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Modeling and simulation of customer dissatisfaction, worker unpunctuality and tolerance to delay in make-to-order supply chains measured through customer lifetime value performance¹

Modelado y simulación de la insatisfacción de los clientes, impuntualidad de los trabajadores y tolerancia al retraso en las cadenas de suministro make-to-order, medido a través del rendimiento del valor de la vida en la empresa del cliente²

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Abstract

Introduction: We developed a model for a make-to-order supply chain to evaluate the effects of worker unpunctuality, tolerance to delay and word-of-mouth according to customer waiting time (dis)satisfaction in four customer lifetime value measures (CLTV): switching customers, the number of sales per customer, the average customer loyalty and the potential market reached. *Methods:* We developed a hybrid (agent-based and discrete-event) simulation in a $3^3 * 4$ experimental design. *Results:* All of the variables were significant in the four CLTV measures, except for tolerance to delay. The positive word-of-mouth effect was greater than the negative word-of-mouth effect. There were significant interactions between positive and negative word-of-mouth. *Conclusions:* This type of model becomes a decision support tool for businesses to evaluate their mid-to-long term performance taking into account their customers' long-term behaviors and the relationships between potential customers in repetitive and competitive environments.

Keywords: Hybrid simulation; customer lifetime value; word of mouth; tolerance to delay; worker unpunctuality.

Resumen

Introducción: Se desarrolló un modelo para una cadena de abastecimiento make-to-order evaluando simultáneamente los efectos de: a) la impuntualidad del trabajador b) la tolerancia del cliente a los retrasos en la entrega y c) el boca a boca debido a la (in)satisfacción del cliente en cuatro medidas de valor de la vida en la empresa del cliente (CLTV): clientes que cambian de empresa, número de ventas por cliente, lealtad promedio del cliente y mercado potencial alcanzado. *Métodos:* Se utilizó simulación híbrida (basada en agentes y de eventos discretos) en un diseño experimental $3^3 * 4$. *Resultados:* Todas las variables fueron significantes en las cuatro medidas de CLTV, excepto la tolerancia del cliente a retrasos. El efecto del boca a boca positivo fue más alto que el del boca a boca negativo. Se presentaron efectos de interacción entre el boca a boca positivo y el negativo. *Conclusiones:* Esta clase de modelos ofrecen una herramienta para la toma de decisiones en negocios, permitiendo evaluar el desempeño a mediano y largo plazo teniendo en cuenta el comportamiento a largo plazo del cliente y la relación entre clientes potenciales en entornos competitivos y repetitivos.

Palabras clave: Simulación híbrida; valor de la vida en la empresa del cliente; boca a boca; tolerancia a los retrasos; impuntualidad del trabajador.

1. Introduction

When simulation models evaluate the performance of supply chains, it is common to look at performance measures, such as cost (including inventory and operating costs) and customer responsiveness (including stock-out probability and fill rate) [1]. These approaches overlook customer (dis)satisfaction behaviors that affect future demand, such as the probability of future purchases and the effects of word-of-mouth in current and potential customers [2, 3]. As a consequence, a complete view of the business performance is lacking, particularly when the business environment is repetitive (i.e., future purchases of the same customer are expected and desirable) and competitive (i.e., the customer can easily switch to another provider).

Performance measures based on the customer lifetime value (CLV) might fill this gap. CLV includes a conjoint valuation of customers' past purchases and expected future purchases due to a sense of loyalty to the company. Loyalty, in turn, can be influenced by the degree of service promise fulfillment by the company in the past [4].

When assessing service promise fulfillment, supply-chain simulation models do not usually address the effects of worker unpunctuality on delivery lateness. Furthermore, we were unable to find a previous simulation study that included customer psychological tolerance to lateness. The inclusion of both phenomena enhances the external validity of the simulation and its usefulness in decision-making without significantly increasing the computational effort.

The aim of this work was to develop a simulation framework in which customer behaviors due to (dis)satisfaction might help to evaluate supply chain performance based on CLV. We also included worker unpunctuality and customer tolerance to delivery lateness as possible moderators within the aforementioned supply chain environment. We expect to produce a simulation model that will help to fill the gap between operations and marketing, leading to a more comprehensive decision support tool in the supply chain.

2. Theoretical background

2.1 Customer lifetime value in supply chain and simulation

Usually, CLV research has focused on attracting, retaining and generating value based on customer loyalty, not on analyzing their impact in the supply chain [5]. Studies on operations research and supply chain, the impact of which is measured through a CLV measure, such as customer satisfaction, loyalty or switching behavior, are hard to find. Several studies claim to measure customer satisfaction, but they do perform that measurement indirectly through service levels or queue performance, such as in [6-8]. Recently, some studies have included basic CLV measures in operations decisions, stressing the need for a more comprehensive vision of metrics between operations and customer satisfaction [9]. Niraj et al. [10] showed the difficulties of estimating CLVs at different stages of the supply chain.

Regarding the specific field of simulation, a review on agent-based simulation in marketing has showed that links with supply restrictions are usually not considered and that word-of-mouth analysis will be beneficial when included in simulation approaches [11]. Among the few

manuscripts connecting simulation and CLV, the early work of Ackere et al. [12] applied Monte Carlo simulations to evaluate customer reaction in a waiting line in the long term, although the model was deterministic. Hara et al. [13] modeled the lead time for customer satisfaction using a customer satisfaction index, but the model did not allow for repeated consumption. Switching behavior has also been modeled for supply chains in a competitive environment with a focus on combined contracts [14]. Finally, [15] analyzed mid-term profit for returning customers using a hybrid of agent-based and events simulation to find equilibrium points, but did not address supply chain disturbances. All of the reviewed manuscripts worked with customer satisfaction or switching measures rather than with a unified CLTV measure.

A suitable model of for measuring CLV in a supply chain was recently developed by Tukul and Dixit [4]. In this model, the CLV of a customer j is evaluated as follows:

$$CLV_j = (PPC_j) + LI_j * (FPC_j) \quad (1)$$

PPC_j is the profit contribution of past purchases from customer j

FPC_j is the forecasted contribution of future purchases from customer j

LI_j is a loyalty index of customer j

PPC_j and FPC_j are calculated as follows:

$$PPC_j = \sum \sum_{it} p_{it} * q_{it} \quad (2)$$

$$FPC_j = \sum \sum_{it} Fp_{it} * Fq_{it} \quad (3)$$

where p_{it} is the profit contribution of product i in time period t and q_{it} is the total quantity of product i sold to customer j in time period t . Fp_{it} and Fq_{it} are the forecasted profit contributions of product i in time period t and the forecasted total quantity of product i sold to customer j in time period t , respectively.

2.2 Worker unpunctuality and unpunctuality tolerance

Worker unpunctuality has been primarily researched in psychology. Porter & Steers [16] noted several psychological characteristics that influence unpunctuality. Ferris et al. [17] found a relationship among unpunctuality, anxiety and absentees. A similar work [18] found relationships of unpunctuality and several labor and psychological factors, including work satisfaction and alcoholism. A possible distribution function for worker unpunctuality is a power-law function [19], in which a large portion of delays are short, but extreme delays are still possible.

Therefore, it is not surprising that unpunctuality perception differs among cultures. For instance, Brazilian and United States workers differ in their perception of unpunctuality and, as a consequence, in their tolerance to unpunctuality [20]. Particularly important for the present study,

tolerance to unpunctuality - called On Time Window (OTW) - has been found to be highly negatively correlated with the Human Development Index [21].

2.3 Customer behavior after (dis)satisfaction

Known models of responses to dissatisfaction have found three different responses from dissatisfied customers: a) ending the relationship with the company or reducing purchasing frequency, b) complaining, or c) maintaining their loyalty to the company in spite of their dissatisfaction [22]. Another possible behavior after dissatisfaction is negative word of mouth (NWOM), which involves communicating dissatisfaction to others, without including the service provider [23]. As a consequence of NWOM, organizations might suffer a loss of credibility, which in turn, affects their reputation within the market and significantly reduces their profits [24]. In the case of satisfied service, there can also be positive word of mouth (PWOM) [25]. The effect sizes of word of mouth are difficult to determine. Some studies have shown that word of mouth can account for up to 50% of sales [26]. A cross-industry study, ranging from restaurants to technology industries, showed that the force of PWOM is usually greater than the force of NWOM for purchasing behavior and that it differs across studies; however, the probability of an effective influence due to PWOM did not surpass 50% [27]. A recent meta-analysis also showed that PWOM force was greater than NWOM force, but warned that there was a possible deviation from linearity in the decision making process [28].

To be important to an industry, the above explained customer behaviors need to be exerted in business models in which customer loyalty can affect company results. Particularly, the possibility of a customer expressing (dis)satisfaction through repeated consumption of the products/services of the company and the possibility of a customer switching between providers are of the utmost importance for the CLV effects to be measured. Therefore, it is necessary to emphasize that the developed model is particularly applicable in repetitive and competitive environments.

Several simulation models have addressed the issue of customer behaviors as agents and their impact on operations performance [29] or marketing research [11]. However, to the best of our knowledge, none of these simulation models have addressed this specific issue in the supply chain through CLV measures or by taking into account the issue of worker unpunctuality.

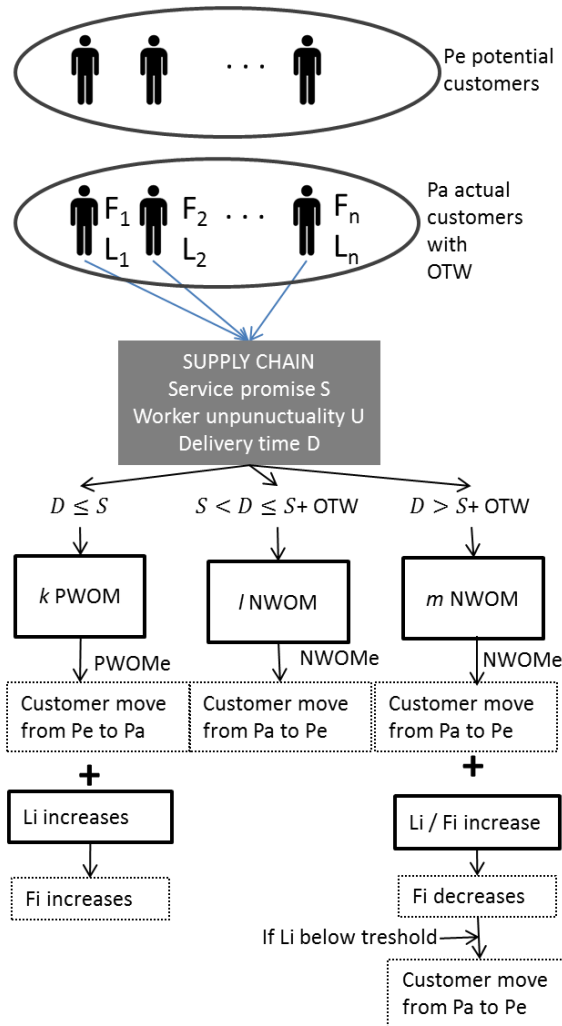
3. Simulation conceptual model

We decided to work with a hybrid model (i.e., agent-based and discrete-event based). Agent-based simulation allowed us to model behavior at the customer level with detail; on the other hand, simulation at the service level was facilitated by well-known discrete-event simulations. As a consequence, properties emerged from the lower (customer) level to the higher (service) level [30].

There is an initial set P of potential customers. From them, a subset P_a of potential costumers becomes the actual customers at the beginning time t and places orders with the company. A complementary subset P_e of customers remains potential customers. Each customer belonging to P_a is assigned a frequency intention of purchase F_i that depends on its loyalty L_i . All potential customers have the same tolerance to delay OTW (Figure 1). These behaviors are modeled through agent-based simulation.

The company delivers a service promise S , which is the time when it expects to deliver the product with a confidence level. Then, using discrete-event based simulation, the supply chain makes the product, spending time D to deliver the product, which is the sum of the entire time of the supply chain process (supplier, producer and distributor), including possible delays due to worker unpunctuality. This unpunctuality is governed by a probability distribution law U .

Figure 1. Conceptual model of the simulation



Source: Authors' own creation

For each customer of P_a , one of the following might happen, as modeled through agent-based simulation:

D is below or equal to S . The customer is satisfied and therefore performs the following two actions: a) The customer sends PWOM messages to k customers of P_e , with an effectivity probability $PWOM_e$. If the message is effective, a new customer passes from P_e to P_a . b) The

customer updates their loyalty L according to their recent experience with the company, remaining a customer of P_a with an updated frequency F_i .

D is above S , but below or equal to the S plus customer tolerance window to delays (OTW). The customer is temporarily dissatisfied and, as a result, sends NWOM messages to l customers of P_a , with an effectivity probability $NWOM_e$. If the message is effective, a customer passes from P_a to P_e .

D is above $S + OTW$. The customer is dissatisfied and therefore performs the following two actions: a) The customer sends NWOM messages to m customers of P_a , with n effectivity probability $NWOM_e$. If the message is effective, a customer passes from P_a to P_e . b) The customer updates their loyalty L_i according to their recent experience with the company. If their loyalty is below a loyalty threshold L_h , the customer passes from P_a to P_e . If the customer loyalty is above L_h , the customer continues to purchase with an updated frequency F_i .

4. Experimental design and results

The system under study in the simulation was a make-to-order supply chain with two suppliers, two sequential production processes, and a single distributor.

An experimental design of $3^3 * 4$ was proposed to evaluate the effects of different values of $PWOM_e$, $NWOM_e$, OTW and U on the percentage of switching customers, number of sales per customer, customer loyalty and percentage of potential market reached.

The levels of the effectiveness of $PWOM_e$ and $NWOM_e$ were chosen from the cross-industry study of East et al. [27]. Three values of effectiveness were selected for $PWOM_e$ and $NWOM_e$, the highest (39% and 20%), the average (20% and 11%) and the lowest (1% and 3%), across industries. OTW was calculated based on its relationship with Human Development Index described by [21]. The United States, Estonia and Colombia were selected as representative of low, medium and high OTW levels (20.8, 26.3 and 32.5 minutes, respectively), respectively, given their position in the Human Development Index of 2014. U (the unpunctuality function) was set to a Pareto distribution according to a field study. This distribution allowed a Pareto rule to be modelled in which short delays account for a high proportion of the total delays and is consistent with the power-law findings in an unpunctuality distribution [19]. The values of the α parameter were selected to match 15 minutes differences according to the research of With et al. [21], including a fourth level for punctuality.

At zero simulation time ($t=0$), a random number $[0,1]$ was generated to define P_a , the initial fraction of P customers that become current customers. Notice that each customer belonging to P_a starts to purchase depending on its frequency of purchase F_i .

Loyalty was initially set for each client as a random number between $[L_h,1]$, and L_h was set to 0.2 because a minimum loyalty is needed to start buying.

According to the literature, loyalty is mainly influenced by two factors: service quality and commitment to the provider [31], also called brand equity. The influence of service quality is

usually direct, whereas the influence of brand equity is mediated and indirect [32]. Our model suggests that brand loyalty is tied to past experiences. Therefore, loyalty at time t can be calculated as

$$L_t = r * 0.6 + L_{t-1} * 0.4 \quad (4)$$

where t represents a cycle of purchase for the customer and r is a binary variable, which is 1 if the customer is finally satisfied and 0 if the customer is dissatisfied. Thus, we weighted service quality as having a higher impact than brand equity.

To avoid a system that is too idle or too busy, the relationship between the number of potential customers and frequency of purchase was kept constant.

The values of k , l and m (the number of word-of-mouth messages) were set at eight to attempt to simulate a basic family and some friends.

The following validation tests were conducted: a) A supply chain without independent variables effects was tested to deliver products within the expected values according to the assigned probability functions; b) the values of the independent variables were set to the middle value, and the results were tested for face validity; c) each single independent variable parameter was set to their highest value and the other independent variables were set to zero to produce the expected main effects for each variable; and d) the results of the dependent variables were graphed against time to graphically determine the appropriate simulation length for the steady state to be reached.

At the simulation production stage, we performed 87 replications for each of the 108 treatments, all of which with a length of 10,000 time units. The number of replications was calculated based on a middle size effect.

To analyze the experiment, ANOVAs were performed on each dependent variable. The percentage of switching customers and the percentage of potential market reached were transformed with the square root, as suggested by Jaeger [33]. Given that the ANOVA assumptions did not hold, a confirmatory Kruskal-Wallis test were conducted. To estimate the effect sizes, Tukey DHS tests were conducted.

The main effects results, with their directions, are shown in Table 1. Lower unpunctuality levels led to better results for the company (a lower percentage of switching customers, higher sales per customer, higher loyalty, and higher market reached). The effects ranged from a 4.4% to 6.3% increase, on average, of the market reached, 1.5 to 4.5 additional average purchases per client and from a 9% to 15% average loyalty increase. Although the impact of delays on satisfaction has been measured [34], the effects on CLTV measures are hard to measure due to its long-term nature, and this manuscript is a first step towards the measuring these impacts.

Table 1. Significant effects and directions of independent variables in CLV metrics

Independent variables	<i>PWOMe</i>	<i>NWOMe</i>	α: unpunctuality
Dependent variables			
Percentage of switching customers	Negative	Positive	Positive
Sales per customer	Negative	Positive	Negative
Market reached (%)	Positive	Negative	Negative
Loyalty	Positive	Negative	Negative

All effects significant at 1% level

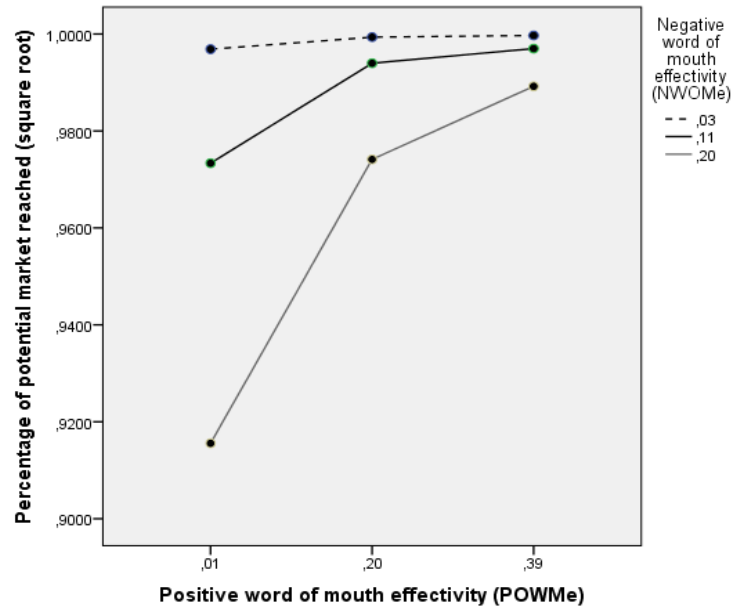
Source: Authors' own creation

As expected, higher PWOMe led to better results for the company, whereas higher values of NWOMe led to poorer results. However, there was a strong interaction between PWOMe and NWOMe. Previous research has measured WOMe effects in isolation. As a consequence, our results represent a first attempt to explain the better interwoven and non-linear relationships between PWOMe and NWOMe suggested by [28].

Figure 2 shows this interaction effect for the percentage of the market reached, but the same effect held for all CLV measures. When there is a low PWOMe effectivity, changes in NWOMe effectivity have a specific impact on CLV measures. As long as the PWOMe effectivity increases, the effects of NWOMe are reduced and almost disappear (Figure 2). Thus, a smoothing effect of PWOMe over NWOMe was observed.

Note that OTW had no significant effects on the dependent variables. It seems that the inherent variability of the entire supply chain took on the fluctuations generated by worker unpunctuality.

Figure 2. Interaction between NWOMe and PWOMe for the percentage of market reached



Source: Authors' own creation

5. Conclusions

We developed a scalable and flexible model that helps to assess the impact of customer and worker behaviors on CLV metrics. This model helps to improve mid- and long-term analyses of industries in which the competitive environment is tough and a high frequency of customer purchase is important to succeed. Our expectation is that this tool might enlighten business decision-making.

From the proposed variables that affect CLV, the relationships between PWOM and NWOM are important to consider. It is possible that moderator effects between these factors might help to explain some literature findings, particularly the non-linear relationships between PWOM, NWOM and CLV measures. It is important to note that PWOM counteracts the effects of NWOM only until a certain level. Beyond this level, delays of the supply chain must be fixed through operational research and operational strategies.

The assumptions made are important to understand the limitations of the present work. Given that a single-level supply chain was modeled, our results are not generalizable to more sophisticated supply chains. Other possible customer reactions to delays on delivery were not taken into account. Moreover, different reactions of different segments clients were not modeled. The results are only valid for competitive high purchase frequency environments with single-level supply chains, such as the food retail industry or clothing industry. However, we believe that our results open an avenue of research that combines hybrid and discrete-event simulations, allowing customer level psychological phenomena to be simultaneously considered along with the operations level performance and modeling.

Further developments will include developing tools for make-to-stock supply chains, calculating a more precise OTW for specific industries, developing agents for different market segments and analyzing thoroughly warming times.

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