False Information in Internet Auction Communities

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Abstract

As one of the most important features, the Internet enables individuals to make their personal thoughts and opinions easily accessible to the global community of Internet users. Numerous studies have shown that the Internet's anonymity can result in a high rate of false information, which may lead to suboptimal decisions by deceived users. Little is known what drives users to post false information. Therefore, the aim of this paper is to identify the drivers of false information in communities where users neither have incentives to make false statements nor spread information at all. Thereby, we conduct a laboratory experiment creating a controlled community. By identifying the drivers of false information, we can derive valuable implications for designing Internet communities.

1. Introduction

Since the very beginning of computer networks, information sharing has been an actively researched area. Descriptive studies confirm that employees in some organizations share information and help others including strangers whom they will never meet in person ([1], [2]). [3] suggest two explanations for sharing information: First, the process of providing information in virtual communities is a means of self-expression and can increase self-esteem, respect from others and status attainment. Second, the technological and social structure of the Internet supports that behavior. People can participate easily within the comfort and safety of their own homes and can exit easily from unpleasant situations [4]. Furthermore, the accumulation of supportive processes can be seen within the whole community and can establish an image of mutual and reciprocal aid. People know that they will not receive help from persons they supported but from another member of that virtual community ([5], [6]). [7] identify several factors that motivate consumers to articulate themselves on the Internet und study i. a. the unobservable factors "Concern for others" and related altruistic behavior and "Venting negative feelings".

Virtual communities come in numerous varieties such as e-mail, message boards, online games and chat rooms. For all type of communities it is necessary that the members are active since communities tend to die out when there is not enough activity [8]. Moreover communities rely on cooperative behavior [9] and too much uncooperative behavior like the spreading of false information can negatively influence or even break up communities as people that have been disappointed will not participate in the community anymore [10].

So what drives people to spread false information? We expect two main types for false information: First, acting deliberately can certainly be a driver of false information. This behavior is commonly known as lying: A lie is a statement made by someone who believes or suspects it to be false in expectation that the listeners (in this case: readers) may believe it [11]. The second type of false information can be erroneous inputs that can happen due to typos, transposed digits or individual's bounded memory [12].

The aim of this paper is to identify the drivers of false information in Internet communities and derive implications for community design. For achieving that aim, we examine a community in a laboratory setting where spreaders of false information do not benefit from doing so but where no obstacles prevent this behavior. We analyze the impact of identified drivers on the spread of false information in a Logit-type model. Finally, we give some advices for community design to decrease the fraction of false information depending on the identified drivers.

The remainder of this paper is organized as follows: Chapter 2 describes a community that shares information about auction outcomes giving them advantages for the bidding process whereas false information might turn this advantage into a disadvantage. Chapter 3 describes the experiment's setup in detail, whereas findings are presented in chapter 4. Chapter 5 discusses the results and concludes the paper with final remarks and directions for future research.

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2. False Information in Internet Auction Communities

Many communities share information and community members are helping each others. Nevertheless, some information is false and there are certain members who spread false information more often. One such community can be found at BiddingForTravel (http://www.biddingfortravel.com).

The aim of this community is to share its experience with bidding at different travel services like Priceline (http://www.priceline.com) or Expedia (http://www.expedia.com). These travel services sell flight tickets, hotel rooms, rental cars and vacation packages applying a dynamic price mechanism called "Name-Your-Own-Price" auction.

A NYOP-auction lets both, buyer and seller, influence the price of a product. A seller defines a secret threshold price unknown to buyers, which indicates her minimum acceptable selling price. Buyers can submit a bid for this product offered. If the bid value is equal or above the seller's threshold price, the transaction is initiated for the price denoted by the buyer's bid. Otherwise the bid is rejected and further bids on that product are not allowed for a predetermined period, e.g. seven days in case of Priceline [13]. Note that buyers do not compete against each other like in standard auctions, but the buyers' aim is solely to overbid the secret threshold price.

Beside the individual willingness to pay (WTP), consumer's belief about the threshold price is necessary to optimize the buyers' consumer surplus (CS) where the CS is defined as the difference between the price a consumer is willing to pay (reservation price) and the actual price.

[14] develop an economic model explaining bidding behavior. Consumer's belief about the threshold price can be updated by additional information like previously accepted or rejected bids on that product. Therefore, the community at BiddingForTravel shares its latest experience with bids placed on the website by Priceline or Expedia and optimizes thus the individual bidding strategy. As a result, information can save money, whereas false information can not only lead to less CS, but also to a total loss of welfare when the bid was rejected due to false information.

False information in this community is detected by discrepant bid results ex post only. Hence, a high rate of false information destroys the credibility of the community, may lead to a loss of members and in the worst case to a breakup of the community itself. It is necessary to understand what causes the posting of false information and to identify its drivers in order to derive recommendations for diminishing the fraction of false information.

The special case of BiddingForTravel has an important advantage concerning information compared with other communities: Posts on BiddingForTravel can easily be judged as true or false whereas e.g. customer reviews (see for example customer reviews at http://www.amazon.com or http://www.dooyoo.com) give leeway to hermeneutical interpretation. Moreover, customer reviews heavily depend on individual preferences and perceptions and are therefore biased to an unknown extent.

Utilizing this characteristic of bid information, we developed an experiment to study the phenomenon of false information.

3. Laboratory Experiment

For the identification of the drivers of false information it is mandatory to develop a special design for the laboratory experiment. Since communities can not be created artificially by an algorithm but develop over time, we focus on a community in a very early phase where social ties are very weak. We are aware, that this is a strong limitation but it is crucial to start at a very simple point to yield validated results. Further research could relax this limitation.

We use a two-stage experiment: In the first stage, subjects had the possibility to bid on ten different hypothetical products (e.g. a flight to New York, neither airline, nor airport of departure is specified). We controlled for consumers' product valuation using an induced values paradigm ([15], [16]) by informing them about the resale value of the given product. Each product has a resale value inducing the subject's WTP. The difference between the induced valuation and a successful bid is personal bargain. Additionally, a message board is filled with posts containing information about rejected and accepted bids from other buyers. In this way, the information in the posts and the induced WTP is the basis for the subjects' bids.

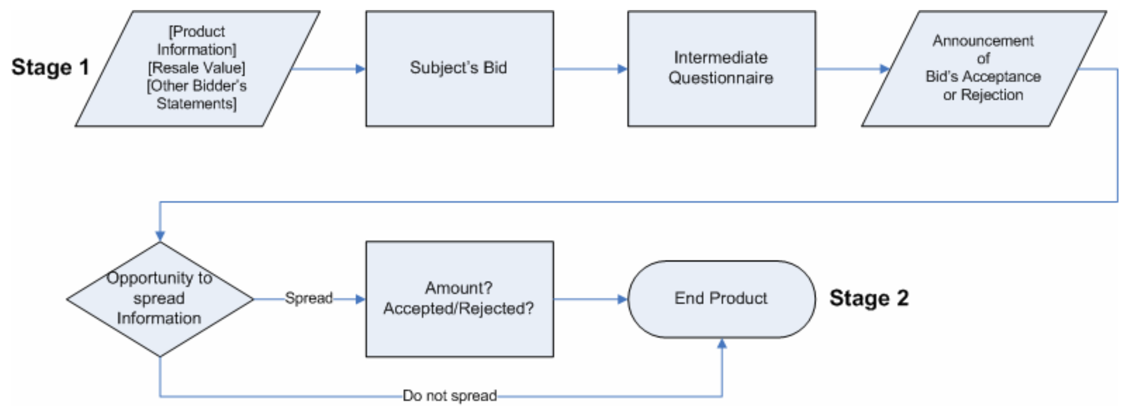

Figure 1. Experiment flow

After placing the bid the subjects had to answer a short questionnaire including questions about the usefulness of the statements made by others. Thereafter, the result of the bid is announced, i.e. the bid's acceptance or rejection. Then, the subject enters the second stage of the experiment, where she is asked, whether she wants to spread the result of her bid or not. If she is willing to share her experience, she must enter her bidding amount and the result of her bid. Note that the subject can enter false information by accident or maliciousness. By completing this section the first iteration and the process for the first product ends. Figure 1 depicts the experiment flow. This process had been repeated ten times since each subject had the opportunity to bid for ten different products. Finally, participants were presented with an extensive survey.

To have a full control over the experiment we present the subjects with five different classes of treatments (see Table 1). The posts are preassigned to treatments and do not depend on the sharing behavior of other experiment participants. Naturally, this procedure is not disclosed to the subjects making them believe that other subjects in this room or somewhere else have made the posts.

Table 1. Experimental Treatments

Treatment1	No Information (control treatment)
Treatment2	One statement about a rejected bid
Treatment3	One statement about an accepted bid
Treatment4	One statement about a rejected bid, two statements about accepted bids
Treatment5	One statement about an accepted bid, two statements about rejected bids

The information in the posts presented are absolutely true, e.g. "A bid of 120 EUR has been rejected" and "A bid of 180 EUR has been accepted" indicates unquestionably that the threshold price lies between 120 EUR and 180 EUR.

The within-subject design used in this experiment allowed us to control for order or product effects by systematic variation of scenarios and random assignment of participants to different scenarios. The subject's success is measured by her bidding success and subjects were remunerated accordingly. All subjects were informed about that rule. Apparently, there is no economic incentive to post one's own bid experience. Actually it takes time and therefore "free riding" (see [17] for a detailed description of the problem that can be often encountered in P2P-networks or other communities) may be a dominant strategy from a purely economic point of view.

Nevertheless, we expect subjects to post their bidding results due the reasons already mentioned in [3] and [1]: This behavior is driven by some kind of indirect reciprocity, an attachment to virtual communities and the posters feel they get more from the community.

As mentioned before, the posts presented to the subjects are taken from the database and are not related to the statements made by the subjects. These "real" statements are stored in the database and are not piped back to the community. In this way, we assure that people are not confronted with false information and therefore start to be disappointed by the community and dilute experimental control. Unfortunately, we can not examine interesting feedback-loops using this setting, but it is possible to find the drivers of false information, which are not caused by subjects following a tit-for-tat-strategy. The statement about the bid and its success can easily be judged as true or false and can be used for further evaluations.

After the last iteration the subjects have to complete a questionnaire which tries to identify psychographics that are not observable directly. We derive factors from literature in terms of achieving this aim. We hypothesize, that altruism and cooperation have a negative effect on false information as altruistic and cooperative subjects do not lie as often as subjects without this characteristic resulting in a lower total amount of false information. Price Mavens are price experts and are used to talk about prices, thus we expect price mavens to make fewer faults and therefore have a lower fraction of false information. Moreover, we asked for demographic data in the questionnaire.

For conducting the experiment we created a web-based application and applied the latter described experiment settings.

The experiment was conducted in an experimental lab fully equipped with PCs and subjects were separated by boxes to limit the visual field and prohibit communication. Participants were randomly assigned to different sessions. The following chapter describes the empirical findings.

4. Empirical Findings

4.1 Descriptive Statistics

112 subjects participated in the laboratory experiment. A basic reward of 6 EUR was offered for participation plus an additional variable proportion, which depended on the success during the bidding processes. The difference between the induced WTP and a successful bid was multiplied with 0.01 and added to the reward. In this manner the best subject earned a total of 11.25 EUR.

The subjects were mainly recruited from MBA students (109 students, 3 non-students) and the majority of subjects was male (45 female, 67 male). Totally, 1120 bids were placed, 507 were rejected and 613 accepted. Using numeric simulations we actually expected a fraction of 50% for both groups. This means that the subjects bid quite closely to their induced WTP which leads to more accepted bids but a relative small realized CS per bid. In the following, the standardized consumer surplus (SCS) is used, calculated through SCS=CS/WTP, for having comparable values across the different induced WTP for the different products.

In 56.3% (total 630) of all iterations information about accepted and rejected bids was provided by participants using the possibility to state the result. Out of these 630 statements 103 statements were false, either in the amount or the statement about acceptance. This high ratio of false information (16.3%) is quite astounding since the process is considered rather simple letting us not expect this high rate of false information. Nevertheless, the result reveals that false information is a relevant problem for the described community and is most likely a general problem in communities.

Table 2. Classification of false information

		Amount true	Amount false	Total
Direction	**true**		64	**64**
	false	16	23	**39**
Total		**16**	**87**	**103**

Examining the false information in detail, we found that 39 statements were false in the declaration of acceptance and rejection whereas 87 statements specified the false amount. That seems quite intuitive, since a binary statement is not as difficult as a statement on a continuous dimension. Table 2 shows this classification of false information observed in the experiment.

4.2 Classification of False Information

Close inspection of the false information suggests that behavioral patterns can be identified. Although it is impossible to separate deliberately posted false information from information which is false by accident precisely, we develop classification rules and motivate reasons why the resulting classes should be considered as a lie or false information by accident.

Before applying the classification rules all false information is considered as false information by accident. Thereafter, the classification rules are applied and shift some cases to the class of deliberate false information.

Classification Rule 1 (false amount and false direction posted):

Looking at the whole dataset we had 630 posts which are composed of two statements (direction and amount). We can calculate the probability for P(falseDirection) and P(falseAmount) using the empirical data:

$$P(\mathit{falseAmount}) = \frac{64+23}{630} = 0.138$$

$$P(\mathit{falseDirection}) = \frac{16+23}{630} = 0.062$$

In the case of accidentally posted false data, the events of falseAmount and falseDirection should be independent to a large extent since it is very unlikely that subjects make a mistake in terms of stating the amount and then also make a mistake in terms of direction. If we assume that the events of falseAmount and falseDirection are independent of each other, we can calculate the probability for a post that is composed of two false statements using the combined probability:

$$\hat{P}(bothFalse) = P(falseDirection) \cap P(falseAmount) =$$
$$P(falseDirection) \cdot P(falseAmount)$$
$$\hat{P}(bothFalse) = 0.138 \cdot 0.062 = 0.008556 = 0.8556\%$$

Even though we expected less than 1% posts that were false in direction and amount, the data reveal a ratio of 3.565% which is significantly higher than the expected ratio of 0.86% and is a first indication that the assumption of independence is wrong. To prove the difference statistically we apply the binomial test, which confirms that the assumption of independent events can be rejected on the 1-% level. On this account, we decide that this class of posting should be considered as deliberate false information and hence these 23 messages are classified as lie.

Classification Rule 2 (repeated false information within subject):

It is noteworthy that there are some subjects who posted more than one false message. Certainly, this can happen by accident, but the probability gets lower with every other false message within a subject. The probability for events, where outcomes of any trial are only success or failure, trials are independent, and the probability of success is constant throughout the experiment can be calculated using the binomial distribution:

$$P(X = i) = \binom{n}{i} \cdot p^i \cdot (1 - p)^{n-i}$$

where n=Number of posted messages by subject; i=Number of false messages by subject; p=Overall likelihood for a false message, here p=103/630=0.162.

This classification rule runs a binomial test for every subject. We use a significance level of 95% as the maximum base size of 10 makes it difficult to reach higher significances. For example: A subject that made 6 posts and 4 of them were false is classified as liar. All 4 false posts are then categorized as lie. In contrast, a subject that posted only 3 messages with 2 being false can not be classified as liar. We would need a significance level of approx. 93% for this categorization decision.

Applying this test we identify 13 subjects that are responsible for a total of 69 false messages.

According to our classification rules 1 and 2, we get the following results: 84 messages are classified as deliberate false information. The likelihood for their event is too low to be random errors. 19 messages are not affected by the classification rules 1 and 2. Therefore, these messages are still considered as false information by accident.

Table 3. Resulting classification of false information

Deliberate / Accident		**Amount true**	**Amount false**	**Total**
Direction	**true**		47 / 17	**47 / 17**
	false	14 / 2	23 / 0	**37 / 2**
Total		**14 / 2**	**70 / 17**	**84 / 19**

Table 3 shows the classes in detail. Obviously the structure of the two classes is quite different, which could be valued as sign for a good classification by the above described classification rules. We see that the ratio of lie vs. accident is approx. 4.5:1, which points out the need for reputation systems rather than the need for systems that help users to avoid making mistakes. Especially these results are based on the very defensive basic assumption that all false information is reclusively due to accident and only improbable behavior patterns are classified as lie.

We are aware of the fact that this ex-post analysis can not detect the type of posted false information precisely, but we are confident that it can help to deliver a meaningful insight to the proportion of the classes.

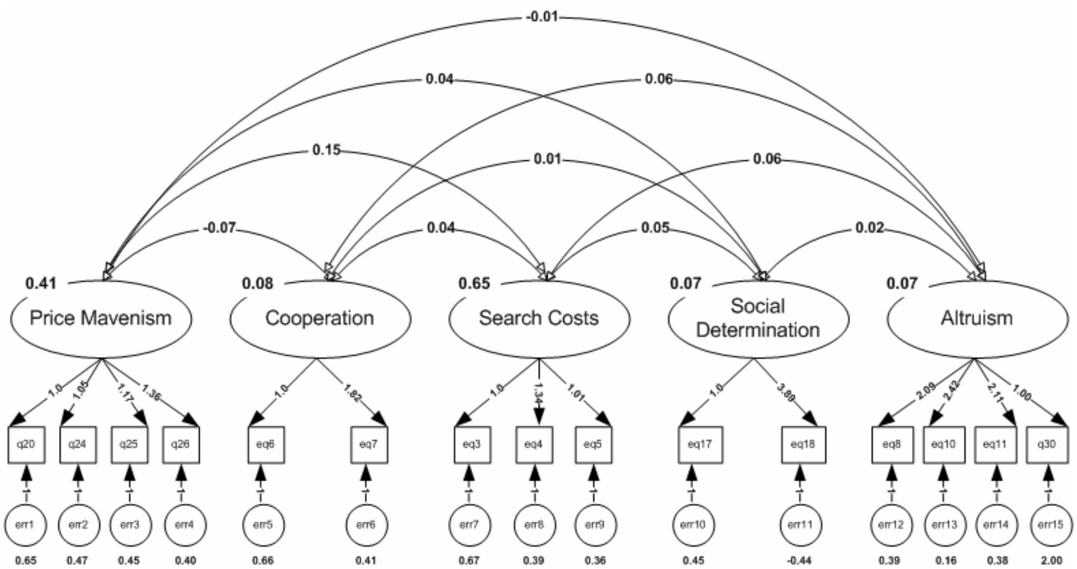

Figure 2. Confirmatory Factor Analysis for tested scales

4.3 Drivers of False Information

The previous chapter 4.2 identifies a high ratio of deliberate false information. In this chapter we try to identify demographics, psychographics, and external influence factors that drive the posting of false information.

For this purpose we analyze the bidding process and the data from the questionnaire. First, we use a confirmatory factor analysis to verify the scales that we derived from literature. We restrict the factor analysis to the scales that could have influence on the spreading of false information.

We include the following scales in the confirmatory factor analysis:

- Altruism[18]
- Cooperation [19]
- Search Costs [20]
- Determination of Social Position [21]
- Price Mavenism [22]

Items that do not load significantly on the corresponding factor are eliminated. Figure 2 depicts the final model. We test our particular model using confirmatory analysis (see [23] for more information). With a goodness-of-fit index (GFI) of 0.908 and an adjusted goodness-of-fit index (AGFI) of 0.862 being above the benchmarks for acceptable fits, the model can be judged as acceptable.

In a next step we use these factors in a logistic regression to determine their influence on the probability of posting false information. We use factor scores calculated as mean values of a participant's items' scores for a particular factor.

The logit model analyses the impact of these factors on the probability of a subject to post messages with false information in comparison to posts with true information. Therefore, we restrict the data on the cases where information was shared (n=630). Posting false information is the endogenous variable in this model and the determined factors, additional single questions from the questionnaire and the bidding outcomes are the exogenous variables. First, we need to look closely at the model specification: There are no high correlations between the relevant predictors except "Bid Accepted" and the "Standardized Consumer Surplus". Obviously, the SCS equals 0 when a bid is rejected. Therefore, we have a significant positive correlation of 0.564. To test the influence of this correlation, the logit model was reestimated without these two predictors but the results did not differ from the latter described findings and the model seems to be stable. Thus, Multicollinearity appears not to be an issue here.

The overall goodness-of-fit-measures for the model indicate a good fit. The Nagelkerke (Pseudo) R-Square (0.361) is quite high given our cross-sectional data (for more information see [24]), the goodness for the classification rose from initial 83.7% to 88.1%. Note that Table 4 lists all factors and some additional items that have significant influence on the probability of posting false information. The remaining insignificant items were omitted to due readability and lack of space.

Table 4. Logit model identifying drivers for false information (n=630)

	Coef.	Std. error	Wald	Sig.	Ex(B)
Factor Price Mavenism	.235	.206	1.304	.254	1.265
Factor Cooperation	-.160	.272	.345	.557	.852
Factor Search Costs	-.178	.157	1.293	.255	.837
Factor Social Position	.669	.260	6.603	*.010*	1.953
Factor Altruism	-.798	.291	7.518	*.006*	.450
Stand. Consumer Surplus	-5.035	1.415	12.654	*.000*	.007
Bid Accepted (0/1)	.919	.300	9.364	*.002*	2.508
Information is helpful for bidding	-.843	.162	27.053	*.000*	.430
When I talk with friends about prices, I'm giving (0:no information – 5: lots of information)	-.781	.193	16.405	*.000*	.458
I have talked to people about prices in the last 6 months (0:never – 5:very often)	.316	.189	2.790	*.095*	1.371
I like giving away my place to someone else, when standing in a queue (0:does not fit well – 5: fits very well)	.823	.163	25.644	*.000*	2.278
Sex (0=male / 1=female)	-.675	.339	3.962	*.047*	.509
I really like being part of virtual communities	-.585	.170	11.805	*.001*	.557
I enjoy making someone an April fool on the 1st of April	.559	.131	18.213	*.000*	1.749
Constant	2.007	1.568	1.639	.200	7.444

-2 Log-Likelihood	410.361
Cox & Snell R-Square	0.213
Nagelkerke R-Square	0.361

Table 4 shows that the factors "Price Mavenism", "Cooperation" and "Search Costs" have no significant influence, whereas a high score of altruism lowers the probability of posting false information. We know from the classification in chapter 4.2 that the largest part of false information is due to deliberate false information making this correlation quite reasonable. The questionnaire also contained some items about the subject's numeracy and memory skills but we could not prove a significant influence on the probability of false information. This result is consistent with our conclusion from chapter 4.2 and shows that the false information is mainly posted deliberately.

The factor "Determination of social position" identifies subjects that usually compare their attitudes with others. People with a high score on this factor seem to share false information more often. Probably they are more used to adapt attitudes.

Amongst "Altruism" and "Determination of social position", the logit model reveals some more predictive psychographics confirming our assumption: People enjoying being part of virtual communities do not spread false information as often as people with low score in this question.

[25] already reported the relation between several demographic variables and cheating. Specifically, men are more likely to cheat than women. Alike, we see that men post significantly more false information.

Out of the bidding process two predictors have a significant influence on the probability of spreading false information: On the one hand, an accepted bid increases the likelihood of false information, but on the other hand a high consumer surplus lowers this probability. Combining these two predictors, we conclude that subjects who realized rather low prices and high consumer surplus are satisfied with their deal and spread the realized prices. Subjects with bad deals seem to be unsatisfied and are spreading even more false information than people with rejected bids. That is quite interesting and this "destructive" behavior bears analogies to behavior reported in the so-called ultimatum game. In this two-person game, player 1 divides an amount of money between himself and a player 2. The remainder goes to player 2. Player 2 can either accept the division of the money proposed by player 1 or reject it. If he rejects it, both players receive a payoff of zero. If player 2 accepts it, both get the amount of money proposed by player 1. If player 2 is rational, he will accept any proposed division, because something is better than nothing. Player 1 should anticipate that behavior and split the money, that he receives almost everything and player 2 nearly nothing ([26], p. 238).

Interestingly, this predicted result could not be observed in a series of experiments conducted by [27]. Subjects who took the role of player 2 often rejected the proposed division of the money when they felt that their share was too low, willing to receive no payment. The perception of unfair prices may drive the posting of false information [28]. These findings might be very specific for the analyzed community and the preceding bidding process, although [7] find a general, significant influence of "Venting negative feelings" for the platform visiting frequency as well. We thus checked the influence of satisfaction with the auction outcome which revealed that satisfaction (coeff.=-0.2; p<0.053) has a negative impact of the probability of posting false information. Note that we have omitted this variable in the general analysis since it is highly correlated with SCS and "Bid Accepted". More generally spoken, satisfaction with the preceding process might be a driver for false information. As the bargaining game shows, unsatisfied people tend to behave irrational or even destructive.

Next, we conclude from the questionnaire item "I enjoy making someone an April fool on the 1st of April" (positive sign) and "The presented information is helpful for bidding" (negative sign) that the false information is considered as a harmless lie. On the 1st April it is a common custom in Middle and Western Europe to spoof others, reveal the truth and tease them as "April fools". Since the information is not helpful for the bidding process in the eyes of the liar, they judge their false information as harmless, forgetting that other subjects may take their information into account and change their bidding behavior under wrong assumptions.

Lies can be divided into classes - injurious or malicious, officious, and jocose. A jocose lie is some-thing, which is told in jest and without injury to anyone. An officious lie is a false statement to benefit oneself or another without injuring anyone else. A malicious lie is a false statement made to the injury of another [29].

In our case only two classes of lies (jocose und malicious) are relevant and the classification depends upon the perspective: Following the logit predictors, the spreader of false information considers this a harmless, jocose lie. However, the largest part of the community considers information about other subjects' bids as useful (median: 4.00, mean: 4.08 on a 5-point Likert scale) and would judge the false information thus as malicious lie.

5. Discussion and Conclusion

Beyond the classification and identification of drivers of false information this paper shows that communities need to be designed carefully. Although there were no incentives for lying, we found a high fraction of false information. This fraction could be even higher when the liar could benefit from cheating on others.

Naturally, our findings are restricted due to the conduction of the experiment in laboratory settings. It is not possible to create the social ties found in online communities in such a short time but we detected drivers for false information which certainly play a role in even mature communities.

Another limitation is our very homogenous sample since most of the subjects were MBA-students and we may thus loose a couple of probably significant determinants for behavior in the real world like age, education and income. We can hence generalize our findings to a limited extent only. But since subjects were concentrating on the bidding process we are quite confident that we examined an overall realistic behavior:

We discovered various indicators that false information in virtual communities is posted deliberately in most cases. Frustration might be one driver for false information. This also shows that communities can decrease the fraction of false information by a pro-active quality control. A high number of satisfied community members seems to be a crucial success factor.

Also the composition of the community itself has an influence on the reliability of the members' actions since altruistic people and people enjoying membership in virtual communities post less frequently false information than people with low scores for these factors. Likewise, females do not post false information as often as males. So, the composition of the community might alter the design options that need to be chosen.

Moreover, the asymmetric appreciation of information might cause problems for communities: Subjects, who do not appreciate information, post false information considering it as harmless joke. Other people might take this false information into account for decision-making, e.g. the bidding process in our case, trusting in the truthfulness of the acquired information. This might cause disappointment and create potential for conflict. Simple feedback and learning may diminish this problem. Also netiquette guidelines by the community itself might help to prevent this behavior.

Obviously, these findings are made in a community in a very raw state, without identification using nicknames or pseudonyms, without reputation system and without netiquette guidelines. For a successful buildup of a community from this raw state, trust and trust-supporting functionalities are of major importance. [30] identify two major trust-supporting factors for the development of trust, namely perceived competence and perceived goodwill and show how community design can positively affect these factors.

A popular concept to advance trust in online environments is the application of reputation systems since [31] found that even the most successful community requires a system to monitor and sanction members' behavior. However, she found this works best when the monitoring is carried out by the community members themselves rather than by an external authority. Three designs of reputation systems have been identified by [32]: First, mutual appraisal of transaction partners can be used for reputation indicators. This feature has been implemented for various online auction platforms and enables involved partners to mutually evaluate themselves after a transaction. Second, the appraisal of opinions is a popular feature to evaluate a member's action (e.g. a transaction or posted information on a message board). This feature seems promising to solve the problem of false information for the auction communities mentioned in chapter 2. The third design option for a reputation system is the concept of relationship networks. This concept focuses on the totality of relationships in a community or market, rather than individual or dyadic relationships. It is based on the assumption that a member can trust a trustworthy friend of a trustworthy friend.

Besides the monitoring, [33] also recommends that members should be allowed to resolve their own disputes without outside interference. Members that have posted too much false information should therefore be banned from the community by leading community members or majority decision.

Although empirical research has been done for the impact of various design options (e.g. [34]), further research should evaluate systematically the influence of the latter described design options on the probability of posting false information. Research in this area could give more detailed insight in behavior of community members and evaluate alternatives for controlling it. This could thus help software and community designers to manage their community optimally.

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