Assessing Success Factors of Selling Practices in Electronic Marketplaces

A. Pereira  D. Duarte  W. Meira Jr.  
Federal University of Minas Gerais  
Department of Computer Science  
Av. Antônio Carlos 6627 - ICEX - 31270-010  
Belo Horizonte – Minas Gerais – Brazil  
{adrianoc,diegomd,meira}@dcc.ufmg.br

P. Góes  
The University of Arizona  
Management Information Systems Dept.  
McClelland Hall 430, 1130 East Helen Street  
Tucson – AZ – USA  
pgoes@eller.arizona.edu

ABSTRACT

Electronic markets have early emerged as an important topic inside e-commerce research. An e-market is a digital ecosystem intended to provide their users with online services that will facilitate information exchange and transactions. This work presents a characterization and analysis of fixed-price online negotiations. Using actual data from a Brazilian marketplace, we analyze selling practices, considering seller profiles and selling strategies. There are important factors that can be considered when analyzing selling practices, such as the seller’s reputation and experience, offer’s price, duration, among others. We evaluate which factors impact on the success of selling practices in e-markets, which can be used to support seller’s decision and recommend selling practices. Moreover, we investigate some important hypotheses about selling practices in online marketplaces, which allow us to state interesting conclusions, such as: a seller profile can achieve success or not in a trade, depending on the adopted strategy; the offer’s price and how it is being advertised are two important success factors.

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, B2C, selling practices, digital ecosystems

1. INTRODUCTION

Electronic commerce (e-commerce) has been established as a research field that attracts contributions from different disciplines (such as Computer Science, Information Systems, Economics, etc.). Electronic markets (e-markets) have early emerged as an important topic inside e-commerce research. Companies and individuals are using computer networks to conduct increasing amounts of their daily business. Web search engines auctioned some US$10 billion of ad space in 2007, accounting for almost half of all online advertising revenue. Sales at Amazon.com were US$4.13 billion in the first quarter of 2008, including a fast-growing revenue stream from selling Web services to other companies. At eBay, sales reached US$15.7 billion in the second quarter, with 84.5 million active users [8].

An e-market can be considered an emergent virtual environment where thousands of buyers and sellers interact and trade with each other. An e-market is therefore a digital ecosystem intended to provide their users with online services that will facilitate information exchange and transactions. In the past years, e-markets began to stand out as a distinct research field with multiple dimensions including organizational, economic, technical and others [11].

One of the biggest challenges in online marketplaces is the understanding of the complex mechanism that guides the negotiation results. In order to address this challenge, it is essential to assess how the negotiation (offer) inputs are correlated to the outcomes. There are important factors that can be considered in this analysis, 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.

This work is part of a research to analyze selling practices in fixed-price e-markets. In a previous work [15], we characterize online negotiations, with focus on successful transactions. Moreover, we confirmed 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.

In this work we want to identify and understand which factors have impact on the success or failure of selling practices in e-markets, which can be used to support seller’s decision and recommend practices. A seller practice is defined as the selling strategy (the strategy adopted to offer a product in an e-market) adopted by a seller profile (a group of user behavior, considering some characteristics, such as market’s experience and reputation). We are going to analyze the selling practices for successful (with negotiations, resulting in sale) or failed (that do not generate sale) offers.

The main contribution of this research is to provide a methodology and technique to identify which factors (in
terms of seller profile and selling strategy) affect the success of e-market trading. Moreover, Table 1 presents some hypotheses that motivate this research.

<table>
<thead>
<tr>
<th>Id</th>
<th>Hypothesis Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>There are seller profiles that achieve success, but also fail in other situations.</td>
</tr>
<tr>
<td>B</td>
<td>There are seller strategies that achieve success, but also fail in other situations.</td>
</tr>
<tr>
<td>C</td>
<td>There are seller practices that achieve success, but also fail in other situations.</td>
</tr>
<tr>
<td>D</td>
<td>There is a significant impact of the amount of offer's views on transaction's success.</td>
</tr>
</tbody>
</table>

**Table 1: Research Hypotheses**

We are going to evaluate these hypotheses by performing an analysis of a real case study. The evaluation of these hypotheses will provide knowledge to understand how some characteristics of seller profile and seller strategy impact on the results, mainly determining the success of an offer. This knowledge is important to design personalized techniques to recommend selling practices, according to product category, seller profile and selling strategy.

The remainder of this paper is organized as follows. Section 2 discusses some related work. Section 3 briefly presents TodaOferta marketplace and Section 4 describes an overview of our methodology. Sections 5 and 6 present the analyses of seller profiles and selling strategies, respectively, performed for successful and failed negotiations. Section 7 explains the selling practices. Finally, Section 8 shows our conclusion.

2. RELATED WORK

Electronic markets are becoming more popular each day. This subject is an active research field that attracts growing international attention, and the volume of related publications is increasing every year.

In [13], the authors investigate how different dimensions of consumer perception and consumer attitude may affect behavior in electronic commerce environments. Their aim is to define a conceptual framework in order to establish the role played by reference groups and social information in the development of these variables. Their results indicated that fashion effect impact on consumer’s behavior in electronic commerce environments. However, the study found inconsistent results between different dimensions of perception and its effects on buying decision.

Alex Rogers et al. [17] develop a mathematical model of the eBay auction protocol and perform a detailed analysis of the effects that the eBay proxy bidding system and the minimum bid increment have on the auction properties. They found out some interesting results and use them to consider appropriate strategies for bidders within real world eBay auctions. They conclude that while last-minute bidding (sniping) is an effective strategy against users engaging in incremental bidding, in general, delaying bidding is disadvantageous even if delayed bids are sure to be received before the auction closes.

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 [12] checks the validity of the well-known results of revenue equivalence. Bajari and Hortacsu [3] address how the starting bid, set by the seller, affects the winner’s course. Gilkeson and Reynolds [9] show the importance of a proper starting bid price to attract more bidders and make an auction successful.

Resnick et al. [16] show that sellers with high reputation are more capable to sell their products, but the gains in final prices are reduced. Becherer and Halstead [4] 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 [2] the authors analyze the correlation between different variables of the auction for sales 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.

In [19], the authors propose a novel incentive mechanism for eliciting fair ratings of selling agents from buying agents. In their approach, the buyers model other buyers and select the most trustworthy ones as their neighbors from whom they can ask advice about sellers. In addition, however, sellers model the reputation of buyers. Reputable buyers always provide fair ratings of sellers, and are likely to be neighbors of many other buyers. As a result, in marketplaces operating with their mechanism, sellers will increase quality and decrease prices of products to satisfy reputable buyers.

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 [7] and [1], 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 [18], they focus on the consequences of bidder risk aversion on seller revenue. They find that the buy-it-now auction raises seller revenue even if the buy price is not accepted at the auction open by any bidder type.

To our best of knowledge, there is not any specific work that analyzes selling practices for a fixed-price e-market, as we do in this work.

3. MARKETPLACE - BRIEF DESCRIPTION

This section describes TodaOferta¹, which is a marketplace from the largest Latin America Internet Service Provider, named Universo OnLine Inc. (UOL)².

<table>
<thead>
<tr>
<th>Coverage (time)</th>
<th>Jun/2007 to Jul/2008</th>
</tr>
</thead>
<tbody>
<tr>
<td>#categories (top-level)</td>
<td>32</td>
</tr>
<tr>
<td>#sub-categories</td>
<td>2,189</td>
</tr>
<tr>
<td>Average offers per user</td>
<td>10.1</td>
</tr>
<tr>
<td>Negotiation options</td>
<td>Fixed Price and Auction</td>
</tr>
</tbody>
</table>

**Table 2: TodaOferta Dataset - Summary**

Table 2 shows a short summary of the TodaOferta dataset. It embeds a significant sample of users, offers, and negotiations. We have a huge amount of offers from this dataset (with successful transaction or not), from which the amount

¹[www.todaoferta.com.br](http://www.todaoferta.com.br)
²[www.uol.com.br](http://www.uol.com.br)
of successful offers are lower than failed ones (without trans-
action). Due to a confidentiality agreement, the quantitative
information about this dataset cannot be presented.

There are 32 top-level categories, which include 2,189 sub-
categories, in TodaOferta, providing a variety of distinct
products, from collectibles to electronic and vehicles. The
current top sales sub-categories are cell phones, MP3 players
and pen drives. The next section presents a description of
our characterization methodology.

4. CHARACTERIZATION METHODOLOGY

This section presents an overview of our characterization
methodology, which we applied to TodaOferta, using
the dataset described in Section 3.

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 varied. Thus, understanding how
this 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.

The Seller’s characteristics provide information about the
person who is offering the product. An e-market can pro-
vide a variety of information about the seller, such as its
enrollment date on the system and a reputation measure.

Offer configuration is the set of variables directly related
to a given product being negotiated, such as its price and its
state (new or used). Sellers may become experts on generat-
ing attractive configurations for their product’s offer, while
other sellers may face difficulties during this task, due to
lack of experience or available time.

The set of seller’s characteristics leads to the identification
of seller profiles (Section 5). In addition, offer configuration
analysis results in selling strategies (Section 6).

4.1.1 Seller’s characteristics

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

• Retailer: indicates whether the user is considered a
powerful seller (e.g., high volume of products).
• Certified: denotes the seller who has a quality certi-
fication. This certification is provided by a third party
company to guarantee the idoneity.
• Reputation: is the seller reputation rating. For ev-
ery transaction that takes place in TodaOferta, buyers
and sellers have the opportunity to rate each other by
leaving a feedback (positive, neutral or negative).
• Time: how long the seller has been registered in the
e-market.
• Items: the amount of items the seller has already sold.

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 ad-
vertised with highlight.
• Price: is the price the product has been offered.
• Duration: negotiation duration (in days).
• Images: number of product pictures used in offer.
• 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. Dif-
ferent outcomes may be selected according to the goals of
the characterization. Examples of outcomes are the sale’s
price and the transaction’s qualification.

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

• Price (P): the value of the performed transaction.
• Volume (V): the percentage of offer’s items that has
been sold.
• Views: the number of offer’s visualizations (visits).
• Qualification (Q): is the transaction rating given by
the buyer to the seller.
• 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 results.
A small number of offers with inconsistent data and outliers
were removed from the dataset. We consider the attributes
of each category to perform the clustering. Moreover, to set
the same weight to all attributes, normalizing them in the
interval (0,1).

5. SELLER PROFILES

The identification of seller profiles is based on the seller’s
characteristics. In order to find seller profiles and selling
strategies, we employ a data mining technique called clus-
tering [5], which can be used to identify clusters with similar
characteristics in terms of their attributes.

Many clustering algorithms have been proposed by liter-
ature [6]. It is very important to choose the best algorithm
based on the dataset characteristics (i.e., dimensionality,
number of transactions). We employ X-means[14], which is
an efficient algorithm that extends the popular K-means [10]
by estimating the best number of clusters k inherent to the
data.

We test different configurations of the algorithm in or-
der to identify the best number of clusters, considering the
tradeoff between similarity and error reduction. We use sta-
tistical metrics, such as average, median and dispersion met-
rics (standard deviation, co-variance) to analyze the charac-
teristics of each profile. The analyses of these metrics show
that the cluster assignments were satisfactory. Determining
seller profiles can help us understanding better the results
achieved by the selling strategies.

We define a notation to represent the values of attributes
and outcomes. For the boolean values (Retailer and Certi-
fied), 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 3. This notation
will be also used in selling strategies and practices analyses.

Next, we are going to characterize and analyze successful
(Section 5.1) and failed (Section 5.2) offers. At the end, we
present a comparative analysis of them in Section 5.3.
5.1 Successful Offers

In this section we analyze the successful offers. 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 4 describes each seller profile (SP), presenting the cluster’s frequency (the number in parenthesis), and the characterization in terms of the seller attributes, previously explained: Retailer, Certified, Reputation, Time, Items.

![Table 4: Seller Profile - Clusters](image)

5.2 Failed Offers

This section analyzes failed offers. The best value found for \( k \) (#clusters) was 9, from which only 3 are different (labelled FP) from seller profiles of successful offers (SP). The clusters SP13\(_A\) and SP13\(_B\) are similar, considering average values, however we keep them separately, since SP13\(_A\) has higher experience than SP13\(_B\) in terms of registration time (despite both have very low experience).

Table 5 describes these seller profiles, considering the same attributes analyzed for successful offers. There are no Retailer, neither Certified seller. In general, there are seller with average (51.75%) and low reputation (47.46%). The most part of them are newcomers (78.83%) and quite all also have sold very low amount of items. The unique seller who has sold many items also has experience in the e-market. Only one profile (FP2), which is rare (0.79% of frequency), has achieved good transaction qualification and is a newcomer with average volume of sales.

![Table 5: Seller Profile - Success Indicators](image)

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 SP6, which has good reputation and occurs in 5.17%. Sellers from SP6 are considered retailers with experience in terms of negotiation time, with high reputation and average volume of sales in the given e-market.

Table 5 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.

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 values of success indicators.

In terms of price (considering the price normalized for each product category), these seller profiles present the same classification - average (Price = •). Considering the amount of visualizations the offer has achieved, SP3 and SP4 have low value. SP3 and SP5 present an average value of visits. SP6 has a high number of visits and SP14, a very high. Observe that it is not possible to explain these behaviors without analyzing how these seller profiles configure their offers. The qualifications of the negotiations performed by SP14, SP5, SP4 and SP3 are high.
sold items and little experience.

5.3 Remarks

The analysis of successful offers shows that the different seller profiles achieve different results. Moreover, it is possible to formulate some preliminary conclusions:

- There are a small number of retailers in TodaOferta, who perform 25.20% of the negotiations.
- There are a small number of certified sellers in TodaOferta (4.76%) and they perform a small percentage of sales. Considering that SP15 is also a retailer, the exclusive certified seller (SP12) participates in only 0.32% of negotiations.
- Newcomers account for 75.66% of all completed transactions in the e-market. This fact is related to the fact that TodaOferta has been growing each day.

In the case of failed offers, we observe that:

- Almost all seller profiles (99.10%) do not present significant sales history (Items: low and very low).
- There are no retailers or certified sellers.
- The most part of seller do not have experience.

Moreover, comparing the seller profiles who have failed and successful offers, we can conclude that:

- The seller profile is not the main reason to have a successful offer (e.g., SP4, SP9), since there are same profiles that have success or not in different proportions.
- To be retailer or certified do not guarantee a good selling practice, however these conditions avoid the fail.
- Almost all common seller profile (failed and successful) obtain more unsuccessful results compared to success, except SP9 that has more experience.

The set of analyses presented in this section confirm the hypothesis A, that is, “There are seller profiles that achieve success, but also fail in other situations”.

6. SELLING STRATEGIES

Selling strategies are identified by grouping the set of inputs related to offer configuration. Analogously to what has been done for seller profiles, a clustering technique was employed. The attribute values that define each strategy may be analyzed using statistical metrics, such as the average, median and dispersion metrics.

Next, we are going to characterize and analyze the selling strategies for successful (Section 6.1) and failed (Section 6.2) offers. Then, we show a comparative analysis of them in Section 6.3.

6.1 Successful Offers

In this section we analyze the selling strategies of successful offers. In order to identify the selling strategies, we also executed X-means algorithm and the best value found for the number of clusters was 15.

Table 7 presents each selling strategy (SS), 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.

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

<table>
<thead>
<tr>
<th>Cluster (%)</th>
<th>Seller Strategies - Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS1 (164)</td>
<td>Y * * * * *</td>
</tr>
<tr>
<td>SS2 (615)</td>
<td>N * * * * *</td>
</tr>
<tr>
<td>SS3 (94)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS4 (488)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS5 (118)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS6 (118)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS7 (155)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS8 (118)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS9 (118)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS10 (52)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS11 (625)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS12 (625)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS13 (625)</td>
<td>N Y Y Y Y T</td>
</tr>
<tr>
<td>SS14 (625)</td>
<td>N Y Y Y Y T</td>
</tr>
</tbody>
</table>

Table 7: Seller Strategy - Clusters

- SS6: 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%.
- SS9: 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.
- SS11: Offers that are similar to SS9 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%.
- SS10: set of offers with similar configuration to SS6 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.
- SS3: 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 account for 55.61% of all negotiations. It is important to say that only SS8 has used items.

Table 8 shows the success indicators for each selling strategy for successful offers. These indicators (Volume, Views, Qualification, Duration) have already been described. We omit the Price indicator, since it is also an input of each offer. We also perform an Analysis of Variance (ANOVA), confirming that the success indicators of the groups are statistically different.

<table>
<thead>
<tr>
<th>Seller Strategy</th>
<th>Volume</th>
<th>Views</th>
<th>Qualification</th>
<th>Duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>SS0</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS1</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS2</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS3</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS4</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS5</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS6</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS7</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS8</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS9</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS10</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS11</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS12</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS13</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>SS14</td>
<td>Y</td>
<td>Y</td>
<td>*</td>
<td>*</td>
</tr>
</tbody>
</table>

Table 8: 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.
In terms of sale’s volume, SS9 has a very high value and the other four clusters are on average. Considering the number of visits to offer ads, SS0 and SS6 have a high value. SS3 and SS11 present a low value and SS9, a very low one. In terms of the transaction qualification, SS0 and SS6 achieve a very high value. SS3 and SS11 have an average qualification and SS9, a low one. Considering the time spent to effectuate the transaction, SS0, SS6 and SS11 spend an average time to do it. SS3 has a low value of Duration and SS9, a very low.

6.2 Failed Offers

In this section we analyze the failed offers. The best value found for k (number of clusters) was 12, none of them is equal to strategies observed in successful offers.

Table 9 presents selling strategies for failed offers (FS), considering the same attributes analyzed for successful offers. This analysis considers the average values measured from successful offers, therefore the attribute Price has some values higher than the defined values from the previous scale notation. Considering this, we adopt two special notations (▲▲▲ and ▲▲▲▲). In general, offers of used and new products are balanced, with 52.84% of new items. Almost all of them do not highlight offers (98.92%) and have very low amount of items (97.95%). Moreover, the most part of them set a short duration for the offers (73.01%).

![Table 9](image)

Table 9: Seller Strategy - Clusters - Failed

The most frequent strategies are FS6, FS10 and FS5, which together account for 68.48%. These strategies present sales price extremely higher than successful offers and very few amount of offered items. None of them adopts highlight, show small number of pictures to describe the offer, and 27.17% of them are for used items.

6.3 Remarks

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

- The most part of failed strategies (93.67%) present very expensive prices in comparison to successful ones.

Moreover, comparing the selling strategies that have failed and succeeded, we can conclude that:

- The typical offer durations are short and very short for 73.01% of failed offers and 37.41% of successful ones.
- In terms of the state of product item, almost half of used items are offered for failed strategies, while in successful set there is only approximately 5%.
- The Highlight feature is adopted by only 1.10% of failed offers, while 36.06% of successful ones used it.

From the analyses explained in this section we can evaluate the hypothesis B and verify it is not true, that is, “There are not seller strategies that achieve success, but also fail in other situations.” This can be concluded since all selling strategies for failed offers are different from the successful strategies. Consequently, this allow us to anticipate the analysis of hypothesis C, confirming it is also false, that is “There are not seller practices that achieve success, but also fail in other situations”.

It is important to emphasize that performing the sale is not always the best alternative, since some fails are preferable than a sale with disadvantageous outcomes (e.g., qualification or price). These conclusions suggest how complex these e-market’s interactions are, showing the importance and relevance of this kind of research. In the next section we will analyze the correlation between seller profile and selling strategies, which defines the seller practice.

7. SELLING PRACTICES - ANALYSIS

This section discusses seller practices, showing details about the correlation between seller profiles and selling strategies. Selling practices for successful and failed offers are described in Sections 7.1 and 7.2, respectively.

7.1 Successful Offers

As previously explained (Sections 5.1 and 6.1), there are 16 seller profiles and 15 selling strategies. A seller practice can be defined as the selling strategy adopted by a seller profile. Considering the Cartesian product, there would have 240 selling practices, however 198 different selling practices actually occur in TodaOferta for successful offers.

We are going to identify which selling strategies (SS0 – SS14) are adopted by each seller profile (SP0 – SP15). 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. SP13, which is the most popular seller profile, uses the following selling strategies, in order of frequency: SS11, SS3, SS12, SS5 and SS0. Analyzing the results, we can see that different selling strategies (with different proportions) are adopted by different seller profiles.

Table 10 shows the most frequent selling practices of TodaOferta. They account for 31.78% of all practices. For each one, it is presented the previous success indicators and some new combinations of them to analyze the practices.

As can be seen, the two most popular seller practices (SP13-SS11 and SP13-SS3) present bad indicators in terms of Qualification (low), Price * Volume (low) and Qualification * Price (low). The third popular practice (SP14-SS6)
is good because it achieves a high qualification with average values for the other dimensions, such as Price * Volume (P*V), except for Volume per Views (V/Views).

As expected, the seller profile SP13 dominates the most popular practices, since it corresponds to 34.72% of all profiles. The same is observed for selling strategy SS9, which is the most frequent one (considering Table 10).

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

### 7.2 Failed Offers

This section presents an analysis of selling practices, considering the unsuccessful offers. Figure 2 shows an histogram of the selling strategies used by the common seller profiles from successful and failed offers, which are the clusters SP13, SP4, SP7, SP8 and SP9.

Observing the two most frequent profiles, SP13 and SP4 (together represent 71.9%), we can see that they typically adopt failed strategies. Comparing these two profiles in Figure 1, we confirm they used other strategies, which allow them to achieve success in that negotiations.

From this analysis, we can also observe that FS6 is a popular failed strategy adopted by all the five common seller profiles with a significant frequency. The profile SP0 uses mainly a success selling strategy (SS9), however it is a very rare profile in failed offers (only 0.11%). These analyses of unsuccessful offers also confirm that different selling strategies (with different proportions) are adopted by different seller profiles.

Table 11 shows the most frequent selling practices for group of failed offers. These top10 practices account for 61.56% of all practices, which indicates a very dense concentration in these most popular practices. There are 95 valid practices, quite half of the amount of distinct selling practices observed for successful offers (198). For each one, it is presented the attribute Views, which is the unique indicator to analyze in this unsuccessful scenario.

<table>
<thead>
<tr>
<th>Selling Practice</th>
<th>Frequency (%)</th>
<th>Views</th>
</tr>
</thead>
<tbody>
<tr>
<td>SP4-FS10</td>
<td>19.83</td>
<td></td>
</tr>
<tr>
<td>SP13-FS6</td>
<td>9.99</td>
<td></td>
</tr>
<tr>
<td>SP4-FS8</td>
<td>7.83</td>
<td></td>
</tr>
<tr>
<td>SP13-FS9</td>
<td>5.64</td>
<td></td>
</tr>
<tr>
<td>SP7-FS5</td>
<td>4.41</td>
<td></td>
</tr>
<tr>
<td>FP1-FS6</td>
<td>4.22</td>
<td></td>
</tr>
<tr>
<td>SP10-FS9</td>
<td>3.76</td>
<td></td>
</tr>
<tr>
<td>FP7-FS6</td>
<td>3.68</td>
<td></td>
</tr>
<tr>
<td>SP4-FS8</td>
<td>3.52</td>
<td></td>
</tr>
</tbody>
</table>

### 8. CONCLUSION

This paper investigates which factors impact on the success of selling practices in e-markets. We identify and characterize the seller practices for successful and failed transactions. We perform a case study of a fixed-price online negotiations, using actual data from TodaOferta. As explained in the paper, the quantitative information about this dataset can not be presented due to a confidentiality agreement.

The main contribution of this research is to allow us to identify which factors (in terms of seller profile and selling strategy) affect the success of online trading. Moreover, we evaluate some important hypothesis. The analyses of seller profiles allow us to conclude that: (i) the seller profile is not the main reason in order to determine the success; (ii) to be retailer or certified do not
guarantee a good selling practice, however these conditions avoid the fail; and (iii) almost all common seller profile (from failed and successful offers) obtain more unsuccessful results compared to success. We confirm the hypothesis A, that is, “There are seller profiles that achieve success, but also fail in other situations”.

From the analyses of selling strategies, we conclude that: (iv) the failed strategies present prices extremely higher than ones applied for successful offers; (v) almost half of used items are offered for failed strategies, while in successful set there is only 5%; and (vi) the Highlight feature is adopted by only 1.1% of failed offers, while 36% of successful ones used it. We verify that hypotheses B and C are false, that is, “There are not seller strategies that achieve success, but also fail in other situations”, and “There are not seller practices that achieve success, but also fail in other situations”, respectively.

The analyses of selling practices for failed and successful offers allow us to identify the most frequent practices and their effectiveness. We verify the importance of the offer visibility (Highlight). Moreover, we confirm the hypothesis D, that is, “There is a significant impact of the amount of offer views on transaction’s success”. We also conclude that the success of a selling practice depends on the right combination of a seller profile and a selling strategy.

Besides the analyzed hypotheses can be seen as quite simple conceptually and the final results could be argued to be expected, the evaluation of these hypotheses can provide some relevant knowledge to understand how the studied characteristics of seller profile and selling strategy impact on the results, mainly determining the success of an offer.

As future work we want to characterize the buyer profiles, investigating their trading practices. The current and future results can be applied in the development of new mechanisms to provide decision support tools to recommend negotiation practices to sellers and buyers.

9. ACKNOWLEDGMENTS

This work was partially sponsored by Universo OnLine S.A. - UOL (www.uol.com.br) and partially supported by the Brazilian National Institute of Science and Technology for the Web (CNPq grant no. 573871/2008-6), CAPES, Finep, and Fapemig.

10. REFERENCES


