

The Effect of Dishonest Sellers on E-commerce: An Agent-Based Modeling Approach

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Abstract

This paper studies dishonest sellers in the e-commerce market, specifically their impact on the market under different conditions. We consider the role of consumers' social and individual learning and social network branches on the market. We rely on a quality uncertainty market model (Izquierdo *et al.*, 2007) and a trust game model (Wierzbicki *et al.*, 2014) to establish an agent-based model. Our approach considers the proportion of honest and dishonest sellers, the reputation of sellers, and the expectation of quality among consumers after purchasing the goods. The results of the study reveal that when dishonest sellers appear in a market with a high degree of quality uncertainty, there is a negative impact on the market, including a decline in consumer expected quality of products in the market, a decrease in commodity transaction volume and market price, and a decrease in seller income. The impact is more pronounced in markets with a higher proportion of dishonest sellers.

JEL classification numbers: C15, C63, D21, B82, B83.

Keywords: Agent-Based modeling, E-commerce market, Dishonest sellers, Trust game, Reputation of sellers.

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1. Introduction

Today, e-commerce has become a main component of retail and includes companies such as Amazon, eBay, PChome, Shopee, Open Air, JD.com, Tmall, and Taobao. As online consumption continues to increase, consumers will tend to rely more heavily on information sources such as online information, community opinions, or e-commerce advertisements.

E-commerce embodies the credit system. The scope of the market is constantly expanding with technology. However, not all consumers can adapt and trust this new market. E-commerce provides a role for middlemen to establish a system of integrity for the online market via information transparency and legal provision of online shopping or auction services, which improves consumers' trust in online information.

This paper uses an agent-based model to simulate an uncertain market. What will be the effect on the e-commerce market if there are dishonest sellers? This study hopes to explain and contribute to the understanding of the e-commerce market and the behavior of consumers.

The rest of the paper is structured as follows. Section 2 of contains a literature review on Internet transactions, social networks, and discussions of e-commerce markets. Section 3 describes the relationship between the reference model and the parameters, and the experimental design. Section 4 discusses and describes the experimental results. Section 5 summarizes the experimental results, reviews research limitations, and suggests future directions.

2. Literature Review

Leon Festinger developed the social comparison theory in 1954, which pointed out that everyone makes self-evaluation by referring to the opinions of social groups and using others as a benchmark for comparison (Festinger, 1954).

Albert Bandura pointed out that the key to social learning lies in behavioral changes through observational learning and self-regulation and attention to the interaction between their own behavior and the environment. People can thus learn through social observation, quickly grasping many behavioral patterns and looking for role models for imitation learning, adding learned experience to the decision-making process (Bandura, 1977).

The concept of a social network can be traced back to 1736, when Euler, a Swiss mathematician, used the concept of a network for mathematical research and proposed graph theory. Euler used a graph to prove that it is impossible to walk all seven bridges without repetition. The term social network was first used by scholar John Arundel Barnes in 1954. Barnes (1954) proposed a social structure composed of multiple node connections, where nodes can represent organizations or individuals, and different network connections represent various social relationships. The nodes are connected by one or more specific conditions, and the social meaning of the network is given according to the prevailing conditions.

Due to varying numbers of consumers and the potential for information manipulation to benefit content providers, consumers often encounter content with low credibility on the web (Wierzbicki *et al.*, 2014). Therefore, before buying or selling, consumers may refer to the opinions of others or the statistics of commodity data provided by the public on the Internet to judge the quality of commodities and information. Experience increases or decreases the desire to spend.

Interpersonal relationships play an important role in needs, work and careers and play a decisive role in the diffusion of information (Granovetter & Soong, 1986). Weaker connections become more frequent with the development of human society and the maturity of network technology.

Janssen and Jager (2001) pointed out that market dynamics and network exchange of information dominate the consumer decision-making process as well as communication with different products in the market and changing consumer behavior. Imitation of other people's consumption patterns results in product lock-in consumption and trends developing. The unlimited potential of e-commerce development, coupled with the small geographical restrictions, means that the size of e-commerce is increasing

Hayek (1946) believed that the market economy is a decentralized system of interacting independent agents. Vriend (2002) designed an agent model for independent decision-making and decision-making learning ability in a society that repeatedly provides binary choices under a limited number of consumers through limited choices and continuous experiments, observing the imitation ability of agents. Hayek's theory provided the idea of evolved learning and adaptive behavior. Through a model that simulates the trustworthiness of Internet content, we investigate how the association between information aggregation behaviors of Internet populations and agents affects the trade-off between "collective intelligence" and "collective stupidity" and the quality of agent decision-making (Wierzbicki *et al.*, 2014).

Akerlof (1978) proposed the idea of lemon markets. In the lemon market, even if someone wants to trade, there may be a market failure due to information asymmetry. In transactions, buyers are only willing to pay the average price because it is difficult to know the quality of the product. Sellers with higher-than-average products suffer losses due to higher costs, while sellers who sell dishonest products benefit from lower costs. Over time, high-quality products gradually withdraw from the market, inferior products fill the market, and the average price drops due to the average quality. Next, consumers will naturally think that the market is full of inferior goods and will only buy them at lower prices. In the e-commerce market, even if consumers have better access to information, they cannot fully grasp the information and real value of products, which results in the lemon market problem. When people cannot fully grasp all the information in an e-commerce market due to excessive information and an inability to judge authenticity, people must rely on limited information to ascertain the quality of the market. As consumers attempt to identify a product, knowledge of the product is limited to their own knowledge and experience. When dishonest products appear on the market, the average quality of

the product will decline, and the size of the market will be reduced. Even honest sellers or consumers in the marketplace are affected.

When the quality is uncertain, the seller has more information, and if this situation persists, a buyer may doubt the quality of a product or even be reluctant to consume or be satisfied with the sub-optimal product, leading to adverse selection. Consumers lowered their willingness to pay, which made sellers in the market reluctant to offer high-quality goods, and the market shrank until it disappeared.

3. Model and Data

The model of this paper adapts Izquierdo *et al.* (2007) 's Market Effects of Quality Uncertainty (MEQU) to simulate different market situations. Various quality expectations, individual comparisons and social comparisons, and the proportion of honest and dishonest manufacturers are set in the model, and an agent-based model is established to simulate the interaction between e-commerce and consumers in the online market. The above agent-based model has been written using NetLogo, version 6.2.0 (Wilensky 1999, 2005). This paper uses the MEQU model and refers to the trust game design used by Wierzbicki *et al.* (2014) and Yu *et al.* (2017) to set seller agents with different honesty ratios to simulate a market with uncertain quality and consumers' online influence of the Internet.

3.1 MEQU (Market Effects of Quality Uncertainty) Model

Izquierdo *et al.* (2007) proposed the MEQU model, arguing that people can learn from experience, use the model to explore the impact of product quality uncertainty on the market, and observe the effect of market information asymmetry on buyers and sellers under different networks.

In the MEQU model, it is assumed that buyers learn from the experience of others through the links on the network and form views on the expected quality of the product based on past direct experience and that of others. In the model, each seller generates a selling price $sp_i (i = 1, 2 \dots n_s)$. The seller's lowest selling price (cost) is $m_{sp}_i = i$. In each trading session, the seller can sell at most one commodity. If the market price (p_t) is not less than the seller's lowest willingness to sell price ($p_t \geq m_{sp}_i$), then there will be a supply in the market.

Table 1: Description of model parameter

Parameter	Description
Seller agents	
n_s	Number of Sellers
sp_i	Selling price of seller i
mSP_i	Lowest selling price of seller i
Strategy	Seller i 's strategy: (honest) / (dishonest)
Rating	Seller i 's reputation
Buyer agents	
n_b	Number of Buyers
R_i	Reservation price of buyer i
q_i	Expected quality of buyer i
SR_i	Standard reservation price of buyer i
$q_{i,t}$	The accumulated expected quality of the buyer i in t
$\hat{q}_{i,t}$	Buyer i 's current (t) expected quality
λ_{ind}	Individual comparison weight in $[0, 1]$
λ_{soc}	Social comparison weight in $[0, 1]$
F	The expected quality discount factor after the purchase of dishonest goods, which is set to 0.05
Market parameters	
i	Index of agents
p_t	Market price of time (t)
$\bar{q}_{i,t}$	Market average expected quality
y	Number of transactions
Links	Number of social network connections

Each buyer generates a reservation price (R_i) and an expected quality, ($\hat{q}_{i,t}$) and will multiply its reservation price ($R_{i,t}$) by the t^{th} transaction round. The expected quality $\hat{q}_{i,t}$ of t^{th} rounds, forming the standard reservation price (SR_i) by reservation price (R_i) and the expected quality ($\hat{q}_{i,t}$). When the buyer's initial expected quality ($\hat{q}_{i,0}$) is 1, the standard reservation price of buyer i (SR_i) will remain unchanged at the beginning. Each buyer's initial reservation price ($R_{i,0}$) is equal to the standard reservation price (SR_i), until the buyer's expected quality ($\hat{q}_{i,t}$) is updated. At any trading round, the individual reservation prices for all the n_b buyers will be ranked as follows:

$$R_{1,t} \geq R_{2,t} \geq \dots \geq R_{n_b,t}. \quad (1)$$

The initial demand price is $[0 < p \leq n_b]$ and the demand quantity is $[n_b + 1 - p]$. In each transaction, buyers will receive new products, they will update the expected quality (q_i) due to the quality of the purchased products, and the standard reservation price (SR_i) will vary with the buyer's expected quality ($\hat{q}_{i,t}$) changes, so the demand function changes accordingly.

In each transaction, the buyer can buy at most one commodity, while the seller can sell one commodity, and the transaction will be completed at the equilibrium point of supply and demand every t rounds. The formula for the market price is as follows:

$$p_t = \frac{1}{2} [Min(SR_{y,t}, msp_{y+1}) + Max(SR_{y+1,t}, msp_y)]. \quad (2)$$

In each round of transactions, the maximum number of transactions y is equal to the maximum value of i , for example $[SR_{i,t} \geq msp_i]$ and Buyer's reservation price ($R_{i,t}$) greater than or equal to the willingness to sell price (msp_i).

In the simulation process, buyers update their expected quality after each transaction, and when buyers update their individual expected quality, they are mainly determined by social-weight and individual-weight.

The initial expected quality ($q_{i,0}$) of each buyer is 1. Each buyer will use the social weight (λ_{soc}) and the individual weight (λ_{ind}) as the sensitivity to online information. If the social weight (λ_{soc}) is large, the consumer will rely more heavily on opinions in the online community. If the individual weight (λ_{ind}) is large, buyers will consider their past experience more to form expected quality ($q_{i,t}$). In addition, $\bar{q}_{i,t}$ is the market average expected quality, while $\hat{q}_{i,t}$ is the expected quality by each buyer in the current period.

Individual and Social Comparison Comprehensive:

$$\hat{q}_{i,t+1} = \hat{q}_{i,t} + \lambda_{ind}(q_{i,t} - \hat{q}_{i,t}) + \lambda_{soc}(\bar{q}_{i,t} - \hat{q}_{i,t}) \quad (3)$$

When a buyer buys a product, but there is no link on the network to which it is connected ($\lambda_{soc} = 0$):

$$\hat{q}_{i,t+1} = \hat{q}_{i,t} + \lambda_{ind}(q_{i,t} - \hat{q}_{i,t}) \quad (4)$$

When the buyer has no experience of the product ($\lambda_{ind} = 0$) but has a link on the connected network:

$$\hat{q}_{i,t+1} = \hat{q}_{i,t} + \lambda_{soc}(\bar{q}_{i,t} - \hat{q}_{i,t}) \quad (5)$$

The weight ratio in the model is set between 0 and 1. When the λ_{ind} value and the number of social network connections in the market are 0, the market quality will not change. When λ_{ind} is 0, consumers have no individual learning effect; when the number of social network connections is 0, consumers cannot exchange

information with each other. Therefore, consumers' expected quality will not change, and all results will remain equivalent to those produced by the initial conditions. Section 3.3 describes the weight variable settings used in this paper.

In Figure 1, the commodity quality (q) parameter of the market in the MEQU model has three different distribution modes: *exponential distribution*, *uniform distribution*, and *trimmed normal distribution*. The commodity quality q follows a predetermined fixed mass distribution. This experiment adopts *uniform distribution* as well as the *exponential distribution* and assumes that the expected value of the quality $E(q)$ of each commodity is equal to 1.

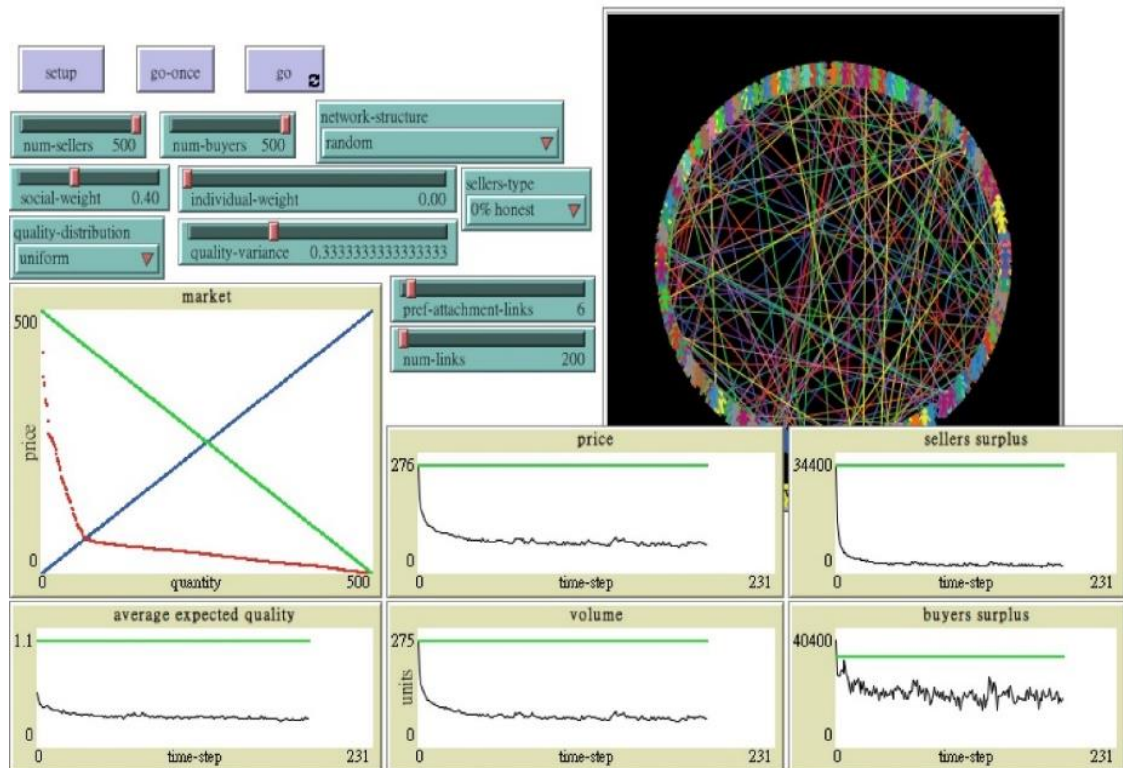


Figure 1: Operation interface of this study (The NetLogo Demonstration)

3.2 The Model

This study relies on the trust game model (Wierzbicki *et al.*, 2014.) to add reputation variables and capture honesty strategies by sellers. Buyer adjustments to expected quality ($q_{i,t}$) made after purchasing the item are simulated. In the face of dishonest sellers, we investigate whether consumers are affected by dishonest sellers in terms of market prices, transaction volumes, and seller earnings.

There are two kinds of agents in the agent-based model of this paper, consumers (buyers) and e-commerce sellers (See Figures 2 and 3). Referring to the game modeling method of Wierzbicki *et al.* (2014), the seller's honest strategy is added

to the MEQU model. When the buyer purchases the product, when the buyer's λ_{ind} value and the number of social network connections are both greater than 0, the buyer will update the personal reservation price ($SR_{i,t}$) and the expected quality ($q_{i,t}$). In this study, 100 buyer agents and 100 seller agents are modeled, and the social network is modeled as a random network and preferential attachment network. When the number of network connections is 200, 100 buyers are connected to an average of 2 buyers on the network, and when the number of network connections is 1000, they are connected to an average of 10 buyers. Buyers linked through this manner can exchange opinions with each other.

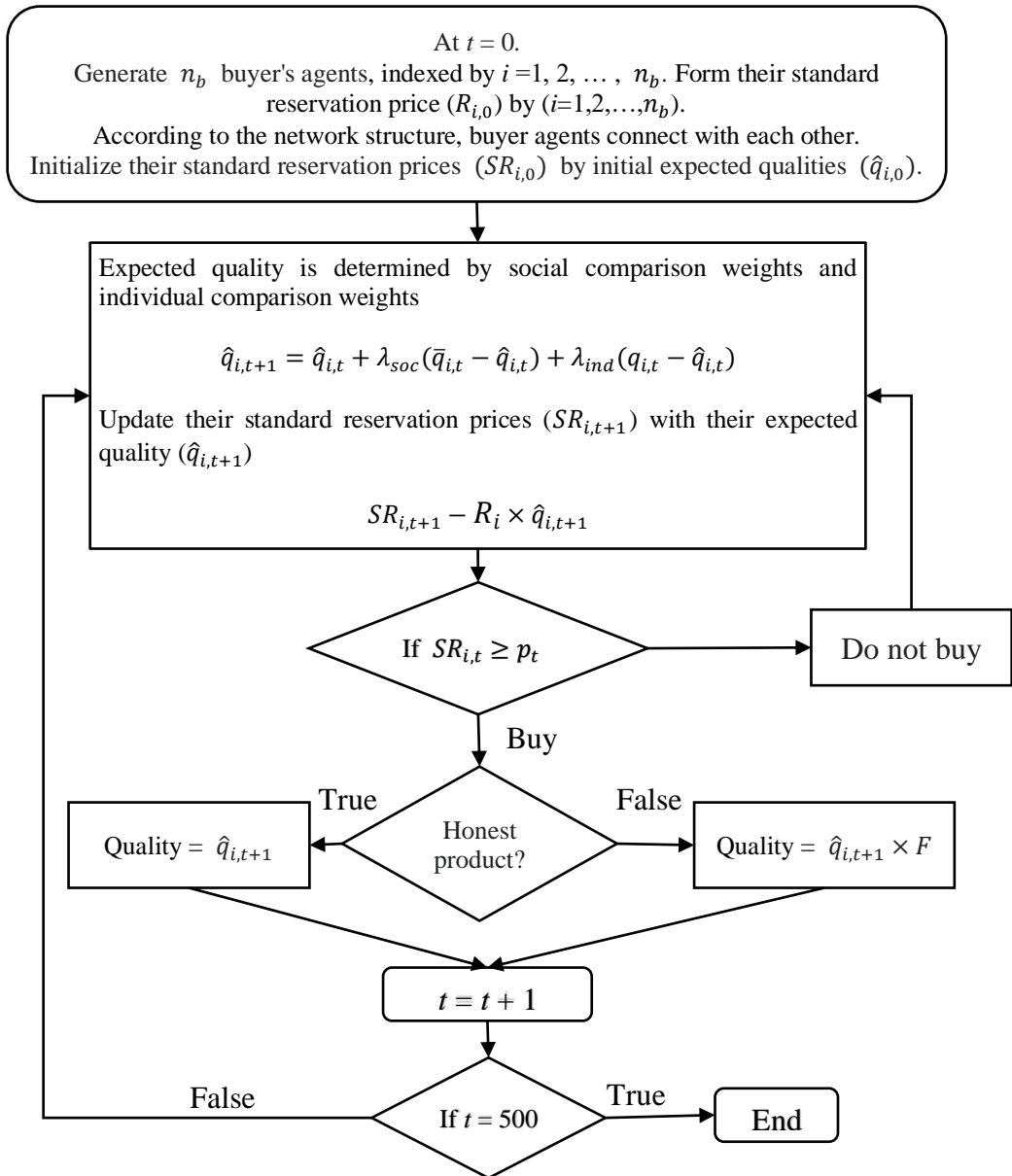


Figure 2: The formation process of buyer agents

The buyer agent learns the quality (q) information of the new commodity by purchasing it in the market. When the buyer's expected quality after purchase ($q_{i,t}$) is higher, the chance of purchasing new products is higher. When the buyer buys a dishonest product in the market, the post-purchase expected quality ($q_{i,t}$) will decrease. The expected quality of the updated product after the buyer is deceived is $(q_{i,t}) \times F$. We set F as 0.05, simulating a loss of trust in the seller after being deceived. In each transaction round, the buyer will select the commodity whose reserved price (SR_i) is prioritized in the market, but there may still be honest or dishonest sellers in the market at the same time.

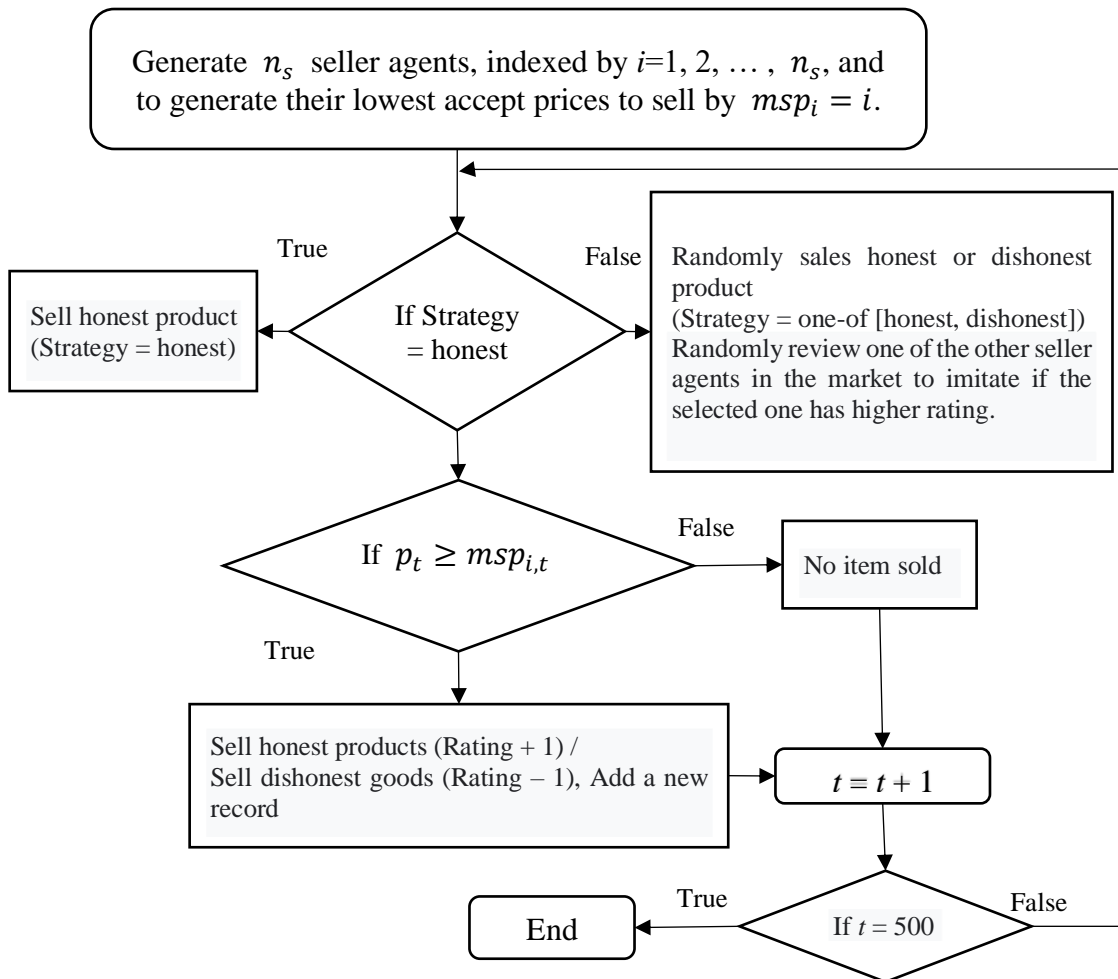


Figure 3: The formation process of seller agents

The honest ratios among the 100 sellers in this study are 100%, 50%, and 0%, respectively, corresponding to 100, 50, and 0 honest sellers, with the remaining share being dishonest sellers. A reputation mechanism, as used by Wierzbicki *et al.* (2014), is added to record the seller's evaluation of the buyer's agent in the market.

When a buyer buys a dishonest product, the buyer posts a negative review and writes it into the seller's reputation record. On the contrary, if the buyer buys a honest product, a positive review record will be added to the seller. The law of imitation and learning among sellers, when the seller's agent finds that the reputation of the seller's agent that he chooses to view is better than herself, the seller's agent will follow the strategy of the seller's agent he viewed in this round. For example, when the seller's agent chooses to refer an honest seller, if the seller's reputation is higher than herself, she will choose to be an honest seller. When the seller's agent chooses to refer a dishonest seller, if the seller's reputation is higher than herself, she will choose to be an dishonest seller.

3.3 Experimental Design

In this paper, four groups of experiments were performed, and each group of experimental parameters was repeated 100 times, with 500 ticks each time. There were 100 buyers and 100 sellers' agents. Whether the seller's agents were honest, the number of network connections of the buyer's agent, the social comparison weight, and the individual comparison weight were set at the outset. Observed changes in market commodity volume, market prices, sellers' income, and buyers' average expected quality was also set at the outset. The experimental parameters are as follows:

Network structure [network-structure = "random", "preferential attachment"], Quality distribution [quality-distribution = "uniform", "exponential"], Social weight [λ_{soc} = 0, 0.5, 1], individual weight [λ_{ind} = 0, 0.5, 1], number of links [links = 0, 100, 200, 300, 400, 500, 1000, 3000, 6000, 9900], with different honest seller ratios [0%, 50%, 100%].

For two network structures and two quality distributions, there are a total of four sets of experiments, each of which will generate 27,000 experimental results for the results of 500th rounds. The average value of the transaction results of the last round of the 100 simulated markets are compared, and the influence of dishonest sellers on the e-commerce market are observed.

4. Simulation Results

In this section, the changes in commodity transaction volume, market price, seller's income, and buyer's average expected quality are organized.

4.1 The Tendency of the Market

Buyers in the market can use the ability of individual learning to yield improvements when purchasing new products. Its expected quality, Figure 4, reflects the changes in the market trend of commodity volume, market price, seller's income, and buyer's average expected quality with the increase of transaction rounds when there are honest sellers in the market.

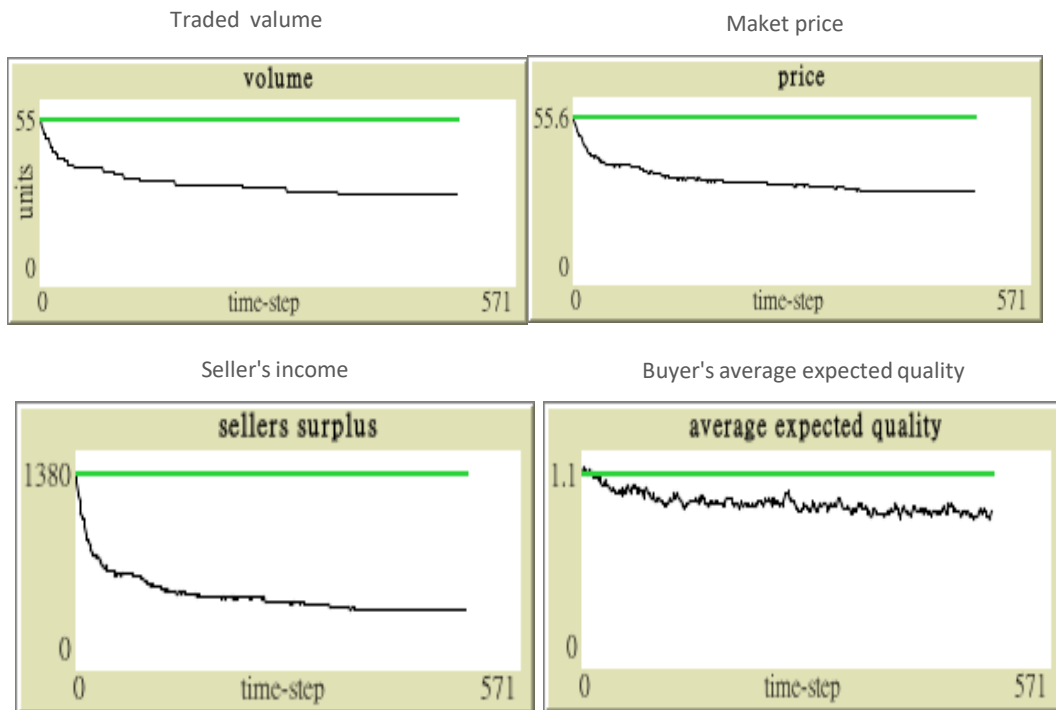


Figure 4: Line chart of market transaction status of 100% honest sellers at $\lambda_{ind}=0.2$, $\lambda_{soc}=0$, Links=200 (quality distribution = exponential, network structure = preferential attachment)

The results in Figure 4 show that the decline in transaction volume and price reflects the decrease in buyer demand and sellers' income under saturated market conditions, which is consistent with the results of Izquierdo *et al.* (2007).

When dishonest sellers appear in the market, if buyers do not have a social network, they soon lose confidence in the products on the market. The commodity quality declines rapidly, and as the trading time goes on and the market may even shrink to the point at which trading stops, resulting in market failure. In other experiments, the result of this market failure is that with the addition of social learning and social network connectivity, the negative impacts of quality uncertainty brought about by individual learning begin to decrease and are presented in subsequent experimental results.

In this paper, the ratio of honest sellers (Honest ratio), number of social network connections (Links), individual comparison weight (λ_{ind}) and social comparison weight (λ_{soc}) are used for independent factors. From Tables 2 to 5, the regression results of each variable are all significant, reflecting the existence of dishonest sellers. Significant positive impact on the market across the settings of quality distributions and network structures.

Table 2: Regressions of the number of connections, individual weight, social weight, and honest ratio to the market price, traded volume, seller's income and buyer's expected quality at the 500th round (quality distribution = exponential, network structure = preferential attachment)

Variable	Dependent Variable			
	Market price	Traded volume	Sellers' income	Buyer's expected quality
Links	0.002*** (75.94)	0.002*** (75.11)	0.023*** (52.07)	0.000*** (88.03)
λ_{ind}	-7.526*** (-57.67)	-7.763*** (-60.41)	-162.776*** (-59.90)	-0.535*** (-92.65)
λ_{soc}	7.393*** (54.38)	7.290*** (54.26)	34.207*** (12.41)	-0.240*** (-40.99)
Honest ratio	11.819*** (55.30)	11.585*** (54.66)	240.604*** (45.77)	0.358*** (61.60)
Adj R ²	0.54	0.54	0.36	0.39

*p<0.05, **p<0.01, ***p<0.001. Robust standard errors in parentheses.

Table 3: Regressions of the number of connections, individual weight, social weight, and honest ratio to the market price, traded volume, seller's income and buyer's expected quality at the 500th round (quality distribution = uniform, network structure = preferential attachment)

Variable	Dependent Variable			
	Market price	Traded volume	Sellers' income	Buyer's expected quality
Links	0.002*** (79.93)	0.002*** (79.54)	0.036*** (69.56)	0.000*** (90.24)
λ_{ind}	-6.126*** (-41.81)	-6.436*** (-44.42)	-179.653*** (-58.91)	-0.306*** (-65.01)
λ_{soc}	12.444*** (80.74)	12.291*** (80.43)	132.785*** (41.46)	0.029*** (6.09)
Honest ratio	12.534*** (57.00)	12.285*** (56.30)	248.452*** (46.53)	0.334*** (63.02)
Adj R ²	0.63	0.63	0.48	0.40

*p<0.05, **p<0.01, ***p<0.001. Robust standard errors in parentheses.

Table 4: Regressions of the number of connections, individual weight, social weight, and honest ratio to the market price, traded volume, seller’s income and buyer’s expected quality at the 500th round (quality distribution = exponential, network structure = random)

Variable	Dependent Variable			
	Market price	Traded volume	Sellers’ income	Buyer’s expected quality
Links	0.003*** (123.80)	0.003*** (123.30)	0.081*** (108.20)	0.000*** (105.40)
λ_{ind}	-2.674*** (-12.03)	-2.944*** (-13.30)	-59.504*** (-10.29)	-0.416*** (-68.90)
λ_{soc}	8.581*** (40.08)	8.411*** (39.45)	66.528*** (11.58)	-0.199*** (-33.33)
Honest ratio	12.320*** (48.78)	12.105*** (48.22)	251.587*** (37.47)	0.409*** (69.19)
Adj R ²	0.57	0.57	0.45	0.34

*p<0.05, **p<0.01, ***p<0.001. Robust standard errors in parentheses.

Table 5: Regressions of the number of connections, individual weight, social weight, and honest ratio to the market price, traded volume, seller’s income and buyer’s expected quality at the 500th round (quality distribution = uniform, network structure = random)

Variable	Dependent Variable			
	Market price	Traded volume	Sellers’ income	Buyer’s expected quality
Links	0.003*** (128.60)	0.003*** (128.50)	0.083*** (123.50)	0.000*** (109.80)
λ_{ind}	-1.175*** (-5.50)	-1.508*** (-7.09)	-66.114*** (-11.73)	-0.222*** (-48.51)
λ_{soc}	12.086*** (59.05)	11.894*** (58.33)	126.558*** (22.79)	0.013*** (2.90)
Honest ratio	13.528*** (55.72)	13.275*** (54.96)	268.600*** (41.32)	0.408*** (81.67)
Adj R ²	0.65	0.64	0.51	0.47

*p<0.05, **p<0.01, ***p<0.001. Robust standard errors in parentheses.

4.2 The Regression Results

The results of price and trading volumes were obtained after 500 transactions in each market. When the market has more honest sellers, more network connections and higher social comparison weight λ_{soc} , the price, traded volume, seller's income and buyer's expected quality increase steadily. Izquierdo *et al.* (2007) showed that when the social weight λ_{soc} is lower and the individual weight λ_{ind} is higher, buyers rely more on individual experience to generate expected quality. In this case, buyers generally underestimate the actual quality of goods, and the willingness to pay decreases.

When dishonest sellers begin to appear in the market, the traded volume falls. Some buyers buy dishonest goods, which greatly reduces the expected quality, and the price of the goods in the market also falls. When there are a higher number of network connections, the higher the market price and traded volumes, the weaker the impact of dishonest products. Because buyers will share more information due to the connection, the less they will be attacked by dishonest sellers. Confidence in market is less likely to underestimate the expected quality of commodities. However, when the ratio of dishonest sellers is higher, the negative impact on market price and traded volume is more obvious.

The observation results show that the higher the network connection and the social comparison weight λ_{soc} , the higher the seller's income, whether in a completely honest market or a market containing dishonest sellers. When buyers can obtain more information, the lower the impact of dishonest goods on buyers' expected quality in the market.

There is a significant negative effect on the average expected quality results of buyers after 500 transactions in each market under the individual comparison weight (λ_{ind}). Whether in a completely honest market or a market with dishonest sellers, as the number of network connections increases and the social comparison weight λ_{soc} increases, the average expected quality of buyers will be higher. However, as the social comparison weight λ_{soc} increases, the average expected quality of buyers will become lower under the *exponential* quality distribution but becomes higher under the *uniform* quality distribution. As the number of network connections increases, the market will be positively affected, and the average buyer's expected quality is thereby significantly improved. When more and more sellers become dishonest, the market is easy to be influenced by inferior goods brought by dishonest sellers to drive out high-quality goods.

5. Conclusions

By adding the attributes of honesty and dishonesty to the seller's agent in the MEQU model and dishonesty products to the market, changes in the expected quality ($q_{i,t}$) among consumers are modeled, and changes in consumers' mentality after being deceived is moderated.

This paper makes a summary of the experimental results. Through the experiment, we find that when consumers have network connections, the higher the social

comparison weight λ_{soc} , they are more willing to accept the opinions of other buyers in the market, and the expected quality is higher and less affected by dishonest sellers. From the results, it can be observed that the higher the social comparison weight λ_{soc} and the higher the number of network connections, the more stable the market transaction results, prices, and sellers' income. Under such market conditions, through news dissemination and information sharing, a stable expected quality among consumers ($q_{i,t}$) emerges and *vice versa*. When the number of network connections is low, the transaction results and prices of the market and the income of sellers gradually decrease, and the destructive effect of dishonest products is more severe.

At the same time, when the buyer's individual comparison weight is higher, the buyer's individual learning ability is correspondingly improved, but in a market with uncertain quality, depending on the quality of the market, this may impact the consumer's expected quality ($q_{i,t}$). If an individual comparison weight λ_{ind} is higher, and the social comparison weight λ_{soc} is lower, it is likely to have an extreme reaction to the market. From the experimental results, it can be found that, for example, there are dishonest purchases. From then on, potential buyers may think that the quality of the products is unreliable and therefore refuse to buy the products, and the honest e-commerce sellers in this market may withdraw from the market due to the size of the market shrinking.

The above market results are generally like the results of the "lemon market." When dishonest products appear in the market, a defective market is formed, causing buyers to refuse to purchase. With the increase in the degree of connection and the improvement in the ability to grasp information, buyers are able to independently judge expected quality, and because of the existence of dishonest products in the market, they will not leave the market. Buyers are able to observe and grasp information from others. This phenomenon can also be found in a market with higher social comparison, individual learning ability, and network connections. In such a market, buyers have higher quality expectations, and higher sellers' income. However, when facing dishonest sellers, the average quality of the entire commodity market will be affected by these dishonest commodities, and buyers will therefore lose confidence in commodities and their expected quality ($q_{i,t}$) will decline.

Therefore, for e-commerce to be successful, consumers need to trust the online market. It is possible to fail or even destroy the market due to dishonest goods or information that overestimate the quality of goods in the market. Only when information is shared and disseminated on social networks, consumers with low expectations are more likely to change their perceptions and reduce the occurrence of adverse selection in the market.

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