Combating Online In-Auction Fraud: Clues, Techniques and Challenges*

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ABSTRACT

The number of Internet auction shoppers is rapidly growing. However, online auction customers may suffer from auction fraud, sometimes without even noticing it. In-auction fraud differs from pre- and post-auction fraud in that it happens in the bidding period of an active auction. Since the in-auction fraud strategies are subtle and complex, it makes the fraudulent behavior more difficult to discover. Researchers from disciplines such as computer science and economics have proposed a number of methods to deal with in-auction fraud. In this paper, we summarize commonly seen indicators of in-auction fraud, provide a review of significant contributions in the literature of Internet in-auction fraud, and identify future challenging research tasks.

Keywords: online auction, in-auction fraud, fraud indicators, auction fraud prevention, shill detection

1. Introduction

1.1 Online Auctions

The Internet revolution and advances in information and communication technology have laid the groundwork for online auction systems to become a new profitable business platform [1]. To cite just one well-known example, eBay, the world's largest auction website, announced $2.19 billion revenue for the first quarter of 2008. Clearly many buyers and sellers are attracted to online auctions.

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According to one source [2], at least 31% of Americans who have Internet access regularly participate in online auctions, accounting for a sizeable total of 35 million people.

There are dozens of traditional auction types; however, the types of auctions on the Internet are limited. The primary auction types are the English auction, Dutch auction, first price sealed-bid auction and second price sealed-bid auction (also known as Vickrey auction) [3-5]. Due to its widely known auction rules and its efficiency as a resource allocation mechanism, the English auction has become the most popular type of online auction among both service providers and consumers. It is a typical open, ascending-price auction in which bidders compete with each other by placing higher bids. When a predefined time expires or the highest bid reaches the pre-determined buyout price (a price that any bidder can accept during the auction), the highest bidder wins the auction. The winner pays the highest price, namely, the one just bid. According to a preliminary study [6], the English auction and its variants account for 88% of Internet auctions while Dutch auctions account for 1%; others such as sealed-bid auctions and double auctions comprise the remaining 11%.

Unlike the English auction, the Dutch auction is a type of descending-price auction [7]. This type of auction requests a high price at the beginning, and then the price is lowered gradually until a participant is willing to accept the price, or a predetermined minimum price is reached. The winning participant pays the last asked price. Dutch auction is also used in online auctions where multiple identical items are sold simultaneously to one or more winning bidders. It is equivalent to a multi-unit English auction in the economics literature [8].

While both English and Dutch auctions are open auctions in which participants know each bidder’s bidding price, sealed-bid auctions are auctions in which each bidder bids just once and the bid price is kept as a secret during the auction. The first price sealed-bid auction is an auction in which all bidders submit their bids at the same time, and all participants are ignorant of others’ bids. The winner is the one with the highest bid, and pays that bid. The second price sealed-bid auction (Vickrey) is also a sealed-bid auction, like first price sealed-bid auction. The only difference is that, in second price sealed-bid auction, the winner pays the second highest bid rather than the winner’s own bid. It has been proved that the second price sealed-bid auction is a mechanism strategically equivalent to the English auction, but it gives bidders an incentive to bid their true values, making this type of auction important for auction theory [9]. To understand the impact of a second price sealed-bid auction, consider that a bidder could possibly fail to acquire the item if the bid is less than the bidder's true valuation when one of the other bidders bids only a slightly higher figure that is still within the first bidder's acceptable range; on the other hand, if the bidder bids more than the bidder's actual valuation and a second sealed bidder also overvalues the item but slightly less so, the first bidder runs the risk of winning the auction at this second price, which is more than the bidder was originally willing to pay. The second price sealed-bid auction has been used in the stamp collection auction market [10]. From the auction theory point of view, eBay's automated proxy bidding is similar, but not identical, to the Vickrey auction. On eBay, the winning buyer as determined by the automatic proxy bidding system does not pay their own highest bid, but instead pays the second highest bid plus a predefined minimum increment. This is different from a Vickrey auction because eBay's bidding proxy can submit bids multiple times in an auction on behalf of the buyer, and the buyer can also change the maximum bid accordingly. However, in a Vickrey auction, every bidder can only submit a bid once and the bid is not changeable.

In English, Dutch and sealed-bid auctions, there is usually only one seller in an auction. However, in a double auction, there might be many sellers, where sellers and buyers offer and submit bids in any order [11]. Then bids are ranked from highest to lowest, and offers are ranked from lowest to highest to generate a supply and demand profile. When offers and bids are matched (bids move down and offers move up), the required quantities of goods are exchanged. Double auctions are commonly used in futures markets.

One more way to classify auctions is according to their schedules. Some auction sites have a fixed time schedule, in which when time runs out, the auction is closed. For instance, a one day auction on eBay lasts exactly 24 hours. Other auction sites such as uBid and Yahoo!Auction (US Yahoo!Auction has declared its retirement since June 16, 2007) have a time schedule similar to that of some traditional auctions – when the time limit runs out, time is extended as long as someone outbids the others.

A bidding strategy is a plan of bids designed to achieve a particular goal, such as winning an item at a low price or exposing highest bidders. In auctions, bidders may choose a single bidding strategy or use mixed bidding strategies. In fact, there may be as many bidding strategies as bidders. In Table 1 we list some representative bidding strategies that are commonly used in auction markets [12].

Table 1. Five Common Bidding Strategies

STRATEGY	DESCRIPTION
Skeptic	Bid multiple times but bid as low as possible each time.
Proxy bidding	Specify a maximum bid initially and then authorize the proxy to bid automatically as many times as necessary up to the maximum.
Sniping	Bid in the last seconds, leaving no time for anyone else to outbid.
Unmasking	Bid several times in a short period of time with the purpose of exposing the maximum bid or the highest bidders.
Evaluator	Bid just once at an early time with a high value.

1.2 Online Auction Fraud

Although the number of sellers and buyers attracted by online auctions is growing rapidly, this contemporary business medium faces an important challenge – auction fraud [13-16]. Both sellers and buyers can participate in auction fraud for their own benefit. Data released by the U.S. Federal Bureau of Investigation's Internet Crime Complaint Center (IC3) reveals that 93,771 auction complaints were received in 2006, representing 45 percent of all Internet fraud complaints [17]. Auction complaints remain the largest source of Internet-related complaints, consistently ranking at the top of the list for many years [18].

According to IC3, there are several ways online auction fraud can occur: misrepresentation of a product for sale, non-delivery of merchandise or services sold, triangulation (fraudsters purchase items using a stolen credit card, selling the items to uninitiated buyers thereby retaining the cash and transferring the risk of seizure to the end recipient), fee stacking (charging extra money after an auction is over), selling black market goods, multiple bidding (buyers inflate prices using aliases, which frustrates competitors, then at the last moment the high bids are withdrawn to secure a low bid), and finally shill bidding (sellers or their associates place bids on their own auctions for fraudulent purpose).

To understand online auction fraud, it is convenient to first classify the various types of online auction fraud according to the three time periods in which the fraudulent behavior can take place: pre-auction, in-auction and post-auction (Figure 1). Misrepresentation of items, selling of black market goods and triangulation usually occur before the auctions start, so we classify them as pre-auction fraud; and non-delivery of goods and fee stacking occur after auctions close, so we consider them as post-auction fraud. In-auction fraud is the main focus of this paper and so the discussion of in-auction fraud is postponed to the following sections.

Because both pre-auction and post-auction frauds involve offline behaviors that can often easily be noticed by buyers and sellers, investigation of such frauds relies more on real-world evidence than on online prevention and detection mechanisms. However, in-auction fraud happens while transactions are in progress, thus it may occur without leaving direct physical evidence, and worst of all may not even be noticed by the victims. In addition, while pre-auction fraud and post-auction fraud have already attracted researchers' and policy makers' attention, in-auction fraud has attracted much less attention due to its complexity in detection [19, 20]. In order to reduce the loss to victims and to protect online business participants, in-auction fraud deserves more attention and effort from mechanism designers and information technology researchers.

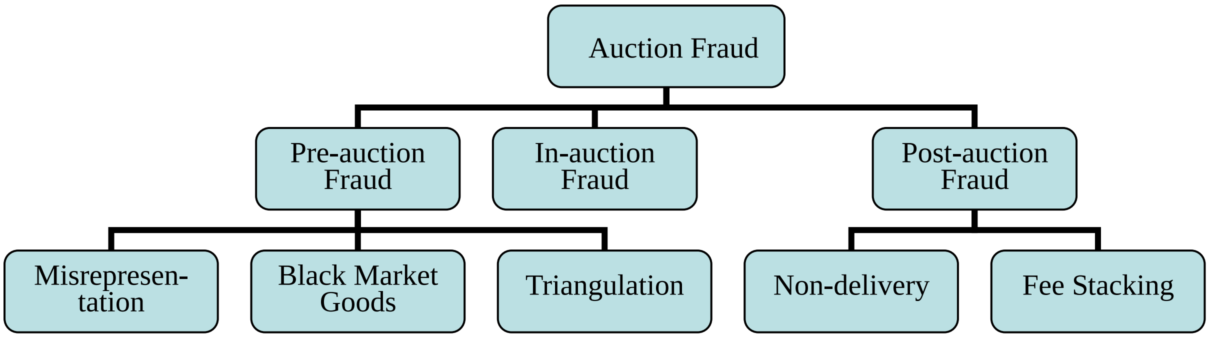

Figure 1. Auction Fraud Categorization

Many consumer guidance websites and newspapers have provided auction fraud detection tips, such as checking if a seller and a suspicious bidder are from the same geographic region; and searching a shill suspect's bidding history to determine if a seller and the shill suspect have a partnership. However, even if a suspected shill and a seller are located far from each other, they still could be partners. With modern Internet communication applications, sellers and shills can communicate with each other very easily as if they were sitting next to each other. In addition, whereas there may be a large number of historical records for long-time sellers, it is difficult and time-consuming for a bidder to discover the partnership between sellers and shills. Unfortunately, in-auction fraud is so sophisticated and tricky that such tips are extremely difficult for consumers to effectively apply.

Many researchers from economics, business, system science and computer science have realized the severity of this problem [21-23]. They are working to combat auction fraud and have produced some preliminary work. In this paper, we aim to provide an overview of the state-of-the-art Internet in-auction fraud prediction, prevention and detection techniques, and to highlight challenging research issues in this interesting new area. The surveyed countermeasures are from both the economics and the computer science perspectives.

The rest of the paper is organized as follows. Section 2 discusses important concepts and indicators of in-auction fraud, revealing motivations behind fraudulent behaviors. Section 3 presents existing solutions to the problem of in-auction fraud, while Section 4 identifies some problems and tasks that remain as research challenges in this domain. Section 5 concludes the paper and mentions future work.

2. The Nature of Online In-Auction Fraud

Current and emerging state-of-the-art auction platforms rely heavily on information technology, and hence any weakness in information systems could be utilized by malicious users to maximize their own profits. Although in-auction fraud has an important influence on new technology-based sectors of the economy such as e-commerce, there is a lack of mechanisms to fight against in-auction fraud. This is because in-auction fraud has not been a major issue in traditional auctions, and therefore, it was barely considered in traditional literature.

Due to the nature of Internet applications such as a high degree of anonymity, incomplete legal constraints and lower barriers to entry and exit, it is difficult to combat in-auction fraud. The Internet characteristics inevitably result in information asymmetry between sellers and buyers in online auctions, where one party of the transaction has more or better information than the other party. In an auction, sellers usually have better knowledge about the item than buyers; therefore shills who are associated with the sellers also have better knowledge than other buyers. The fraudulent participants intentionally make use of this information asymmetry to obtain benefit and deliberately hide their fraudulent or opportunistic behaviors so as to avoid being detected and caught. Since most of the fraudsters sign up on auction sites with fake identity information, when fraudulent behaviors are exposed, it is hard for investigators to find out the real identity under the meaningless net IDs. Afterwards the fraudsters could start over again using new net IDs so as to conceal their identities and reduce the chance of being punished.

Online auction houses do not always exhibit a positive commitment to actively solving the auction fraud problem. Some researchers claimed that the policies of existing auction houses typically would not discourage users from cheating [24]. Chua, et al. pointed out that with the current oversimplified evaluation practice that relies on transaction feedbacks, the online auction platforms provide leverage for a con-man to manipulate the system with the intent of deceiving [25]. So far, though a few online auction fraud detection approaches have been proposed, online auction systems that support smashing auction fraud are still very few [26,27].

Furthermore, unlike traditional auctions, online auction rules usually impose fixed time durations for auctions, and online auctions typically last longer than traditional auctions. For example, eBay offers users the option of 1, 3, 5, 7 and 10 day auction durations. These optional auction durations on the one hand satisfy the sellers' need to attract more bidders, but on the other hand they leave malicious buyers and sellers more time to do cheatings. The longer the auction lasts, the more chances for fraudsters to make their fraudulent behaviors look normal. With enough time, cheaters could potentially behave like normal bidders with few clues left for fraud investigation. Thus, detection of auction fraud using statistical evidence related to time would be compromised by the normalized behavior. For example, if an auction lasts one day, the fraudsters may place their first several fraudulent bids within the first few hours after the auction begins. However, if an auction lasts many days, the cheaters may not be in much of a hurry to place shill bids. A bidder might be suspected if this bidder places a high bid for a common item in one auction, but places no bid in another auction of an identical item at a lower price, running concurrently on the same site. Nevertheless, given enough time, the seller or seller's accomplice can wait until there are no sellers selling the same item for less, and then place a shill bid with less chance of being caught. The statistical investigation would therefore be highly affected.

Last but not least, although many existing cheating patterns have been suggested, they can merely be used as clues for investigation rather than evidence. Each pattern in itself may have more than one rational explanation, including the fraudulent one. We postpone further discussion on this until Section 2.3.

2.1 Impact of In-Auction Fraud

In-auction fraud has become more and more severe, especially shill bidding, which is probably the most prevalent form of online auction fraud. A shill is a person posing as a legitimate buyer who feigns enthusiasm for the item on auction by bidding up the price, thus serving as an accomplice to the seller. The role of a shill can be played by an associate of the seller, such as a friend or family member, or by the seller himself posing as a legitimate buyer under a fake online auction ID. Mass media including Consumer Affairs, the New York Times and USA Today have covered this kind of auction fraud frequently in the last few years [28-30].

Online in-auction fraud severely violates commonly perceived notions of fairness in auction markets. Wang, et al. showed that private-value English auctions with shill bidding could result in a higher expected seller profit than other types of auctions, violating the classical revenue equivalence theory [31]. Kauffman and Wood examined the effects of shill bidding on final bid price in rare coin auctions and showed that some bidders might view shill bids as signals that an item is worth more, thus they might pay more than other bidders who cannot see such signals [32].

In a worst-case scenario, in-auction fraud could result in an insufficient market or even market failure, which has not been considered in traditional auction literature. In-auction fraud could lead to a vicious spiral of auctions. Taking shill bidding as an example, in-auction fraud could result in the "shiller's curse" as indicated in [33]. When buyers suspect the existence of shill bidding, they may shield their bid and wait for the seller to keep the item and sell it for less in the next round of the auction. If no bidder outbids the shill, the seller will probably try to sell the item again later. If the shill phenomenon exists in an auction market persistently, buyers would fear the existence of shills whenever they want to buy something through online auctions, and such buyers would likely bid at a price that is much lower than their valuation, considering the existence of potential shill bidding. The above process can be repeated, and then both sellers' and buyers' trust toward the auction market deteriorates. Consequently, the chaos may lead to inefficient or failed markets.

Researchers from economics, system science, computer science and other subjects have noticed the severity of the problem and have made some efforts to solve it. In Section 3, we review representative solutions to the problem of in-auction fraud.

2.2 Key Concepts in In-Auction Fraud

The current online auction literature reflects a consensus that regards buyers as bidders, even though the actual entity that places bids up to a certain limit could be an automatic bidding system, such as the proxy bidding system on eBay or the bid butler on uBid. Nonetheless, sellers and auctioneers are different according to the literature. In some auction models, researchers regard auctioneers the same as sellers, considering an auction as an online transaction between auctioneers (sellers) and buyers. Therefore, they often use the two terms "sellers" and "auctioneers" interchangeably [34, 35]. However, as online auction fraud becomes increasingly popular, the role of the auctioneer can no longer be overlooked. Wang, et al. made a distinction between "auctioneer" and "seller." They argued that auctioneers, who are agents that conduct auctions as a third party with self-interest, play an essential and critical role in auctions, especially in in-auction fraud prevention [31]. Therefore, in this paper, we define sellers as people who own the item for auction, while auctioneers are the entities who coordinate auctions. In online auctions, an auctioneer is simply an auction house, such as eBay. Table 2 provides a comparison between auctioneer and seller.

Table 2. Online Auctioneer vs. Online Seller

ROLE	DESCRIPTION	MAJOR RESPONSIBILITIES	GOALS	EXAMPLE
Auctioneer	An entity that provides auction services to online auction users.	1. Provide a transaction platform and services to both sellers and bidders. 2. Make arrangements for auctions. 3. Place advertisements for auctioned items.	Provide a trust-worthy auction environment to customers and earn commissions.	eBay
Seller	An entity that offers items for sale. The seller may or may not be the owner of the item.	1. Run the auction by posting item descriptions and pictures, and taking bids. 2. Receive payments and provide the auctioned item(s) to the winner. 3. Pay commission fees to the auctioneer.	Obtain a high sale price and reduce commission costs.	A person who hosts an auction on eBay.

Before discussing details on in-auction fraud, it is useful to first understand some basic concepts related to the fee structure of auction houses. Auction houses charge user fees for the services they offer. For instance, the total cost on eBay includes an insertion fee and a final value fee, where the insertion fee is charged whenever a seller lists an item for sale, and the final value fee is charged if the item is sold. The insertion fee is calculated as a function of the starting price or the reserve price, whichever is higher. The starting price is an initial price of an auctioned item, while a reserve price is the minimum price at which the seller is willing to sell the item. Since a high starting price may drive away potential bidders, a seller typically sets a low starting price to attract bidders and a high reserve price to insure that the seller can "reserve" (keep) the item in case the winning bid is below a satisfactory value, i.e., the reserve price.

In-auction fraud may include shill bidding, bid shading, false bidding, multiple bidding, and bidding rings. Shill bidding happens in open auctions in which, by definition, bidders are allowed to compete with each other to bid multiple times. It could not happen in a sealed-bid auction due to the nature of concealed bids. Bid shading and false bidding are specific terms for cheating behaviors for first-price auctions and second-price auctions, respectively.

From the literature, it is clear that there are many different types of in-auction fraud, which are related to the role of the auction participants, namely the sellers and buyers. We now subdivide in-auction fraud into sellers' fraud and buyers' fraud, and explain them in detail. We adapt the taxonomy presented in [36] and elaborate the concept of shill bidding, one type of seller-based fraud, into three concrete forms of shilling behavior that can occur in online auctions. As Figure 2 shows, sellers' fraud includes competitive shilling, reserve price shilling, buy-back shilling and false bidding, while buyers' fraud consists of bid shading, multiple bidding and bidding rings.

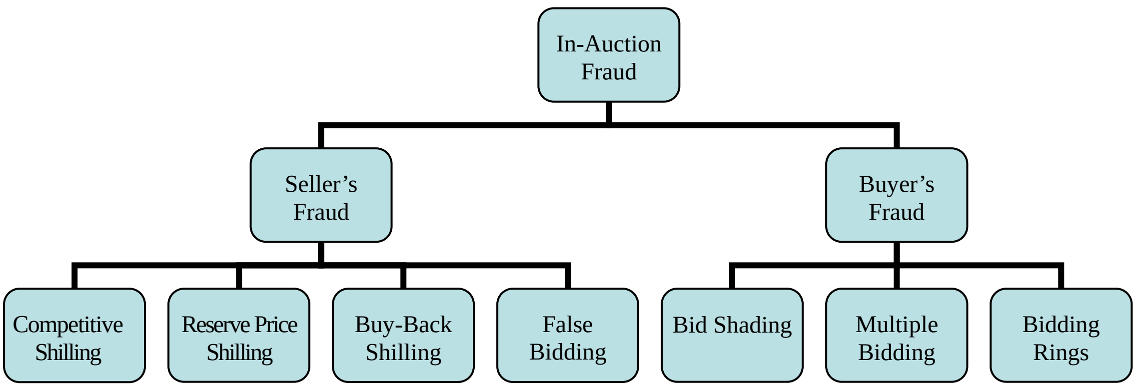

Figure 2. In-auction Fraud Categorization

Shill Bidding includes any activity in which a seller or an associate of a seller bids on the seller's own item in an auction. Shill bidding can be performed either by the seller or by individuals associated with the seller (including friends and family members), who may have a level of access to the seller's item information that is not available to the general community [37]. We distinguish three types of shilling behaviors based on the seller's or shill's motivation to cheat either the other bidders, as in types (1) and (3) below, or the auction house itself, as in type (2).

(1) *Competitive shilling* is a bidding behavior that artificially drives up the bidding price of the auctioned item with no intention of actually buying. The purpose is to make a legitimate winner pay more than this person would otherwise pay, so that the seller can gain more profit [32]. The competitive shilling behavior can occur in both live and online auctions as long as the collusion between the seller and the shills remain unknown to the auction house and the other bidders. Intuitively, one can surmise that the shill bidders engaged by sellers pretend to be legitimate competing bidders, and use the shill bid to lure legitimate high-value buyers not only to bid up to their valuations but also to exceed them. This behavior cheats other bidders by inducing them to pay more for the item than they would have without the shill bids. To better understand competitive shilling, consider the following example situation. A seller hosts an auction of an item, say an unlocked cell phone. Initially, nobody places any bid at the auction. So, to attract some bidders to the auction, the seller, acting under another alias, places a competitive shill bid for the purpose of stimulating other bids. After someone outbids the shill bid, the seller places another shill bid for the purpose of driving up the bidding price. The seller hopes other legitimate bidders will outbid all further shill bids. All bids placed on behalf of the seller can be regarded as competitive shill bids and the bidding behavior is called competitive shilling.

(2) *Reserve price shilling*, first defined by Kauffman and Wood [23], is a bidding behavior motivated by the desire to avoid payment of the reserve price fee. By accepting the reserve price service, a seller is agreeing to pay the auction house a fee for the service. To minimize the payment of auction house fees but still reserve the item below a certain price, some high volume sellers will not set an "official" reserve price but instead engage shills to place bids on their auctions. For example, a seller may wish to sell an item at $200. If the seller chooses eBay's optional service to

set a reserve price of $200, this seller would automatically incur an insertion fee of $3.00 according to eBay's fee structure of 2008. To avoid payment of the reserve price fee but still reserve the item if the final bid for the item is under $200, the seller might first list the item at $9.99, paying the auction house a low insertion fee of $0.35. Then, either an associate of the seller, or the seller himself, places a bid at the price of $200 in hopes that a legitimate bidder will make a purchase at $201 or more. In fact, eBay in its rules against shill bidding also gives an example of reserve price shilling [38]. Note that sellers do take a monetary risk when employing reserve price shilling: if nobody makes a purchase at more than the hidden reserve price, the seller must still pay both an insertion fee and a final value fee.

(3) *Buy-back shilling*, which to our knowledge has not been previously identified in the literature, is a bidding behavior employed by sellers, or other shills as agents of the seller, when the legitimate bidders do not bid an acceptably high price. The seller or shills would rather buy back the item and sell it again than sell the item now at a low price that does not reach their expectation. In this situation, shills behave as a normal bidder with the goal of buying the item at a bargain price and completing the transaction. Such activity cheats the other bidders by depriving them of purchasing an item at a bargain price. For example, as in the previous example a seller may wish to sell an item at $200 but initially sets the starting price at $9.99, producing an insertion fee of $0.35. When the auction is close to termination, if the highest bid has only reached $15, the seller may place a shill bid at $16.00 in order to buy the item back, even though the seller must pay the auction house a final value fee of $1.40 in addition to the $0.35 insertion fee. Nonetheless, this cost to the seller is trivial compared to the profit-loss the seller would have incurred if the item was sold at $15. The profit of buy-back shilling is obvious; hence we speculate that the buy-back shilling behavior does actually exist in online auctions.

Any of the above three shill bidding types can be enacted in one of the different forms described below, depending on who acts as the shill:

1. Acting alone: A seller, or owner of the item for sale, carries out shill bids by himself or herself. The seller is able to register several IDs in an auction house, e.g., eBay or uBid. Using different

IDs and pretending to be different legal bidders in order to bid multiple times in the seller's own auction, the seller can inflate the final auction price and profit.

2. Seller collusion: Several sellers help each other to place bids on each others' transactions for their mutual benefits.
3. Accomplice: A seller hires or invites family members and friends to serve as shills who will place bids on the seller's item, but instructs them to avoid winning.

Other types of in-auction fraud as shown in Figure 2 are described as follows.

False bidding: In a second price sealed-bid auction, each bidder bids only once in the auction and the winner pays the second highest bid rather than the highest. An auctioneer can help a seller profitably cheat by examining the bids under the table after all buyers have submitted their bids. Knowing all bids, the auctioneer can submit an extra bid to make the second highest price very close to the current highest price such that the seller can gain more profit [39]. For example, after all buyers have submitted their maximum bids, the auctioneer learns that the highest bid is $200.00 for the auctioned Razor cell phone and the second highest bid is $120.00. The auctioneer (who could possibly be working on behalf of the seller) can help the seller insert an extra bid, say $198.00, which is quite close to the highest bid $200.00, but not beyond the highest bid. After the auction ends, the seller receives $198.00 rather than $120.00, and the extra $78.00 in revenue is gained by false bidding. This type of auction fraud may appear in auctions held by eBay when bidders are using the auction site's automatic bidding proxy system. Every buyer using the bidding proxy has to submit a sealed maximum bid to the bidding proxy. The bidding proxy then bids repeatedly by setting increments until the bid exceeds the buyer's predetermined maximum bid. When the seller is able to obtain all existing maximum bids, this seller can then place a second highest bid as a shill bid, which is slightly lower than the highest maximum bid. By doing so, the seller's revenue increases.

In addition to sellers' in-auction fraud, buyers can also cheat in Internet auctions. Bid shading, multiple bidding and bidding rings are common cheating approaches used by buyers:

Bid shading: In first price sealed-bid auctions, the winner of the auction pays the highest bid. If a bidder could use an unfair method to know the highest bid before the bids are disclosed, then the bidder could insert a bid just above the highest bid. The fraudulent bidder would thereby increase the probability of winning while minimizing the payment to the seller [40]. Let's take an auction of the game console Wii as an example. Assume Bidder 6 is willing to pay up to $400 for the game console before submitting any bid. When the auction begins, all bidders except Bidder 6 submit their bids. These bid values are lower than Bidder 6's valuation, ranging from $200 to $300, as shown as in the left-side table of Figure 3. Since the auction is a sealed one, a bidder typically cannot see the highest bid. By knowing the highest bid in some unusual way, Bidder 6 may guarantee a win by placing a bid at $301.

Figure 3. An Example of Bid Shading

Another slightly different bidding strategy that is not regarded as fraudulent also goes by the name of bid shading [41]. In this case, bidders place bids below their true valuation of the item in order to avoid overpaying for the auctioned item.

Multiple bidding: Multiple bidding, also known as bid shielding, is similar to shill bidding except that it is a fraudulent behavior of buyers rather than sellers. The buyers register several aliases and use them to place multiple bids for the same item. By driving up the price with multiple auction identities, the buyers discourage other potential competitors. After that, they retract all high bids, leaving the lowest winning bid on the auction. At the end, the winner gets the auctioned item at a much lower price. For instance, consider a scenario for a Motorola Razor cell phone auction in which Bidder 3 bids $134.90. Bidder 1, who may have bid previously on this item, now realizes that Bidder 3 is a potential competitor. In order to try and force Bidder 3 out of the competition, Bidder 1 places 3 bids consecutively, namely $135.00, $270.00 and $280.00. The last two bids are obviously much higher than the previous bids; thus, when risk-neutral bidders see this situation, they will quit the auction instead of paying beyond the valuation. Therefore, Bidder 1 can secure the winning position. But, the cheating behavior comes about when Bidder 1 retracts the two high bids at the last minute of the auction, leaving only the $135.00 bid, which is the lowest cost to win the auction. This cheating method works only at auction websites that allow retracting bids. While almost all current auction websites' rules generally disallow retracting bids, they still allow retracting bids under exceptional circumstances such as a typographical error in entering the bid [42].As we observe, bids retractions occur often in many active auction websites.

Bidding Rings: Bidding rings is also a term related to bidders' fraud. It refers to collusive auction fraud behaviors conducted by several bidders. Several fraudulent bidders form a ring, and the ring members have an agreement not to bid against each other, either by avoiding bidding on the auction or by placing phony (phantom) bids to not compete with each other. The result is that the winner can win the auctioned item at a very low price.

2.3 In-auction Fraud Indicators

From the perspective of sellers' fraud, the following bidder characteristics may indicate the existence of shilling behaviors. We assume that when a buyer is interested in an item, the buyer is able to know key sale information related to the item, such as auctioning prices of the same item in other auctions on the same website, the auctions' end time, etc.

1) In concurrent auctions, when bids are placed on an auction with a higher price rather than the ones with lower prices, the bidder might be a shill. For example, three sellers are auctioning the same brand new Motorola Razor cell phone concurrently. The current bidding prices for auctions held by seller 1, seller 2, and seller 3 are $80.00, $100.00, and $150.00, respectively. To simplify matter, we assume that the Razor cell phones sold in the three auctions are identical, the three auctions end almost at the same time, and the reputation rankings of the three sellers have no effect on the bidders' decision. Now if a bidder places $160.00 on the auction held by seller 3, knowing that a currently winning bid could be placed at a lower price with Seller 1 or Seller 2, the bidder should be highly suspected as a shill. This indicator can be supported by the fact that the legitimate buyers are usually looking for bargains at auction websites but unlike normal bidders, shill bidders do not care about price very much because they do not really intend to buy a cell phone and their real intention is to drive up the price.

2) Shills usually have higher number of Bids Per Seller ratio (hereafter BPS) than that of normal bidders. The auction house maintains records of the number of bids a bidder has placed for every seller that the bidder has interacted with. Normal active bidders should have placed a number of bids on several different sellers' auctions, but shill bidders usually only deal with a very limited number of sellers, and most shill bidders only place bids on one or two sellers' auctions. A simple example is shown in Table 3, where users *S1*, *S2* and *S3* are all professional cell phone sellers. *B1* and *B2* are bidders who have recently placed bids for cell phones. Bidder *B1* has only placed bids on auctions hosted by *S1*. Also, this bidder completed 6 transactions with *S1* with a total number of 39 bids. For *B1*, the BPS ratio for *S1* is 39; the BPS ratio for seller *S2* and *S3* are both 0. The bidder *B2* bids separately on each seller's auction. For *B2*, the BPS ratio for *S1*, *S2* and *S3* are 10, 6 and 8, respectively. The statistical result of BPS ratio shows that *B1* is possibly a shill because *B1* behaves strangely compared to normal bidders who bid on any auctions instead of a specific one, where *B1* only bid with one seller, *S1*.

Table 3. An Example of Shill Indicator

Seller / Bidder	S1		S2		S3	
	No. of auctions	No. of bids	No. of auctions	No. of bids	No. of auctions	No. of bids
B1	6	39	0	0	0	0
B2	1	10	1	6	1	8

3) Shills generally avoid winning auctions. Because the general purpose of sellers in deploying other people as shills or acting as shills themselves is to inflate the price but not to obtain the item, this indicator is straightforward. As we mentioned previously, the total cost of selling an item at an auction house includes an insertion fee and a final value fee. When listing an item at the auction house, the seller is charged an insertion fee. If the item sells successfully, the seller is also charged a final value fee. If the shill wins, the seller needs to pay both fees to the auction house, and the partnership of the shill and the seller together would not come out ahead because of the fees paid to the auction house. Therefore, shills bid with caution to avoid outbidding potential winners. There is an exception in buy-back shill. In this case, if at the end of the auction the price is much lower than the sellers' expected value, then the seller would bid aggressively to buy the item back with the hope to sell it at a high price in the next round of the auction.

4) Shills usually place bids at the very beginning of auctions if the auction duration is not long enough. By doing so, (1) sellers could set up a hidden reserve price earlier; 2) the early bids can serve as stimulating bids which attract other bidders; and (3) shills could leave legitimate bidders sufficient time to outbid the shill bids, thus reducing the chance of an unexpected, and undesired, winning of the auction.
5) Shills may bid with the minimum increment that is established by an auction house. Especially during the later stage of an auction, if a shill's bidding increment is too large, the bidding prices may drive away other buyers, resulting in the shill accidentally winning the auction.
6) Shills usually do not receive many feedbacks. This indicator stands because the easiest way for a seller to manage a shill is for the seller to act alone. Since a shill seldom wins auctions, the seller does not need to provide any feedback for the shill. Note that online auction houses typically allow users to provide feedback to either sellers or buyers. However, this evidence alone is insufficient for incriminating a shill, because it is possible that the bidder is a newly registered user and does not have any feedback yet.

Now from the auction perspective, the following characteristics of auctions themselves indicate that shills may be involved:

1) Auctions with shills have more bids on average than those without shills. Shills tend to outbid the legitimate bids frequently until the price reaches their expected value, or when the risk of winning the auction becomes high. The bids that the shills stimulated and placed contribute to the extra amount of bids in the auction.
2) The average minimum starting bid in an auction with shills is less. It means that the higher the starting bid (compared to book value), the less possibility that the auction involves a shill. Conversely, if the starting bid is much less than the book value, it is more likely it involves a shill. This indicator is explained and tested in [23].

Each of the above characteristics could be used as an *indicator* of the existence of shills, but not as evidence, because each characteristic may have some "innocent" explanations other than the existence of shilling behaviors. For example, one explanation for the first bidder characteristic given above could be as follows: some experienced buyers may prefer high rated sellers over low rated ones, even though highly rated sellers may sell the same item at a higher price. This preference for dealing with particular sellers is reasonable; common sense tells us that sellers with high reputations are trusted for quality of service. When a bidder has bidder-characteristic 1, it is also possible that the bidder simply does not have enough information about the price of other identical items. As another example, consider bidder-characteristic 2, as given previously. This behavior might well indicate the existence of shilling, but it might instead indicate something more innocent. For example, maybe the sellers are the unique sellers of a specific kind of hard-to-find item, and the buyers solely collect this kind of item in online auction houses. Finally, consider the following question: what if the bidder is aware of the existence of other similar rated sellers who also sell the same item on the same site? It could still be possible that the bidder simply trusts some particular seller and that seller's goods have always met the buyer's requirements. Hence, each indicator in itself cannot serve as obvious evidence of shills; a combination of several indicators may be more persuasive than a single indicator in detecting shills.

3. Solutions for Online In-Auction Fraud

In this section, we present some solutions to online in-auction fraud in the following categories: trust management framework, prediction/prevention approaches, and detection approaches.

3.1 Trust Management Framework

Internet fraud has severely undermined the trust on which members of electronic application communities used to rely. Current existing electronic commerce applications such as online auction systems do not provide completely trustworthy services. There is a high demand for trusted online auction systems that provide trusted, secure and worry-free services.

Xu, et al. recently presented an agent-based trust management (ATM) framework for online auctions [26]. The ATM is defined as a multi-agent system [43] that consists of a security agent, an analysis agent, a set of monitoring agents, auction agents, and bidding agents. Human bidders can specify flexible and complex bidding strategies in the interface of bidding agents so a bidding agent, on behalf of a human bidder, can communicate with auction agents to place bids automatically [44].

Meanwhile, the security agent can dispatch monitoring agents to watch for bidding activities and detect suspicious users, and an analysis agent is responsible for analyzing users' bidding behaviors using live auction data and users' history information. Based on the analytical results, the security agent can re-evaluate a user's trust values in order to verify whether a suspect is a shill bidder. The proposed agent-based trust management module facilitates real-time trust re-evaluation by updating user roles and access permissions dynamically. As a result, the framework provides a solid foundation towards building a trustworthy networked system.

Similarly Yi, et al. also applied software agent technology [45-47] as well as cryptographic technology [48] to automate and secure online auctions [49]. They presented a secure agent-mediated online auction framework. The framework consists of three components: online auctioneer, auction agent and online bidders. Before the auction starts, the auctioneer advertises an item for auction on the Internet, and all bidders who are interested in the item can register for the coming auction by showing their certificate to the auctioneer. When the auction starts, the online auctioneer generates and launches an auction agent. Following a route specified by the auctioneer, the agent traverses a list of online bidders B_1, B_2, …, B_n on the Internet by showing the auctioneer's certificate. The auction agent informs every bidder of the minimum increment along with the current highest bid for each round, collects bids from bidders and finally brings the bids back to the auctioneer. The procedure is repeated until the highest bid does not increase for three times.

In the agent-mediated online auction framework, public key and private key infrastructures are used to protect the auction from malicious bidders. Each bidder's bid message is first signed by the bidder and then encrypted with the public key of the auctioneer, so the auctioneer can check the authenticity of each bid. Since only the auctioneer can read the bid information and others do not know the private key of the auctioneer, no one can check the bids except the auctioneer. Thus, the framework can prevent malicious bidders from scanning or modifying another bidder's bid. In addition, before an auction agent leaves a bidder, the bidder is asked to update the non-repudiation database and send it to the next bidder. Once the auction agent arrives at the next bidder, the first thing the bidder needs to do is to reply the previous bidder with a signature on the auction agent. Therefore, once any malicious action is detected by the auctioneer, an investigation can be launched by checking the non-repudiation database to discover the malicious user. A significant aspect of cryptography-based online auction fraud detection methods is that the mechanisms of cryptography are able to provide non-repudiated evidence for investigation.

3.2 Prediction/Prevention Approaches

Preventive measures can be more effective in online auctions than reactive measures. Wily traders usually exploit loopholes left in procedural rules to “attack” honest users and challenge system and mechanism designers. If the auction procedural rules embedded in the software programs of online information technology applications are airtight, fraud activities can be easily prevented, avoided and eliminated.

Wang, et al. designed a Shill-Deterrent Fee Schedule (SDFS) mechanism, which could reduce the extra profit brought by shill bidding in the context of independent private value (IPV) English auctions so as to deter opportunistic shills [31]. Under the SDFS mechanism, the auctioneer charges the seller a listing fee and a commission fee. The seller sets only a single starting bid or a reserve price, without the option of setting both a low starting bid and a higher secret reserve price to lure in buyers (as currently allowable on eBay). The listing fee is a function of this initial reserve price, and the commission fee is calculated by the product of the commission rate and the difference between the winning bid and the reserve price. If the reserve price is too high, then the listing fee will be higher and the seller will probably lose the chance to sell the goods. If the reserve price is set too low in an effort to lower the listing fee, then the difference between the reserve price and the selling price will be high, with a correspondingly high commission fee. Therefore, SDFS encourages the sellers to set the reserve prices honestly. The commission rates vary from market to market and are mathematically determined by the online auction systems to guarantee no extra profit for shill bidding compared to honest sale. On the whole, SDFS is reasonable to inhibit shilling behavior.

Some items are not sold in the first round of an auction. This can occur for many reasons, including no bidders having placed bids on the auction, the final price of the auction not reaching the reserve price of the auction, or a seller engaged in a shill and accidentally won the auction. When an item is not sold the first time it goes up for auction, it will typically be offered for resale in a next round. Because there are a significant number of identical auctioned items in the same auction house, a great number of goods are sold after multiple rounds. Wang, et al. analyzed shill bidding in multi-round online English auctions, and proved that there is no equilibrium without shill bidding in these auctions [33]. They interpreted the finding as an incentive for shills and suggested a corrective pricing such as SDFS and a fair intermediary should be used to reduce the damage to the market.

Preventing in-auction fraud from happening is possibly the best solution, nonetheless, in some cases, when in-auction fraud cannot be prevented, approaches that can predict its occurrence can also reduce the risk to auction participants. Kauffman and Wood [23] examined how the fee structure on eBay may motivate shill bidding and first identified “reserve price shilling” based, in part, on their research into eBay auctions of rare coins in April 2001.They tested whether some questionable bidding behaviors are attributable to reserve price shilling. According to the test results, they built an empirical probit model to predict reserve price shilling based on the seller’s previous behavior before the auction begins.

In addition, researchers have tried to design bidding strategies using game theory in order to help honest users counteract scams [50]. Porter and Shoham proposed two equilibrium bidding strategies to counteract bid shading and false bids in sealed-bid auctions, namely first price sealed-bid auction and second price sealed-bid auction [40]. An equilibrium bidding strategy is a Bayes-Nash equilibrium if the bidder’s expected gain is maximized when the bidding strategies for all other bidders are fixed. Usually, the expected gain or utility function equals the product of the probability of winning and the difference between a winner’s highest willing-to-pay price and the actual winning price. The probability of winning can be estimated by the probability of cheating and the probability that a bidder’s highest willing-to-pay price is higher than that of a shill’s. Therefore, when knowing the possibility of cheating, equilibrium can be derived to counteract a shill and maximize a bidder’s expected gain.

Motivated by Porter and Shoham’s work, Jenamani, et al. derived an equilibrium bidding strategy for honest bidders to deal with shills in English auctions, and translated the equilibrium strategy into an algorithm called shill counteracting bidding strategy (SCBS) [38, 51]. By bidding according to the algorithm, honest bidders could counteract shills in English auctions. Experiments are conducted to evaluate the proposed strategy and compare it with five other popular bidding strategies. The average expected utility of the agents with the proposed strategy is found to be the highest when the auction continues for a longer duration. In a later paper, Jenamani, et al. showed that both theoretical and experimental results confirm that the equilibrium bidding strategy increases the bidders' expected utility; meanwhile, the authors also explained why English auction is popular over the Internet.

To date, research in fraud prevention and prediction is quite rare. Very few techniques are proposed for combating in-auction fraud proactively. To prevent in-auction fraud, online auction mechanisms should be improved in order to deter fraudsters from committing fraud. In addition, the underlying information system design should be verified to make sure the properties of the system do not violate any auction mechanism and leave no space for a participant to engage in fraud.

3.3 Fraud Detection Approaches

3.3.1 Using Statistical Methods

Current Internet auction systems rely solely on feedback based reputation systems to evaluate both buyers and sellers. Nevertheless, the existing traditional reputation system for auction houses has already shown its weakness in providing trusted information. Several researches have shown that the reliability of the reputation system of current auctions house, e.g., eBay, is debatable [52-55]. First, the positive feedbacks are overwhelming but the negative feedbacks are deflated. Deceptive auction users take advantage of the weakness of current rating mechanisms in reputation systems by helping each other artificially build up a good reputation history regardless of their actual behaviors. Rubin, et al. found 95% of eBay sellers have good reputation and 98% of their feedbacks are positive [56]. Furthermore, existing reputation systems are easily manipulated. Malicious users could first accumulate a high feedback score by selling low value goods, and then deal high value goods with that good reputation. For example, a seller first sold pencils and gained a good rating. Now the same seller is selling used cars on the same auction site. Can we trust this seller? No. Because the seller could cheat some used car buyers and then shift again to rebuild a reputation from pencil buyers. Moreover, the existing reputation system provides little information about sellers' degree of honesty. Users may find auction fraud information in feedbacks but when dealing with a seller with a long history, it is impractical to look at the feedbacks page by page. Unfortunately, the anti-fraud information has not been directly reflected in the reputation system so far. In all, the current reputation system can no longer satisfy people's need for evaluating trustworthiness in online transactions.

Rubin, et al. [56] proposed a new reputation system for auction sites to help users protect their interests by indicating auction fraud. The reputation score in the system is a 3-tuple $<N, M, P>$, where each variable is a number between 0 and 100 (100 indicates 100% confidence of anomaly, and 0 indicates no signs of fraud). The three variables come from three statistical models: average number of bids model (N), average minimum starting bid model (M), and bidders' profile model (P), respectively. The first model identifies sellers whose auctions, on average, attract more bids than auctions posted by other sellers. In this case, the abnormal situation could be produced either by fierce competition among buyers or by shilling behaviors. The first model does not provide an explanation of the cause for this abnormal situation. The second model, M, identifies sellers who have a large number of bids that cannot be explained by their low minimum starting bid (in the statistical model considered by the authors, each starting bid is associated with a number of bids it can attract). Although statistical results show a correlation between minimum starting bid and high volume of bids, it is still not reasonable for the anomalous auctions to attract an overly-high number of bids. Finally, the P model identifies anomalous sellers, whose auctions include a group of bidders who bid repeatedly and lose repeatedly as well. The last model explains that the high average number of bids is possibly caused by shill activities. This detection method is indeed a statistics based method.

Trevathan, et al. designed an algorithm called *shill score* (SS) to detect the presence of shilling behaviors in online English auctions that have already completed [57]. The algorithm targets six very common shill strategies (like the shill indicators described in Section 2.3). By examining each bidder's behavior over auctions hosted by the same seller, the algorithm gives ratings to each bidder based on how the bidder's behavior fits into each of the explicitly defined shill patterns. A bidder's final shill score is calculated in the form of an average of the weighted ratings. The higher the score, the more likely the user is a shill. However, the proposed approach failed in detecting collusive shills, i.e., multiple shills in collaboration with each other. The collusive strategies used by shill groups are much more complicated and sophisticated than the single shill strategies. Collusive shill could thwart the SS algorithm by normalizing the shill group's shill score. To address this problem, Trevathan, et al. extended the SS algorithm and proposed a new algorithm [58] named the "collusion score" to detect collusive shills controlled by one seller. They analyzed three kinds of collusive bidding strategies that could be adopted by shill bidders: (1) alternating bid strategy, in which shills bid alternatively in the same auction; (2) alternating auction strategy, where different shills bid on different auctions and each shill bids exclusively in one auction; (3) hybrid strategy, which is the most complicated one that combines the first two strategies. Collusion graphs are utilized to examine shills in terms of the above three identified collusive shill strategies. Combining ratings of each examination, the collusion score is assigned to each bidder, indicating the likelihood that the bidder is engaging in collusive shilling behaviors. The situation where multiple sellers work in collaboration to do shilling is even more complicated than collusive shill controlled by one seller, thus, the proposed collusive score approach is not suitable for this case.

Dong, et al. identified and summarized a series of shill bidder properties and normal bidder properties [59]. Since each property involves uncertainty in incriminating auction shills, they employed the mathematical theory of evidence, called *Dempster-Shafer theory*, to combine evidence in order to reduce the uncertainty. Meanwhile, the conflict between evidence is also measured. A degree of belief is assigned as a shill score in order to quantify the likelihood of certain bidders being shills. Experiments showed that the approach is practical and quite effective in reducing the number of false positives generated by any single piece of evidence.

The aforementioned reputation models of detecting in-auction fraud essentially make use of statistical methods. The model proposed by Rubin, et al. can be used to test the statistical significance of how far the tested auctions are away from the benchmark auctions, and then to hypothesize that the statistical anomalies represent shills. The *SS* method statistically measures how the bidders' behaviors fit into the shill patterns, and calculates a score indicating the likelihood of shill. The Dempster-Shafer theory approach proposed by Dong, et al. aims to reduce the uncertainty and resolve the conflicts between evidence that is used to incriminate shills. Note that most statistical methods have to analyze a large amount of data, where auction data must be carefully selected for comparison because unreliable benchmark auctions can decrease the statistical significance of differences, thus compromising the accuracy of the results.

3.3.2 Using Data Mining

Data mining (also called knowledge discovery) is a powerful computer-assisted process designed to analyze and extract useful information from historical data [60]. It allows users to analyze data from different dimensions or perspectives in order to uncover consistent patterns, anomalies and systematic correlations between data elements. The ultimate goal of data mining is to predict future behaviors and trends based on the discovered patterns and association rules. Several researchers have adopted data mining methods to detect shill associations and suspicious patterns.

Pandit, et al. designed and implemented an online auction fraud detection system named NetProbe [61-63]. The key idea of the NetProbe is to infer properties of a user by properties of other related users. In particular, given a graph representing associations between auction users, the likelihood of a user as a fraudster is inferred by looking at the behavior of the user's immediate neighbors. The NetProbe system models auction data as a network graph in which sellers and bidders are represented by nodes, and transactions are represented by edges between sellers and bidders. Markov random field and belief propagation algorithms are utilized to unearth suspicious trading patterns created by fraudsters, and thus to detect possible fraudsters. In addition, to deal with the dynamic nature of online auction data, an incremental version of the NetProbe has also been proposed [62]. The motivation behind incremental NetProbe is that the addition of new edges in the graph will not affect the whole graph, but only leads to minor changes to the immediate neighborhood of the edge. Properties of affected nodes are updated incrementally without wasteful re-computation. Experiments using large synthetic and eBay data sets demonstrated that the NetProbe was effective with high accuracy, and the incremental NetProbe had significant speedup in execution time with negligible loss of accuracy. It is worth noting that the NetProbe does not need to treat single shill and collusive shill separately; instead, it could detect compliances together with shill.

Shah, et al. applied data mining techniques in detecting shill behaviors in eBay video game console auctions [12]. They mined associations between buyers and sellers during a period of time and found that some users only bid in auctions hosted by one particular seller and seldom won, e.g., once or twice in all the transactions in which they were involved. They considered these as possible cases of shill bidding.

Data mining approaches, like reputation approaches, also require analyzing huge amounts of historical data, and therefore take a very long time to get results. Although incremental NetProbe can reduce the execution time to almost half of the original, it still cannot achieve real-time performance so far. As a tradeoff, data mining approaches do have the advantage of accuracy compared to other approaches.

3.3.3 Using Formal Methods

Formal methods use formal notations and logic, which are mathematically rigorous techniques, for the specification, development, and verification of software and hardware designs [64]. Model checking is one of the many automated formal methods that are used to check the correctness of a system. Specifications about a system are expressed in the form of logic formulas, and efficient algorithms are used to verify certain properties of a system by means of an exhaustive search of all possible states that it could enter during its execution. There are also researchers making use of formal methods to detect in-auction fraud.

Xu, et al. introduced a formal model checking approach to detect shilling behaviors, especially the competitive shilling behaviors [65]. They first derive a formal auction model from real world auction data according to a predefined auction model template. The model is then verified using the SPIN model checker for behavioral properties, which are specified in pattern-based LTL (Linear Temporal Logic) formulas. The formulas are translated from some of the aforementioned shill strategies. Experiments showed that the proposed formal approach is feasible and efficient. Recently, this work has been extended for real-time detection of auction shills by defining a dynamic auction model (DAM) [66]. Shilling behaviors in different stages of an auction, namely early stage, middle stage and final stage, are formally specified in LTL, and verified on the DAM using real-time model checking technique in order to discover shills suspects.

The primary advantages of the model checking solution are accuracy and the potential to support detection of shilling behaviors in real-time. The mathematical rigor of the model checking technique can explain the accuracy of the solution. Moreover, the authors used the model checker to verify bidders' behavior at the bid level rather than the auction level, so when a shill bids on an auction, the shill's behavior could not pass the check so can be detected immediately.

The proposed real-time model checking approach is very promising because it can possibly detect in-auction fraud before any payment and thus prevent most of the monetary loss for victims. Once the fraud is verified, the system can notify all participants immediately, and may also suspend or cancel the auctions.

Sections 3.1, 3.2, and 3.3 discussed three different types of solutions to the problem of in-auction fraud, namely trust management frameworks, prediction/prevention methods, and detection methods. In Table 4, these solution techniques are compared based on some performance issues such as time-efficiency and data requirements.

Table 4. In-auction Fraud Solution Techniques

Solution Techniques		**Real-Time**	**Historical Data**
Trust Management Framework	ATM	Supported	Required
	Cryptography-based	Supported	Not required
Prediction or Prevention Approaches	Equilibrium Bidding Strategy	N/A	Not required
	Shill-Deterrent Fee Schedule	N/A	Not required
Detection Approaches	Statistical Methods	Not supported	Required
	Data Mining	Not supported	Required
	Formal Methods (Model Checking)	Supported	Not required

4. Research Challenges

In-auction fraud is quite different from pre- and post-auction fraud in that the latter two can be easily detected by the victims while in-auction fraud cannot. This difference makes solutions to pre-auction and post-auction fraud not adoptable for in-auction fraud. Research on combating in-auction fraud has only recently begun and several challenging research tasks are still open problems. Since this is a new research area, we identify, and briefly discuss, some research challenges that we feel are important in this area.

Development of effective reputation systems. Reputation systems are the easiest accessible tool that online auction participants can rely on to evaluate a seller or a buyer. However, as we analyzed previously in this paper, current reputation systems in major auction houses fail to provide users trustworthy and accurate information. Thus, it is important to propose effective reputation mechanisms to provide users with convincible ratings. By giving users an explicit indication of the genuineness of the rated user behind the reputation score, next-generation online reputation systems should be able to encourage trustworthy behaviors and significantly prevent in-auction fraud.

Real-time fraud detection. The most efficiency way to reduce the loss resulting from in-auction fraud is to detect the fraudsters as early as possible. If the auction system can successfully detect the presence of auction fraud immediately after it happens, the auction house can cancel involved auctions so that the shills can be caught, and the victim can be protected from losing money and property. However, most existing fraud detection techniques cannot guarantee real-time detection of in-auction fraud. Efficient shill detection algorithms such as using a model checking based approach could be a very promising approach for real-time shill detection as demonstrated in [65, 66].

The lack of ground truth. Development of techniques and tools that aim to assist with detection of in-auction fraud, such as shilling behavior, is clearly not an easy task. But, even more challenging is the assessment of effectiveness of such techniques. How well do they really work in practice? This assessment is complicated by the subtle behaviors associated with such fraud and the lack of example data that includes actual, verified fraud behavior – we cannot count on obtaining shill confessions. So, how to obtain the ground truth becomes a problem. How does one demonstrate that a shill-detection technique is effective on a set of sample auction data, when the existence of actual shill behavior in the sample data is not known?

Capture of in-auction fraud evidence. As we have discussed in Section 2.3, researchers have summarized several in-auction-fraud-bidding pattern. However, these patterns cannot serve as direct evidence of auction fraud because even if the bidders are detected to employ these bidding patterns, they still can be innocent. There may be other reasonable explanations to the questionable behaviors. Further quantitative and qualitative analyses of auction fraud are critical for capturing in-auction fraud evidence. Once sufficient auction fraud evidence can be retrieved, the suspicious in-auction fraud could be verified automatically and accurately.

Adaptive anomaly detection. Similar to computer and network security, auction fraud detection faces the difficulty of becoming a battle between fraudulent online auction users and auction integrity researchers. Driven by the opportunity to achieve monetary profits, it can be expected that fraudulent auction participants will not stop fraud practices, but instead change their habitual bidding behaviors to circumvent existing anomaly detection systems. In order to make auction houses trustworthy, it is important to develop adaptive anomaly detection algorithms for capturing in-auction fraud. The adaptive anomaly detection algorithms must be adaptive to new conditions, and thus able to effectively detect and respond to new forms of fraud.

Fraud detection and verification using artificial intelligence techniques. Detection and verification of in-auction fraud requires human knowledge and reasoning capability. This provides motivation for exploring the challenging task of adapting artificial intelligence techniques (e.g., agent-based architectures and reasoning) to represent human knowledge for shill detection and verification. Success in this area would be valuable for achieving the goal of automated detection and verification of in-auction fraud.

5. Conclusion and Future Work

With the prevalence of Internet auctions, auction fraud has become one of the major concerns in electronic commerce. In-auction fraud happens during the auction process and is often covered up. Hence it often makes victims suffer without notice. In-auction fraud produces undesirable effects not only on the auction participants but also on the auction mechanism itself as a resource allocation market. In the worst case scenario, in-auction fraud could lead to auction market failure. Because most of the existing online auction systems suffer from user distrust, trustworthy systems that could provide reliable services are highly desired. Current work on Internet auction fraud prevention and detection has taken a simplistic approach, which is not rigorous or complete enough to solve the problem. To prevent in-auction fraud, robust auction rules need to be proposed by economists. On the computer technology side, there is a need of airtight transaction process design to foil the efforts of fraudsters. In this paper, we summarized the indicators of in-auction fraud, and pointed out that because no single indicator will be accurate or strong enough to assure the presence of in-auction fraud, a combinatorial way using multiple indicators would be more effective and precise.

The volume of transactions in online auctioning business is compounding each year, and unfortunately so is in-auction fraud. Now is the time to act to reduce and stop in-auction fraud. We hope that the ideas from many researchers summarized in this survey can help auction policy makers and information technology designers develop future trustworthy environments for online auctions

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