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Understanding customer loyalty through system dynamics

The case of a public sports service in Spain

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Abstract

Purpose – The aim of this paper is to propose a model for understanding a complex management issue – the customer loyalty in a public sports service.

Design/methodology/approach – Customer loyalty is discussed through the methodology of system dynamics. The proposed model considers the dynamic, non-linear, asymmetric, and reciprocal relationships between its elements, and permits the analysis of the evolution of the system under hypothesized conditions.

Findings – The model reproduces historical data of abandonment and consumers' attitude toward the service (ATS). The achieved simulations showed how the future entry of new competitors can severely threaten public service performance. Furthermore, it was also found that the consumers' ATS was not a very good predictor of the consumers' behavior.

Research limitations/implications – System dynamics methodology can also be applied to understand the loyalty in the remaining services offered by the public institution. Other services, such as fitness, aerobics, martial arts, can be analyzed by considering their respective different competitive environments.

Practical implications – The new competitive environment can dramatically affect the number of consumers per year if a public institution does not differentiate its service. In addition, the entry of new competitors will affect the evolution of the system, as the customer satisfaction rates will be modified.

Originality/value – Understanding customer loyalty is one of the most important concerns for academics and practitioners in the areas of management and marketing. The system dynamics approach is an under-utilized methodology in the field of sports management, which overcomes simplistic linear approaches. The paper shows how system dynamics can provide attractive insights into the field of sports management.

Keywords Customer loyalty, Sports, General management, Public sector organizations, Information modelling

Paper type Research paper

1. Introduction

Understanding customer loyalty is one of the most important concerns for academics and practitioners in the areas of management and marketing. Customer retention is the ultimate goal for relationship marketing, and it is positively linked with the firm's profit (Kamakura *et al.*, 2002). Loyalty is not only based on the measures of consumer behavior, but the positive attitude toward the company and the likelihood to recommend the product/service usage (the willingness to provide favorable word of mouth (WOM)) are also the manifestation of this concept (Zieithaml *et al.*, 1996). Thus, firms obtain tangible and intangible revenues through loyal customers: repeat purchases, brand image, and prescription.

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For public organizations management, customer loyalty, although not *per se* the primary goal of their strategy, plays a prominent role. Satisfying consumers and proving high rates of efficiency are the key aims of public management (Scharitzer and Korunka, 2000). Generally, public and non-profit organizations do not have the pressure of competitiveness unlike private firms, and must support loss-making services. However, customer loyalty is desirable for two main reasons:

(1) for the increase in efficacy of marketing instruments (and the consequent gains in efficiency);

(2) for the favorable WOM and corporate image evaluation (politician's returns).

Nevertheless, understanding customer loyalty is a complex task for academic research. In our study about loyalty, several issues emerged as important factors:

- the necessity of adopting a dynamic perspective;
- the consideration of customer purchasing alternatives and switching costs;
- the non-linear and asymmetric relationships between service evaluations and repurchase intentions (RI); and
- the relationship between RI and customer behavior.

The objective of this research was to understand customer loyalty in the specific context of the public sports service in Spain, provided by a City Council – swimming pool activities during summer time. This service is provided in a competitive framework with boundary conditions: a quasi-monopolistic situation. In this study, we dealt with this complexity of analyzing customer loyalty through the methodology of system dynamics. The proposed model counts for dynamic, non-linear, asymmetric, and reciprocal relationships between its elements (including attitudinal and behavioral variables), and allows analysis of the evolution of the system under hypothesized conditions. After the analysis of three cross-sectional studies about the customer evaluation of the service and the database analysis of abandonment, we proposed a conceptual dynamic model that describes the observed situation. Using system dynamics, we stabilized the system and simulated the future system evolution under hypothesized simulated conditions, to study the effect of the entry of new competitors on the evolution of the system. This model is believed to serve as a strategic tool for understanding the causes of the current situation and developing policies for mitigate oscillations. In addition, the system dynamics approach can provide new insights into the field of sports management[1], and overcome traditional econometric treatment of data for understanding the dynamic marketing problems.

2. Research framework

The complexity of analyzing customer loyalty

Customer loyalty is one of the oldest concepts in marketing, whose definition remains elusive (Shugan, 2005). For example, Jacoby and Chestnut (1978) identified 55 different definitions of brand loyalty in the marketing literature. Despite the difficulty in defining customer loyalty, in line with Aaker (1991), we can consider this concept as the degree of linkage between the company/brand and the customer. Loyalty must extend beyond repeated purchase behavior, and must include attitude toward the company/brand and the consideration set (Mehta *et al.*, 2003). This attitudinal

dimension is important, because it enhances the linkage between the customer and the firm from a relational point of view. We must bear in mind that repeated purchase behavior could be due to routine and inertia (Huang and Yu, 1999), or because of the lack of purchasing alternatives (Fullerton, 2005). The latter is the case of monopolistic markets, where customers do not have any option for choosing a substitutive brand. However, this kind of loyalty is somewhat misleading, if it is not accompanied with positive attitude toward the company. The market situation could change and the number of customers could diminish, if they perceive that alternative brands provide superior value. Therefore, if the link between the customer and the firm is strengthened with an attitudinal component, switching cost would be larger and consequently, the likelihood of defect would be lower.

Considering the fact that understanding customer loyalty is a complex task for marketing researchers, we proposed analyzing this problem by taking into account several important premises.

First, customer behavior is dynamic and evolves along with time (Johnson *et al.*, 2006). This is due to the purchasing behavior being driven by several attitudinal, situational, and personal factors that are susceptible to change. Attitudinal factors refer to the customer subjective evaluation of the firm performance. Several constructs have been studied as the drivers of loyalty – customer satisfaction (Bolton, 1998; Chandrashekaran *et al.*, 2007), perceived quality (Brady *et al.*, 2002; Zieithaml *et al.*, 1996), and corporate image (Bloemer and De Ruyter, 1998; Selnes, 1993) are probably the most important among them. As these constructs are considered similar to an attitude (Iacobucci *et al.*, 1994; Oliver, 1997) and as there is evidence that attitude evolves along with time (Homburg *et al.*, 2006), the necessity of adopting a dynamic perspective emerges as a demand for obtaining better information. A single cross-sectional research provides only a snapshot of a dynamic process, and therefore, conclusions obtained from these studies are severely limited. Situational and contextual factors encompass a variety of different elements, such as the social context (influence of peer groups, parents, colleagues, etc.), legal restrictions to the supplier choice, time pressure, temporary budget restrictions, or exceptional shopping situations like vacations. These factors are considered as the moderators of the relationship between consumer evaluations of the firm performance and customer retention (Hennig-Thurau and Klee, 1997). Finally, a series of personal factors also act as the moderating variables: age, sex, income, education (Mittal and Kamakura, 2001), customer experience with the company (Rust *et al.*, 1999), experience with other companies (Ekinci, 2003), or predisposition to variety seeking (Hennig-Thurau and Klee, 1997; Oliver, 1999). Situational, contextual, and personal factors are, therefore, relevant elements to consider when studying customer attitudes (Dabholkar and Bagozzi, 2002).

Second, it is necessary to consider customer purchasing alternatives and switching costs. Customer purchasing behavior is driven by perceived value. Perceived value is defined as "the consumer's overall assessment of the utility of a product based on perceptions of what is received and what is given" (Zeithaml, 1988). This utility function comprises multiple variables having different weights, varying from customer to customer. We presumed that customers will select the alternative that provides superior value[2]. Therefore, drivers of loyalty are also drivers of perceived value (Agustín and Singh, 2005). In monopolistic markets, there is a lack of purchasing

alternatives and hence, the customer has to compare the value of making a purchase against the value of not achieving it. When alternative brands exist, customer sensibility to marketing variables (Gupta *et al.*, 1996) and switching costs (Rust *et al.*, 2004) play a prominent role in the customer's choice. Again, attitudinal, situational, contextual, and personal factors are involved in the final choice. This shows the importance of the emotional linkage between firms and customers. When a customer is committed to the firm, switching costs increase (Bell *et al.*, 2005) and therefore, the perceived value of the current choice is enhanced with respect to other alternatives. This does not mean that customers will always necessarily choose the same brand; customers may leave and return, and be monogamous or polygamous in terms of the number of firms with which they conduct business in a particular category (Rust *et al.*, 2004). However, the greater the commitment of the customer to the firm, the greater is the likelihood to repurchase and prescribe.

Third, there are non-linear and asymmetric relationships between service evaluations and RI and WOM. This can be observed in prospect theory (Kahneman and Tversky, 1979) and the discrete nature of emotions (Herzberg *et al.*, 1959), and these perspectives were explained by Mittal *et al.* (1998) and Hennig-Thurau and Klee (1997). Basically, the ideas behind these theories are as follows:

- losses loom larger than gains;
- negative information is more perceptually salient that positively valenced information;
- marginal values of both gains and losses decrease with their size (diminishing sensitivity);
- some evaluated attributes act as rewards or motivators, while others work as hygienes or non-compensatory penalties.

This signifies that few product/service failures can severely hurt a highly efficient firm, there are thresholds, from where the efforts made by the firms for improving quality and satisfaction, with no marginal gains, or there are attributes that may not increase the purchase likelihood, but the absence of them decrease that likelihood. Although there are studies that question these asymmetric and non-linear relationships (Johnson *et al.*, 2006; Streukens and de, Ruyter, 2004), there is ample empirical evidence contradicting these relationships (see Cooil *et al.*, 2007). Phenomenon like hysteresis in market response (Hanssens and Ouyang, 2002), and the asymmetries and time delays in the relationships between changes in the objective quality and the perceived quality (Mitra and Golder, 2006) also support the extreme complexity of analyzing customer loyalty.

Fourth, we studied how RIs are related with effective repurchase behavior. Evidence reveals that many customers who state that they are satisfied with a service provider nevertheless defect (see Chandrashekaran *et al.*, 2007; Hennig-Thurau and Klee, 1997; Oliver, 1999). Even consumers' self-reported purchase intentions are poor predictors of their future purchase behavior[3] (Chandon *et al.*, 2005; Morwitz, 1997). The conversion of intent into repurchase is moderated by various factors, including the type of product, demographics, experience, or time lapse (Seiders *et al.*, 2005). As indicated by Chandon *et al.* (2005), in practice, the studies adjust the intention scores by analyzing the actual purchase behavior of the consumers whose purchase intentions have been measured

previously. The popular ACNielsen BASES model forecasts aggregate purchase rates by applying conversion rates to measured purchase intentions (e.g. it assumes that 75 per cent of the consumers who checked the top purchase-intentions box will actually purchase the product). Jamieson and Bass (1989) described the multiple conversion schemes that marketers use to forecast purchase behavior from the intentions. For example, 75 per cent-25 per cent-10 per cent-5 per cent-2 per cent for each purchase-intention box (e.g. 75 per cent of consumers who state that they would "definitely buy" actually do so, 25 per cent of consumers who state that they would "probably buy" actually do so). Chandon *et al.* (2005) concluded that because of the effect of self-generated validity[4], conversion rates should be regressed toward their means (e.g. the correct weighting scheme might be 60 per cent-20 per cent-15 per cent-10 per cent-8 per cent). Therefore, predicting loyalty is a complex task. Although the attitudinal element of loyalty is driven by other attitudes toward the brand/company, neither these attitudinal drivers nor RI are good predictors of the behavioral element of loyalty.

To sum up, understanding customer loyalty is a real challenge for marketing research. The dynamic nature of customer attitudes and behaviors, the multiplicity of contextual, situational, and personal factors moderating the relationships between attitudes and behaviors, the structure and competitiveness of the market under study, the non-linear and asymmetric relationships between customer evaluations and future RI, and the incapacity of survey research to accurately predict the customer behavior severely complicate the research. Traditional methodology for studying customer loyalty is based on econometrics models applied to cross-sectional and longitudinal data. However, we presume that econometric models are insufficient for modeling the discussed complexity of the loyalty phenomenon. A system dynamics approach is the methodology used for dealing complexity with more efficiency, using real data and simulation tools.

Why system dynamics?

System dynamics is a methodology for understanding change, using differential equations. System dynamics is grounded in the control theory and the modem theory of non-linear dynamics, and relies on the systems thinking and modeling for a complex world (Sterman, 2002). System thinking is the ability to see the world as a complex system where everything is connected with everything else, and when the whole is more than the sum of its parts. This paradigm allows faster and more effective learning, identify the high leverage points in systems, and avoid policy resistance. A systemic perspective enables one to make decisions consistent with the long-term best interests of the system as a whole (Sterman, 2001).

This holistic view for studying the phenomena permits the representation of mental models about the research problem as a dynamic system. The objective of system dynamics is to understand the structural causes that provoke the behavior of the system. The research problem is defined using qualitative and quantitative information, and consequently reflected in a causal diagram. This causal diagram embodies the equations that relate the variables in the proposed model. The researcher must assign values to several parameters to assure that the model simulation reproduces historical data under plausible conditions. If the proposed model is coherent with the past and present situation, the researcher can simulate the impact of different

policies and interventions on the system, as well as locate the leverage points through sensibility analysis.

Dynamic complexity arises because systems have certain important characteristics (Sterman, 2001):

- Systems are constantly changing.
- The actors (variables and constants) in a system interact strongly with one another and with the natural world, and everything is connected to everything else.
- Because of the tight link among the actors, our actions feedback on themselves.
- Non-linear relationships exist, where the effect is rarely proportional to cause.
- The system is history-dependent – past behavior influences future outcomes.
- The dynamics of system arise spontaneously from their internal structure. Often, small, random perturbations are amplified and molded by the feedback structure, generating patterns in space and time. There are self-organized critical states.
- The capabilities and behaviors of the actors in complex systems change over time. Evolution leads to selection and proliferation of some actors, while others become extinct.
- Time delays in feedback channels indicate the long-run response of a system to an intervention, often different from its short-run response.
- In complex systems, cause and effect are distanced in time and space, whereas we tend to look for causes near the events we seek to explain.

Thus, our attention is drawn to the symptoms of difficulty rather than the underlying cause. High-leverage policies are often not obvious and counterintuitive.

Therefore, we rapidly analyzed how the problem of understanding customer loyalty fits into system dynamics approach. Table I shows examples of how the study of customer loyalty phenomena falls under the requirements of the aforementioned characteristics of complexity.

System dynamics approach outperforms traditional econometric treatment of data for understanding dynamic marketing problems. Cross-sectional designs are deficient for studying feedback loops (Kaplan *et al.*, 2000; Kline, 2006). Longitudinal designs are more flexible (also more expensive), allow autoregressive effects, and lag periods can be observed in some situations. However, when reality does not remain stable, i.e. when there is a change in the initial conditions, longitudinal designs are also problematic (Martín, 2004). For example, we can analyze a consumption behavior model in a monopolistic market using a longitudinal design, but would this model continue being useful under a new competitive environment? Traditional statistical treatment of cross-sectional and longitudinal models is also questioned from the point of the accuracy of prediction, sensibility to small perturbation of the data, and the much idealized assumptions underlying the majority of statistical models (Breiman, 2001). Therefore, it is not strange that the increasing growth of the new methodologies for analyzing data arises from the computational science techniques. Neural network or support-vector machines are the examples of these new techniques. These algorithmic techniques improve the predictive accuracy of traditional data models (Cui and Curry,

Constant change	Customer attitudes and behaviors evolve over time
Tightly coupled and feedback	Past attitudes and behaviors influence the present, and the present influence the future. Attitudes and behaviors are endogenous variables and there are feedback loops
Non-linear relationships	There are asymmetry and non-linear relationships between customer attitudes and behaviors
History-dependent	Successful brand loyalty programs enhance the customer switching cost and also the competitor's costs, derived from the investment to get new customers. Services, failures, and dissatisfaction can result in severe decline in the number of customers, some of whom may not return forever
Self-organizing	A small negative perturbation (as a negative rumor or news about a firm) can be amplified by the feedback structure, generating a priori non-expected collective behavior (to boycott the firm or defend it)
Adapting and evolving	Customer learning through experience can change the expectations about firm performance. Psychological effects, such as contrast or assimilation can appear depending on the customer and the context situation
Time delays	There are different lag periods for similar causes. A similar investment for improving the customer attitude toward a service made by two firms (e.g., adopting a quality system management) can yield different effects depending on the firm's reputation
Counterintuitive behavior	In many competitive markets, customer defects are satisfied. Some brand-loyalty programs should focus on creating monopolies in the customers' mind, instead of enhancing customer satisfaction

Table I.
Dynamic complexity and customer loyalty research

2005). Computer-intensive techniques are also used for studying the emergent phenomena in marketing (Bonabeau, 2002a). Emergent phenomena result from the interactions of the individual entities and can have properties that are decoupled from the properties of the individuals. Agent-based modeling (ABM) is a relatively new bottom-up technique that deals with this interactivity. In ABM, a system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Agents may execute various behaviors appropriate for the system they represent – for example, producing, consuming, or selling (Bonabeau, 2002b). This is an example of the slow, progressive change of the social sciences research studies, moving toward statistical physics for studying complex phenomena (Ball, 2004).

In this context, system dynamics remains unexpectedly under-used in marketing research. Though it is a widely used research tool in other fields, such as engineering, epidemiology, ecology, or operation management, there is no evidence of such studies in the major, marketing scientific journals. Surprisingly, we did not find any articles on system dynamics studies in a recent special issue of *Journal of Business Research* (2007), which deals with complexity in markets, containing articles mainly focused on ABM. The ABM allows detailed representation of individuals and captures their heterogeneity and network of interactions among them, while the system dynamics assumes homogeneity and perfect mixing within compartments. However, ABM

increases the costs and the extra complexity significantly increases the computational requirements, constraining the ability to conduct sensitivity analysis. Rahmandad and Sterman (2007) made an excellent comparison between these two methodologies; the superiority of ABM over system dynamics is little significance in some settings. Nevertheless, if we focus on the policy analysis where resources are limited and policymakers must make tradeoffs among the level of detail, the breadth of the model boundary and the ability to carry out sensitivity analysis, then the system dynamics will be more appropriate. As concluded by Rahmandad and Sterman (2007), data availability significantly affects the model choice. The ABM will be useful when data or the underlying "physics" of a situation specify the network structure, suggesting that it is critical in the results, and that structure is stable over the time horizon of interest. Data on contact networks and the distribution of individual attributes are often hard to obtain and are highly uncertain, requiring extensive sensitivity analysis to ensure robust results. Similarly, in our research, we have not modeled individuals, i.e. autonomous decision-making entities or agents (see Zhang and Zhang, 2007), but actors (constant and variables), which represent aggregate states (including attitudes and behavior). It must be kept in mind that there are only limited cross-sectional historical data about service usage and customer attitude toward the service (ATS). Lastly, as we simulated changes in the structure of the system to study the effect of the entry of new competitors on customer loyalty, and also carried out sensitivity analysis, consequently concluding that system dynamics methodology is more adequate than ABM.

3. The service under study

We have focused on analyzing a specific service provided by the Council of a Spanish city – swimming pool activities during summer time (June-August). This public institution offers several courses catering to different individuals, segmented by age and skills, such as:

- babies, from three to five years;
- beginners, from six to eight years;
- intermediate I, from nine to 11 years;
- intermediate II, from 12 to 14 years;
- advanced, from 15 years; and
- adults.

These are very flexible categories that also depend on the swimming skills of the individuals, for example, a nine-year old child with highly developed swimming skills could join the advanced group. As can be seen, the activities at the facility are mainly focused on children who want to learn to swim, although there is also a more creative course for the adults.

The service portfolio was designed to cover a wide range of swimming skills and ages, in line with the philosophy of a public service. Therefore, children can advance from one course to another, and even remain as users when adults. However, it is not uncommon that some individuals in the advanced group leave because of the lack of motivation, but this percentage is negligible. It must be noted that only around 6 per cent of the users belong to the advanced group.

There are other private companies in the city with swimming-pool facilities, but they are not comparable with this public service under study, as some of them are closed during part of the summer, while others remain mainly focused on the military environment. Therefore, this facility does not have any true direct competitors.

4. Proposed model

We had three sources of available quantitative information: database of registration and abandonment, customer surveys research, and the competitive environment description. Likewise, qualitative information provided by a technical manager of the analyzed service was also used. The available data refer to three years: 2002, 2003, and 2005 and the data analysis was carried out in 2006.

The database revealed a soft decrease in the number of consumers per year. However, around 90 per cent of the customers were satisfied with the service delivered. Taking into account that the competitive situation approaches a monopolistic market, we were interested in understanding the causes of this tendency as well as the behavior of the system under a new competitive setting.

Table II shows the main quantitative information provided by the database and survey researches. The surveys were designed by the authors of this paper. Customers were asked about several attitudinal issues (satisfaction, global perceived quality, WOM, and RI). All variables were measured using a single question (Bergkvist and Rossiter, 2007; Hayduk, 1996; Rossiter, 2002) and with an ordinal scale that ranged from 1 to 5, with 3 being a neutral location (Table III). Considering the discrete nature of the scale[5] and the aforementioned differences between positive and negative attitudes, we decided to split the sample of consumers into two groups with respect to

	2002	2003	2005
Database consumers	1,084	1,000	980
New subscriptions (%)	273 (25.18)	352 (35.20)	350 (35.71)
Abandonment (%)	436 (40.22)	382 (38.20)	
Survey research sample	99	146	194
Percentage satisfied (+)	96.9	93.1	90.2
	(91; 99)	(87.7; 96.6)	(85.1; 93.9)
Percentage satisfied (−)	2.0	4.1	3.6
	(0.2; 7.0)	(1.5; 8.7)	(1.4; 7.2)
Percentage perceived quality (+)	90.9	86.3	92.2
	(0.834; 0.957)	(79.6; 91.4)	(87.5; 95.6)
Percentage perceived quality (−)	0	4.1	2.0
	(0; 3.6)[a]	(1.5; 8.7)	(0.5 – 5.1)
Percentage word of mouth (+)	86.8	83.5	93.2
	(78.5; 92.8)	(76.5; 89.7)	(88.8; 96.3)
Percentage word of mouth (−)	2.0	8.2	4.1
	(0.2; 7.0)	(4.3; 13.9)	(1.7; 7.9)
Percentage repurchase intentions (+)	95.9	86.9	93.2
	(89.9; 98.8)	(80.4; 91.9)	(88.8; 96.3)
Percentage repurchase intentions (−)	3.0	6.8	3.6
	(0.6; 8.6)	(3.3; 12.2)	(1.4; 7.2)

Note: [a] One side confidence interval (97.5 per cent)

Table II.
Historical data

the evaluation of the variables. Thus, we estimated the exact binomial confidence interval for the proportion of consumers pertaining to the two groups using STATA 8.2.

Table II also shows how WOM and RI has similar values to satisfaction and perceived quality (confidence intervals overlap), i.e. the percentage of consumers who have a positive ATS is very similar along the attitudinal variables and across the ages, and this percentage is extremely high. The same occurs for the percentage of consumers who have a negative attitude, and this percentage, on the contrary, is almost trivial. This signifies that the consumers carry out a positive evaluation of their service experience (satisfaction and quality) and this is transferred to a positive WOM and RI. However, under this idyllic situation, we observed a great percentage of decline in the number of consumers.

We proposed the dynamic model through writing the equations that depict the relationships between the elements of the system. The following equations show the basic mathematical form of the proposed model. We used Vensim PLE Plus 5.5d for building the model and running the simulations.

$$L_t = \int_0^T R_t dt \tag{1}$$

$$R_t = g(L_t, A_t, C) \tag{2}$$

$$A_t = f(L_t, A_t, C) \tag{3}$$

$$L_t = h(L_0, A_0, C) \tag{4}$$

In these equations, g, h, and f are arbitrary, non-linear, and potentially time varying, vector-valued functions. Equation 1 represents the evolution of the system over time, where L_t is the Levels (or state variables) that define the dynamics of a system. Equation 2 shows the computation of the Rates (R_t) determining the evolution, while Equation 3 provides the intermediate results necessary to compute the rates, and Equation 4 represents the initialization of the system. The A and C represent Auxiliary and Constant variables, respectively, that permit a better visualization of the aspects that determine the behavior of the rates. Thus, feedback loops and non-linear relationships are defined in these equations.

We defined the number of consumers per year (NCY) as the unique state variable (L_t), while the number of new subscriptions (NNS), the number of defections (ND), and

Attitudinal variables		Source
Satisfaction	I am satisfied with my participation in this activity	Teas (1993)
Globally perceived quality	This company provides an excellent service	Brady and Cronin (2001)
Word of mouth	I recommend this service to other persons	Zieithaml *et al.* (1996)
Repurchase intentions	Probably, I will participate again the next year	Zieithaml *et al.* (1996)

Table III.

the rates (R_t) determine the evolution of the system. The remaining elements represent the auxiliary and constant variables of the system. Table IV shows all the equations that form our proposed model (see Figure 1).

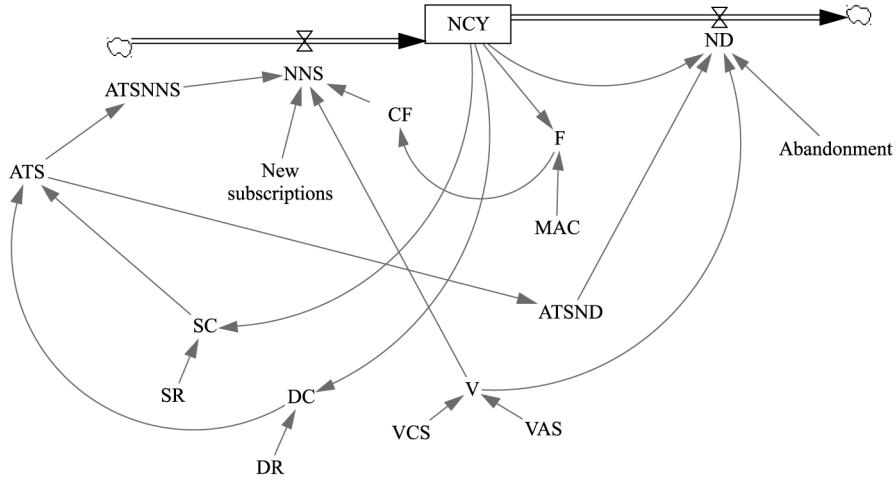
We hypothesize that positive ATS affects the NNS through WOM. Similar scores of all attitudinal variables support the accuracy of this statement. The ATS is a multiplicative factor that increases or decreases the number of consumers who have decided to make the enrolment decision (new subscriptions). In addition, ATS also influences ND, because the consumer's evaluations of the service are the important determinants of the repurchase behavior. The ATS is built as a quotient between satisfied (SC) and dissatisfied consumers (DC). Both SC and DC are the functions of the percentage of satisfied and dissatisfied rates (SR and DR). The ATS makes an asymmetric and non-linear influence on the NNS and ND (ATSNNS and ATSND, respectively), in line with the prospect theory and the discrete nature of emotions. Figure 2 shows a form of graphical interpolated function.

Consumers who have made the decision of using the service may choose the alternative that provides superior value (V). As there are no competitive companies that offer a similar service, we proposed that this auxiliary variable would be the

(01) Abandonment = RANDOM UNIFORM(0.38, 0.4, 1)
(02) ATS = SC/DC
(03) ATSND = WITH LOOKUP (ATS,([(0,0)-(1000,10)],(0.5,3),(1.1315,1.8),(1.95719,1.6),(2.72171,1.3),(3.42508,1.2), (3.88379,1.1),(990,1)))
(04) ATSNNS = WITH LOOKUP (ATS, ([(0,0)-(1000,5)],(0.795107,0.0219298), (1,0.5),(1.5,0.8),(2,1.07456),(3.058,1.1),(10.0612,1.2),(900,1.3)))
(05) CF = IF THEN ELSE(F < 1, 1, 1/F)
(06) DC = NCY *DR
(07) DR = RANDOM UNIFORM(0.05, 0.1, 99[a])
(08) F = NCY/MAC
(09) FINAL TIME = 2010
(10) INITIAL TIME = 2001
(11) MAC = 1400
(12) NCY = INTEG (NNS-ND,1200)
(13) ND = NCY *ATSND *Abandonment/V
(14) New subscriptions = RANDOM UNIFORM(300, 357, 99[a])
(15) NNS = ATSNNS *New subscriptions *V *CF
(16) SC = NCY *SR
(17) SR = RANDOM UNIFORM (0.8,0.95,99[a])
(18) TIME STEP = 1
(19) V = XIDZ(VCS, VAS, 1)
(20) VAS = STEP(1[b], 2008)
(21) VCS = 1

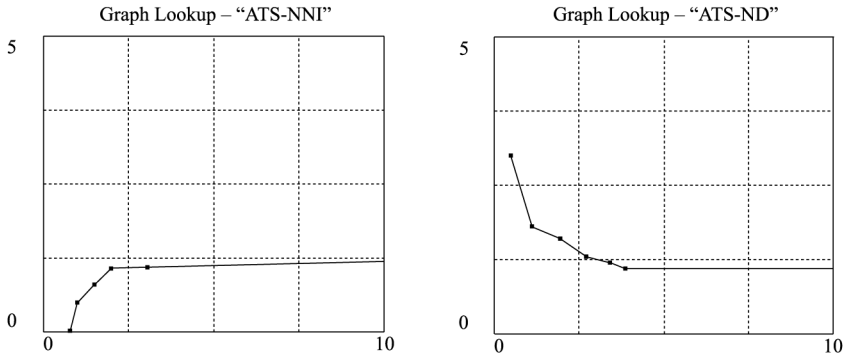
Notes: [a] Parameter for the calculus of the random number; [b] 1 for Simulation 1; 1.5 for Simulation 2; 2 for Simulation 3. Notes about some VENSIM functions: WITH LOOKUP: specifies a nonlinear relationship between the input x and the output by passing the input through a series of *x, y* pairs specified as numbers; IF THEN ELSE: Returns first value if condition is true; second value if condition is false; INTEG: Returns the integral of the rate; XIDZ: The XIDZ function performs division except when that division would be by 0, in which case it returns the third argument; STEP: Returns 0 until the step time and then returns the first argument

Table IV.
Model syntax



Notes: ATS, attitude toward the service; ATSND, attitude toward the service-number of defections; ATSNNS, attitude toward the service-number of new subscriptions; CF, factor of correction; F, factor that counts for the maximum admissible number of consumers; DC, dissatisfied consumers; DR, dissatisfaction rate; MAC, maximum admissible number of consumers using the service; NCY, number of consumer per year; ND, number of defections; NNS, number of new subscriptions; SC, satisfied consumers; SR, satisfaction rate; V, perceived value; VAS, perceived value of choosing a hypothetical alternative service; VCS, constant value of choosing the current service

Figure 1.
Proposed model



Notes: Attitude toward service (ATS) has a non-linear effect on the number of new subscriptions and number of defections. We hypothesize that when ATS is below 2 (there is more than 33% of dissatisfied consumers), it yields a negative effect on the number of new subscriptions (NNS) (through word of mouth). The damage made by few dissatisfied consumers can be relatively more important than the benefits created by a great amount of satisfied consumers. Likewise, dissatisfaction exerts a non-linear influence on the number of abandonment. If all consumers were satisfied, there will be no negative effect, and defection would be caused by other reasons (seeking variety, etc.)

Figure 2.
Interpolated non-linear functions

quotient between the constant value of choosing the current service (VCS) and the perceived value of choosing a hypothetical alternative service (VAS). This latter auxiliary variable permits the simulation of a new environment, where consumers have other purchasing options. If VAS $>$ VCS, then $V < 1$, and therefore, NNS and ND would decrease and increase, respectively.

The logic and mathematical specification of V is straightforward. For example, if VAS $= 2$, then $V = 0.5$, and hence, V acts as a multiplicative factor that reduces NNS to 50 per cent of its score. This is a great negative effect that also affects the NCY. At the same time, it is expected that ND will increase by a factor of 2, because V is a divisor of the determinants of ND; and all these specifications are shown in Table IV. The specification of VAS is a qualitative assertion that we have addressed using qualitative information.

Finally, we considered a factor (F) that counts for the maximum admissible number of consumers using the service (MAC) to correct (CF) the potential NNS, when the NCY exceeds the maximum permissible value given by the public institution for delivering high quality service (Figure 1).

Furthermore, we assigned values to certain parameters of the system using the available information. The values of SR and DR were taken from the surveys. As discussed earlier, the attitudinal variables have similar values across the ages. Considering these values as estimates that have certain variability, we used the random uniform function to model the variability of these variables. Thus, SR and DR were random variables moving along the lower and upper limit of the values derived from the confidence interval of the estimates. New subscriptions and Abandonment were also modeled with certain variability (10 per cent around the mean of the observed values). This fact permits the increase in the flexibility of the simulation, accepting the uncertainty in some key variables.

We carried out the first simulation to stabilize the model. We chose a temporal horizon of ten years, from 2001 to 2010. In this first simulation, we did not include the possible scenario of potential competitors. The initial value of consumers in 2001 (1200) was in agreement with the suggestion of the technical manager of the service. The first simulation (S_1) provided an output that reproduced the historical data, showing how NCY softly decreased in time, under the simulated conditions (Figure 3).

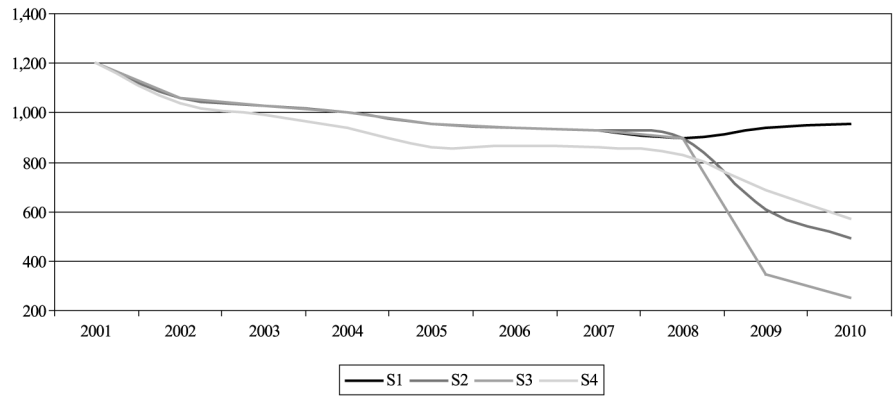


Figure 3.
Number of consumer per year (NCY) after simulations

Simulating new scenarios

We were mainly interested in the simulation of the two new scenarios. First, what will be the state of the system under a new competitive environment? It is fairly probable that the competitive situation would change after 2007, when two new sports complexes will be opened simultaneously. To simulate this hypothesized situation, we changed the VAS parameter to the values of 1.5 and 2. This means that there will be many persons who would prefer one of the alternative services instead of the public service. In addition, great marketing efforts are expected for the new sports complexes to obtain a critical mass of customers. The effects of these two simulations on the NCY are depicted in Figure 3 (S_2 and S_3). Regrettably, for the public service, high rates of satisfied customers and the consequent positive WOM are not sufficient to counteract the effects of the new competitors.

Second, we hypothesized that the new competitors will not be capable of overcoming some of the advantages that the public service offers. As the technical manager claims, the differentiation of public service lies in their personal relationship with the costumer and in the several years of experience in offering the service. In addition, prices are highly competitive because public services are financed by the state. Swimming-pool activities are mainly focused on children, and parents could be resistant to changes. In short, customer satisfaction can enhance switching costs in this specific service. However, what will be the state of the system if the level of satisfaction decreases? We hypothesized that under the new competitive environment, normative expectations would influence the judgment of satisfaction. Consumers have more information (advertisement, WOM received, etc.) to compare the current service with the alternative ones. Therefore, if public service does not implement any program to improve the level of service quality, probably the satisfaction rates would decrease, which we have simulated in our study. We programmed a 20 per cent decrease of SR and an increase in DR of the same magnitude, from 2008. The results (Figure 3) show how NYC decreases after 2008 ($S4_1$). However, this slope is not as important as the slope encountered with S_2 and S_3.

Given the magnitude of the effects shown in S_2 and S_3, we have conducted a sensitivity analysis on the VAS parameter by performing a Monte Carlo simulation with Vensim PLE Plus 5.5d. We specified a random normal function for the parameter, from 1 to 2.5. Thus, we covered a wider range of negative effects on the variables of interest. We hypothesized the normal distribution with mean = 1.75 and standard deviation = 0.382. These specifications represent a Gaussian curve, where 95 per cent of the data fall between 1 and 2.5 and thus, consider the minimum and maximum value of the VAS parameter, such as the critical points of the normal standard distribution with the same confidence level. We chose the normal distribution instead of, for example, random uniform distribution, because we did not consider that all the VAS values have the same probability. It appears plausible to believe that the most probable values for VAS would be in the "middle-point" between the best and the worst scenarios.

After carrying out 200 simulations, the results, as expected, revealed that VAS can be considered as a leverage point of the system. We arranged the values for NCY for the last two years (2009 and 2010), from the lowest to the highest score, to apply this empirical distribution to build a confidence interval for the mean of each value.

Therefore, 95 per cent confidence intervals for the mean of NCY_{2009} and NCY_{2010} were calculated, (174; 818) and (172; 765), with mean as 479 and 387, respectively.

These results indicate how the most probable hypothesized negative scenario (under the normality assumption) chiefly decreases the NCY, while the other factors remain equal. Sensitivity analysis provides more robust results that are in accordance with simulations S_2 and S_3. We can easily observe that the mean of NCY_{2009} and NCY_{2010} falls between the two curves, as shown in Figure 3.

5. Discussion, implications, and further research

Through the methodology of system dynamics, we analyzed a model for understanding the customer loyalty in a specific sports service provided by a City Council. In this study, we attempted to show a different perspective in understanding the loyalty phenomenon, taking into account the complexity involved in studying it. Moreover, we considered feedback loops and non-linear relationships among the different variables, using the methodology of system dynamics, to overcome the limitations of the linear-static perspective.

Our hypothesized model was derived from the four premises as follows:

(1) Customer behavior is dynamic and evolves along with time, because it has a strong attitudinal component that evolve with time.

(2) It is neccesary to consider customer-purchasing alternatives and switching costs, which can be taken into account with the perceived value variable.

(3) There are non-linear and asymmetric relationships between service evaluations and RI and WOM. As prospect theory defends, attitudes and behavior are not linearly and symmetrically related.

(4) The RI are not very good predictors of the effective repurchase behavior.

Although Agustin and Singh (2005) acknowledged that the determinants of loyalty are still unclear, we believe that these four premises may be the neccesary conditions for building models to study customer loyalty, because they capture the most important concerns of the academic research. In addition, researchers can rely on several moderator variables that can be modeled in more comprehensive models.

It has already been explained in our conceptual framework that the attitudinal variables are related to the service evaluations (e.g. satisfaction and perceived quality), and variables related to customer intentions (e.g. WOM and RI) are the determinants of loyalty. We have considered attitudinal variables in our model, and explained how we simplified all these variables into a single variable – "atittude toward the service" (ATS), because quantitative analysis of historical data showed that all these variables had similar values (see Table II). These similarities of values increased the information carried out by the ATS variable. For example, Chandrashekaran *et al.* (2007) distinguish between satisfaction level and satisfaction strength, where the latter was the most relevant for determining loyalty. Our ATS variable provided more relevant information regarding attitudes than a single satisfaction-level variable. In this case, statistical information was the same between variables that form ATS, while the content information of ATS was higher. This is a relevant issue for the study of attitudes and their impact on actual behavior. Researchers could build a more general

ATS variable, including information from measures of trust, disconfirmation or corporate image, enhancing the content information of ATS.

Our results have shown how the variables, such as satisfaction, perceived quality, and RI are not very good predictors of the behavioral elements of loyalty. In fact, although around 80-95 per cent of the consumers had a positive ATS and claimed that they probably would participate the next year, the retention was around 60 per cent only. This is an interesting result because it confirms the conversion rates determined by Chandon *et al.* (2005) for predicting the consumer behavior from RI. Therefore, to satisfy the consumers is not enough to retain them. These results can be compared with that of Ajzen and Fishbein (2005, p. 194) reasoned action model, where the intention was the immediate antecedent of actual behavior, influenced by a wide range of moderator variables.

As defended by Yi and Jeon (2003), the goal of a loyalty program is to establish a higher level of customer retention in the profitable segments, by providing more satisfaction and value to certain consumers. Our model predicts the effects of enhancing satisfaction and value of consumers, and shows how the latter factor is more important than the former. These results are in agreement with the studies of several marketing researchers, who viewed marketing in a more practical (and low virtuous (see Cherrier and Murray, 2004)) fashion. For example, Iacobucci *et al.* (1994) asserted that businesses are in business to make money and not to satisfy consumers and we also agree with this reasoning. This statement does not contradict marketing principles, but simply prioritize the decisions for managers. Thus, loyalty programs should mainly focus on enhancing the switching costs, as the perceived value would be high and the aim would be to create monopolies in the consumer mind. There is no doubt that increasing satisfaction is a way to achieve this objective, but there are other ways to enhance the switching costs, for example, through enhancing commitment by creating a sense of "community," as explained by Oliver (1999). However, in the context of public organizations management, they are in "business" to satisfy the consumers (citizens), and they should perform high rates of management efficiency. We believe that once satisfaction rates are high (such as the case under study), then public management decisions have to focus on obtaining loyal customers.

Results have also shown how defection rates have no dramatic effect on the NCY, because of the almost similar rate of new subscriptions. Fortunately, positive ATS influences the number of new subscriptions for the subsequent year. Positive WOM not only comes from loyal consumers, but also from the consumers who defect. Therefore, providing high-quality service and satisfying consumers have a desirable effect that can partly counteract the defection rate. The current competitive situation is idyllic for the public company and hence, this institution can maintain a stable NCY, owing to the fact that practically all their consumers are happy with the service delivered. However, as it is derived from the fourth simulation, the entry of new competitors will affect the evolution of the system, as the satisfaction rates will be modified. This is a difficult situation for the public institution; if under a monopolistic situation, and getting extraordinary rates of satisfaction does not increase the institution's NCY, it is highly probable that, even in the future's best scenario, the number of consumers will decrease.

Simulations two and three show that the new competitive environment can dramatically affect the NCY, if the public institution fails to differentiate the service.

The strengths of this specific public institution lie on the personal relationship with the costumers, several years of experience in offering the service, and low prices. However, this could not be enough to counteract the predictable aggressive marketing efforts of the new competitors. Again, this is a drawback for the public institution because enhanced differentiation requires marketing investments, and investments are limited to a very restricted public budget.

In this situation, we believe that marketing efforts have to be turned to create loyalty programs based on familiar discounts, long-term relationships, and reinforcement of social links with the consumers. As the service in our study is only delivered for three months a year, the possibilities to retain consumers are lesser than the competing organizations that will be opened around the year and are capable to develop promotions during all months. Therefore, it would be necessary to develop long-term promotions, from one year to the following years, to treat and link the customers who are sensible to price. In addition, social links with the consumers could be strengthened, for example, by creating a web platform that facilitates communication with the consumers during the entire year, especially during the months when the service is closed. All these management actions would be easy to implement and require few resources.

This system dynamics approach could also be applied in understanding loyalty in the remaining services offered by the public institution. Other services, such as fitness, aerobics, martial arts, etc., can be analyzed by taking into account the different competitive environments where they are placed. In addition, a global systemic approach to the consumption of physical activities could be designed for different variable levels and rates, considering the possible cannibalization effects in the service portfolio. We acknowledge that this is a more complicated task, but we encourage researchers to advance in the sports management using this tool, generalizing its applications to the other areas of sports management, and analyzing the phenomena, such as fan sports consumption or sports motivations.

System dynamics methodology acknowledges the multiplicity of models that can represent the phenomena under study. Our proposed model is a subjective representation of reality and can be compared with other alternative models and thus, creating a room for other different representations. The flexibility of this tool permits the implementation of managerial models that could be enriched with more relevant information. For example, for further research in sports management, the use of this methodology can focus on the decomposition of the perceived value function, i.e. identifying the main determinants of the function and modeling them from a systemic point of view. This would require obtaining richer information from the surveys, specifically situational, contextual, and personal factors. This kind of information was very important for our research, because of the possibility of being more precise in the simulations of the hypothesized new competitive environment. In addition, information pertaining to geographical location of the companies and consumers (geographical information systems) could be included to consider the consumer's preferences and cost derived from their journeys.

Notes

1. Surprisingly, we have not found any significant system dynamics studies with respect to sports management, since the research of Haywood-Farmer *et al.* (1988). These authors

developed a simple Lotus 1-2-3 model of the flow of golfers through a high-demand championship golf course, to help course managers understand the course's queuing problems better. Currently, however, managers and researchers rely on more powerful tools to use this methodology more effectively, because of the development of computer intensive techniques, as discussed in this paper.

2. We agree with Zhang and Zhang (2007); when facing multiple purchase choices, the consumer will calculate all purchase motivations, compare them, and choose the one that brings the most advantage.
3. For example, Sheppard *et al.* (1988) determined a frequency-weighted average correlation of 0.53 between intentions and behavior, with wide variations across the measures of intentions and types of behavior (for a review, see Morwitz, 2001).
4. The studies assumed that they can extrapolate the intention-behavior relationship of non-surveyed consumers on the basis of the relationship that the surveyed consumers exhibit. In doing so, the studies ignored the potentially important problem that the measurement of intentions itself might generate in some of the associations between the intentions and the behavior of a particular consumer (Feldman and Lynch, 1988).
5. We treat the ordinal scales as discrete, instead of the most-extended continuous treatment (Coenders and Saris, 1995; Jöreskog and Sörbom, 2001; Vermunt and Magidson, 2005).

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