Analyzing Seller Practices in a Brazilian Marketplace

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ABSTRACT

E-commerce is growing at an exponential rate. In the last decade, there has been an explosion of online commercial activity enabled by World Wide Web (WWW). These days, many consumers are less attracted to online auctions, preferring to buy merchandise quickly using fixed-price negotiations. Sales at Amazon.com, the leader in online sales of fixed-price goods, rose 37% in the first quarter of 2008. At eBay, where auctions make up 58% of the site's sales, revenue rose 14%. In Brazil, probably by cultural influence, online auctions are not been popular. This work presents a characterization and analysis of fixed-price online negotiations. Using actual data from a Brazilian marketplace, we analyze seller practices, considering seller profiles and strategies. We show that different sellers adopt strategies according to their interests, abilities and experience. Moreover, we confirm that choosing a selling strategy is not simple, since it is important to consider the seller's characteristics to evaluate the applicability of a strategy. The work also provides a comparative analysis of some selling practices in Brazil with popular worldwide marketplaces.

Categories and Subject Descriptors

K.4.4 [**Computers and Society**]: Electronic Commerce; H.3.5 [**Online Information Services**]: Web-based services

General Terms

Experimentation

Keywords

e-commerce, e-markets, marketplaces, selling practices

1. INTRODUCTION

In the past few years, there has been an explosion of online commercial activity enabled by the Internet and World Wide Web (WWW). Electronic marketplaces, such as Amazon [1] and eBay [12], have reached great popularity and revenue, emerging as one of the most relevant scenarios of Business-to-Consumer (B2C) and Consumer-to-Consumer (C2C) e-commerce models. This scenario combines characteristics from conventional retail market with Web technologies, establishing a new dimension of the world economy that has not been well understood yet [7].

An electronic marketplace (or electronic market system) is an interorganizational information system that allows the participating buyers and sellers to exchange information about prices and product offerings [6]. E-markets provide an electronic or online method to facilitate transactions between buyers and sellers that potentially provides support for all steps in the order fulfillment process.

In this rich and complex scenario of e-markets, thousands of players trade billions of dollars, interacting with each other to buy and sell products, exchange information and knowledge, establishing different kinds of relationships. One of the biggest challenges in online marketplaces is the understanding of the complex mechanism that guides the results of the negotiation. In order to address this challenge, it is essential to assess how the negotiation (offer) inputs are correlated to the outcomes.

Previous work has focused on analyzing how different input factors are related to the success of the auction, the ending price, and the attraction of bidders [3, 8]. However, identifying consistent and robust correlation patterns, which represents part of the selling practices, is a challenge. In this context, we call a correlation pattern a frequent behavior observed between some seller and offer characteristics (inputs) and negotiation outcomes (outputs). An example would be the relation between the seller's reputation and the reached sale's volume.

In the context of electronic markets, there are important factors that can be considered to analyze selling practices, such as the seller's reputation and experience, offer's price, duration, among others. Understanding how these factors affect the auction results is useful for buyers, sellers and e-market's provider. The buyers may choose to negotiate with more trustable sellers and save money. On the other hand, the sellers can make decisions that increase the chances of achieving success in the negotiation or to sell faster. Finally, the marketplace can provide specific services that will help buyers and sellers, increasing its popularity and revenues.

In this paper we follow a methodology to characterize fixed-price online negotiations. We are interested in determining and analyzing the selling practices in a Brazilian marketplace. Negotiation inputs are divided into: (1) seller characteristics and (2) offer configuration, that contains product characteristics. By characterizing seller's attributes we may identify seller profiles. In a similar way,

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characterizing how seller configures the offer we can determine selling strategies. We will explain better the concept of seller profile and seller strategies in Section 4.

Besides identifying and analyzing selling practices, we are specifically interested in investigating 2 hypotheses: (1) Seller profiles choose different strategies to configure their offers; (2) the impact of the selling strategy on negotiation results depends on the seller profile.

We are going to investigate these hypotheses because they address important questions about sellers and their practices in online marketplaces and previous work have not already provided enough information to study them. We are going to test these hypotheses by performing a characterization and analysis of a real case study. Our results can be applied to provide support decision strategies for sellers in e-markets.

The remainder of this paper is organized as follows. Section 2 discusses some related work. Section 3 presents an overview of *TodaOferta* marketplace. Section 4 describes a complete case study and its analysis using actual data from this marketplace. In Section 5 we present an important discussion about the results. Finally, Section 6 shows our conclusion and future work.

2. RELATED WORK

Electronic markets are becoming more popular each day. One of the most common e-market application is online auctions, which have been studied extensively lately. Many studies focus on validating concepts from the classic economic theory of auctions in the online environment. For example, Lucking-Reiley [19] checks the validity of the well-known results of revenue equivalence. Bajari and Hortacsu [5] address how the starting bid, set by the seller, affects the winner's course. Gilkeson and Reynolds [13] show the importance of a proper starting bid price to attract more bidders and make an auction successful.

Studies about sellers have focused on reputation systems and trust in online auctions. Some of them have analyzed the importance of reputation in auction outputs, mainly on final prices. In [4], the authors investigate the effectiveness of reputation systems and how reputation correlates to auction results. They conclude that reputation plays an important role in trust and leads to higher ending prices. In [18], is analyzed the effect of trust and reputation on the profits obtained by intermediaries in electronic commercial connections. Different trust and distrust propagation schemes in e-commerce negotiations are studied and evaluated in [14].

Resnick et al. [21] show that sellers with high reputation are more capable to sell their products, but the gains in final prices are reduced. Using a controlled experiment, Resnick et al. [22] study more accurately the reputation's impact on the auction outputs. The results show that, in general, bidders pay higher prices to sellers with higher reputation. Becherer and Halstead [8] sent e-mail questionnaires to some sellers of eBay. Using factor analysis they study seller profiles and selling strategies, showing the diversity of sellers and business practices on eBay.

There are specific works that deal with selling strategies. However, in general these works evaluate online auctions. In [3] the authors analyze the interrelationships between different variables of the auction, using correlation coefficients, for sales of the Palm Vx on eBay. They categorize sellers by their negotiation frequency during data collection. Sellers with high amount of sales are defined as retailers. The results show that retailers who set low starting bids attract more bids than any other type of seller. Moreover, they found out that sellers with high reputation are more able to describe their products.

Buy-it-now prices (BIN) have become increasingly popular among buyers and sellers. Several empirical papers have studied the Buy-it-now option on eBay. For example, in [11] and [2], it has been found that experienced sellers use the BIN price more frequently and that BIN price offers of sellers with a high reputation are accepted more frequently. In [24], they focus on the consequences of bidder risk aversion on seller revenue. They find that the buy-now auction raises seller revenue even if the buy price is not accepted at the auction open by any bidder type.

To the best of our knowledge, there is not any specific work that analyzes the selling practices for a fixed-price marketplace in an Ibero-American country, as we do in this work.

3. MARKETPLACE DESCRIPTION

This section describes *TodaOferta*[1], which is a new marketplace from the largest Latin America Internet Service Provider, named Universo OnLine Inc. (UOL)[2].

Today, with more than 12 years of history and a faithful audience in constant amplification, UOL is synonymous with Internet in Brazil. It provides access in more than 3,000 Brazilian localities, connection in more than 100,000 places in more than 150 nations overseas and it has about 1.7 million subscribers.

At UOL Shopping, an intelligent search compares products' prices on the Internet. UOL Shopping hosts a supermarket, bookstores, CD and computer stores, and car sales. In two new fronts, UOL products motivate and speed up the electronic trade in the country: UOL PagSeguro, launched in June 2007, is an online Brazilian payment solution that allows users to trade with safe; *TodaOferta*, officially started in August 2007, allows anyone to buy and sell through the Internet in a direct, fast, and secure way. At *TodaOferta*, buyers and vendors can talk freely.

3.1 TodaOferta

Table 1 shows a short summary of the *TodaOferta* dataset. It embeds a significant sample of users, offers, and negotiations. Due to a confidentiality agreement, these figures can not be presented, although they were used in our research. We consider active users in our analysis, that is, users who have negotiated (bought or sold) at least one item at *TodaOferta* using fixed-price.

URL	www.todaoferta.com.br
Coverage (time)	Jun/2007 to Jul/2008
#categories (top-level)	32
#sub-categories	2189
Negotiation options	Fixed Price and Auction

Table 1: TodaOferta Dataset - Summary

There are 32 top-level categories, which include 2189 subcategories, in *TodaOferta*, which provide a variety of distinct products, from collectibles to electronic and vehicles. The current top5 negotiated products are cell phones, MP3 players, courses, digital cameras, and consoles (games).

[1]www.todaoferta.com.br

[2]www.uol.com.br

Todaoferta employs a quite simple reputation mechanism. After each negotiation, buyers and sellers qualify each other with a rate of value 1 (positive), 0 (neutral), or -1 (negative). User's reputation is defined as the sum of all qualifications received by him/her. To avoid cheating by the creation of fake users to provide several positive feedback's to a given user, *TodaOferta* considers only unique feedback's in the calculation of users' reputation score.

The next section presents our characterization of selling practices using real data from *TodaOferta*.

4. CHARACTERIZATION AND ANALYSIS

This section presents our characterization of *TodaOferta* through the application of a methodology that we have previously used in eBay [23]. We aim to characterize this marketplace, which was described in Section 3, distinguishing the sellers from their selling strategies. Moreover, we are interested in testing the two aforementioned hypotheses previously presented about sellers and their selling strategies. In order to achieve this goal, our methodology is based on two key points:

1. Instead of identifying correlations among inputs and outputs, we propose to first identify significant patterns among the inputs and then to correlate these patterns with the negotiation outcomes.
2. Since some inputs may have different roles (e.g., seller characteristics as qualification, offer details as description of the product being negotiated), it is necessary to group them into separate sets and consider each set separately to identify meaningful patterns.

The next subsections describe our characterization of *TodaOferta*.

4.1 Identifying Negotiation Inputs

First we have to identify the inputs that will be part of the characterization process.

The set of variables that affects the negotiation results can be large and varied. Thus, understanding how these variables are correlated with the negotiation results is a complex task. To deal with this complexity, we distinguish the negotiation inputs according to their characteristics and functionalities, dividing them into seller's characteristics and offer configuration.

- **Seller's characteristics**: the inputs related to the seller provide information about the person who is willing to sell the product. An e-market can provide a variety of information about the seller, such as its enrollment (registration) date on the system, a reputation measure, or a forum where buyers would comment their experiences with such seller.
- **Offer configuration**: the set of variables directly related to a given product being negotiated, such as the price, the state (new or used) and the number of pictures about the product. Differently from seller information, the offer configuration is a free choice of the seller. Sellers may become experts on generating attractive configurations for their product's offer, while other sellers may face difficulties during this task, due to lack of experience, available time or interest. A specific part of the offer configuration is the product information.

The set of seller's characteristics leads to the identification of seller profiles, which will be explained in Section 4.4. In addition, offer configuration analysis results in the identification of selling strategies, which will be explained in Section 4.5.

In the next subsections we describe the selected inputs for seller and offer configuration.

4.1.1 Seller's characteristics

We define a set of meaningful information about sellers provided by *TodaOferta*:

- **Retailer**: indicates whether the seller is considered a participant that sells high volume of products.
- **Certified**: denotes the seller who has a quality certification. This certification is provided by a third party company to guarantee the idoneity.
- **Qualification**: indicates the seller reputation rating. For every transaction that takes place in *TodaOferta*, buyers and sellers have the opportunity to rate each other by leaving a feedback. Each feedback consists of a positive, negative, or neutral rating, as well as a brief comment left by the buyer or the seller. Feedback ratings are cumulative, adding points to the participant's score. *TodaOferta* considers only unique feedbacks in order to compute the score. The attribute Qualification refers to the unique feedback's score.
- **Time**: how long the seller has been registered in the e-market. Remembering *TodaOferta* was launched in June of 2007, we have more than one year of data.
- **Items**: it is the amount of items the seller has already sold in the e-market.

4.1.2 Offer Configuration

We choose the following attributes to characterize the offer configuration in *TodaOferta*:

- **Highlight**: indicates when the offer is set to be advertised with highlight.
- **Price**: is the price the product has been offered.
- **Duration**: negotiation duration (in days).
- **Images**: number of pictures used by the seller to present the product he wants to sell.
- **Quantity**: the number of items in the offer.

4.2 Identifying Negotiation Outcomes

After identifying the inputs of interest, it is necessary to define the negotiation outcomes that will be evaluated. Different outcomes may be selected according to the goals of the characterization. Examples of outcomes are the price obtained for the product being traded, the success of the transaction (qualification), and the time that has been spent to sell the item.

These negotiation outcomes can be seen as success indicators. We choose five indicators, as follows:

- **Price (P)**: the value of the performed transaction.
- **Volume (V)**: the number of offer's items that has been sold.
- **Views**: the number of visualizations (visits) the offer has achieved.
- **Qualification (Q)**: is the transaction rating given by the buyer to the seller. As previously explained, each feedback consists of a positive, negative, or neutral rating.
- **Duration (D)**: the amount of time spent since the offer was created until the negotiation has occurred.

4.3 Data Engineering

We pre-process the data to improve the quality of the characterization results. A small number of offers with inconsistent data and outliers were removed from the dataset. It is also important to say that we consider in this analysis only offers that have negotiations.

Employing clustering techniques on attributes with skewed distributions may result on low quality clusters, as the difference between the values may not be representative. For example, the probability distribution of the offer's prices shows that there are huge variations in these values and also a skewed behavior in the distribution of values. To address this problem, we consider prices of each product category. Moreover, to set the same weight to all the attributes we normalized them in the interval (0,1).

4.4 Identifying Seller Profiles

The identification of seller profiles is based on the seller's characteristics. In order to identify seller profiles and selling strategies, we employ a data mining technique called clustering [9], which can be used to identify clusters (groups) with similar characteristics in terms of their attributes.

Many clustering algorithms have been proposed by literature [10, 17]. It is very important to choose the best algorithm based on the dataset characteristics (i.e., dimensionality, number of transactions). We employ X-means[20], which is an efficient algorithm that extends the popular K-means [15] by estimating the best number of clusters k inherent to the data. It adopts the concept of centroid, which is an imaginary point that has the average properties of a given cluster, so we can use it to represent that cluster. We test different configurations of the algorithm in order to identify the best number of clusters, considering the tradeoff between similarity and error reduction.

We use statistical metrics, such as the average, median and dispersion metrics (standard deviation, co-variance) to analyze the characteristics of each profile. Determining seller profiles can help us understanding better the results achieved by the selling strategies.

As an example, suppose we identify a given seller profile P_a, which exhibits high reputation and has been selling products for a long period. Sellers that present this profile may obtain a success rate higher than others of another hypothetical profile P_b, which presents low reputation and is composed by newcomers. We could infer possible reasons for a higher success rate for P_a as the impact of their reputation and experience.

In order to identify seller profiles we executed the x-means algorithm for different values of k on the seller attributes. The best value found for k (number of clusters) was 16.

Table 3 describes each seller profile, presenting the cluster's frequency (the number in parenthesis), and the characterization in terms of the seller characteristics, previously explained: Retailer, Certified, Qualification, Time, Items.

Notation (symbol)	Meaning
▼▼	very low value
▼	low value
●	average value
▲	high value
▲▲	very high value

Table 2: Attribute values - Notation

For the boolean values (Retailer and Certified), we adopt the labels Y (yes) or N (no). For the other characteristics, in order to simplify the analysis, we classify each of them according to the mean value (and considering standard deviation) to a scale (very low, low, average, high, very high). We also adopt a special notation to present these classes in the tables, as explained in Table 2.

	Seller Profile - Characteristics				
Cluster	Retailer	Certified	Qualification	Time	Itens
P0 (2.25%)	Y	N	▲▲	●	▲
P1 (2.51%)	N	N	●	●	▲
P2 (0.93%)	N	N	▲	▼	▲
P3 (6.57%)	N	N	●	▼	▼
P4 (6.6%)	N	N	●	▼	▼▼
P5 (10.05%)	N	N	●	▼▼	▼▼
P6 (5.17%)	Y	N	▲	▲	●
P7 (2.25%)	N	N	●	▼▼	▼
P8 (2.71%)	N	N	●	▲	▼▼
P9 (2.48%)	N	N	●	▲▲	▲▲
P10 (4.78%)	N	N	●	●	▼▼
P11 (0.88%)	N	N	●	▼	●
P12 (0.32%)	N	Y	●	▼	▼▼
P13 (34.72%)	N	N	▼	▼▼	▼▼
P14 (13.34%)	Y	N	●	▼	▼
P15 (4.44%)	Y	Y	●	●	▼

Table 3: Seller Profile - Clusters

This notation will be also used in selling strategies characterization analysis. We will then explain soon seller profiles, choosing the most frequent ones, due to lack of space.

- **P13:** sellers who are neither a retailer or a certified participant. They have low reputation, are newcomers and present a very low amount of sales. This seller profile represents 34.72% of *TodaOferta* players.
- **P14:** retailers without certification, that have an average reputation value, a short registration time and a small number of sales. This group occurs in 13.34%.
- **P5:** group of sellers who are neither a retailer or a certified participant, with average reputation. They are newcomers with very small amount of items sold. This profile occurs 10.05%.
- **P4:** this seller profile is similar to P5, except that it represents sellers that are not newcomers, besides having a short registration time in the e-market. It occurs 6.6%.
- **P3:** this group of seller profile is similar to P4, except it has a small number of items sold, which is higher than P4. It occurs in 6.57%.

It is important to emphasize that together they represent more than 70% of the seller that negotiate in this e-market and are sellers with reputation varying from the lowest to the average values. Thus, we are going to talk about one more profile, choosing one with good reputation, P6, which occurs in 5.17%. Sellers from P6 are considered retailers with experience in terms of negotiation time, with high reputation and average volume of sales in the given e-market.

Table 4 shows the success indicators for each seller profile. These indicators (Price, Volume, Views, Qualification, Duration) have already been described. We perform an Analysis of Variance (ANOVA), which is a statistical method used to compare two or more means. The results confirm that these indicators are statistically different.

Seller Profile	Success Indicators				
	Price	Volume	Views	Qualification	Duration
P0	●	●	▲	▲▲	●
P1	▼▼	▲▲	▼▼	▼	▼▼
P2	▼	▼▼	●	▼	▼
P3	●	▲	●	▲	●
P4	●	●	▼	▲	●
P5	●	●	●	▲	●
P6	●	▼	▲	▲▲	▼
P7	▼	▼	▲▲	▼▼	●
P8	▲	▼	▼	▲	▼
P9	▼▼	▲▲	▼▼	▲▲	▼▼
P10	▲	▼	●	▲	●
P11	▼	▼	▲▲	▼	▼
P12	▲▲	▼▼	▼	▲▲	▲
P13	●	●	▼	●	●
P14	●	▼	▲▲	▲	▲
P15	▲	▼	▼	▲▲	▲▲

Table 4: Seller Profile - Success Indicators

For sake of providing more details about seller profile, we are going to deepen in the analysis of seller profiles and outcomes. It is interesting to observe that the most frequent profiles do not present the same success indicators.

In terms of price (considering the price normalized for each product category), we can see that these seller profiles present the same classification - average (Price = ●). In terms of sale's volume, P13, P4 and P5 show an average value. P14 and P6 present a low value and P3, a high volume. However, it is important to explain that this indicator can not be analyzed in isolation, since it is important to know the amount of items that were offered and also to compare the indicator with the Price indicator. Considering the amount of visualizations the offer has achieved, P13 and P4 have low value. P3 and P5 present an average value of visits. P6 has a high number of visits and P14, a very high. Observe that it is not possible to explain these behaviors without analyzing how these seller profiles configurate their offers. The qualifications of the negotiations performed by P14, P5, P4 and P3 are high. P13 presents an average qualification to its negotiation and P6, a very high. The Duration, which represents how fast the sale occurs, is on average for P13, P5, P4 and P3. For P14, the Duration is high, and low for P6.

The analysis of success indicators for each seller profile shows the different profiles achieve different results. However, this analysis does not provide enough details to verify the two hypotheses presented in Section 1. Despite this, it is possible to formulate some preliminary conclusions:

- There are a small number of retailers in *TodaOferta*, who perform 25.2% of the *TodaOferta* negotiations.
- There are a small number of certified sellers in *TodaOferta* and they perform a small percentage of sales (4.76%). Considering that P15 is also a retailer, the exclusive certified seller (P12) participates in only 0.32% of negotiations.
- Newcomers correspond to 47.02% of all completed transactions in the e-market. This fact also has a direct relation to the fact that *TodaOferta* has been growing each day.

The next subsection presents the characterization of selling strategies.

4.5 Identifying Selling Strategies

Selling strategies are identified by grouping the set of inputs related to offer configuration. In order to identify the selling strategies, we also execute x-means algorithm and the best value found for the number of clusters was 15.

Table 5 presents each selling strategy, showing the cluster's frequency (the number in parenthesis), and their characterization in terms of the attributes previously explained: Highlight, Price, Duration, Images and Quantity.

Cluster	Seller Strategies - Characteristics				
	Highlight	Price	Duration	Images	Quantity
S0 (10.12%)	Y	●	●	▲▲	●
S1 (1.96%)	N	▲▲	●	●	▼▼
S2 (6.78%)	Y	▼	▲	▲	▲▲
S3 (9.37%)	N	▼	▼	●	▼▼
S4 (4.89%)	N	●	▼	▲▲	▼
S5 (4.34%)	N	●	▲	▲▲	▼
S6 (12.83%)	Y	●	●	▼	▼
S7 (3.84%)	N	●	●	▼	▲▲
S8 (5.27%)	N	●	▼	▼	▼▼
S9 (11.88%)	N	▼▼	▼▼	▼▼	▼▼
S10 (1.55%)	N	●	●	▲▲	▲▲
S11 (11.41%)	N	▼	●	▼▼	●
S12 (6.24%)	N	▼	▲▲	▼	▼▼
S13 (3.19%)	N	▲	●	▼	▼▼
S14 (6.33%)	Y	●	▲▲	●	●

Table 5: Seller Strategy - Clusters

Analogously to the seller profile analysis, we present an explanation of the selling strategies, choosing, due to lack of space, the most frequent ones.

- **S6:** Offers with highlighted advertisement, average values of price and duration, low number of product images and low quantity of items. This is the most frequent selling strategy, corresponding to 12.83%.
- **S9:** group of offers that does not have special advertisement, with very low price and duration. Also, these offers present a very small number of images and quantity of items. They represent 11.88% of the performed transactions of *TodaOferta*.
- **S11:** Offers that are similar to S9 in terms of Highlight and product Images. However, their prices are low, have an average duration and quantity of items. This cluster occurs 11.41%.
- **S0:** set of offers with similar configuration to S6 in terms of Highlight, Price and Duration. These offers present a very high number of images and average quantity of items. 10.12% of *TodaOferta* transactions follow this strategy.

- **S3:** group of offers that does not have Highlight. Their prices and durations are low. They provide an average number of product images and very low quantity of offered items. This cluster corresponds to 9.37%.

As can be seen, each selling strategy has its own peculiarities, besides the similar characteristics. These five most popular strategies correspond to 55.61% of all negotiations from *TodaOferta*. It is also important to say that used items exist only in offers from S8. Moreover, used items occur only in approximately 5% of all negotiations from *TodaOferta*.

Table 6 shows the success indicators for each selling strategy. These indicators (Volume, Views, Qualification, Duration) have already been described. We omit the Price indicator, since it is also an input of each offer, therefore we have already explained it in last analysis of the clusters. We also perform an Analysis of Variance (ANOVA), confirming that the success indicators of the groups are statistically different.

Seller Strategy	Success Indicators			
	Volume	Views	Qualification	Duration
S0	●	▲	▲▲	●
S1	●	▼	▲	●
S2	▼	▲▲	▲▲	▲
S3	●	▼	●	▼
S4	●	●	●	▼
S5	●	●	▼	▲
S6	●	▲	▲▲	●
S7	▼▼	▼	●	●
S8	▲	▼▼	▲	●
S9	▲▲	▼▼	▼	▼▼
S10	▼▼	▼	●	●
S11	●	▼	●	●
S12	●	▼	▼	▲▲
S13	●	▼	▲	●
S14	●	▲	▲▲	▲▲

Table 6: Seller Strategy - Success Indicators

From the analysis of the success indicators of selling strategies, we can see that the most frequent strategies do not present the same success indicators, as can be observed from the analysis of Tables 5 and 6.

In terms of sale's volume, that consider the relative amount of items sold compared to the number of items offered, S9 has a very high value and the other four clusters are on average. Considering the number of visits to offer's ad, S0 and S6 have a high value. S3 and S11 present a low value and S9, a very low one. In terms of the transaction qualification, that is made by the buyer after negotiation, S0 and S6 achieve a very high value. S3 and S11 have an average qualification and S9, a low one. Considering the time spent to effectivate the transaction (between publishing the offer and confirming the negotiation), S0, S6 and S11 spend an average time to do it. S3 has a low value of Duration and S9, a very low.

From the analysis of selling strategies applied to offers in *TodaOferta*, it is possible to identify some preliminary conclusions, as follows:

- Offers with Highlight do not necessarily sell a high volume of items, since the volume depends on the amount of offered items. Using Highlight is an efficient mechanism to attract visits, as can be observed by the success indicator Views. A highlighted offer is not a condition to sell faster.
- It is interesting to note that the transactions with the best qualifications are the ones which offers have adopted the Highlight option. One explanation to this observation can be the fact that a highlighted offer has more visits, but also this raise the responsibility of its success. As an example, see S0 and S2.
- Offers with lower average prices (e.g., S2) would attract more visitors, however this behavior was observed only for the ones which also pay to be highlighted.
- We can observe a direct correlation between the offer Duration (Seller Strategy input) and Duration as a success indicator (meaning the time to sell), except for cluster S8.
- There is not a direct correlation between Quantity input (number of offered items) and Volume (success indicator, which represents the percentage of items sold considering the offered amount).
- Different from what could be expected, a lower value for the price of an offer do not determine a lower time to sell (the same conclusion is valid for a higher value).
- The number of images used in offer's description does not present a direct correlation to the transaction qualification.

These conclusions suggest how complex these e-market's interactions are, showing the importance and relevance of this kind of research. In order to test the two hypotheses of this work (see Section 1), it will be necessary to correlate the seller profiles and selling strategies.

In the next section we will present and analyze the correlation between seller profile and selling strategies, which defines the seller practice, and also we will address some important characteristics that can be observed in this Brazilian marketplace in contrast to what has already been published about some popular international marketplace leaders.

5. DISCUSSION

This section presents a discussion about the seller practices, showing details about the correlation between seller profiles and selling strategies. Moreover, in Section 5.2, we describe a comparative analysis of our research results and other conclusions from important studies about worldwide marketplaces, such as Amazon [1] and eBay [12].

5.1 Analysis of Selling Practices

In this section we present the seller practices in *TodaOferta*. As described in Section 4, there are 16 seller profiles and 15 selling strategies. A seller practice can be defined as the selling strategy adopted by a seller profile. In potential, considering the Cartesian product, there would have 240 selling practices, however 198 different selling practices actually occur in *TodaOferta*.

Our first hypothesis to address states that "Seller profiles choose different strategies to configure their offers." We are going to identify which selling strategies ($S0 - S14$) are adopted by each seller profile ($P0 - P15$). It is important to evaluate whether the same seller profile adopts or not the same selling strategies.

Figure 1 shows an histogram of the selling strategies used by the most frequent seller profiles, which were previously described. P13, which is the most popular seller profile, uses the following selling strategies, in order of frequency: S11, S3, S12, S5 and S0. Analyzing the results, it is possible to see that different selling strategies (with different proportions) are adopted by different seller profiles.

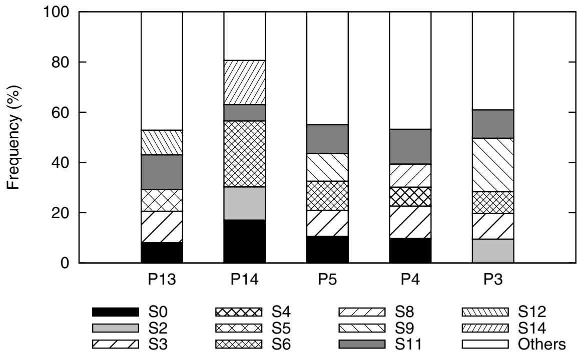

Figure 1: Distribution of Seller Strategies

These previous analysis test our first hypothesis, confirming that sellers apply different strategies.

The second hypothesis states that "The impact of the selling strategy on negotiation results depends on the seller profile." A given selling strategy may be effective to lead to good results for some profiles, but not to others. In order to test it, we will perform a more detailed analysis of the seller practices.

We are going to analyze these selling practices, analyzing how these combinations of seller profiles and selling strategies affect the negotiation outcomes. As there are so many different practices, we decide to present the analysis of the best and worst practices, considering different aspects. We define the following dimensions to analyze (we omit the explanations of isolated indicators, as we have already explained them - Volume, Qualification, Duration, Price and Views):

- Price * Volume: represents a relationship between the sale's price and volume. It is important since there exists a tradeoff between selling more expensive and selling more items.
- Volume / Views: indicates how effective is the number of visits to an offer in terms of sale's volume.
- Qualification * Price: provides a measure that correlates the transaction qualification considering the offer's price.
- Duration * Price: measures a relation between the time to sell and the sale's price.

We assume the same weights for these four combined success indicators.

Table 7 shows the top5 best and worst selling practices, considering Volume, Qualification and Duration, and these four dimensions that we have just described. We classify the practice as best or worst considering how it performs according to each of these dimensions. For example, as higher the Volume or Qualification as better; as lower the Duration as better; as higher the Volume per Views as better. Next we explain these practices according to each dimension.

Dimensions	Selling Practices	
	Best	Worst
Volume (V)	P9 - S9	P0 - S11
	P11 - S4	P12 - S7
	P9 - S8	P8 - S10
	P1 - S13	P15 - S10
	P9 - S13	P12 - S2
Qualification (Q)	P9 - S9	P11 - S12
	P6 - S4	P7 - S1
	P15 - S12	P2 - S13
	P15 - S11	P7 - S4
	P4 - S10	P11 - S4
Duration (D)	P9 - S1	P15 - S12
	P9 - S13	P15 - S5
	P1 - S13	P12 - S12
	P9 - S9	P14 - S12
	P9 - S8	P15 - S14
Price (P) * Volume (V)	P1 - S13	P0 - S1
	P9 - S13	P1 - S8
	P9 - S1	P9 - S8
	P1 - S1	P15 - S10
	P4 - S1	P12 - S2
Volume (V) / Views	P1 - S1	P0 - S1
	P9 - S1	P10 - S2
	P1 - S8	P12 - S2
	P9 - S13	P7 - S2
	P9 - S9	P5 - S2
Qualification (Q) * Price (P)	P0 - S1	P2 - S13
	P3 - S1	P7 - S1
	P15 - S1	P7 - S4
	P8 - S1	P7 - S9
	P4 - S1	P7 - S11
Duration (D) * Price (P)	P14 - S1	P1 - S8
	P13 - S1	P9 - S8
	P15 - S1	P1 - S9
	P5 - S1	P9 - S9
	P12 - S1	P9 - S1

Table 7: Best and Worst Selling Practices

Volume: the best practice is *P9-S9*. P9 is the group of sellers with very high registration time and they sell many items. S9 is a strategy which applies very low prices, without highlight, with very small duration and quantity per offer. These aspects explain why this practice is the best, considering only the Volume criterion. The second best practice is *P11-S4*. P11 are newcomers with average qualification that sell average amount of items per offer. They do not sell a high volume of items in general. However, using S4 strategy, which offers low amount of items, an average price, low duration and many images to describe the product, they achieve a good Volume of sales. Analyzing the worst practices in this criterion, we can see *P0-S11*. P0 are retailers, with very good reputation, average time of registration and sell many items. However, by adopting a strategy of using none or few images to describe the offer and an average amount of items, they do not achieve success in terms of sale's volume.

Qualification: the two best practices are *P9-S9* and *P6-S4*. The first strategy, which we have already explained in the last analysis, is strange because it consists of older sellers with average reputation, selling very fast and cheap without resources (Retailer, Quality Certification, Offer Highlight). We suspect this practice is a test or anomalous behavior in the e-market, which motivates us to better investigate this profile. *P6-S4* consists of retailers with good reputation and experience, offering small amount of items with many images and average price. Despite the strategy S4 is not very good in general, it becomes a good strategy in terms of this criterion when adopted by P6. Considering the worst practices, it is interesting to note the profiles P2, P7 and P11 represent new sellers with transactions with bad qualifications, what becomes determinant to those results, despite some selling strategies adopted are good in general.

Duration: P9 is indicated by four best practices, as expected by its characteristics. *P1-S13* is a good practice for this criterion. It is interesting to note that S13 is not a good strategy for this aspect, however it is a good option in terms of Qualification, Price and Volume. Despite this, when used by P1, which are seller with average experience that sell much, it becomes a good strategy to sell fast and with a very good Price * Volume tradeoff, as we see in the next dimension analysis. Considering the worst practices, we can see strategies S5, S12, S14, which all of them set a long or very long duration for their offers, are listed. S5 and S12 do not use Highlight to give distinction to their offers and achieve bad qualification for their transactions. S14 adopts Highlight, however is adopted by P15, who is a retailer, certified and get high prices with good qualification, besides sells a few amount of items and attract few buyers to its offers.

Price * Volume: it deals with profit, since the idea is to maximize this relation. The practice *P1-S13* achieves a good result, joining a profile who sells much with low prices with a strategy that applies a high price and small quantity. S1 is a strategy that achieves good results in this analysis, it applies very high prices to sell very low quantities, probably a unique item, what justifies this result. P9, P1 and P4 achieve good results when using S1. Considering the worst practices, we identify that *P0-S1* is not good because P0 achieves average price and volume, in general, since is a group of retailers who offers many items. S8 is not a good strategy for this criterion when adopted by seller of P1 and P9 who set the cheapest prices in *TodaOferta*.

Volume/Views: the strategies S1, S8 and S13 dominate, since they provide good results in terms of Volume with small number of Views and good qualification. Considering the worst practices, we identify that *P0-S1* is not good because P0 are retailers who offer many items (average sale's volume). S2 appears many times as the worst practices because it uses Highlight (achieving a huge number views), however with a small sale's volume, since it offers also a huge amount of items.

Qualification * Price: S1 is the best practice when it is adopted by P0, P3, P15, P8 and P4, profiles with high or average reputation. It is interesting to note this strategy is one worst practice when adopted by P7, which represents newcomers that achieve low prices with very low transaction qualification. Observe that P7 dominates the worst practices, together with P2, which is a profile with similar success indicators for price and qualification.

Duration * Price: S1 is also the best practice, when it is adopted by P14, P13, P15, P5 and P12, profiles with average or low (P13) reputation. This is explained by the fact that this strategy achieves a very high price in average time to sell. The worst practices are the ones who are applied by P1 and P9, who set a very low price to their offers.

As previously explained, we decide to investigate with more details the seller profile P9. It occurs 2864 times, 99.5% adopting the S9 strategy. This seller profile consists of a mature seller in terms of registration time, with average reputation, which sells very fast and cheap without resources (Retailer, Quality Certification, Offer Highlight). As suspected, these 2864 negotiations are performed by an unique person with ridiculous price, suggesting it would be a testing or fake profile.

The analysis of these best and worst seller practices confirm our second hypothesis, which states that the effect of the selling strategy on negotiation results depends on the seller profile. A given selling strategy (e.g., S4) may be effective in terms of qualification when used by P6, but it is not when adopted by P7 or P11. Another example is S1 that is a good strategy in terms of Volume per Views when practiced by P1, but it is not for P0. The same strategy S1 is the best one when considering Duration * Price, however it produces a bad result when applied by seller from P9. Moreover, this analysis led us to a better comprehension about how complex is to qualify the practices, since it depends on the criterion used as target. Therefore, a support decision system to recommend seller practices should consider that the seller first has to rank with weights the importance of each criterion she/he wants to consider.

Table 8 shows the ten most frequent selling practices performed in *TodaOferta*. These practices correspond to 31.78% of all negotiation practices. For each of them, it is presented the success indicators to analyze the practices, the same that were previously explained.

Practice (%)	Most Frequent						
	V	Q	D	P*V	V/Views	Q*P	D*P
P13-S11(4.78)	●	▼	●	▼	▼	▼	●
P13-S3 (4.35)	●	▼	●	▼	▼	▼	▼
P14-S6 (3.50)	●	▲	●	●	▼	●	●
P13-S12 (3.41)	●	▼	▲	▼	▼	▼	●
P13-S5 (3.01)	●	▼	▲	▼	▼	●	●
P13-S0 (2.81)	▼	▲	●	▼	▼▼	●	●
P13-S9 (2.59)	▲	▼	▼	●	●	▼	▼▼
P1-S9 (2.50)	▲▲	▼	▼▼	▼▼	▲	▼▼	▼▼
P9-S9 (2.48)	▲▲	▲▲	▼▼	▼▼	▲	▼	▼▼
P14-S14 (2.35)	▼	▲	▲▲	▼	▼▼	●	▲

Table 8: Most Popular Selling Practices

As can be seen, the two most popular seller practices (*P13-S11* and *P13-S3*) achieve bad indicators in terms of Qualification (low), Price * Volume (low) and Qualification * Price (low).

The third popular practice (*P14-S6*) is good because it achieves a high qualification with average values for the other dimensions, such as Price * Volume, except for Volume per Views (V/Views).

As expected, the seller profile P13 dominates the most popular practices, since it corresponds to 34.72% of all profiles. The same is observed for selling strategy S9, which is the most frequent one.

From this analysis we can conclude that the most popular seller practices performed in *TodaOferta* are not good practices, in general. This conclusion motivates to develop mechanisms to provide decision support tools to help sellers recommending practices them. Moreover, it is important to emphasize, according to the hypotheses we tested in this work, that the best practices should be personalized, since the effect of the selling strategy on negotiation results depends on the seller profile.

5.2 Comparative Analysis with other worldwide marketplaces

This section presents an analysis about our electronic marketplace in Brazil, based on *TodaOferta* - this new marketplace from UOL, which is the largest Latin America Internet Service Provider - and about famous worldwide marketplaces, such as Amazon [1] and eBay [12]. Our objective is to show a comparative analysis about selling practices in Brazil with these most popular marketplaces. Brazil is the fifth largest world's population[3] and tenth largest world's economy[4] (largest in Latin American and second largest in Ibero American). It is important to say that this analysis is restrict to the public information available in the Web.

5.2.1 Auction versus Fixed-price

A recent article from Business Week [16] addresses the adoption of dynamic (auction) versus fixed-price in online markets. According to the article, as the business of buying and selling over the Internet has matured, the thrill and novelty of auctions have given way to the convenience of one-click purchases.

Auctions were once a pillar of e-commerce. People didn't simply shop on eBay. They hunted, they fought, they sweated, they won. These days, consumers are less attracted to auctions, preferring to buy stuff quickly at a fixed price. Sales at Amazon.com, the leader in online sales of fixed-price goods, rose 37% in the first quarter of 2008. At eBay, where auctions make up 58% of the site's sales, revenue rose 14%.

In Brazil, probably by cultural influence, online auctions have not been popular. Only to exemplify, in *TodaOferta* marketplace the percentage of fixed-price negotiations corresponds to 98.2%. Besides the significant trend to raise the fixed-price negotiation in international e-markets, such as eBay, we can observe that Brazilian online customers have a completely different behavior.

eBay's "Buy It Now" business, where shoppers can purchase items at a set price even when the merchandise is also listed in an auction, makes up 42% of all goods sold on eBay. It's growing at an annual 22% pace, the fastest among eBay's shopping businesses. At the current pace, this may be the first year that eBay generates more revenue from fixed-price sales than from auctions [16].

5.2.2 Retailer Practices

Considering the sellers who sell a high volume of products, called Retailers, there are some interesting research conclusions about worldwide marketplaces.

Anderson et al. [3], analyzing an eBay dataset, observed that seller ratings are higher for retailers than for the rest of the seller profiles, which follows from our discussion of how *TodaOfertaâĂŹs* seller reputation favor more frequent sellers.

5.2.3 Newcomer Sellers

Another important analysis address how a newcomer seller usually behaves. Also in [3], the authors found out that the eBay marketplace has a large number of newcomer sellers, with heterogeneous characteristics who tried a wide range of strategies. In particular, these sellers did not follow the strategies of retailers, even if they present similar characteristics (such as having a high seller rating), and the product that they were selling was also similar to those being sold by retailers (for example, being new).

Considering this aspect, our research achieves a similar conclusion. The newest sellers of *TodaOferta* try a variety of selling strategies. For example, the seller profiles P5 and P13 adopt all strategies in a well-distributed manner. Moreover, we observe that the newcomers from *TodaOferta* present different characteristics and distinct success indicators in their negotiations.

5.2.4 Quantity of Offered Items

In terms of the amount of offered items, Anderson et. al [2] showed that the "Buy it Now" option was used more often by sellers with higher ratings (awarded by previous buyers) and offering fewer units. In our investigation, we found a different result.

Analyzing the three most qualified seller profiles (P0, P2 and P6), we did not find a typical correlation between the quantity of offered items and their reputation ratings. For example, P0 has offers with low and average amount of items, while P6 presents very high, average and low amount of offered items in distinct selling strategies adopted.

5.2.5 Qualified Sellers

One important aspect to analyze is how seller reputation rating affects the negotiation outcomes, such as final prices.

Anderson et. al [2] focus their empirical analysis on the determinants of the sellerâĂŹs choice of whether to use a "Buy it Now" option, which allows a buyer to essentially bypass the entire auction process. This option can be seen as the fixed-price strategy available in eBay. They conclude that seller reputation, as measured by eBay, did not appear as significant in determining the final price as expected.

Different from their conclusions, in our research we found out that reputation rating has a significant impact on negotiation outcomes, however this fact can not be analyzed separately, since we have verified that the selling strategy has a crucial impact on the outcomes (e.g., final price), not just the qualification of the seller profile. One example of this importance can be confirmed by the P0 profile when adopting the S1 strategy, which is considered the best selling practice in the criterion that considers qualification and price (see Table 7).

6. CONCLUSION

This paper presents a characterization of a fixed-price online negotiations, using actual data from *TodaOferta*. We analyze the seller practices in this Brazilian marketplace, considering seller profiles and selling strategies. More than identifying and analyzing seller practices, we investigate two hypotheses. The first hypothesis states that seller profiles choose different strategies to configure their offers. And the second one says that the impact of the selling strategy on negotiation results depends on the seller profile. We test these two hypotheses, confirming they are true for this real e-market scenario.

The validation of the first hypothesis shows that the seller behavior is not random, that is, different sellers adopt their strategies according to their interests, capacities and experience. The second hypothesis suggests that choosing a selling strategy is not simple, since it is important to consider the seller's characteristics to evaluate the applicability of a strategy. Moreover, it indicates the importance of recommendation services in order to provide a support decision tool to select a proper configuration set for the negotiation.

There are some interesting conclusions we were able to confirm from the characterization. Some of them are: (i) There are a small number of retailers in *TodaOferta* and

[3]Population Reference Bureau - www.prb.org
[4]World Bank - www.worldbank.org

also a small percentage of negotiations performed by them (25.2%); (ii) The newcomers correspond to 47.02% of all complete transactions in the e-market. This fact also has a direct relation to the fact that *TodaOferta* has been growing each day; (iii) Offers with Highlight do not necessarily sell a high volume of items, since the volume depends on the amount of offered items. Using Highlight is an efficient mechanism to attract visits, as can be observed by the success indicator Views. A Highlight offer is not a condition to sell faster. These conclusions illustrate how complex are this e-market interactions, showing the importance and relevance of this kind of research.

We also provide a comparative analysis about selling practices in Brazil with famous worldwide popular marketplaces, such as eBay [12] and Amazon [1]. We analyze interesting aspects, such as the use of auction versus fixed-price, the retailer practices, newcomer seller practices, and how reputation rating affects the negotiation outcomes. There are similar and distinct conclusions about these analyses.

As future work we are going to investigate with more details the selling practices, considering the top product categories. We plan to perform a similar characterization to offers that do not result in sale, comparing the results with the ones obtained in this work. Moreover, we want to characterize the buyer profiles, investigating the buying practices. The current and future results can be applied to develop mechanisms to provide decision support tools to recommend negotiation practices to sellers and buyers.

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8. REFERENCES

[1] Amazon.com. http://www.amazon.com.

[2] S. Anderson, D. Friedman, G. Milam, and N. Singh. Buy it now: A hybrid internet market institution. Industrial Organization 0412003, EconWPA, Dec. 2004.

[3] S. Anderson, D. Friedman, G. Milam, and N. Singh. Seller strategies on ebay. Industrial Organization 0412004, EconWPA, Dec. 2004.

[4] S. Ba and P. A. Pavlou. Evidence of the effect of trust building technology in electronic markets: price premiums and buyer behavior. *MIS Quarterly*, 26(3):243–268, 2002.

[5] P. Bajari and A. Hortacsu. The winner's curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *RAND Journal of Economics*, 34(2):329–55, 2003.

[6] J. Y. Bakos. A strategic analysis of electronic marketplaces. *MIS Q.*, 15(3):295–310, 1991.

[7] R. Bapna, P. B. Goes, and A. Gupta. Insights and analyses of online auctions. *Communications of the ACM*, 44(11):42–50, 2001.

[8] R. C. Becherer and D. Halstead. Characteristics and internet marketing strategies of online auction sellers. *Int'l Journal of Internet Marketing and Advertising*, 1(1):24–36, 2004.

[9] H.-H. Bock. Data mining tasks and methods: Classification: the goal of classification. pages 254–258, 2002.

[10] S. Chelcea, A. D. Silva, Y. Lechevallier, D. Tanasa, and B. Trousse. Pre-processing and clustering complex data in e-commerce domain. In *1st Int'l Workshop on Mining Complex Data MCD'2005*, Houston, Texas, November 2005. IEEE.

[11] M. R. Durham, Y. and S. Standifird. ebay's buy-it-now function: Who, when and how. *Topics in Economic Analysis & Policy*, 4(1):28, 2004.

[12] ebay. http://www.ebay.com.

[13] J. Gilkeson and K. Reynolds. Determinants of internet auction success and closing price: An exploratory study. *Psychology & Marketing*, 20(6):537–566, 2003.

[14] R. Guha, R. Kumar, P. Raghavan, and A. Tomkins. Propagation of trust and distrust. In *WWW '04: Proc. of the 13th Int'l Conference on World Wide Web*, pages 403–412, New York, NY, USA, 2004. ACM.

[15] J. Hartigan. *Clustering Algorithms*. John Wiley and Sons, Inc., New York, NY, April 1975.

[16] C. Holahan. Auctions on ebay: A dying breed. *BusinessWeek online*, jun 2008.

[17] M. Kearns, Y. Mansour, and A. Y. Ng. An information-theoretic analysis of hard and soft assignment methods for clustering. In *Proc. of the 13rd Conf. on Uncertainty in Artificial Intelligence*, pages 282–293, Providence, Rhode Island, USA, 1997.

[18] T. B. Klos and F. Alkemade. Trusted intermediating agents in electronic trade networks. In *AAMAS '05: Proc. of the 4th Int'l joint Conference on Autonomous Agents and Multiagent Systems*, pages 1249–1250, New York, NY, USA, 2005. ACM.

[19] D. Lucking-Reiley. Using field experiments to test equivalence between auction formats: Magic on the internet. *American Economic Review*, 89(5):1063–1080, 1999.

[20] D. Pelleg and A. W. Moore. X-means: Extending k-means with efficient estimation of the number of clusters. In *ICML '00: Proc. of the 17th Int'l Conf. on Machine Learning*, pages 727–734, San Francisco, CA, USA, 2000. Morgan Kaufmann Publishers Inc.

[21] P. Resnick and R. Zeckhauser. Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. *The Economics of the Internet and E-Commerce*, edited by M.R. Baye. Amsterdam: Elsevier Science B.V.:127–157, 2002.

[22] P. Resnick, R. Zeckhauser, J. Swanson, and K. Lockwood. The value of reputation on ebay: A controlled experiment. *School of Information, University of Michigan*, Ann Arbor, Michigan, USA:34, 2003.

[23] A. Silva, P. Calais, A. Pereira, F. Mourao, J. Almeida, W. Meira Jr., and P. Góes. A seller's perspective characterization methodology for online auctions. In *ICEC '08: Proc. of the 10th Int'l Conference on Electronic Commerce*, pages 1–10, New York, NY, USA, 2008. ACM.

[24] J. Wooders and S. S. Reynolds. Auctions with a buy price. Econometric Society 2004 North American Summer Meetings 130, Econometric Society, Aug. 2004.