier also meant there were mostly longer-term, stable relationships in this industrial B2B context.

Research method

Research Design

Our study design used a RCS research design (Lebo & Weber, 2015; Moretti, 2004) which is often referred to as a 'pseudo-longitudinal' research design (Yee & Niemeier, 1996). We applied our measurement model to 10 sequential quarters of data from the same firm. Data collection was collected from the same target population at different time points, and was used for analyzing aggregate change over time (Wang & Cheng 2020).

Questionnaire development

The items, constructs, and response scales are presented in Appendix A. Customer satisfaction consisted of a composite of 2 indicators, one question for 'overall satisfaction' and one question for 'met expectations' as practiced in other research studies (Williams et al., 2011). Following Williams et al. (2017), contract renewal intentions consisted of a composite of 'likelihood to renew' and 'willingness to recommend', product quality was measured with 4 items, and price competitiveness was measured with 3 items. The service performance of account representatives consisted of 6 items, technicians 5 items, and call center personnel was measured with 3 items (Williams et al., 2011).

Sample

The data was collected from the CRM database of business customers of a facility management firm. There were 10 consecutive financial quarters of customer data collected over a 3-year period, with each quarter resulting in at least 600 respondents. There was no overlap of customers between samples from each of the financial quarters. After further discussions with the executives of the focal firm, the respondents from each quarter were considered broadly representative of the whole customer-base of large facility management services customers. Over half of the sample had dealt with the supplier for over 10 years (51.3%), and 81.2% of respondents had five or more years of experience with the supplier. There were 81.0% of respondents who were the primary decision maker or a major influencer in the selection of suppliers. There were 70.5% of respondents who indicated that they were a facility or building manager. These people supervised the running of the building systems and were typically the main point of contact between the customer organisation and the service provider for all building management issues. These people were therefore considered well qualified to comment on the satisfaction levels and the service provider's performance.

Data were collected for each quarter utilizing structured telephone interviews of around 10–15 minutes each, with a random sample of customers who held an annual service contract with the firm. The customers were interviewed at the mid-point of their annual contract to allow time for service recovery if issues were identified. Providing this customer satisfaction feedback was a necessary contractual obligation in the service contract and enabled high response rates to the surveys. Finally, non-response bias was assessed by evaluating the sample profile characteristics of non-respondents and respondents. Following Armstrong and Terry (1977), we compared different waves of respondents and found there was no significant difference at the 0.05 level between early and late respondents with regard to length of contract, size of contract, size of firm, and position of the respondent. Moreover, with the large samples per quarter participating in each survey, non-response bias was unlikely to be a problem. Feedback from non-respondents also provided a reliable assessment of non-response bias (Jean & Tan, 2019). A selection of non-respondents explained that their lack of participation was due to a lack of time, sensitivity of business data and being over-surveyed. This feedback suggests that non-response bias is not a serious concern in this study.

Analytical techniques

SmartPLS 3.0 software was applied to assess the measurement model and the structural model, as well as PLS-Multi-Group Analysis (MGA) to examine the heterogeneity of the collected data, which enabled hypothesis testing across each of the 10 quarters of data. The PLS analysis was initiated by conducting factor analysis using the total sample to assess convergent and discriminant validity. This was followed by an examination of the structural model to determine the significance of path relationships using the bootstrapping approach with 2000 iterations and PLS-Multi-Group Analysis (MGA) (Hair et al., 2017) where we assessed for measurement invariance across the models representing the 10 quarters of data.

Data analysis

Preliminary analysis

Initial data quality tests indicated that the data was normally distributed. Before examining the measurement model, we completed a goodness-of-fit assessment as proposed by Henseler et al. (2016). The standardized root mean square residual (SRMR) fit index for the full dataset was 0.052 which is less than 0.08 (Hair et al., 2017) and suggests good model fit. As part of measurement model evaluation, we also examined composite reliability, Cronbach's α values, average variance extracted (AVE), outer loadings, and discriminant validity. All factor loadings and Cronbach's α for the full dataset were above 0.7 (Henseler et al., 2016), demonstrating the reliability of constructs. The AVE values for all constructs were also above the minimum required level of 0.50. Discriminant validity was also demonstrated following Fornell and Larcker (1981) and the Heterotrait-Monotrait (HTMT) ratio of correlations as recommended by Henseler et al. (2015).

We then employed Henseler's et al. (2016) three-step procedure to assess the measurement invariance of composite models (MICOM) when using SmartPLS. The three steps involved configural invariance, compositional invariance and the equality of composition mean values and variances. In all tests, all minimal thresholds were met which indicated that there was no evidence of measurement invariance and the models were stable across the 10 quarters of data.

Structural model analysis

Before examining relationships in the model, we compared mean responses using an independent samples *t*-test on a quarter by quarter basis. The findings are summarized in Table 2 and highlight where significant differences were found ($p < 0.05$).

Table 2 shows that for the vast majority of the mean responses, there is minimal change in customer attitudes over the 10 quarters. For technician performance, product quality, customer satisfaction and contract renewal intentions there are no significant differences between any of the quarters. For account representatives and call centre personnel there is only one quarter (Q8) where the subsequent quarter response is statistically significant. The majority of customer attitudes where there there is a personal interaction between the supplier and customer are largely consistent over time. However, for price competitiveness, there are differences in the mean responses for subsequent quarters (Q2; Q4; Q5; Q7). This attitude is considered to be the most dynamic part of the value proposition in a B2B contract relationship and may explain why it

Table 2. Test differences of means.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Account Rep Performance	3.74	3.79	3.74	3.78	3.66	3.68	3.81	*3.66*	3.67	3.60
Technician Performance	3.93	3.99	3.96	4.01	3.96	3.96	4.08	4.05	4.02	4.06
Call Centre Performance	3.76	3.82	3.83	3.81	3.74	3.78	3.85	*3.68*	3.64	3.62
Product Quality	3.69	3.76	3.76	3.73	3.73	3.75	3.84	3.79	3.79	3.78
Price Competitiveness	2.39	*2.60*	2.55	*2.43*	*2.54*	2.55	*2.44*	2.5	2.55	2.54
Customer Satisfaction	3.84	3.83	3.85	3.79	3.85	3.79	3.91	3.95	3.92	3.91
Contract Renewal Intentions	4.25	4.13	4.13	4.21	4.22	4.17	4.28	4.25	4.28	4.24

Numbers in italics have a statistically significant difference to the previous quarter ($p < 0.05$)

changes so often. This finding aligns with studies where price variability in B2B industrial situations is common (Töytäri et al., 2015).

Next, we examined the structural model for each of the 10 quarters using bootstrapping through 2000 resamples (see Table 3). The blindfolding algorithm provides the assessment of predictive accuracy of the model. The high Q^2 value of 0.353 indicates that all exogenous constructs have predictive relevancy to customer satisfaction. Table 3 shows considerable variability in the relative strength of each predictor of customer satisfaction. For example, in some quarters account representatives are the strongest predictors, and in other quarters technicians are the strongest predictor. The service performance of call centre personnel did not affect satisfaction in some quarters. Product quality is the strongest predictor in only one quarter (Q5). This variability is demonstrated graphically in Figure 2.

To establish the existence of significant differences in the path coefficients across the 10 quarters of data, we applied PLS-MGA in SmartPLS 3.0 using bootstrapping. The results

Table 3. Drivers of satisfaction: R^2, coefficients and significance.

	Q1 *n*=666	Q2 *n*=994	Q3 *n*=708	Q4 *n*=948	Q5 *n*=686	Q6 *n*=850	Q7 *n*=686	Q8 *n*=772	Q9 *n*=628	Q10 *n*=862
Effect on Satisfaction (R^2)	.538	.486	.568	.503	.517	.495	.413	.469	.398	.457
Account Rep	.392	.265	.260	.113	.273	.116	*.078*	.175	.232	.117
Performance	*t*=6.66	*t*=5.29	*t*=5.25	*t*=2.70	*t*=6.30	*t*=2.67	*t=1.45ns*	*t*=4.58	*t*=4.33	*t*=3.18
Technician	*.081*	.188	.296	.271	.180	.324	.251	.373	.367	.344
Performance	*t=.1.43ns*	*t*=3.84	*t*=5.74	*t*=4.81	*t*=3.22	*t*=6.49	*t*=4.13	*t*=7.42	*t*=5.85	*t*=8.98
Call Center	.258	.157	.116	.169	.204	.113	.207	*.043*	*.022*	*.014*
Performance	*t*=4.74	*t*=3.00	*t*=2.50	*t*=3.51	*t*=4.01	*t*=2.33	*t*=3.39	*t=1.10ns*	*t=0.49ns*	*t=0.50ns*
Product Quality	*.069*	.157	.179	.246	.271	.240	.192	.217	.142	.309
	t=1.29ns	*t*=4.29	*t*=3.35	*t*=6.19	*t*=6.63	*t*=5.27	*t*=4.15	*t*=4.82	*t*=4.06	*t*=7.54

Numbers in italics are not significant, others are statistically significant at $p < 0.05$ level

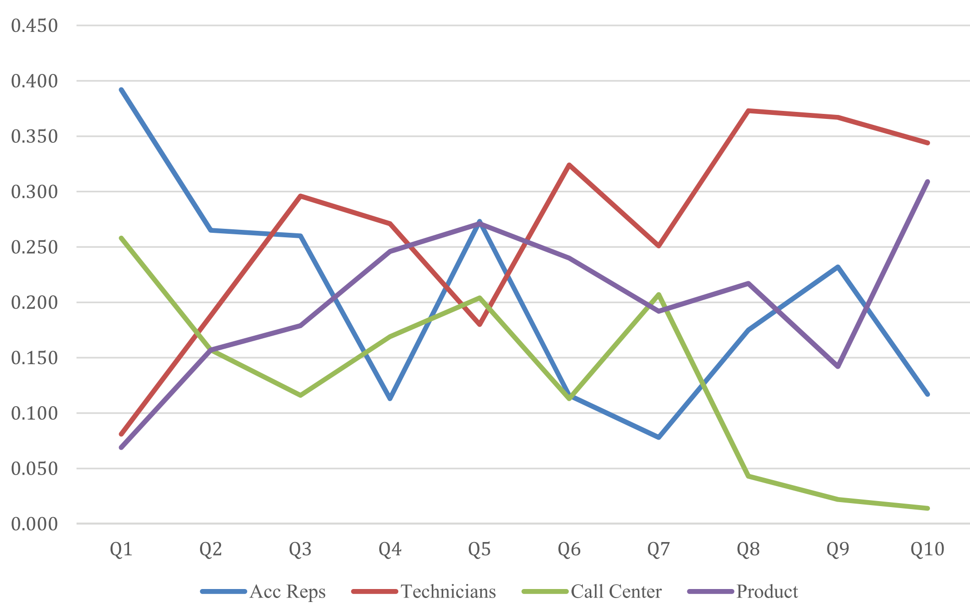

Figure 2. Drivers of satisfaction.

Table 4. PLS_MGA results for customer satisfaction.

	Q1 - Q2	Q2 - Q3	Q3 - Q4	Q4 - Q5	Q5 - Q6	Q6 - Q7	Q7 - Q8	Q8 - Q9	Q9 - Q10
Effect on Customer Satisfaction									
Account Rep Performance	t=1.66	t=0.07	*t=2.23*	*t=−2.60*	*t=2.53*	t=0.55	t=-1.49	t=-0.88	t=1.84
Technician Performance	t=-1.42	t=-1.49	t=0.32	t=1.12	*t=−1.96*	t=1.00	t=-1.56	t=0.08	t=0.32
Call Center Performance	t=1.29	t=0.06	t=-0.77	t=-0.49	t=1.29	t=-1.22	*t=2.32*	t=0.36	t=0.16
Product Quality	t=-1.40	t=-0.35	t=-1.03	t= 1.44	t=-1.25	t=0.73	t=-0.38	t=1.27	*t=−2.95*

Numbers in italics are statistically significant differences at $p < 0.05$ level

are shown in Table 4 and show that a number of path coefficients differed significantly between quarters. This again reinforces the variability of attitudes on a quarter-by-quarter basis and offers a more complete picture of the drivers of satisfaction over time.

We also examined the structural model and the path coefficients of customer attitudes predicting contract renewal intentions (see Table 5). The high Q^2 value of 0.365 indicated that all exogenous constructs had predictive relevancy to contract renewal intentions.

Results show that there is relative stability in attitudes. In all 10 quarters, the strongest predictor of contract renewal intentions is customer satisfaction. This relative stability is graphically illustrated in Figure 3.

Table 5. Drivers of contract renewal intentions: coefficients and significance.

	Q1 *n*=666	Q2 *n*=994	Q3 *n*=708	Q4 *n*=948	Q5 *n*=686	Q6 *n*=850	Q7 *n*=686	Q8 *n*=772	Q9 *n*=628	Q10 *n*=862
Effect on Contract Renewal Intentions (R^2)	**.522**	**.474**	**.527**	**.556**	**.504**	**.477**	**.404**	**.502**	**.400**	**.478**
Satisfaction	.603	.603	.709	.727	.694	.674	.609	.696	.595	.665
	t=26.7	t=33.6	t=34.9	t=38.9	t=32.3	t=29.7	t=20.7	t=30.9	t=18.9	t=26.7
Price Competitiveness	.122	*.033*	.089	.104	.072	.076	.086	.062	.125	.115
	t=4.01	*t=1.46ns*	t=3.38	t=4.49	t=2.54	t=2.80	t=2.53	t=2.30	t=3.57	t=3.98

Numbers in italics are not significant, others are statistically significant at $p < 0.05$ level, ns not significant

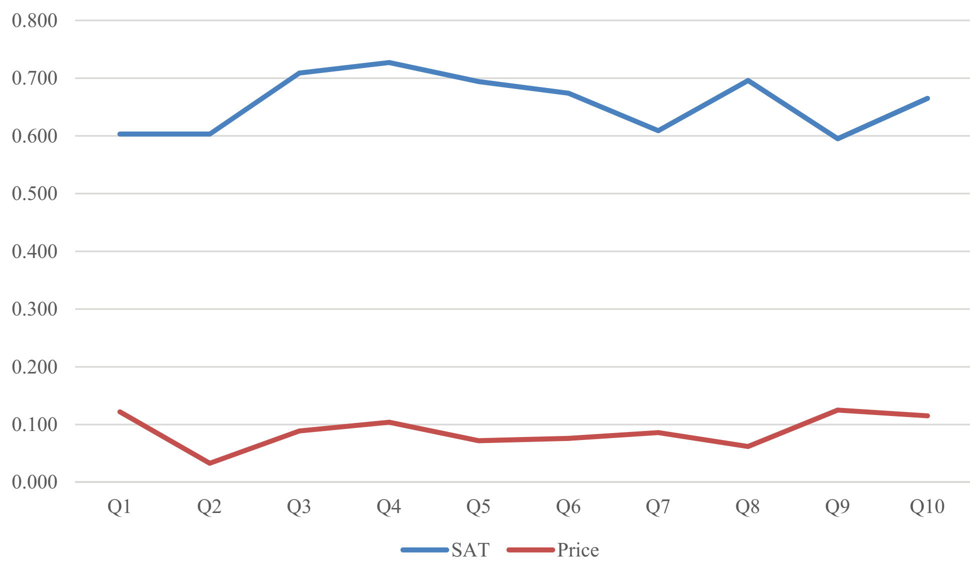

Figure 3. Drivers of contract renewal intentions.

Table 6. PLS_MGA results for contract renewal intentions.

	Q1 – Q2	Q2 – Q3	Q3 – Q4	Q4 – Q5	Q5 – Q6	Q6 – Q7	Q7 – Q8	Q8 – Q9	Q9 – Q10
Effect on Contract Renewal Intentions									
Customer Satisfaction	*t*=0.00	***t*=−3.59**	*t*=-0.65	*t*=1.15	*t*=0.62	*t*=-0.23	*t*=0.56	*t*=-1.45	*t*= 0.22
Price Competitiveness	***t*=2.40**	***t*=−1.82**	*t*=-0.43	*t*=0.88	*t*=-0.10	*t*=1.60	***t*=−2.27**	***t*=−2.57**	***t*=−1.78**

Numbers in italics are not significant, others are statistically significant at $p < 0.05$ level

We again applied PLS-MGA in SmartPLS 3.0 using bootstrapping to establish the existence of significant differences in the path coefficients across the term quarters of data. Table 6 shows that satisfaction is relatively stable with only one quarter (Q2 to Q3) demonstrating a statistically significant difference with the previous quarter. For Price competitiveness, however, there are significant differences in 5 out of the 9 quarters where a difference could be calculated.

Finally, the predictive validity of our model was assessed using holdout samples, following the procedure described by Carrión et al. (2016). The datasets for each quarter were randomly divided into a training sample and a holdout sample to determine how the model in the training set performed with the holdout sample for validation. The training sample model achieved R^2 values for customer satisfaction of 0.56. 0.48, 0.55, 0.52. 0.49. 0.51, 0.43, 0.49, 0.39 and 0.44 across the 10 quarters, and 0.49, 0.46, 0.51, 0.53. 0.47. 0.51. 0.38, 0.48, 0.41 and 0.50 for contract renewal intentions. Holdout sample data was then standardized, construct scores for the holdout samples were calculated, and prediction scores for satisfaction and renewal generated. The R^2 values of for customer satisfaction in the holdout samples were 0.57, 0.51, 0.55. 0.48. 0.49, 0.52, 0.40, 0.45. 0.38 and 0.44, and 0.47, 0.45, 0.54, 0.55, 0.47, 0.45, 0.38, 0.52, 0.41 and 0.50 for contract renewal intentions, respectively. These similarities in R^2 values in both samples suggest that our model is able to predict values in practice for both customer satisfaction and contract renewal intentions.

Discussion and implications

The results highlight some new and interesting observations of B2B relationship capabilities and their impact on customer satisfaction and contract renewal intentions. We analysed a structural model for 10 quarters of data using PLS modeling. PLS is highly appropriate to use when analyzing change in constructs in longitudinal studies (Roemer, 2016). The same indicators, constructs and path relationships between variables directions emerged consistently across each of the quarters. All of the tests for robustness of the model were above the minimum thresholds for reliability and model specification, with no evidence of measurement invariance. The model demonstrates variability in the magnitude of the path coefficients and provides some useful insights into which drivers are more influential in predicting satisfaction and contract renewal intentions over time. In addition, the predictive ability of the model was strong when comparing the data to a hold-out sample. This finding reinforces the usefulness of this framework in predicting future attitudes and behaviours, and extending the model to other B2B services environments.

Using a pseudo-longitudinal framework of analysis at the firm level provides some useful insights beyond the snapshot nature of most research designs. The use of a RCS design to collect large samples of data from the same population of the firm's customers presents a more holistic picture of customer relationship capabilities on customer satisfaction and loyalty across sequential time points in this B2B context. The study findings show that some customer relationship drivers are more dynamic than others, with several drivers relatively stable and others changing on a quarter-by-quarter basis. For example, in three of the quarters account rep performance is the strongest predictor, and in seven other quarters technician performance is the strongest predictor. This makes sense as technicians are likely to be in close and regular contact with building services managers most of the time. Account reps are likely to be in more regular contact during contract renewal negotiations or perhaps at the end of a financial year, although no patterns of this behaviour could be observed in our data.

The nature of the customer relationship drivers on satisfaction also changed across a relatively short period (3 months) and this is strange with such large samples, in a relatively stable B2B industrial services environment. It is interesting to note that the two drivers of contract renewal intentions are relatively stable over time. The path coefficient between satisfaction and contract renewal intentions is the strongest driver in each of the 10 quarters, whereas price competitiveness is consistently a significant but less influential driver in each quarter. It may be that the attitudes of satisfaction and contract renewal intentions are developed over longer periods of time, and customers consider this long-term experience when expressing their attitudes. This retained organisational memory at a high level leads to very stable relationships variables (Bolton et al., 2006; La Rocca, 2020) where more enduring attitudes are less subject to contextual variation in a dynamic business environment. This cannot be said for the more specific service performance dimensions, however, as these independent variables are perhaps more immediate and top of mind.

The study findings therefore highlight the need for firms to actively manage their business relationships closely, and be agile to changes in the environment that stimulate changes. Social network theory may be particularly relevant to these types of B2B relational exchanges (Chung et al., 2021; Palmatier, 2008). These networks must involve close integration within a supplier firm among customer touch-points and across boundary spanning roles or activities external to the organisation. Wong et al. (2009) found that relationship-based differentiation is hard for a competitor to match. Relationship differentiation is very appropriate for the supplier–customer interactions in this industry. The implication is that suppliers must manage the frequency and depth of interaction with customers as a planned strategy. This reinforces the need for strategic key account management to gain a deeper understanding of how the firm wants to interact with its account representatives and its technicians. However, further research is needed to understand why it changed in some quarters and not others.

Based on our results, managers, in B2B industrial markets, must consider the use of RCS research designs as they help to recognize and respond to changes in customer relationship capabilities quickly and over time. Managers would then be able to develop marketing strategies more consistently to help their businesses maintain successful partnerships with their customers. In our study, technician performance predicted customer satisfaction in several quarters, but account reps performance in others. Relying only on technicians for customer relationship capabilities would clearly be inappropriate. This implies that managers should use a team-based approach to capturing changing customer needs and developing customized solutions to build strong long-term B2B relationships (Rajamma et al., 2011). If B2B customer and supplier relationships are moving toward relational exchange that stresses supplier agility and innovation (Narayanan et al., 2015; Noordhoff et al., 2011), there must be a continuous feedback system that replaces periodic surveys. It should also be recognized that the dynamics of inter-firm relationships change over time (Forkmann et al., 2018; Lemon & Verhoef, 2016). We have addressed the calls from these researchers that deeper insights will only emerge through the use of longitudinal, field research that sheds light on how relationships evolve and adapt.

Conclusions

We conclude that customer relationships, even in large B2B industrial markets, change over time. Over the 10 sequential samples in our study firm, the influence of the respective customer relationship drivers were consistently shown to be significant in all the models, but there was some variability on which driver was the strongest predictor of satisfaction. We acknowledge that the firm in our study operates in a very specific industry, B2B services and that business relationships tend to be long term. Studies in different industries might find different results. Our results therefore need to be validated in other industries.

While we statistically tested for metric invariance and sample comparability, and used large samples of data to minimize sampling error, we accept that such variation in attitudes could be due to our random selection of customers who had different attitudes with their supplier. This is unlikely due to the large samples, but possible. Although independent sampling is advantageous in maintaining integrity of data and ensuring consistent sample sizes (Lebo & Weber, 2015), we recommend that future research track 'identical' samples of customers over time, to assess for the differences between the two approaches. Similarly, our research design did not control for all possible influences on customer attitudes. Competitive intensity in the industry, health of the economy and the industry, and supply chain issues could influence customer satisfaction and contract renewal decisions (Williams et al., 2011). We were not able to control for these variables in the study. In future research, it would be fruitful to examine how environmental changes, directly influence customer attitudes, and desired value propositions. There is little research examining how soon the impacts of extraneous trigger events cause changes, if any, in customer attitudes. Nor is there any research that suggests how enduring changes in customer attitudes might be. These shortcomings are due to the cross-sectional nature of most research, a single study at a point in time. From an academic perspective, researchers need to move away from the commonly used cross-sectional surveys and towards more RCS or pure longitudinal studies that depict current reality (Zhang et al., 2016).

A final interesting conclusion of this study is the relative consistency of the measurement and structural models. Statistically speaking, our models held up to many of the rigorous tests of validity, metric-equivalence, and goodness-of-fit. While the customer attitudes may have changed, as indicated by the structural models, the CFA models were statistically stable, for all 10 samples. Future research may be able to replicate our findings in other contexts, but using similar instruments and modeling techniques used in this study. It would be interesting to see if other customer-related CFA models also tend to be stable across independent samples. While collecting longitudinal data is often difficult due to the dynamic nature of business and the limited time available to researchers, firms should still endeavor to measure these attitudes over different time periods to help manage long-term buyer–seller relationships.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Appendix A. Constructs and Measurement Items

Construct	Measurement Items
Technician Service	• Courteous and friendly • Technical competence • Communicating effectively • Advance notification • Preventive maintenance
5 point scale (Excellent to Poor)	
Account Reps Service	• Keeping in touch • Timeliness of quotes • Listening • Proposals • Technical knowledge • Arriving when promised
5 point scale (Excellent to Poor)	
Call Center Service	• Call handling promptness • Handling service need • Scheduling service
5 point scale (Excellent to Poor)	
Price Competitiveness	• New system prices • Replacement parts prices • System maintenance prices
5 point scale (Sig above to Sig below industry average)	
Product Quality	• Overall product quality • Dependable products • Product innovativeness • Availability of parts
5 point scale (Excellent to Poor)	
Customer Satisfaction	
Significant exceeded to significant below	• Met expectations • Overall customer satisfaction
5 point scale (Very satisfied to Very dissatisfied)	
Contract Renewal Intentions	• Willingness to recommend • Likelihood to renew
5 point scale (Definitely to Definitely-Not recommend/renew)	