Malicious Selling Strategies in Livestream E-commerce: A Case Study of Alibaba's Taobao and ByteDance's TikTok

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Due to the limitations imposed by the COVID-19 pandemic, customers have shifted their shopping patterns from offline to online. Livestream shopping has become popular as one of the online shopping media. However, various streamers' malicious selling behaviors have been reported. In this research, we sought to explore streamers' malicious selling strategies and understand how viewers perceive these strategies. First, we recorded 40 livestream shopping sessions from two popular livestream platforms in China—Taobao, and Tik-Tok. We identified 16 malicious selling strategies that were used to deceive, coerce, or manipulate viewers and found that platform designs enhanced nine of the malicious selling strategies. Second, through an interview study with 13 viewers, we report three challenges of overcoming malicious selling in relation to imbalanced power between viewers, streamers, and the platforms. We conclude by discussing the policy and design implications of countering malicious selling.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**; • **Applied computing → Online shopping**;

Additional Key Words and Phrases: Livestream shopping, livestream e-commerce, malicious selling strategy, Taobao, TikTok, Douyin, deception, taxonomy, deceptive design, dark pattern, interview

1 INTRODUCTION

Livestream, or livestreaming, shopping has become a popular, new form of online shopping [9, 11]. In a typical 30-minute to one-hour livestream session, the streamer, who is often a shop owner, model, influencer, or celebrity, spends a few minutes introducing each product (e.g., food or clothes) and then encourages their viewers to place an order for it right away. Livestream platforms have an integrated "shopping window" feature, whereby whenever the streamer goes over the product

one by one, viewers can see a purchase link for that product pop up on their screen. They can then make a purchase within the livestream with a simple click without needing to enter their address or credit card information. Despite seeming similar to Quality Value Convenience or the Home Shopping Network[1] on television, livestream shopping offers viewers a more interactive and engaging experience [4, 45]. Hundreds of thousands of viewers can watch a livestream session simultaneously and directly interact with the streamer via a built-in chat channel or tip the streamer with a virtual gift (e.g., a virtual flower). Some viewers may eventually make a purchase, while others just enjoy watching the streamer chatting with their viewers.

Since 2019, livestream-based e-commerce has taken off in China [40, 75]. This new form of online shopping benefits from "the increasing tensions [that exist] between the cultural politics and economic ambitions of digital China" [24]. The government encourages small businesses to sell their products via livestreams, which enables small businesses to reach more customers at a lower cost. Moreover, the COVID-19 pandemic fueled the livestream shopping frenzy, as home-bound customers could not go to brick and mortar stores to shop, so retailers had to rely on online shopping platforms for sales. Platforms that support livestream and e-commerce (e.g., Alibaba's[2] Taobao, ByteDance's TikTok or Douyin in Chinese) have integrated a range of features to promote engagement and purchases, e.g., red pockets,[3] fan groups, and loyalty levels [50]. These integrated features enable e-commerce applications to support more social activities and facilitate communication and connections between businesses and customers. Compared to China, livestream commerce in the U.S. and other countries is nascent in terms of platform designs and services. E-commerce platforms (e.g., Amazon) and social media platforms (e.g., Facebook Live) are catching up with trends [11, 83].

This rapid development of livestream e-commerce in China, however, does come with a cost. More and more malicious selling incidents have been reported by the media, such as selling fake products [18] and tax evasion [56]. Recent studies have investigated the motivations of livestream viewers' purchasing behavior and of streamers' selling behavior [9, 10, 49, 74, 87], but the negative side of livestream shopping, i.e., malicious selling strategies used by streamers and platform designs that mediate these strategies, is underexplored.

This research defined *livestream malicious selling* as streamers leveraging unbalanced power and information to deceive, coerce, or manipulate viewers into buying behavior that is against viewers' best interests during livestream sessions. To understand malicious selling on livestream shopping platforms, we ask three research questions.

RQ1: What malicious selling strategies are used by streamers on livestream shopping platforms?

RQ2: How do platform designs mediate these malicious selling strategies?

RQ3: How do viewers perceive (i.e., awareness and attitude) and react to these malicious selling strategies?

We conducted a two-fold research study. The first study explored malicious selling strategies during livestream shopping and how platform designs mediated these strategies, through a qualitative analysis of 40 livestream shopping sessions from two of the top livestream platforms in China, i.e., Taobao and TikTok. The second study sought to provide viewers' perspectives about malicious selling strategies through semi-structured interviews with 13 participants who had shopping experiences on livestream platforms in China.

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[1]"Quality Value Convenience" and "Home Shopping Network" are American free-to-air televised home shopping channels.
[2]Alibaba is a Chinese Technology company, specializing in e-commerce, retail services, cloud computing, online payments, etc.
[3]A "red pocket," or known as "red envelope," is a monetary gift given during holidays or weddings in East and Southeast Asian cultures. It is named after its outer packing, usually taking the form of a red envelope or red pocket. The sending of digital red pockets became popular in the 2010s due to the emergence of mobile wallet systems in messaging applications.

From the first study, we identified 16 malicious selling strategies and categorized them into four categories (i.e., Restrictive, Deceptive, Covert, and Asymmetric) that were defined by Mathur and colleagues [58]. Among the 16 malicious selling strategies, nine malicious strategies were amplified by platforms' designs. The interview study revealed that some participants were not aware of the malicious selling strategies or designs. For other participants, even though they were aware of malicious selling practices, they developed multiple ways to adapt to or push back against these malicious strategies and designs. Participants also reported that they were faced with challenges when defending against malicious selling due to loosely-regulated and individualized streaming practices, and some platform designs worsened the situation. Based on these findings, we discuss policy and design implications to counter malicious selling on livestream platforms.

The contributions of this work are two-fold. First, we identified 16 malicious selling strategies, some of which were new compared to existing typologies (e.g., Playacting). More than half of the strategies were amplified by platform designs, which led to negative effects on viewers when combined with streamers' malicious selling strategies. Second, we provide a rich account of viewers' perspectives about how they perceived and reacted to streamers' malicious selling.

2 RELATED WORK

This work aims to investigate streamers' malicious selling strategies and platform designs in livestream shopping platforms. We first review studies about livestream shopping. Then, we review the selling strategies that have been investigated in traditional online shopping mediums (e.g., TV shopping). Last, we review literature specifically discussing the negative effects platform designs have on users in online shopping and other scenarios.

2.1 Livestream as an Emerging Online Shopping Form

Livestream has been widely used as an engaging way to connect community members [38, 54]. Previous studies have explored engagement motivations, participation demographics, and engagement levels in various livestream communities, including livestreams for entertainment, education [14, 39], skill improvement [53], programming [29], cultural practices [52], creative activities [54], and online communications [76]. Prior research has explored reasons for livestream participation from both streamer perspectives [41, 51, 67] and viewer perspectives [35, 38, 69], how people formed communities between streamers and viewers via livestreams [37], and different types of interactions within livestream communities [35, 48, 68, 90]. For example, streamers on livestream platforms such as Twitch broadcasted the playing of video games to share gameplay skills and common interests with viewers [38, 42, 67, 71, 82]. Prior work has also analyzed viewers' negative behaviors during livestreams and how livestream platforms allowed viewers to report inappropriate content [81]. Livestream platforms have also integrated communication channels to increase viewer engagement [31, 48]. This high degree of interactivity and engagement results in some viewers being more willing to purchase products created by streamers during a livestream [52] or the merchandise designed by the streamers [71]. This suggests that there is great potential for livestream to be a new medium for e-commerce.

Livestream e-commerce, or livestream shopping, has attracted researchers' attention in recent years. Some research has focused on viewers' (i.e., buyers) motivations: why they watched livestreams and bought products during them [9, 10, 49, 74, 87]. By analyzing self-reported data, scholars found that utilitarian and hedonic values were two of the main values that motivated customers to shop during livestreams. Utilitarian value was related to purchase needs, whereas hedonic value was related to affective commitments to streamers [10, 49]. Researchers have also found that trust was an intermediate variable that transferred affective commitment to engagement and buying on livestream shopping platforms [13].

A few researchers have also focused on the streamers' (i.e., sellers') perspectives. Researchers have reported a range of selling strategies that streamers used for increasing sales revenue [12, 83]. But few of them unpacked how platform designs might mediate streamers' behaviors and how these streamer practices might impact viewers' buying experiences. This study aims to explore the questions. In the following, we review selling behaviors in the virtual context (e.g., TV shopping).

2.2 Seller Behaviors on Online Shopping Platforms

Although livestream shopping is emerging, it has similarities to *TV shopping* and *social shopping*, given all the shopping modalities are happening virtually. To better understand seller behaviors and selling strategies on livestream shopping platforms, we review well-studied selling behaviors in TV shopping and social shopping.

TV shopping is a shopping method dating back to the 1980s and is still popular in many countries. During a pre-recorded TV shopping program, a TV host presents products in detail, and viewers can order the products by calling the telephone number shown on the screen [32]. Both livestream shopping and TV shopping show products in a lively way; however, livestream shopping is more interactive than TV shopping [50]. Many studies have investigated selling strategies in TV shopping. For example, Fritchie and colleagues found that social proof, scarcity, authority, commitment and consistency, liking, and reciprocation were used as selling strategies to simulate selling. These selling strategies were based on persuasion theory [19]. TV hosts also built personal and emotional connections with viewers to foster viewer trust [44, 72]. For example, hosts asked questions to establish similarities with viewers [72].

Social shopping is another form of online shopping by which product promotions are disseminated through personal social networks on online platforms (e.g., Facebook, Instagram), negating the need to switch to other e-commerce channels [16]. The salespeople, or "market intermediaries," actively share product information with their social connections on social shopping platforms. Some research has studied the behaviors of market intermediaries in social shopping platforms and found that market intermediaries helped customers detect trending products, evaluated products, and provided a good prices and discounts to customers [15, 16, 43]. In addition to providing product-related support, they also built trust with potential customers by generating and sharing content (e.g., short videos) [36] and providing emotional support [70]. Customers reported that, in addition to trust, culture and social presence were two other factors that impacted market intermediaries' sales [64].

Among these selling strategies, researchers have also examined the malicious side of selling. The existing literature has extensively discussed the negative side of TV selling strategies. For example, consumers believed TV shopping was extremely risky [7] as the product quality might be poor and the price was uncertain [8]. TV shopping hosts were also found to use their knowledge of human behaviors and viewers' desires to implement deceptive strategies that incited purchasing. For example, TV shopping used compliance-gaining techniques to urge viewers. These techniques included using countdown timers and "sold out" signs [3]. The host of TV shopping was found to introduce a product with an emphasis on financial prudence (e.g., bargain price and versatility) and upward mobility (e.g., items looking expensive) [21]. Moreover, studies revealed undisclosed advertising strategies in social shopping [60, 84]. Undisclosed advertising is a form of advertising where influencers on social media platforms such as YouTube do not explicitly disclose their collaborative relationships with advertisers or products. Undisclosed advertising is prevalent on social media platforms, but it is hard for users to be aware of ambiguous disclosures [60].

Livestream shopping combines salesmanship and parasocial interaction characteristics. During a livestream, a streamer serves as the salesman to display products and build social connections

with viewers. For example, a streamer who sells books on her channel may also teach history courses relevant to the promoted books and share her personal stories during her livestream.

On livestream shopping platforms, streamers can use various strategies to attract attention, increase sales, and build customer engagement. For example, Wongkitrungrueng et al. [83] found four sales approaches were used in livestream commerce, i.e., "transaction-based," "persuasion-based," "content-based," and "relationship-based." Through the transaction-based approach, streamers used simple selling, limited quantity/time/offer, and demonstration to facilitate their selling. Through the persuasion-based approach, streamers relied on game-prize, shows, and personal characters to persuade viewers. Through the content-based approach, sellers provided product-related or non-product related information to enrich their livestream's content.

Through the relationship-based approach, streamers shared their personal life, feelings, or experiences and organized community activities to strengthen their relationships with viewers.

These characteristics result in livestream shopping differing from TV shopping and social shopping. It signals a need to investigate whether malicious selling strategies are also existing in livestream shopping. To our best knowledge, the only work that studied malicious selling in livestream is [86]. The study suggested that a viewer's impulsive buying behavior might be related to "emotional energy," which refers to customers' affection for streamers. In this work, we aim to understand what streamers' malicious selling strategies in livestream shopping are and how livestream platform designs mediate malicious selling strategies. To address the latter question, we review the scholarship on the negative effects of interface designs on users.

2.3 Online Shopping Platform Design and Deceptive Designs

Livestream shopping is a new type of online shopping experience; thus, streamers' and viewers' experiences are empowered or bounded by a platform's designs. In the HCI community, one avenue of research that focuses on the negative effects of interface designs on users is "dark patterns." As a concept referring to deceptive marketing practices, nudging public policy, and others, dark pattern does not yet have a consistent definition. Brignull et al. initially defined it as "a user interface that has been carefully crafted to trick users into doing things" [6]. Later, Brignull used a new term "deceptive design" to emphasize the deceptive attribute in the definition and make the term more inclusive [5]. We bring this change to the front and use the new term in the following.[4] Narayanan et al. then added the covert manipulation and coercion aspects and defined that deceptive designs "deceive users while others covertly manipulate or coerce them into choices that are not in their best interests" [63]. These definitions emphasize that deceptive designs undermine individual decision-making and harm their interests [59].

Researchers have developed taxonomies to classify deceptive designs. Brignull proposed a deceptive design taxonomy to categorize the various designs [5, 6]. The taxonomy consists of 12 categories, e.g., "Bait and Switch," "Disguised Ad" [5]. Gray and colleagues criticized that the taxonomy mixed up context, strategy, and outcome. Thus they simplified the taxonomy into five categories: "nagging," "obstruction," "sneaking," "interface interference," and "forced action" [34]. Mathur and colleagues built upon this research and developed a deceptive design taxonomy specifically for online shopping websites [58]. The taxonomy included seven deceptive design categories. Compared to Bringnull's and Gray's taxonomies [34], Mathur's version added "Urgency," "Social Proof," and "Scarcity" for online shopping context, and they combined multiple categories such as "Confirmshaming" and "Trick Questions" into a single "Misdirection" category. Further, Mathur and

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[4]We follow the ACM's inclusive terminology policy https://www.acm.org/diversity-inclusion/words-matter and transition to the new term "deceptive design" in this work regardless of which term prior literature used. We also urge researchers to use the new term in future work.

colleagues summarized five characteristics of deceptive designs, "Asymmetric," "Covert," "Deceptive," "Hides Information," and "Restrictive" [58]. Deceptive designs need to meet at least one of the five characteristics. Gray et al. stated that deceptive designs should be "obnoxious, coercive, or deceitful" [33]. These properties serve to differentiate deceptive designs from non-deceptive designs. Deceptive designs have been reported in various scenarios including e-shopping websites [58, 62], mobile applications [28], gaming [27, 89], robot [47], etc. Studies that were not particularly looking at deceptive designs also reported "bad" design practices that could potentially harm users, such as malicious interface techniques [20], asshole designers [33], privacy paradoxes [77], and impulsive buying [62]. Conti and Sobiesk defined malicious interface techniques as the intention to "deliberately sacrifice the user experience" to achieve designers' goals [20]. Gray et al. found that even without the presence of deceptive designs, asshole designs could still deceive users, such as restricting users' tasks, setting traps that were hard to avoid, and misrepresenting information, which highlighted designers' unethical intentions and motivations [33]. Moser and colleagues [62] studied impulse buying on e-shopping websites. Some impulsive buying features were different from deceptive designs. For example, an impulse buying feature, "Offering Returns," is not a deceptive design because it does not directly benefit e-shopping websites [6, 58].

Studies have started to understand users' perceptions about deceptive designs, i.e., whether users can be aware of deceptive designs [28, 57, 77] and how deceptive designs influence user behavior [55]. Studies indicated that users tended to be insensitive to deceptive designs even with hints [28, 57]. For example, Di Geronimo and colleagues explored users' perceptions of deceptive UI designs in mobile applications. Their online user experiment illustrated that the presence of malicious designs was not easy for users to notice [28]. If users were informed of the existence of deceptive designs, however, they were found to be better aware of them [77]. Maier and Harr [57] found that deceptive techniques were perceived as less malicious by users, and some of them were regarded as just sneaky and dishonest. Luguri and Strahilevitz found that well-educated users were less susceptible to deceptive designs than a less-educated group. The deceptive designs, "hidden information," "trick questions," and "obstruction" were more likely to be manipulative than others, such as "nagging," "sneaking," "forced action" [55]. Mathur et al. discussed the origins of deceptive designs from the disciplines of psychology and behavioral economics and proposed possibilities to evaluate the impacts of deceptive designs on individuals, such as financial loss, violation of privacy, and cognitive burden [59]. These findings indicate the need to better understand users' perceptions of and reactions to deceptive designs with the purpose of mitigating harm.

In this present research, with the reported malicious selling in livestream shopping, there may be some designs that impair viewers' decision-making due to the ways that streamers leverage these designs for malicious selling purposes. Thus, we investigated what malicious selling strategies were used by streamers on livestream shopping platforms and how designs might fluidly turn into deceptive designs during livestream shopping scenarios.

3 METHODS

A two-phase study was conducted to address the research questions. The first phase sought to identify malicious selling strategies and platform designs in recorded livestream sessions via qualitative content analysis (i.e., RQ1& RQ2). In the second phase, an interview study triangulated the findings in the first phase from viewers' perspectives (i.e., RQ3).

3.1 Qualitative Analysis of Livestream Shopping Video Recordings

To investigate streamer selling strategies, a group of 40 publicly available livestream sessions was sampled and archived as video recordings. These 40 sessions were taken from two predominant

livestream shopping platforms in China, Alibaba's Taobao and ByteDance's TikTok. To identify malicious selling strategies, inductive coding was performed with the recorded videos.

3.1.1 Using Two Livestream Platforms as Research Sites. Two top livestream commerce platforms, Alibaba's Taobao, and ByteDance's TikTok, were selected for analysis. They are the top two livestream shopping platforms in China [17]. Taobao was originally an online shopping platform; thus, its livestream feature is an extension of its online shopping website. TikTok is a short video-sharing and livesteam platform; thus, the add-on shopping feature is an extension to its livestream service [45]. Figure 1 demonstrates the primary features of the TikTok livestream platform.

Due to their different origins, the livestream styles and streamer backgrounds were slightly different on these two platforms. The streamers on the Taobao livestream platform were small business owners or temporary streamers (e.g., salesmen) hired by business owners, and they sold products from their own businesses. In contrast, the streamers on TikTok livestream shopping were celebrities, influencers, or professional streamers who collaborated with brands and business owners. Functionality-wise, Taobao livestreams redirected viewers to an online store on the Taobao website; while TikTok provided a "shopping window" feature within the stream session, enabling users to browse a list of products and complete purchases with one click without leaving the livestream session [25].

3.1.2 Data Collection of Livestream Shopping Sessions. Streamers were sampled based on the number of subscriptions, the product type, and livestream time of the day. Some streamers had a huge subscription population (e.g., two top streamers on Taobao had millions of subscribers), whereas some others had a relatively small subscription population (e.g., a farmer streamer had only hundreds of subscribers). To draw a diverse sample, we selected both streamers with small and large numbers of subscribers. We also sampled accounts to cover diverse product types. On the Taobao livestream platform, stream channels were categorized by the type of products, i.e., Food, Apparel, Beauty, Jewelry, Mother&Kid, Home, and Electric. On TikTok, there were no specific livestream shopping categories. Thus, we sampled streamers' accounts on the two platforms based on Taobao's seven product categories. While most livestream sessions occurred in the evening to gain higher customer volume, there were livestream sessions occurring in the morning and afternoon. Thus, we selected three time segments for data collection: the morning segment (10 AM–12 PM China Standard Time), the afternoon segment (1 PM–3 PM), and the evening segment (8 PM–11 PM). The evening segment was longer than the other two segments to accommodate for the increased number of livestream sessions occurring in the evening. The first author conducted the recording task to make sure the sampling strategy was consistent. The researcher used screen recording software to save livestream sessions as video recordings. The researcher used an incognito mode to log on to Taobao and TikTok to avoid any recommendation algorithm bias. All livestream sessions were publicly available.

Normally, one livestream session runs for a few hours each day. During the session, a streamer displayed multiple products in turn. To decide the length of livestream sessions to record, we first recorded five livestream sessions from each platform. Each recording lasted for 15 to 25 minutes. We found that streamers usually spent about five minutes on a single product, and streamers' selling behaviors did not change much from product to product. Thus, we decided to shorten the length of recordings to approximately seven minutes. We collected another 15 livestream sessions from each platform. In total, we collected 40 recordings, 20 from Taobao and 20 from TikTok (Table 1).

3.1.3 Qualitative Coding Procedure. There was an overlap between our coding and the existing typologies [5, 6, 34, 58] so we first conducted a deductive analysis on the first ten recordings (i.e., five from Taobao and five from TikTok) using codes from the existing typologies. The coding
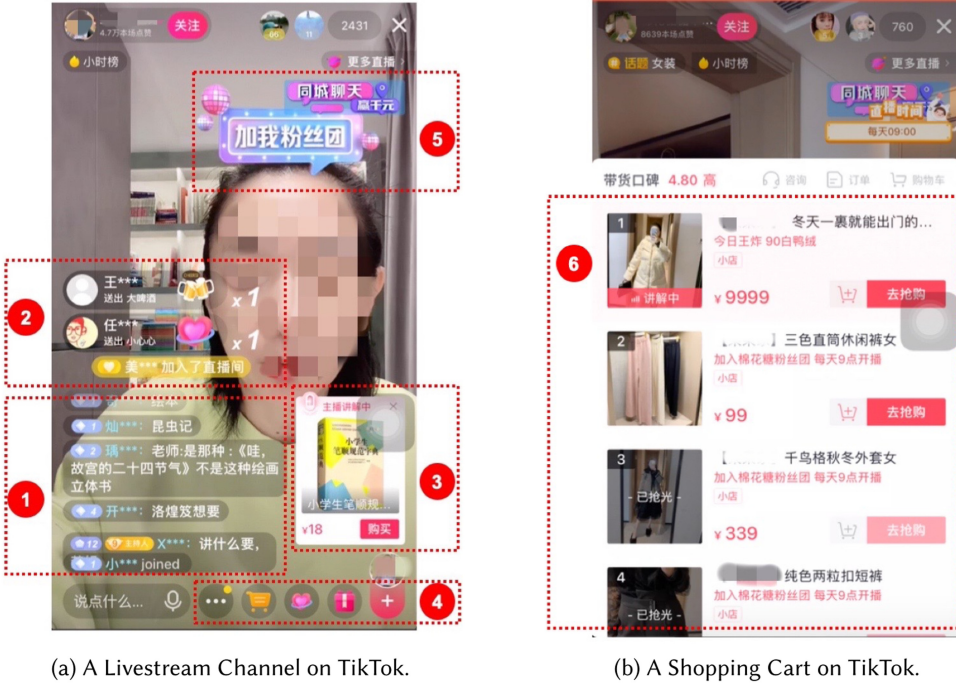
(a) A Livestream Channel on TikTok.   (b) A Shopping Cart on TikTok.

Fig. 1. The TikTok interfaces of (a) a livestream channel and (b) a shopping cart list. The main features are: (1) a chat channel where both viewers and the streamer's assistant can post comments; (2) viewers' action messages, including a sending gifts (to the streamer) message ("*User A (王 ***) is sending beer*"), a sending likes message ("*User B (任 ***) is sending likes*"), a joining the livestream channel message ("*User C (美 ***) is joining the channel*") from the top down; (3) the link of the streamed product; (4) other function buttons: from left to right, more functions button, checking shopping cart button, sending likes button, sending gifts button, and checking the streamer's profile button; (5) the subscribing reminder tag, named "Join my fans group"; (6) the shopping cart with numbered products, one "Streaming" mark on the 1st product, and two "Sold out" marks on the 3rd and 4th products.

was primarily focused on streamers' malicious selling strategies and designs used by streamers together with such strategies. Each researcher viewed the first ten recordings independently and coded multiple video elements, including streamers' speeches and actions, the features or functions used by streamers, the content of comments in the chat channel, the products sold, etc. We wrote down the codes along with the timestamps in an Excel sheet and took notes. All researchers had prior shopping experiences on China livestream platforms.

Notably, we defined malicious selling as "streamers leveraging unbalanced power and information to deceive, coerce, or manipulate viewers into buying that was against viewers' best interests." We carefully checked if the selling strategies met the definition. Since livestreams usually do not allow for post checking,[5] we recorded evidence during the data collection for post check if there would be the potential for a malicious selling strategy. For example, if a streamer applied the "urgency" selling strategy for a product or a discount, we checked whether the product or the discount expired when the streamer said it would. If the product or the discount was still available, then the

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[5]Livestream channels rarely record their videos and allow viewers or subscribers to view them again.

Table 1. The 40 Sampled Livesteam Sessions from Taobao and TikTok, Including the Video ID, the Livestream Channel's Name in Chinese, the Number of Subscriptions, the Number of Real-time Viewers, and the Category of Streamed Shopping Products

Video ID	Plateform	Channel Name	# of Subscribers	# of Viewers	Product Category
VT1	Taobao	薇***a	39 M	1.9 M	All
VT2	Taobao	李***琦	38 M	1.3 M	All
VT3	Taobao	v***d	14 M	11 K	Apparel
VT4	Taobao	C***师	898 K	13 K	Beauty
VT5	Taobao	小***a	776 K	657 K	Apparel
VT6	Taobao	李***响	537 K	613 K	All
VT7	Taobao	美***器	348 K	461	Electronics
VT8	Taobao	老***珀	178 K	39 K	Jewelry
VT9	Taobao	淘***装	146 K	334	Mother & Kid
VT10	Taobao	混***赵	83 K	869	Beauty
VT11	Taobao	栗***品	51 K	5.0 K	Mother & Kid
VT12	Taobao	南***大	27 K	6.0 K	Food
VT13	Taobao	葡***玩	27 K	1.7 K	Mother & Kid
VT14	Taobao	奢***A	21 K	741	Apparel
VT15	Taobao	新***昕	18 K	4.7 K	Jewelry
VT16	Taobao	冰***y	9.5 K	33 K	Beauty
VT17	Taobao	小***直	7.5 K	5.8 K	Apparel
VT18	Taobao	石***道	3.5 K	1.5 K	Jewelry
VT19	Taobao	罗***点	2.3 K	23 K	Home
VT20	Taobao	李***店	976	21 K	Food
VD1	TikTok	主***芳	7.7 M	2.4 K	Education
VD2	TikTok	恩***克	4.7 M	2.6 K	Food
VD3	TikTok	养***明	4.7 M	2.4 K	Food
VD4	TikTok	晨***强	4.0 M	7.0 K	Beauty
VD5	TikTok	三***鼠	3.3 M	4.0 K	Food
VD6	TikTok	彩***妇	2.9 M	4.6 K	All
VD7	TikTok	贾***坊	1.9 M	2.9 K	Apparel
VD8	TikTok	圆***到	1.6 M	3.4 K	Home
VD9	TikTok	新***厂	1.4 M	3.9 K	Apparel
VD10	TikTok	新***店	1.2 M	1.6 K	Apparel
VD11	TikTok	棉***播	795 K	730	Apparel
VD12	TikTok	丹***鲜	777 K	1.7 K	Food
VD13	TikTok	美***）	532 K	3.4 K	Jewelry
VD14	TikTok	阿***炸	412 K	1.7 K	All
VD15	TikTok	每***居	387 K	1.7 K	Home
VD16	TikTok	易***号	374 K	2.9 K	Apparel
VD17	TikTok	自***堂	368 K	50	Beauty
VD18	TikTok	U***制	70 K	1.4 K	Apparel
VD19	TikTok	祥***丸	45 K	5.7 K	Food
VD20	TikTok	湘***菜	26 K	211	Food

Note that the product category "All" indicates that the livestream channel sold multiple types of products.

"urgency" information mentioned by the streamer was fake. We recorded the check process in the videos.

We discussed the deductive coding results together and refined the codebook. We recognized that new codes were derived from the data. Then, we performed inductive coding. Specifically, we compared the new codes with the existing typologies and added the new codes to the codebook,

for example, "Playacting" and "Sophistry." We then coded another ten recordings using the updated codebook. No new codes emerged during the process, and the codebook reached saturation. The inter-coder reliability was 0.91 (Cohen's kappa) [46]. Using the codebook, we then coded the remaining 20 recordings.

In total, we identified 15 malicious selling strategies from the 40 recording sessions (Table 3). We borrowed or referred to codes such as "urgency," "scarcity," "social proof," "forced action," and "nagging" from existing typologies [22, 34, 58]. We added new codes such as "Playacting" and "Sophistry" to our taxonomy. The new codes were marked in bold in Table 3. We found that these strategies fit into the characteristics of deceptive designs initially defined by [58]. Thus, we further grouped the malicious selling strategies into four categories: Restrictive, Deceptive, Covert, and Asymmetric. We re-defined the four categories in the livestream shopping context in the Results section.

During the coding, we also identified 15 interface designs that mediated the malicious selling strategies (Table 4). These designs are also explained in more detail in the Results section.

3.2 Interview Study

To understand viewer perceptions of these malicious selling strategies, we designed and conducted a semi-structured interview study to gather viewers' awareness, attitudes, and reactions to these selling strategies. This study was approved by the IRB of the fourth author's university.

3.2.1 Participant Recruitment. Participants who had a purchase history on livestream platforms in China were recruited to participate using snowball sampling. Recruitment flyers were disseminated through researchers' social networks, and the research team also asked participants to spread the recruitment flyers to their acquaintances. Once one agreed to participate in the interview, they were asked to complete a screening survey. This survey included questions such as "Have you ever watched livestream for shopping?", "How frequently do you watch livestream?", "Have you ever bought products on livestream?", and "What platform(s) do you watch livestream?"

Twenty-three responses to this survey were received. We filtered out the respondents who did not have a purchase history on livestream platforms or did not provide contact information. We interviewed participants from the remaining responses. We kept tracking the insights reported by participants while interviewing participants and found no more new insights reported by P11, P12, and P13. Thus, we stopped recruiting participants. In total, we interviewed 13 participants.

Table 2 presents the participants' demographic information. Out of the 13 participants, 11 participants were female. All participants had a high school degree or higher and were from cities or towns in China. All had online shopping experiences either from Taobao or TikTok or both before the interview. According to a China livestream e-commerce user report in 2020, the ratio of male users to female users on Taobao and TikTok livestream commerce platforms was about 3:7, and users aged between 18 and 40 were about 85% [66]. Thus, our participant sample represented the user population on the two platforms with a slight skew toward females.

3.2.2 Interview Procedure. The interviews were conducted from December 2020 to January 2021 and used video or audio conferencing tools (i.e., WeChat, Zoom) to interview participants based on their preferences. All interviews were conducted in Mandarin Chinese. The first author led the interviews, asked questions, and recorded the audio. The second author took notes. Both researchers were fluent in Mandarin Chinese. Before conducting the interviews, pilot studies were run with two volunteers to test the interview procedure. All researchers participated in the pilot studies and provided feedback. The pilot results were excluded from the results.

Table 2. The Summary of Participants' Demographic Information (i.e., Age and Gender) and General Experiences Watching Livestream for Shopping (i.e., How Often they Watched Livestreams, How Long they had Watched Livestreams, and on What Platforms they Watched Livestreams)

Participant	Age	Gender	Frequency of Viewing	History of Viewing	Platform(s)
P01	26–35	Female	Once a week	1–3 months	Taobao, TikTok
P02	26–35	Male	Once a week	4–6 months	Taobao, TikTok
P03	18–25	Female	Several times a week	7–12 months	Taobao, TikTok
P04	18–25	Female	Once a week	7–12 months	Taobao
P05	26–35	Female	Several times a week	1–2 years	Taobao, TikTok
P06	26–35	Female	Every day	4–6 months	Taobao, TikTok, WeChat
P07	18–25	Female	Several times a week	7–12 months	Taobao
P08	36–45	Male	Once a week	1–2 years	Taobao
P09	26–35	Female	Several times a week	1–2 years	Taobao
P10	36–45	Female	Once a week	4–6 months	Taobao, TikTok
P11	36–45	Female	Several times a week	>2 years	Taobao, TikTok
P12	36–45	Female	Several times a week	7–12 months	Taobao
P13	18–25	Female	Once a week	1–2 years	Taobao, TikTok

The interview contained two primary sections: the first section investigated what malicious selling strategies participants experienced, and the second section let participants share their experiences about how they reacted to malicious selling.

At the beginning of the interview, we started with some icebreaker questions, such as "How often do you watch livestreams?" or "How long have you watched livestreams for shopping?" Then, we dove into participants' shopping experiences on livestream platforms. We asked "Have you bought something on any livestream platforms?" Then, we asked participants to talk about their most recent/impressive shopping experience in detail. We also asked the participants about their perceptions of streamers and other viewers in the livestream channel(s).

The questions were designed to help participants recall as many of their shopping experiences in livestream channels as possible. If the participant had difficulty recalling an experience, we asked them to show us the livestream platform and describe the interface designs. This technique helped participants recall their and the streamers' behaviors.

To avoid leading questions that could bias participants' perceived malicious selling strategies, we did not remind participants of any specific malicious strategy. Instead, when they mentioned experiences related to the strategies in our taxonomy, we asked follow-up questions regarding participants' attitudes, such as "Do you trust the streamer?" or "Are you satisfied with the product?" Then, we probed to further explain why they did or did not think so and how they reacted to this. If participants never mentioned any malicious selling strategy, we asked "Have you noticed anything inappropriate or wrong or that you feel uncomfortable with, including the streamer, the streamer's assistant, viewers, and the interface designs?" If participants answered no, we did not ask any probing questions. In the end, participants were asked to suggest ways to improve the livestream shopping experience.

Each interview lasted approximately 40-50 minutes. Participation in the interview was voluntary. All interviews were audio-recorded with participants' approval and transcribed to text.

3.2.3 *Data Analysis.* The first and second authors conducted an open coding process derived from the grounded theory method [73]. They coded the transcripts at the sentence level independently. All researchers discussed the coding results together and grouped the codes into six themes (i.e., general experiences, motivations for watching livestreams for shopping, purchase procedures, awareness of malicious selling strategies, ways of coping with malicious selling strategies, and challenges when defending against malicious strategies). Then, the researchers applied an axial

coding method [23] and generated the final coding schema with three primary categories: aware-
ness and attitudes towards malicious selling strategies, ways of coping with malicious selling, and
challenges of coping with malicious selling.

3.3 Ethics Discussion

First, as the purpose of this research was not to identify individual livestream sellers who were
applying malicious selling strategies, we de-identified the streamers' channel names. Note that
most of the studied streamers' selling strategies and tactics were not malicious. Readers should
not be misled or biased into thinking negatively about all platforms or steamers. To avoid general
marketing tactics that mistakenly were identified as malicious selling strategies, the researcher
team conducted several rounds of discussion to refine the definitions of malicious selling strategies
in the taxonomy.

Moreover, a critical perspective was used to analyze livestream selling behaviors. We think it
is critical to pay attention to any selling strategies or livestream designs that undermine viewers'
decision-making. Thus, we reported all livestream selling strategies either identified by researchers
or participants, no matter whether these strategies are prevalent in the collected data.

4 RESULTS

This section presents the results from the analysis of video recordings and the interview study.
Then, we present the interview findings relating to how participants overcame malicious selling
techniques and what their challenges were.

4.1 Malicious Selling Strategies on Livestream Shopping Platforms (RQ1)

The content analysis of the livestream shopping video recordings revealed 15 malicious sell-
ing strategies. During the interviews, participants were aware of most malicious strategies ex-
cept for the Pressured Selling strategy.[6] Moreover, three participants mentioned a new malicious
selling strategy, Forced Wholesale. We categorized the 16 malicious selling strategies into four
types—Restrictive, Deceptive, Covert, and Asymmetric—which were developed by Mathur and col-
leagues [58].

Table 3 lists the four categories with 16 malicious selling strategies, along with the explanations
and the participants who were aware of the malicious strategies.

4.1.1 Restrictive Strategies. Restrictive strategies refer to those strategies where streamers ask
viewers to take forceful actions to obtain special rewards or prices. The Restrictive category con-
tains three malicious selling strategies: Forced Subscription, Forced Endorsement, and Forced
Wholesale.

Forced Subscription refers to when the streamer requires viewers to subscribe to the
streamer's channel or the streamer's fans group for rewards (e.g., a discount, cashback). In this
case, the subscription task is forced. In several channels, if viewers did not subscribe, they could
not buy products at a discount.

Forced Endorsement is when a streamer asks viewers to send gifts, which need to be paid for
by viewers, or share the streamer's channel with others to obtain rewards (e.g., a discount). The
endorsement task is also forced. Based on streamers' remarks during livestreams, they claimed that
they could check whether viewers had subscribed to them or if they had performed endorsement
tasks and then decide whether viewers could get a discount.

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[6]If a participant mentioned a livestream shopping experience related to a malicious selling strategy but did not perceive it
as malicious, we did not count the participant for the malicious strategy.

Table 3. The Taxonomy of Malicious Selling Strategies in Livestream Shopping: Four Categories, 16 Strategies, the Descriptions, and whether they were Perceived by the Participants

Category	Strategy	Description	Perceived By
Restrictive	Forced Subscription	Forcing viewers to subscribe to the streamer and the streamer's fans group for rewards	P1, P2, P4
	Forced Endorsement	Forcing viewers to send gifts to the streamer or sharing the streamer with others for rewards	P1, P7
	Forced Wholesale*	Forcing viewers to buy multiple packs or units of a product	P4, P7, P13
Deceptive	Fake Scarcity	Deceiving viewers about the high demand and limited availability of a product	P1, P3, P6, P11
	Fake Urgency	Deceiving viewers that the product being sold or discount will expire soon	P2, P7, P9, P11
	Fake Social Proof	Highlighting fake positive comments, gifts, and likes sent by astroturfers, or providing fake testimonials	P1, P2, P7, P8, P13
	Fake Exclusive Pricing	Providing a fake, exclusive price or discount, or raising the original price before the discount	P2, P9, P10, P13
Covert	Visual Misrepresentation	Misrepresenting a product through visually beautifying or hiding aspects of it	P8, P10
	Playacting	Engaging in pretend behaviors to induce viewers to buy or to gain affection and sympathy	P3, P7, P8, P11, P12
	Fuzzy Targeting	Describing a product is applicable to all customer groups when it is not	P7, P8, P13
Asymmetric	**Sophistry**	Defending oneself against negative comments using implausible language	P5
	Retaining Customers	Keeping viewers staying in the channel by holding unpredictable activities	P7
	Egoistic Norms	Asking viewers to follow self-interested norms and belittling or abusing viewers for anti-norm behaviors	P8
	Disgracing Others	Depreciating the quality of competitive products or the reputation of competitive streamers	P5, P13
	Pressured Selling	Steering viewers into purchasing a more expensive version of a product or additional related products	/
	Nagging	Repeatedly asking viewers to purchase without providing useful product-related information	P10

*: Forced Wholesale is a malicious strategy that was only identified during the interview study.
Strategies in bold were identified as new within this work.

Forced Wholesale occurs when a streamer coerces viewers into buying multiple packs or units of a product in each order. For example, P4 described a forced wholesale experience and commented that it was a common malicious strategy: "I'll regret [buying too many things]. Streamers won't sell a single pack. It's kind of like wholesale. For example, if you want to buy toothpaste, you can only buy a set of four. It's a family package. If I buy them, I must regret it since I can't use them out for a long time." (P4)

4.1.2 Deceptive Strategies. Deceptive strategies refer to those wherein streamers use fake selling or product information to trick viewers into purchasing products. The Deceptive category contains four selling strategies: Fake Scarcity, Fake Urgency, Fake Social Proof, and Fake Exclusive Pricing.

Fake Scarcity refers to streamers deceiving viewers about the high demand and limited availability of a product. Streamers use fake numbers to indicate the low stock of a certain product to make viewers believe that a limited number of items were available. It creates an impression that

viewers needed to make the purchase immediately. This strategy helps incite viewers' desirability for a product and increase the perceived value of the product [61, 65]. For example, the streamer in VT19 warned that she had the last three blankets for viewers who would purchase products on her channel. She said: "You have to buy the bedclothes quickly to get one blanket, first come, first served." However, it turned out the blanket was a defaulted gift, and everyone who purchased the bedclothes got a blanket for free. The channel displayed that more than three viewers bought the bedclothes and got the blankets, but the streamer kept saying only three blankets were left. "Three" was a fake number to indicate scarcity. Streamers also claimed that their products were easy to be sold out on their livestream channels. The fast sold-out reminder induced viewers to buy. But no evidence showed that their products sold out fast after a while.

Fake Urgency occurs whenever a streamer tricks viewers into believing that a sale or discount would end soon or at a certain point in time in an attempt to speed up the viewer's decision to purchase. However, based on our analysis, the product selling or discount did not end as the streamer claimed. The Fake Urgency strategy was usually used in tandem with Fake Scarcity, taking advantage of viewers' scarcity bias and suggesting inaction would result in them losing potential savings [1].

Fake Social Proof refers to when the streamer verbally highlights fake positive information (e.g., positive comments, gifts, likes) sent by astroturfers or provided fake testimonials for a product. Astroturfers (called "water army" in Chinese) were usually paid by streamers and pretended to send positive information on livestream channels. These messages created the impression that the product was very popular or of high quality.

Streamers also claimed that their products had testimonials. However, some testimonials were just verbal claims, and the testimonial origins were forged or unclear. For example, the streamer in VT12 claimed that her jeans were produced by a famous designer's factory. However, there was no label on the jeans or no testimonial presented on the product page to prove her claim.

Fake Exclusive Pricing refers to the practice of providing a fake, exclusive price or discount or raising the original price before providing a discount. Streamers claimed that they had the lowest price or the best discount in their channels compared to anywhere else, which lacked evidence or was a lie. Other streamers raised their original prices. For example, one streamer raised the price of a set of pajamas to 189 RMB (about 30 U.S. dollars) before the livestream started. During the livestream, the streamer announced that he would sell the pajamas for 29.9 RMB (about five U.S. dollars), which was claimed to be an exclusive discount for viewers.

4.1.3 Covert Strategies. According to [58], Covert means the effect or mechanism of dark patterns is hidden from users and creates cognitive bias, which users can rarely realize. One example is the decoy effect—providing an additional option to make other options more appealing [58]. Similarly, we define that Covert strategies make certain products' presence more appealing (than others) to influence viewers' decision-making; but their effect is covert, and users may fail to recognize the presence of these strategies. Covert selling strategies included Visual Misrepresentation, Playacting, and Fuzzy Targeting.

Visual Misrepresentation refers to situations where a streamer misrepresents a product by visually beatifying the product or hiding its defects. For example, P8 mentioned that one streamer used a type of special light in their livestream channel. The special light was different from natural light but made the products look better than they were: "So the color of the stone in the livestream channel will look very good and very bright. But when you get it, the color of the stone is not quite the same as in the livestream channel. It is not very satisfactory, not the ideal effect." (P8)

Playacting is a pretend behavior used by streamers to induce viewers to buy or to gain affection and sympathy from viewers. The Playacting strategy leverages viewers' cognitive and emotional

bias, but viewers may not realize this strategy. For example, in VT5, when one product was sold out, the streamer begged her product manager to restock another 50 units of the same item. The product manager pretended that he tried so hard to find another 50 units for customers. However, this livestream channel sold the same item every day. The scarcity was not as claimed. The Playacting strategy was used for "hunger marketing." Streamers also used Playacting to fabricate a touching story or usage experience to emotionally stimulate viewers to place orders.

Fuzzy Targeting occurs whenever a streamer presents a product in a way to make it apply to all types of customers, regardless of their age, gender, or other characteristics. This approach expands the consumer pool by obscuring who are the target populations of a product. Viewers make the purchase without recognizing they were steered. For example, the streamer in VD20 recommended that her rice cake was a good snack for old people. Later she expanded the customer types to kids and adults. There were no specific targeted customers. The streamer applied the Fuzzy Targeting strategy when selling every product.

4.1.4 Asymmetric Strategies. Asymmetric strategies refer to those where streamers "impose unequal weights or burdens on the available choices presented to viewers" [58]. In the livestream shopping context, streamers created emotional or cognitive weights or burdens through verbal communication. The Asymmetric selling strategies identified were Sophistry, Retaining Customers, Egoistic Norms, Disgracing Others, Pressured Selling, and Nagging.

Sophistry refers to the streamer using implausible language to defend themselves while in an unfavorable situation during the livestream. The process of defending is granting the unfavorable situation more weight and imposing viewers to accept it. For example, in VT15, one viewer sent a message in the chat, saying that he was blocked after he contacted customer service for a wrong item shipment. The streamer was extremely angry when noticing this message in the public chat. To defend herself, she said, "You already got two bracelets from me. I bear the loss myself. Why are you still mentioning the customer service in the chat?"

Retaining Customers refers to how viewers are more likely to buy or buy more products the longer the streamer keeps them in the channel. To keep viewers staying on their channel, streamers offer lotteries or make the sequence of promoted products unpredictable to viewers. For example, the streamer in VD1 promised to deliver a lecture at the beginning of the livestream. However, she kept selling her books throughout the livestream and did not start the lecture until the end of the livestream. The viewers could not predict when exactly the lecture would start, so they needed to watch the bookselling and wait.

Egoistic Norms refers to when a streamer creates norms that are beneficial to themselves and asks viewers to follow the norms. The norms gain more weight and become more legitimate in the streamer's channel. If viewers do not follow the norms, they will be belittled or abused by the streamer for anti-norm behaviors. For example, in VD3, the streamer kept emphasizing that in his livestream channel, most viewers bought honey quickly without asking any questions. He said, "If you (viewers) have any question about a product, you don't take me as your bro."

Disgracing Others is a strategy where a streamer depreciates the quality of competitive products or the reputation of other competitive streamers. For example, the streamer in VD12 argued that some other competitors' (streamers') products were of low quality, so that is why their prices were lower than hers. By disgracing others, the streamer was able to suggest that she had better quality products and made excuses for her higher prices.

Pressured Selling occurs when a streamer steers viewers into purchasing more expensive products or additional products. For example, in VD7, the streamer tricked viewers into buying the newer version of their shoes by listing the advantages of the newer version. However, the new version of the shoes was much more expensive than the older version, which attracted many viewers to the livestream session in the first place.

Nagging refers to when a streamer repeatedly asks viewers to purchase products but, at the same time, does not provide any useful information for viewers to make decisions about them. Non-malicious nagging existed in all video recordings. We only coded the malicious nagging strategy for streamers who pushed viewers to make orders without providing any useful production information.

Based on the recording coding and interview results, Restrictive, Deceptive, and Covert selling strategies were easier to perceive by participants. Asymmetric strategies were more difficult to perceive or verify. They were usually concealed, and viewers were not aware that they were manipulated during the process. The qualitative analysis also revealed that malicious selling strategies were enhanced or hindered by platform designs. The next section presents how the four types of malicious selling strategies were mediated by livestream platform designs.

4.2 Platform Designs Mediating Malicious Selling Strategies (RQ2)

Figure 1 demonstrates the interfaces of a TikTok livestream channel. Table 4 shows 15 platform designs that could mediate the malicious selling strategies. The 15 designs were presented in both TikTok and Taobao platforms. Nine specific strategies were supported by design features or functions within the two livestream platforms. The video recordings demonstrated that Restrictive selling strategies (e.g., Forced Endorsement, Forced Subscription) and Deceptive selling strategies (e.g., Fake Scarcity, Fake Social Proof, Fake Exclusive Pricing, and Fake Urgency) were more likely to be facilitated by platform designs than Covert and Asymmetric strategies. Covert and Asymmetric strategies relied more on sellers' sale skills or styles, so they were less influenced by platform designs. Below, we reflect on how livestream platform designs mediated the four categories of malicious selling strategies.

Designs using **subscription**, **reminder tags**, **sharing**, **liking**, **gifting** or **chat channels** enabled or supported Restrictive malicious selling strategies such as Forced Subscription and Forced Endorsement. It is common for e-shopping websites and livestream channels to apply these designs to require customers' or viewers' subscriptions, sharing, or gifting; however, we found that the backend filtering tool, which was orally claimed by streamers, was the key function to enable Restrictive malicious selling strategies. For example, before starting a lucky draw, the VT6 streamer told viewers that his assistant would check the viewers' subscriptions. If viewers did not subscribe to his channel, the streamer would cancel the viewers' prize. The VT7 streamer required viewers to click the "like" button and send a required message "888" (which stands for fortune in Chinese pronunciation) to the public chat channel. She said: "Everyone who wants a coupon sends 888." However, it is not clear whether and how the filtering tool ran. Viewers could only follow the streamer's requirement to obtain the coupon. Since Restrictive strategies were enabled or supported by platform designs, this suggests the need to modify or remove such design features to constrain malicious selling strategies.

The designs that enabled or supported Deceptive strategies presented misleading information (i.e., **notification messages**, **product pages**, **countdown timers**, **back-ordered warnings**, and **chat channels**) and inductive discounts (i.e., **red pockets**, **coupons**, or **flash sales**). These designs helped streamers create fake scarcity, social proof, exclusive pricing, and urgency to induce viewers to buy products. For example, both Taobao and TikTok have a notification message feature. Once a viewer adds an item to his/her shopping cart, there will be a public notification message on the screen saying, "User X is ordering the item." TikTok also shows the total number of buyers on the screen. Public notification messages can be used as evidence of high demand. Using this evidence, streamers can urge viewers to place an order. In one case, the streamer claimed, "This is really the last one," however, the streamer asked her assistant to restock the product later. Although Deceptive strategies were enabled or supported by specific designs, it took time for viewers

Table 4. The Platform Designs in TikTok and Taobao's Livestream Shopping that Mediated Malicious Selling Strategies

Design	Explanation	Restrictive	Deceptive	Covert	Asymmetric
Subscription	Viewers can click the "subscribe" button to follow the streamer and receive future livestream session notifications.	Forced Subscription			
Reminder tag	The streamer can set up a message tag to display important reminders (e.g., a subscribing reminder tag) or positive comments from viewers. The reminder message tag is enlarged and displayed on the screen (section 5 in Figure 1(a)).	Forced Subscription			
Sharing	Viewers can click the "share" button and share the livestream channel on social media or with other viewers (section 4 in Figure 1(a)).	Forced Endorsement			
Liking	Viewers can click the "like" button to express their like, enjoyment, or support to the streamer (section 4 in Figure 1(a)).	Forced Endorsement			
Gifting	Viewers can click the "gift" button to send gifts to the streamer (section 4 in Figure 1(a)).	Forced Endorsement			
Backend filtering tool	Streamers can use a backend filtering tool to select a group of viewers by a criterion (e.g., the viewers who have subscribed to the streamer).	Forced Subscription, Forced Endorsement			
Notification message	Various events (e.g., purchasing, sold out, sending gifts, sending likes) are displayed on the screen above the chat channel (section 2 in Figure 1(a)).		Fake Scarcity, Fake Social Proof		
Product page	Viewers can see detailed information about products when they click on a product on the product page (section 6 in Figure 1(b)).		Fake Scarcity, Fake Exclusive Pricing		
Red pocket	The streamer can send money to viewers in a red pocket. The red pocket will pop up on all viewers' screens.		Fake Exclusive Pricing		
Coupon	The streamer can send coupons to viewers, which can be redeemed for a discount or a cash rebate. The coupon will pop up on all viewers' screens.		Fake Exclusive Pricing		
Countdown timer	The streamer can set up a countdown timer for a product sale. The countdown timer will be displayed on the screen.		Fake Urgency		
Back-ordered warning	A warning message periodically pops up to remind viewers to finalize the payment.		Fake Urgency		
Flash sale	The streamer can set up a time-limited sale.		Fake Urgency		
Beautify camera filter	The streamer can use a beautification camera filter to beautify their products and themselves.			Visual Misrepresentation	
Chat channel	Viewers can post text-based comments and see others' comments in a publicly displayed section in real-time (section 1 in Figure 1(a)).	Forced Endorsement	Fake Scarcity, Fake Social Proof		Retaining Customers, Egoistic Norms

to detect or verify fake information compared to the Restrictive strategies. It is thus necessary to provide tools to help viewers or customers to identify deceptive selling.

Designs supporting **beautify camera filters** enabled and supported Covert strategies. For example, the visual misrepresentation enabled by the beautify camera filter facilitated malicious selling. The streamer of VD11 used the beautify camera filter provided by TikTok to hide the flaws of her apparel, such as the bad texture and workmanship.

The results also revealed that the **chat channel** supported three types of malicious selling strategies. It was also the only design used by viewers to counter malicious selling strategies. This was not surprising because the chat channel was the only means for viewers to provide negative feedback. For example, some streamers enforced Egoistic Norms by asking viewers to send certain positive terms in the chat channel. Viewers sent comments such as "poor quality products" to fight against malicious selling via the chat channel.

4.3 Viewer's Challenges when Coping with Malicious Selling Strategies (RQ3)

Participants reported multiple ways to cope with malicious selling strategies. The most frequent mechanism was to select professional streamers to watch due to their high reputation. A professional streamer is a salesperson or agent that acts as a liaison between product manufacturers and customers and takes a commission on the sale [30]. Participants noted that choosing brands and stores with a good reputation was a useful means to circumvent malicious selling strategies. In addition, participants suggested "shopping around" or comparing products on different livestream channels before buying. Participants also leveraged the chat channel to push back against malicious selling strategies. For example, they reported low-quality products, poor return service, or astroturfers in the chat to alert other viewers.

Participants reported four ways to deal with malicious selling strategies; however, not all participants considered these effective for some malicious strategies. For example, P5 planned to buy a pearl necklace for her mom. She watched different pearl livestream shopping channels and acquired the pearl knowledge introduced by the streamers. After about a week, she gained a sense of which necklaces were high-quality and found that some streamers had fake testimonials and did not tell the truth. It was also very time-consuming for her to acquire her knowledge. This suggests a need to understand the challenges inherent in defending against malicious selling strategies for viewers.

The interview-based data provided insights into the challenges of coping with malicious selling. These challenges were due to highly personalized stream procedures, malicious designs that impaired viewers, and the visual limitations of livestream for special products.

4.3.1 Highly Personalized Stream Procedures. Stream procedures varied across platforms, streamers, and even products within one streamer's channel. There were no standards to guide streamers about how to sell products. Because the procedures were highly personalized and selected by streamers themselves, viewers encountered high costs when selecting products.

Within the same streamer's channel, non-standardized procedures, including incomplete presentation, versatile scenarios aiming to target multi-type customers, and unpredictable stream orders, led to problems. Unlike product pages on e-shopping websites, where product parameters and functions are presented in detail, product introductions on livestream were incomplete. The features or functions mentioned by streamers were highly selective and personalized. According to participants, some streamers prepared stream scripts in advance, which articulated what aspects of products should be emphasized in the stream and which aspects should not be mentioned. Streamers also communicated with vendors and revised their stream scripts accordingly. P13 provided an example of an incomplete presentation. She said that in a livestream, it was easy to see the

quality and appearance of a product but hard to see the expiration date. The streamer only magnified the advantages of the products and did not tell customers the expiration date. After receiving the product, customers would realize this.

When introducing products, streamers also obscured target users. This was related to the identified malicious strategy, Fuzzy Targeting. It was another type of incomplete presentation, i.e., streamers did not specify the target users, which is usually a parameter on product pages on e-shopping websites. P7 compared the difference between streamers' product recommendations to customers and her recommendation to her friends. If a product was targeted at females aged 20 to 30, P7 would only consider whether the product was suitable for her friends. Alternatively, streamers would convince customers that the product could also be used by their husbands and other family members.

> The streamer will say "even if you don't want to use it, you can give it to your boyfriend or husband." The streamer has a very tricky logic loop. That is, she or he will make you feel that no matter who you are, you can always use this product... (P7)

P13 mentioned another way of Fuzzy Targeting during livestream shopping. Instead of obscuring target users, streamers advocated that a product could be used in multiple scenarios. For example, P13 recalled that one streamer tried to convince customers that a coat was suitable for many contexts, such as home, school, and work. By imagining the contexts, customers would be convinced that it was good to buy this coat for different contexts.

Non-standardized stream procedures not only happened during single product introductions but also throughout the livestream's schedule. Several participants reported that stream schedules were not transparent or predictable. According to P7, livestream channels usually posted stream previews. However, they did not specify the sequence of streamed products or if the preview's sequences were different from the real ones. They also applied strategies such as not forecasting the prices of the streamed products or forecasting only part of the streamed products. P7 explained that the purpose was to keep customers staying in the livestream channels for a longer time and thus buying more products. If customers quit livestream channels, there is no way to know when their desired products will be streamed. They need to wait in the channels, which requires a considerable time commitment.

P9 reported that after shopping on a livestream channel for three months, she could estimate when the product she wanted would be sold based on the forecast. But this only worked in that livestream channel because every product was usually displayed for five minutes on that channel. In other streamers' channels, the duration varied a lot. Participants also reported that many social media accounts were created to serve as livestream preview information hubs. These practices indicate the need for transparent livestream schedules for viewers.

Among different streamers' channels, the non-standardized procedures influenced the effects of the products being displayed. Therefore, customers would like to choose streamers who followed a more standardized and professional way of selling products. P5 pointed out she used non-standardized selling procedures as a criterion to distinguish good streamers and bad streamers. Bad streamers were not good at setting up their livestream rooms or displaying products. There were no guidelines or tools to support them. She suggested that the livestream platforms should help streamers improve their service by providing "intelligent modules," similar to standardized tools for helping vendors to set up product pages on e-shopping websites.

Participants also reflected that there was no standardized procedure for streamers to follow. P5 reported that TikTok streamers had formed specific streaming styles, but Taobao streamers did not. However, these TikTok styles were full of cyber slang, and the purpose was mainly to entertain customers.

4.3.2   Malicious Designs Impairing Viewers. Designs, particularly chat channels, impair viewers' capability as buyers due to a lack of identity and overwhelming numbers of comments.

The identity of viewers in livestreams was anonymous, which yielded astroturfers or fake users. Several participants reported that there were astroturfers who were hired by streamers to post fake comments. The fake comments were usually showing the intention of buying or the action of ordering. When asked whether there were fake comments and whether they could distinguish them from real ones, some participants told us there should be fake comments, but they could not tell which ones were. P8 described his experience of identifying the astroturfers in a seal stone livestream channel accidentally:

> I wanted to buy a seal stone several days ago, but someone raised the price a lot, so I was not able to buy it. But two days later, I saw the same stone selling on the livestream channel again. I realized that the one who raised the price was an astroturfer. (P8)

Astroturfers might also send negative comments to competitors' livestream channels. As far as we know, streamers can block users who have been identified as astroturfers. However, participants reflected that some streamers used fake comments and astroturfers as excuses to deny real customers' complaints. For example, P5 recalled that in one livestream channel, one viewer sent a negative comment. The streamer then blocked the viewer and claimed she was the competitor's astroturfer. At first, P5 believed the streamer's explanation. Later, another viewer sent a comment saying that *"You blocked me? I switched to my friend's account just to prove I am not an astroturfer!"* P5 expressed her shock when she realized how the streamer could silence viewers.

In contrast to streamers, viewers have limited power to identify or block fake comments or astroturfers.

Additionally, the chat channel design does not support conversations between customers. Thus, customers cannot share ideas within the livestream channel. P5 recalled an experience of exchanging products with another viewer on a livestream channel. Since the Taobao livestream platform does not allow direct private messaging between viewers, they need to type in their Taobao account usernames in the chat channel and add each other as friends on Taobao. The chat channel does not allow copy and paste, which made communication much more difficult for P5. This cumbersome design seems to favor streamers. Participants expressed that they would rarely use the stream comments for asking questions.

Participants (n = 3) also reported that comments often overwhelmed them. In some popular stream channels, there was usually an influx of comments. Participants expressed that it was difficult to read these comments. As streamers often use the comment feature for promotional purposes, such as asking customers to send positive messages, e.g., "I want it" or "I have ordered it", streamers often orally highlighted positive comments during the livestream to induce viewers to buy products, but these comments were not helpful for viewers to understand products and added more complexity to the comment stream.

4.3.3   The Visual Limitations of Livestream for Special Products. Livestreams overcome some limitations of online shopping because they create a feeling of presence. However, livestream still cannot fully replace the offline shopping experience for special products. Special products are usually non-industrialized and non-standardized products with large individual differences (e.g., jewelry and artwork). The malicious selling strategy of Visual Misrepresentation is related to this. To leverage the visual limitations of livestreams, streamers often use a special light or embedded camera filters to beautify products. In contrast, during offline shopping, sellers manipulating products is more difficult.

P2 said that livestreams were not suitable for buying non-industrialized and non-standardized products. Because every product is unique, it is risky to buy this type of product through a

livestream. He bought a pair of walnuts on livestream. The pair of walnuts was not food but an "article for amusement." As it was a pair, it required the two walnuts to look almost the same. He said it was impossible to observe the product exactly as it would appear offline. This is the limitation of livestream shopping, and the Visual Misrepresentation strategy amplifies the risky nature of buying non-industrialized products from livestream shopping:

> It [the pair of walnuts] is not the kind of industrialized products, so you are not able to see the product very intuitively, only from streamers' livestream and pictures. You can only get a general idea, and that's based on the fact that everything he [the streamer] says is true. (P2)

To add to this challenge, P8 also pointed out it was difficult to overcome the visual limitations of livestream shopping. P8 was interested in buying seal stones through the livestream. He mentioned he spent a long time figuring out how to select high-quality seal stones. He usually spent a few days staying in a channel and observed the selling process to evaluate if it was worth buying. P8 shared that the light used by streamers could beautify the stones. Some streamers also hid flaws in stones and only showed the parts without flaws. However, without seeing the real product, he still failed to judge the quality of the products. The limitation brings a lot of time and money loss.

In summary, the interview study revealed that viewers faced challenges in coping with streamers' malicious selling strategies and what factors led to these challenges. Next, we will discuss how to address the challenges.

5   DISCUSSION

This research sought to provide an empirical understanding of malicious selling strategies in a newly emerging online shopping platform: livestream-based shopping. We sampled 40 livestream shopping videos as a data corpus and conducted qualitative coding analyses. We identified 16 malicious selling strategies. Out of the 16 strategies, nine were enhanced by the design of the livestream platforms themselves. We further summarized the 16 selling strategies into four categories (i.e., Restrictive, Deceptive, Covert, and Asymmetric). The interview study revealed viewers' awareness of malicious selling strategies, ways to cope with malicious strategies, and challenges when overcoming these malicious strategies. In the following section, we reflect on the main findings and discuss the unbalanced power between viewers, streamers, and platforms, the rapidly changing regulation and cultural context of livestream commerce in China, as well as policy and design implications for countering malicious selling in livestream shopping.

5.1   A Reflection of Malicious Selling Strategies and Deceptive Designs in Livestream Shopping

The recording coding process referred to existing typologies of deceptive designs. Although malicious selling strategies and deceptive designs are two different concepts, bad intentions or strategies behind selling strategies and deceptive designs share some similarities. We borrowed codes such as "urgency," "scarcity," "social proof," "forced subscription," and "nagging" from the existing typologies [22, 34, 58]. More importantly, our study contributes new findings that are different from existing studies in two regards.

First, we found that participants were more aware of Restrictive and Deceptive selling strategies than Covert and Asymmetric selling strategies. One reason could be that the frequency of these strategies was different. On a deeper level, the implementation of Covert and Asymmetric selling strategies relied more on sellers than platform design features or functions. Here, it seems that platform designs serve as checkpoints for malicious selling strategies. Without these checkpoints, malicious selling strategies might be more concealed. Thus, it is worth investigating if the absence

of design features and functions will make the awareness of malicious selling strategies more difficult.

We also found that more than half of the malicious selling strategies were enhanced by platform designs. The chat channel supported more malicious selling strategies than other designs. However, it was the only design used by viewers to fight against malicious selling. Restrictive selling strategies (e.g., Forced Endorsement, Forced Subscription) and Deceptive selling strategies (e.g., Fake Scarcity, Fake Social Proof, Fake Exclusive Pricing, and Fake Urgency) were more likely to be amplified by designs than others. Moreover, the Forced Endorsement and Forced Subscription strategies were amplified by multiple engagement designs such as subscriptions, reminder tags, sharing, liking, and gifting. These features were initially designed to engage viewers. However, they were maliciously used by streamers.

Second, compared to prior studies about malicious selling strategies during TV shopping and social shopping, our study identified new malicious strategies: Forced Subscription, Forced Endorsement, Playacting, Fuzzy Targeting, Sophistry, Retaining Customers, Egoistic Norms, and Disgracing Others. These strategies were enabled by the frequent and various interactions between a streamer and their viewers, such as the streamer's verbal communication and viewers' comments in the chat channel, sending gifts, and likes. This demonstrates that more attention needs to be paid to malicious selling strategies when the interaction between the streamer and viewers is more frequent and diverse.

One might argue that some malicious selling strategies identified in this work seem like traditional marketing strategies. In this work, strategies such as Retaining Customers and Playacting are similar to the content-based approach in Wongkitrungrueng's work [83]. The reminder design is similar to the nudge email design in many online communities [78]. They are not malicious. However, this work emphasizes that these livestream selling tactics were supported by platform functions or features and thus could manipulate viewers' decision-making more easily than offline marketing tactics. As Narayanan et al. argued, deceptive designs could be more aggressive than offline marketing strategies [63]. Because designers can apply A/B tests to pick out the most manipulative design and make great profits for companies, as a result, "even seemingly trivial changes to design elements can result in substantial differences in behavior" [63]. It is thus important to evaluate the malicious side of selling strategies happening on livestream platforms.

5.2 The Imbalanced Power Between Viewers, Streamers, and Platforms

Our research identified negative behaviors from the streamer perspective and revealed the imbalanced power dynamics between viewers and streamers. Although some of the streamers' malicious selling strategies were highly enhanced by platform designs, we also identified seven malicious strategies that were purely implemented by streamers. These problems revealed standardized product stream procedures have not yet been established in livestream e-commerce. On the surface level, participants expressed that streamers were skilled in introducing products and persuading customers to buy. When we asked participants if they thought the ways or the strategies streamers used were malicious, they were not sure. Participants expressed that it was hard to differentiate between exaggeration and deception. They reported cases where customers were controlled by streamers or designs. We found that most malicious strategies were directly or indirectly related to this. Compared to other e-shopping channels, customers were in a much inferior position to streamers during livestream shopping. Streamers had a high level of freedom to decide how they sold products on livestream channels. Prior work has analyzed viewers' negative behaviors during livestreams and how livestream platforms allow viewers to report inappropriate content [81]. For example, viewers reported trolling and being talkative on livestream channels. Given the

unbalanced power between viewers and streamers, the platforms need to provide more ways for customers to combat malicious selling, such as collective reporting.

Participants also shared insights about how to constrain the power of streamers. The participants mentioned that they preferred to watch streams from professional streamers, i.e., professional streamers, celebrity streamers, and influencer streamers. Participants' preference and trust towards these professional streamers were due to their professionalism in choosing high-quality products and introducing products and their authenticity within or outside platforms. For example, before starting livestream selling, influencers shared self-generated content (short videos) on TikTok and drew a large base of fans. To keep the fans, they did not take the risk of applying malicious selling strategies. It suggests that streamers' reputation could counterbalance their power. However, the platforms may be reluctant to adopt the policies or designs to counter malicious selling due to the profit consideration. Next, we share the macro context regarding the governance of livestream commerce in China.

5.3 The Regulation and Cultural Context of Livestream Commerce in China

We studied two popular livestream shopping platforms in China, where the regulation and cultural context of China (e.g., Internet censorship [79]) might impact malicious selling and platform designs. We discuss how regulation and cultural contexts in China impact livestream commerce, especially malicious selling strategies and deceptive designs.

First, from the regulation perspective, livestream e-commerce is regulated by state government departments in China. As previously mentioned, with the ambition of developing "digital China," the state government has provided support to the internet economy, including livestream e-commerce. The ecosystem of livestream commerce mainly consists of three roles: product and service providers (e.g., manufacturers, supply chains), marketers and retailers (e.g., livestream commerce platforms, streamers, online stores), and consumers [45]. The government encourages small businesses to leverage livestream to expand their business. Many small business owners become streamers and sell their products via livestream. This leads to a variety of streamers selling products on livestream platforms, ranging from professional streamers to amateur streamers from different industries (e.g., students, farmers), and thus versatile selling strategies, including malicious selling strategies.

The state government tries to seek a balance between economic development and regulation. Till the time when we conducted this research project, the regulation for livestream e-commerce in China still relied on government policies rather than laws. In 2020, the Cyberspace Administration of China announced that livestream platforms have to build a credit assessment list for livestreamers, where any streamer on the "blacklist" will be prohibited from using all livestream platforms [88]. In 2021, the State Administration of Market Regulation stated that all livestream platforms should "quickly conduct self-control and comprehensive inspections" on product quality and should punish streamers who sell poor quality products or misleading advertising. These regulations demonstrate that livestream platforms take the main responsibility for monitoring and regulating streamers' illegal or inappropriate behaviors. But there are no specific policies or laws to govern deceptive designs on livestream platforms, so the punishment on these platforms can be unpredictable. In the U.S., the DETOUR Act states that it is unlawful "to design, modify, or manipulate a user interface with the purpose or substantial effect of obscuring, subverting, or impairing user autonomy, decision-making, or choice to obtain consent or user data" [80]. Future research could further study the legality of deceptive designs in different online scenarios.

Second, from a cultural perspective, users in China prefer to use one app for many different functions [50]. For example, WeChat has combined social media, e-commerce, payments, and many other functions into a self-contained ecosystem [26]. Such wide platform integration is rarely

seen in the U.S. (e.g., Facebook or Apple). Similarly, with livestream shopping, platforms try to include many features and functions in their interfaces. However, in the U.S. and other countries, the interface design for livestream shopping is much simpler. For example, Amazon has only four main features in its livestream interface: the streaming video, a list of products being sold, a chat area, and a reaction button where viewers can send "likes" to the streamer [2]. Platforms and streamers benefit from a greater degree of opportunity in China and also experience a greater precarity in regulation [24]. It might be fruitful in the future to investigate the roles of different stakeholders in the livestream commerce ecosystem and to understand how they influence platform designs and regulation and how they perceive and cope with streamers' malicious selling strategies.

5.4 Design Implications

The findings suggest that viewers' behaviors are constrained by the current designs of livestream platforms. In the livestream shopping setting, nine malicious selling strategies were enhanced by design features in livestream shopping channels. For instance, multiple notification features (e.g., purchase notification, viewing notification, sold-out warning notification) allowed streamers to create fake scarcity or urgency. The feeling of scarcity led to many impulse buying behaviors. Thus, streamers used such features and capitalized on the behaviors they resulted in. The chat channel, which was the main way for viewers to interact with the streamer and other viewers, was also manipulated by streamers to create fake scarcity impressions. Synchronous chat facilitated knowledge sharing among viewers [85]; however, as the streamer asked their viewers to post required content, such as their desired products in the chat channel, a viewer might only see thousands of "wanting" messages in the channel instead of product-related knowledge shared by other viewers. Additionally, the chat channel did not support viewer-centric functions such as search, filter, and reply. The missing functions further constrained viewers' power to defend malicious selling behaviors. The designs of livestream platforms had a negative side when they were maliciously used by streamers. Gray and colleagues suggested that the intentions and motivations behind designs should be examined even if the designs were not deceptive designs [33]. As our research suggests, engagement and communication designs should be studied with human behaviors (both streamers and viewers). An isolated investigation might overlook the potential negative side of the designs. Our study only investigated the features and functions level. In the future, an interesting direction could be to explore what properties of these features and functions can amplify malicious selling strategies.

Based on these findings, various design implications can be proposed to protect users from these malicious selling strategies and designs. First, it might be helpful to increase the transparency and viewers' autonomy in designs. For instance, the backend filtering tool was the key function for Restrictive selling strategies. Viewers need to know what filter mechanisms are available and used if they comply with such forced actions. The chat channel also needs to be improved to enhance viewers' autonomy. Additional functions can be added to the chat channel, such as filter, search, or reply. Viewers should also be able to switch off message features (e.g., purchase message, viewing message, sold out message) on the screen so that they can focus on the product presentation and avoid being affected by others' decisions. Second, it might be helpful to implement crowdsourced features to validate the information provided in livestream channels. For example, to counter the Fake Exclusive Pricing selling strategy, viewers can check prices across different e-commerce platforms or check other viewers' ratings or reviews to verify whether it was true or a false claimed exclusive pricing. We acknowledge such designs are unlikely to be adopted by the platforms as they may be against their own business interests; however, third-party developers may implement such designs as system add-ons to support viewers.

One general finding is that streamers' selling behaviors were loosely regulated at the time this study was done. Even if they had bragged or promised something during the real-time streaming session, it was very hard for buyers to double-check whether or not it was true at the moment, and it was even more difficult to go back to what the streamer said after the session ended. For example, a streamer may promise an unconditional return policy during the livestream session, but the actual return policy written on the product information page is conditional. Since malicious selling strategies rely more on streamers' sales skills and styles rather than platform features and functions, the platform and regulators should make and enforce policies to regulate streamers' selling practices similar to how they would regulate an offline salesperson. For example, it is important to determine if forced actions are legal or necessary for customers to purchase products during livestream shopping. Platforms should also implement machine learning-based solutions to automatically transcribe and record what the streamer is saying during the livestream session to extract keywords from the transcripts and cross-reference the product information page (e.g., return policy, brand, and manufacture info, etc.). If there is a mismatch, the system may pop up a real-time alert to the viewers. Viewers can also use recorded transcripts as evidence in post-sale customer service.

5.5 Limitations and Future Work

Our study only examined two livestream shopping platforms—Taobao and TikTok and the interview participants were mainly users of the two platforms. The findings of malicious selling strategies may thus not be generalizable to other platforms, given their different platform policies and designs.

The current work is also descriptive. The qualitative analysis and the interview study only identified the presence of malicious selling strategies. Future work could use the taxonomy developed in this study to investigate the prevalence of various malicious selling strategies or run experiments to evaluate how malicious selling strategies could lead to the financial loss of customers.

Additionally, we only recorded 40 livestream sessions over a short period. In the future, it is worth conducting a longitudinal analysis, that is, observing several livestream shopping channels as a real viewer over the long term.

6 CONCLUSION

This research sought to understand the malicious selling strategies that are used on livestream shopping platforms and how platform designs support these malicious behaviors. These findings contribute to the broader HCI discussion about how to counter malicious strategies and deceptive designs and to protect target users' welfare while platforms have the motivation and power to adopt more and more deceptive designs. We welcome researchers from various backgrounds to join our effort to push forward this prominent research agenda.

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