Verbal vs. Nonverbal Cues in Static and Dynamic Contexts of Fraud Detection in Crowdsourcing: A Comparative Study

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ABSTRACT

As an important mode of open innovation, crowdsourcing can effectively integrate external resources, enabling enterprises to obtain stronger competitiveness and more benefits at a faster speed and lower cost. However, this mode has inevitable intellectual property protection challenges, especially on contest-based crowdsourcing platforms. Previous studies mostly focused on the protection of the rights of sponsors while ignoring the rights of workers, rarely paying attention to sponsor fraud, which may reduce the enthusiasm of participants and eventually turn crowdsourcing into a lemon market. This study proposes several fraud detection models to address this problem on contest-based crowdsourcing platforms. Furthermore, this paper explores and compares the value of four types of information as deception cues in crowdsourcing contexts via data mining technology and machine learning methods. The results benefit participants in crowdsourcing markets and contribute to fraud detection research and open innovation in the knowledge economy.

KEYWORDS
Crowdsourcing, Data Mining, Deception Detection, Intellectual Property, Open Innovation

INTRODUCTION

Crowdsourcing is among the most celebrated and successful new emerging digital economy business models. The ability of the online market to efficiently bring together individuals and businesses has redefined and transformed traditional ways of conducting business. Individuals with discretionary time and a shared interest congregate in online communities (Howe, 2008), which generate many participants willing to invest their effort and time in the crowdsourcing market. In particular, enterprises have increasingly leveraged online crowdsourcing marketplaces to seek solutions to business problems (Chen et al., 2020). Big enterprises like Dell have turned customer complaints into increased profit margins by tapping the crowd for solutions to their problems. Furthermore, many individuals and small and medium companies participate in third-party crowdsourcing platforms, such as Amazon.
Mechanical Turk (AMT), CrowdFlower, and Upwork. An essential objective of these crowdsourcing markets is to attract high-quality workers and obtain reasonable, diverse solutions (Terwiesch & Ulrich, 2009; Terwiesch & Xu, 2008). Many scholars have studied the fraudulent behaviors of workers on such platforms, some of whom often try to maximize their financial gains by producing generic answers or copying others’ solutions rather than working on the project (Eickhoff & de Vries, 2011; Hirth et al., 2010; Li et al., 2016). Instead of studying the workers’ fraudulent behaviors, this paper focuses on the fraud actions of sponsors on contest-based crowdsourcing platforms for design tasks, such as 99designs and DesignCrowd. Most of the projects on the platform are related to design, including logos, clothing, and website interfaces. A designer can choose one of the crowdsourcing contests and hand over their work. If a work is selected by the sponsor as the optimal one, its designer will get the reward. This model provides a convenient source of multiple solutions for the sponsor.

Relative to the work-for-hire IT platforms, new sponsors’ fraud problems must be highlighted in the context of contest-based crowdsourcing platforms. Opportunistic, fraudulent sponsors with moral hazards have ample opportunities to misappropriate the solutions without rewarding workers. Cases of sponsor fraud are divided into three types: “double identity fraud”, “solution embezzlement,” and “payment refusal” (Pang, 2015). If a fraudulent project is completed, it will result in direct losses of workers. Furthermore, other non-fraudulent projects suffer because fraudulent projects enjoy the attention the former should have. Finally, sponsor fraud may lead to decreased user engagement and, ultimately, failure of the crowdsourcing market. Therefore, effective identification of these frauds is critical to facilitate the sound development of crowdsourcing (Deng et al., 2016; Pang, 2015; Pennebaker, 2013; Schlagwein et al., 2019). However, most of the existing fraud detection approaches originate from money-driven false fabrications designed to distinguish the true requirements from the false. In contrast, the motives and needs of the initiators in crowdsourcing are not fabricated but real, which may lead to the failure of existing fraud detection cues. This paper will use multiple machine learning models to examine the effectiveness of each type of cue to provide reliable cue selection support for this fraud scenario.

Previous research on fraud detection has involved traditional, face-to-face, and computer-mediated contexts (Chang & Chang, 2012; Drouin et al., 2016; Twitchell & Fuller, 2019; You et al., 2011). Due to the loss of the advantages of face-to-face contexts in detecting fraud, research on computer-mediated fraud detection is mainly based on verbal cues, including content-based and linguistic cues. User behaviors in online environments, including user personal information, engagement records, decision-making choices, etc., are expected to replace the utility of traditional non-verbal cues such as expressions and gestures. For example, in fake review detection, Zhang et al. (2016) explored the effectiveness of nonverbal features (i.e., product ratings, reviewer characteristics, and brands) in detecting fraud. They confirmed that they are more important than verbal ones. However, research on nonverbal cues is still lacking in most areas of online fraud detection. Particularly in crowdsourcing fraud with intellectual property (IP) as the target, the authenticity of project requirement description may make verbal cues lose effectiveness. Thus, nonverbal cues are worthy of further study. Specifically, in crowdsourcing contexts, the sponsor’s characteristics, the project’s basic information, and the winning bidder’s selection are all nonverbal cues that may be effective for fraud detection.

Moreover, computer-mediated fraud can be divided into dynamic fraud and static fraud. Static fraud is a fraudulent purpose achieved by a fraudster unilaterally providing false information. In contrast, dynamic fraud is where the fraudster communicates false information through multiple interactions to achieve the fraudulent goal. For example, website fraud (Zahedi et al., 2015) and trademark infringement (Trappey et al., 2021) are static fraud, and phishing emails and telecom fraud are examples of dynamic fraud (Cheng et al., 2021; Ho et al., 2016; Wang et al., 2016). Generally, cues extracted from a static environment are unilateral and presentational, while cues extracted from a dynamic environment are bilateral and interactive. The novel crowdsourcing contest environment includes dynamic and static contexts and measurable nonverbal cues, allowing the opportunity to explore the value and role of different cues in computer-mediated fraud detection.
This study aimed to address the problem of the detection of sponsor fraud in the crowdsourcing market, which is indicated by various verbal and nonverbal information in dynamic and static contexts. Based on several fraud theories, we explored and compared the value of four types of information (static verbal information, dynamic verbal information, static nonverbal information, and dynamic nonverbal information) as deception cues in this crowdsourcing context via data mining technology and machine learning methods, which enrich the application and popularization of the deception theory. In addition, the analysis and detection of malicious sponsors in crowdsourcing contests contribute to the research from sponsor's perspective. Furthermore, the proposed detection models can help crowdsourcing workers and platforms more conveniently and scientifically detect fraudulent projects. The work will bolster workers’ enthusiasm and the development of crowdsourcing markets and further contribute to open innovation in the knowledge economy.

RESEARCH BACKGROUND AND THEORETICAL FOUNDATION

Crowdsourcing Model

Crowdsourcing is the process of integrating the spare time of crowds by fully mobilizing and utilizing their wisdom and taking advantage of their expertise to achieve efficient access to knowledge and reduce business costs and innovation risks from the external environment (Estellés-Arolas & González-Ladrón-De-Guevara, 2012; Howe, 2006). In addition to the collaborative model, which is utilized by platforms such as Wikipedia, the contest model is widely adopted by various crowdsourcing platforms and is the focus of this study. In the contest model, the sponsor, either an enterprise or an individual, can submit contest projects online to solicit solutions; the winning worker, who submits the best solution, will receive the total reward specified by the sponsor, while other workers are not rewarded.

Research on crowdsourcing falls into three streams according to the three types of players in crowdsourcing. One deals with platforms, examining innovation coordination mechanisms, task recommendation, quality and risk control, and the design of fraud prevention mechanisms (Hao et al., 2014; Kurup & Sajeev, 2020; Qi et al., 2021; Zhong & Lin, 2015). Another stream focuses on sponsors, exploring enterprise crowdsourcing strategy and influential factors of crowdsourcing performance (Caruana et al., 2006; Mahr et al., 2015; Wang et al., 2014). The third stream examines workers’ behaviors, dealing with participation motivation behaviors, fraud behaviors, learning behaviors, and worker performance (Behl et al., 2021; Leung et al., 2021; Liu et al., 2022; Pee et al., 2018; Taylor & Joshi, 2019).

Relatively comprehensive and in-depth research has been conducted from the perspectives of platforms and workers on innovation coordination mechanisms, participation motivation, and a series of risk controls. However, there is a dearth of research from the sponsors’ perspective. Extant research mainly focuses on the performance and strategy of sponsors while ignoring fraud detection and risk control. Some researchers have theoretically discussed the importance of crowdsourcing sponsors’ fraudulent behaviors (Deng et al., 2016; Pang, 2015; Pennebaker, 2013; Schlagwein et al., 2019). However, there are few in-depth empirical studies on this kind of fraud related to intellectual property. In practice, after the reports and feedback of workers are received, the suspected fraudulent projects are judged manually by platform staff through the comparison of suspected works, which requires a lot of workforce and material resources; if not solved in time, the case will have a negative impact on the platform. Thus, it is vital to illuminate the risk of malicious sponsors and how to deal with it. Fortunately, as an online environment with dynamic and static interactions, crowdsourcing provides many cues to employing automated fraud detection. With the support of valuable verbal and nonverbal cues, fraudulent sponsors can be automatically identified using machine learning models.
FRAUD OF CROWDSOURCING SPONSORS

The protection of intellectual property is a topic of great concern in open innovation (Harhoff et al., 2003), and the crowdsourcing field also attaches great importance to it (Albors et al., 2008; Liu et al., 2021). However, most crowdsourcing platforms have rules that favor sponsors’ rights, which are prioritized much more strongly than workers’ rights (Massanari, 2012). Crowdsourcing sponsors are affected by Arrow’s information paradox, as the intellectual property created by workers is an intangible asset (Arrow, 1972). The sponsor needs to have a detailed and complete understanding of all solutions provided by workers in advance before finally choosing the best one, a situation that provides an opportunity for sponsors to steal the solution without rewarding workers. To eliminate this paradox, finding a simple and effective way to ensure the appropriate management of workers’ intellectual property rights is necessary. It is even more important when the ideas put forward by workers are not mature enough to be protected by patents (Natalicchio et al., 2014).

In the crowdsourcing market, as was suspected, workers have a high amount of dissatisfaction and complaints about the malicious behavior of sponsors, as detailed in Table 1. Workers commonly complained about extremely unqualified winning bidders and questionable winning solutions. The complaints about sponsor fraud listed in Table 1 come from an anonymous crowdsourcing platform in China and have been translated from Chinese into English. In the model of the crowdsourcing contest, sponsors may exhibit various types of malicious behaviors. A typical example is a scheme in which sponsors replicate and modify the best solution submitted by a worker, submit the work to the platform through a new ID or their friends, and select the solution they submitted. Excellent works are not given their due reward, so workers provide feedback and report to the platform with supporting evidence, such as the similarity between the registration time, name, and location of the sponsor and the winning bidder. The high similarity of the two accounts serves as evidence of “double identity fraud,” implying that the sponsor and the winning bidder are the same people. Due to the heavy workload of manual processing and verification, workers are dissatisfied with the efficiency of the platform’s response.

Table 1. Workers’ complaints about sponsor fraud

| Complaint details (translated from Chinese) | Abstract |
|--------------------------------------------|----------|
| Every time this person told me how to improve, I followed the instructions. However, he chose a person who has poor credit and no real name verification. | The sponsor chooses a winning bidder who has low credit. |
| The winning bidder won the bid after only participating in one project! | The registration times of the sponsor and the winning bidder are the same. |
| The sponsor and the winning bidder have the same registration time! How do you know that the manager is named Zhang? | |
| The addresses of the winning bidder and the sponsor are both in Shenzhen. | The names of the sponsor and the winning bidder are similar and they are in the same city. |
| Both the sponsor and the winning bidder are in Quanzhou. The winning bidder has only participated in one project since the time of registration and their names both contain “wang.” Please investigate!!! | |
| The winning bidder’s works are not in accordance with the requirements of the project. They do not reflect the delivery, nor are they innovative. | The winning solution does not meet the requirements. |
| The winner is the sponsor himself; the winning bidder’s plan does not follow the marketing plan, but the work schedule of the hotel. Hope that you will check and deal with this as soon as possible; many workers have complaints! | |

Table 1 continued on next page
Generally, crowdsourcing contests guarantee the interests of the demand side but create excessive competition among the knowledge-based talents (workers). Eventually, this situation will create a “lemon market,” which might lead to reduced user engagement and, ultimately, failure of the crowdsourcing market. Akerlof (1978) presented the lemon market theory in his ground-breaking paper about the consequences of information asymmetry. In markets in which it is impossible to assess the quality of a product/service, the seller has more information than the buyer, which has the result that high quality products and services leave the market, since they only sell at the rate of average-market-quality goods. In crowdsourcing markets, although buyers/sponsors hold with an information advantage, which is different from the sellers’ advantage in the lemon market. The workers are the sellers who sell their works and services, the buyer has more information than the seller, this kind of information asymmetry also damages the engagement of high-quality workers. Due to the malicious behavior of the sponsors, high-quality works do not get the reward they deserve, and thus, workers are unwilling to invest substantial time and energy in carrying out high-level innovation and only provide works of average quality; this will lead to the gradual degradation of the quality of work in the crowdsourcing market. On the other hand, Akerlof’s (1978) paper also talked about the “cost of dishonesty,” which lies not only in the amount by which the purchaser is cheated but must also include the loss incurred from driving legitimate business out of existence. Similarly, the projects of honest sponsors will also be affected in that they will not be able to obtain the expected excellent and satisfactory works, which means other sponsors may be reluctant to invest much in rewards. Therefore, the market will gradually deteriorate and maybe even eventually disappear completely.

The fraud of sponsors promotes information asymmetric and causes severe damage to the development of crowdsourcing markets and open innovation. Platforms are obligated to deal with the problem after receiving complaints and feedback from workers. However, accurately detecting the fraudulent behaviors of sponsors is challenging, and manual detection of fraudulent sponsors by workers and platforms is time-consuming and laborious. Previous research on fraud detection involved
the identification of static fraudulent website content (Goel et al., 2017; Zahedi et al., 2015), fraudulent computer-mediated communications that occur dynamically between agents (Ho et al., 2016; Zhou et al., 2004b), and fraud that is based on static and dynamic communications through online platforms (Siering et al., 2016). However, most studies have been conducted on verbal cues due to the lack of traditional nonverbal cues in online scenarios. For example, the studies of Zhou et al. (2004b) and Ho et al. (2016) were conducted for online interactive scenarios, and the experiments in their study aimed to examine the cues leaked by fraudsters in dynamic communication. Siering et al. (2016) considered both dynamic and static scenarios in crowdfunding, which is similar to the crowdsourcing scenario. Still, the difference is that the requirements and descriptions in crowdfunding are often fictitious. In contrast, they are authentic in crowdsourcing, leading to a possible difference in the validity of their linguistic cues. Therefore, this paper focuses on the value of various types of information cues for deception in the IP-oriented crowdsourcing market.

**THEORETICAL FOUNDATION**

Several classical fraud theories provide a deeper foundation for our research, and different theories have different emphases. Some focus on mining cues in verbal information, while others focus on analyzing cues in nonverbal behavior; some cues are mostly from the text prepared by the fraudster in advance, while others are more from the information unintentional leaked in the dynamic communication. Most fraud detection theories involve verbal information in a static environment, including verbal content cues and linguistic structure cues, which can be used to distinguish cheaters from honest people. Meanwhile, other fraud detection theories focus on nonverbal cues in dynamic, face-to-face communication environments; that is, cues captured from people’s movements, gestures, facial expressions, and so on. In a typical example, police often utilize micro-expressions to help them judge whether a criminal is lying.

McCornack (1992) and McCornack et al. (1992) analyzed deception in information manipulation theory (IMT), which is often applied to detect fraud in static contexts, such as fraudulent news (Frieder & Zittrain, 2007), fraudulent corporate announcements (Humpherys et al., 2011), and fake websites (Zahedi et al., 2015). The interpersonal deception theory (IDT) was proposed by Burgoon & Buller (1996), who introduced a method of identifying verbal and nonverbal deception cues. While both IDT and IMT obtain verbal cues in static contexts, IDT pays more attention to the physiological indicators (nonverbal cues) and channels of communication (dynamic). In addition, the four-factor theory (FFT) and leakage theory (LT) focus on verbal and nonverbal cues in dynamic environments. These two earlier theories proposed that nonverbal cues can reveal the true intentions of the communicator directly. From a psychological perspective, Zuckerman et al. (1981) brought forward four underlying factors accounting for the motivation of deception in FFT. Hence, LT argues that deceptive clues can be leaked in the process of deception due to thought processes and emotional reactions (Ekman & Friesen, 1969). Although these theories were not proposed specifically to analyze deception in descriptive statements and e-mails, online communication like emails and traditional communication have much in common. Therefore, these theories can provide theoretical references for the research in this paper. Although there is no clear division standard, in Table 2, we demonstrate the comparative characteristics of these theories, including whether they focus on static or dynamic environments and distinguish between verbal and nonverbal cues in deception.

The four deception theories explain the differences between fraudsters and non-fraudsters regarding verbal and nonverbal cues in static statements and dynamic communication. They provide a good theoretical basis for our fraud detection model. Although the emphasis of each theory is different, we can use them to categorize the four types of fraud-detection cues that have been applied in various scenarios. Next, we will compare the values of the four types of fraud-detection cues in identifying sponsor fraud in the context of crowdsourcing platforms. Specifically, we will utilize the existing verbal cues outlined in the above theories and extend the scope of nonverbal behavior beyond
the traditional definition by mapping nonverbal cues in face-to-face conversation to online nonverbal cues on crowdsourcing platforms. Ultimately, we will have a clear understanding of the extractions of online fraud detection cues and the effectiveness of those cues.

**HYPOTHESIS DEVELOPMENT**

The above theories provide the basis for resolution methodologies in detecting fraudulent crowdsourcing projects. IMT (McCornack, 1992) noted that fraudsters might violate four fundamental communication principles expected in an authentic conversation. First, fraudsters use too little or too much information to conceal or distort their attention. Second, the quality of such information is often questionable or even wholly false. Third, the information may be not completely relevant to the topic or cannot be understood in the context to cover up the truth or mislead the receiver. Finally, the message is ambiguous rather than clear and concise. Similarly, IDT (Burgoon & Buller, 1996) holds that fraudsters adopt strategies to control the information transmitted. These strategies include: (1) Quality manipulations that refer to making the meaning of a sentence ambiguous by reducing adjectives and adverbs to deviate from the facts wholly or partially; (2) Quantity manipulations that refer to becoming silent by reducing the number of words or sentences, shortening the conversation time, or avoiding providing detailed information; (3) Clarity manipulations refer to using more contradictory, ambiguous, or obscure languages to show more uncertainty; (4) Relevance manipulations that refer to the use of redundant details or too many irrelevant languages, such as polite expressions, to increase the indirection and non-relevance of speech; (5) Depersonalism manipulations that refer to the use of different expressions to separate oneself from the conversation content, such as avoiding the use of the first person or preferring to use the passive voice; (6) Image and relationship protection behavior that refers to the fraudster trying his best to have an honest and credible image and avoid transmitting negative emotions.

These two theories of IMT and IDT, which have rich text features and interactivity, lay a foundation for analyzing language information in static text and dynamic interaction on the crowdsourcing platform. For example, fraudulent sponsors may exhibit reticence by using fewer words and sentences than honest sponsors, and use non-immediate language to distance themselves from their messages and the content of those messages, such as a lack of pronouns, especially first-person pronouns. Siering et al. (2016) confirmed the effectiveness of verbal cues (content-based and linguistic) in detecting fraudulent crowdfunding projects. However, the crowdsourcing sponsors fraud is to obtain solutions (i.e., IP) from the workers free of charge. Since the sponsors’ requirement statements are real, the content-based cues focusing on “what is conveyed” are not considered as effective indicators of sponsor fraud. In contrast, linguistic cues concentrating on “how deception is conveyed in a natural
language” are assumed to be valid (Zhou & Zhang, 2008). Due to the fraudulent intent, the linguistic structure of the verbal information, such as the degree of simplicity of a sentence or the emotional affect in messages, may be more effective than content-based cues extracted from factual information. Therefore, in the context of crowdsourcing fraud, we try to explore the role of linguistic cues instead of content-based cues.

In general, fourteen linguistic cues can be grouped into six constructs: complexity, non-immediacy, specificity, affect, diversity, and quantity (Siering et al., 2016). Complexity refers to the degree of simplicity of a sentence, which is measured by the number of words and the punctuation in the sentence. Non-immediacy represents the indirectness of messages, which may prevent recipients from obtaining definite or affirmative information. Specificity indicates the use of words connected with perception and the senses. Affect indicates the emotional intensity of the messages. Diversity suggests the diversity of wording. Quantity represents the number of produced notes. Additionally, as Chinese and English language processing are different, there are no spelling errors or uncertain lexicon in Chinese natural language processing. Thus, three original variables (expressivity, uncertainty, informality) proposed by Siering et al. (2016) are excluded. In this study, verbal cues are processed by the Chinese Linguistic Inquiry and Word Count (Chinese LIWC) tool (Huang et al., 2012), which includes approximately 6,800 words across 42 psychological and 30 linguistic categories. The descriptions of the linguistic cues are listed in Table 3.

| Category   | Cues                        | Explanation                                                      | Theory Base |
|------------|-----------------------------|------------------------------------------------------------------|-------------|
| Affect     | Affect_ratio                | Ratio of positive and negative words to the total number of words| IDT, FFT, LT|
|            | Pos_affect                  | Ratio of positive words to total number of words                 |             |
|            | Neg_affect                  | Ratio of negative words to total number of words                 |             |
| Complexity | avg_sentenceLength          | Average number of words per sentence                              | IDT, IMT    |
|            | avg_wordLength              | Average number of letters per word                                |             |
|            | Pausality                   | Ratio of the number of punctuation marks (periods, commas, semicolons, colons, question marks, exclamation marks) to the number of sentences |             |
| Diversity  | Lexical_diversity           | Ratio of the number of distinct words to the number of total words| IDT         |
| Non-immediacy | Group_reference            | Ratio of the number of words that are connected to the group (e.g., we, us, our) to the total number of words | IDT         |
|            | Individual_reference        | Ratio of the number of words that are connected to individuals, namely, the first-person speaker (e.g., me, myself, I), the group (e.g., we, us, our), and the reader (e.g., you, your) to the total number of words | IDT         |
|            | Self_reference              | Ratio of the total number of words that are connected to the first-person speaker (e.g., me, myself, I) to the total number of words | IDT         |
| Quantity   | Sentence_quantity           | Total number of sentences                                         | IDT, IMT    |
|            | Verb_quantity               | Total number of verbs                                             |             |
|            | Word_quantity               | Total number of words                                             |             |
| Specificity| Perceptual_information_and_sensory_ratio | Ratio of the number of words that are connected with perception and the senses of the total number of words | IDT         |
In previous fraud detection studies, various verbal cues, such as the numbers of words, sentences, self-references, the affect, and the temporal, spatial, and perceptual information within an online environment, can be helpful to indicators (Hancock et al., 2009; Hancock et al., 2007a; Zhou et al., 2004b). Although crowdsourcing sponsors’ fraud is not money-driven, we propose that these linguistic cues could also reveal the fraudster’s unstable psychological state, even when the content is true. Furthermore, crowdsourcing platforms’ dynamic and static communication approached a good chance for us to investigate the importance of different cues in online fraud detection. Specifically, static linguistic cues refer to the text descriptions of projects, which help the workers understand the project requirements and the application scenario. Dynamic linguistic cues refer to the text information in messages on the platform between sponsors and workers during the project period. In the light of the theories discussed and previous deception detection studies, we state that linguistic cues extracted from dynamic and static contexts are valuable for fraud detection in crowdsourcing. Hence, we propose that:

**Hypothesis 1a:** Static linguistic cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

**Hypothesis 1b:** Dynamic linguistic cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

In the FFT, Zuckerman & Miron (1981) identify four underlying factors from a psychological standpoint when deception occurs. These factors are (a) arousal, (b) attempted control, (c) affective response, and (d) cognitive factors. In a similar vein, LT (Ekman & Friesen, 1969) suggests the fraudster’s body movements and facial expressions that fail in concealing the deception act and their emergence as ‘leakage’ or deception cues. Therefore, some behaviors are reflected externally to conceal the corresponding lies, such as using general statements and taking longer pauses for thinking. In the crowdsourcing context, inconsistencies and anomalies can be sensed by individuals (Johnson et al., 2001). In that case, such inconsistencies can be perceived in the general verbal or the more specific nonverbal information. Regarding similarity in synchronicity between online and face-to-face communication, we argue that the four-factor and leakage mechanisms in FFT and LT are still relevant. Various nonverbal behaviors in face-to-face conversation may be mapped to online behaviors on crowdsourcing platforms. For example, liars tend to take more and longer pauses to ensure consistency. Compared with face-to-face communication, the online environment has both disadvantages and advantages. If users’ online behavior can be extracted and their profiles are constructed, it should be possible to detect fraudulent users accurately. This methodology has been widely used in marketing promotions and recommendation systems—identifying what kind of user group is suitable for what kind of products (Callaway et al., 2000; Yanchun et al., 2011). Similarly, we can assess what kind of users potentially have fraudulent intent according to their online behavior characteristics. Therefore, we also include all nonverbal cues on the platform to conduct reliable comparisons and analyses.

Since traditional nonverbal cues, such as gestures and expressions, are not applicable, we define the cues extracted from online nonverbal information as nonverbal cues. Generally, online nonverbal cues can be divided into two categories: the first is the user’s attributes, such as name and age, and the second is the user’s online behavior characteristics on the platform, such as past participation and interaction records. In crowdsourcing contests, the basic information of the project is part of the decision behavior of the sponsor, so it is also an attribute of the sponsor. Specifically, the static nonverbal cues extracted from nonverbal information refer to the basic information of the sponsors, including the time of registration, the location of the registration, the number of friends, and the number of projects in which they have been involved in the past. In the crowdsourcing environment, many fraud cases exist in which sponsors and winning bidders conspire. Therefore, basic information of the winning bidders will also be incorporated into the static nonverbal cues dimension.
Dynamic nonverbal information refers to typical sponsors’ behavior or information in crowdsourcing projects, including the project duration, the reward amount, the reply time of correspondence, the supplementary specifications, and the bid-winning order. The project duration and reward amount are considered as dynamic nonverbal information because these two attributes can be modified when sponsors realize they must attract more workers. The descriptions of the nonverbal cues are listed in Table 4.

Table 4. Descriptions of nonverbal cues

| Category       | Cues                        | Explanation                                                                 | Static/Dynamic |
|----------------|-----------------------------|-----------------------------------------------------------------------------|----------------|
| Project        | pro_total_amount            | Total project size                                                          | Dynamic        |
|                | pro_duration                | Project duration                                                             |                |
| Sponsor        | sponsor_has_truename        | Whether the sponsor has a real name in the user profile: 1=Yes, 0=No        | Static         |
|                | sponsor_sex                 | Employer gender: 1 = male, 2 = female                                        | Static         |
|                | sponsor_has_introduction    | Whether the sponsor has an introduction in the user profile: 1=Yes, 0=No    | Static         |
|                | sponsor_hits                | Number of clicks that have been won by the sponsor                           | Static         |
|                | sponsor_has_group           | Whether the sponsor participates in the group: 1=Yes, 0=No                  | Static         |
|                | sponsor_projects_quantity   | Number of projects in which the sponsor has participated (before the project’s release time) | Static         |
|                | friends_sponsor_quantity    | Number of message contacts                                                   | Static         |
|                | pro_has_extraintro          | Does the project have additional instructions: 1 = yes, 0 = no              | Dynamic        |
|                | pro_extraintro_length       | Supplementary text length                                                    | Static         |
|                | msg_quantity                | Number of e-mail exchanges                                                   | Static         |
|                | msg_reply                   | Responder reply time                                                         | Dynamic        |
| Winning bidder | in_last10(15,20,25,30) per  | Solutions submitted by the winner in the last 10% (15%,20%,25%,30%) of all solutions: 1=Yes, 0=No | Dynamic        |
|                | winner_has_truename         | Whether the winner has a real name in the user profile: 1=Yes, 0=No         | Static         |
|                | winner_gender               | Winner’s Sex: 1=Male, 2=Female                                               | Static         |
|                | winner_has_introduction     | Whether the winner has an introduction in the user profile: 1=Yes, 0=No     | Static         |
|                | winner_hits                 | The number of clicks that have been won by the winner                        | Static         |
|                | winner_has_group            | Whether the winner participates in the group: 1=Yes, 0=No                   | Static         |
|                | winner_projects_quantity    | The number of winning bidders’ that have participated in the project (before the project’s release time) | Static         |
|                | friends_winner_quantity     | Number of the winner’s friends                                               | Static         |
|                | Regist_after_releasetime    | The winner registered after the project was released: 1=Yes, 2=No           | Static         |
|                | Is_same_province            | Whether the bid winner and the sponsor are in the same province: 1=Yes, 2=No | Static         |
These nonverbal cues depict a user’s online image very comprehensively. Workers’ information and submission behaviors will impact their chances of winning (Bockstedt et al., 2015). For example, a sponsor who has many friends, participates in multiple projects, and responds to messages promptly can be considered relatively reliable. Therefore, we propose that dynamic and static nonverbal cues are crucial for fraud detection. Hence, we state that:

**Hypothesis 2a**: Static nonverbal cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

**Hypothesis 2b**: Dynamic nonverbal cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

The online information on crowdsourcing platforms we examine contains four dimensions: static verbal information, dynamic verbal information, static nonverbal information, and dynamic nonverbal information, as listed in Table 5.

- The static verbal information refers to the text descriptions of projects, by which workers are made aware of the project requirements and the application scenario.
- The dynamic verbal information refers to the text information in messages on the platform between sponsors and workers during the project period.
- The static nonverbal information refers to the basic information on sponsors, which includes the time of registration, the location of registration, the number of friends, and the number of projects in which they have been involved. In the crowdsourcing environment, many fraud cases exist in which sponsors and winning bidders conspire. Therefore, basic information on the winning bidders will also be incorporated into the static nonverbal information dimension.
- The dynamic nonverbal information refers to typical sponsors’ behavior or information in crowdsourcing process, including the project duration, the reward amount, the reply time of the correspondence, the supplementary specifications, and the bid-winning order. The project duration and reward amount are set as dynamic nonverbal information because these two attributes can be modified when sponsors realize they must attract more workers.

|                | Verbal information                                      | Nonverbal information                                           |
|----------------|--------------------------------------------------------|----------------------------------------------------------------|
| **Static**     | Textual descriptions of projects                       | Basic information on sponsors, projects, and winning bidders    |
| **Dynamic**    | Textual information of messages between sponsors and workers | Typical behaviors or information of sponsors in crowdsourcing process |

Ho et al. (2016) found that deception can be discovered in verbal and nonverbal information. When a person is conversing messages, verbal indicators mainly focus on the content, while nonverbal cues work as accessory features (Zhou et al., 2004b). The online environment of crowdsourcing platforms provides an ideal environment for exploring and comparing the values of the four types of fraud detection cues. For example, the cues created by nonverbal information in crowdsourcing contests may better reveal whether the sponsor has fraudulent intent, especially for the decision-making behavior in dynamic contexts, which is quite tricky to disguise. As the Italian proverb reminds us, saying something and doing it are two very different things, separated by a vast chasm. The famous
American adage encapsulates another related concept, “actions speak louder than words.” What a sponsor has done carries more weight than what he says he will do. Although various linguistic cues show significant differences in fraudulent and nonfraudulent objects, FFT and LT argue that nonverbal cues can directly reveal the communicator’s true intentions, and deceivers are more likely to leak clues in dynamic environments. In contrast, they are more prepared in static environments (Fuller et al., 2011). Thus, fraudsters tend to spend more effort to create a good image in static contexts (Fiol, 1995). Given that information such as project description in crowdsourcing projects is the real requirement and thoughtfully provided by the project sponsors upfront, we argue that leakage mechanisms may not work in such a static environment. In contrast, it is easier to reveal effective cues in dynamic communication with platform e-mail. Therefore, we believe that the nonverbal cues like user characteristics, project features, and other related cues on crowdsourcing platforms may be more effective in detecting fraudsters compared to linguistic cues, and the cues extracted from dynamic contexts may be more valuable than the static cues. Hence, we state that:

Hypothesis 3a: Nonverbal cues are more valuable than linguistic cues in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

Hypothesis 3b: Dynamic cues are more valuable than static cues in detecting the fraudulent behavior of sponsors in crowdsourcing contests.

METHODOLOGY

Based on the above fraud theories, we utilized natural language processing (NLP) tools and wrote python scripts to clean the data, and quantify the key concepts to obtain a dataset for data analysis. Then, we used machine learning classifiers, such as decision trees and random forests to detect the sponsors’ fraud.

DATA

The data to be analyzed was collected from an anonymous, well-known online crowdsourcing platform in China, which has roughly 11 million members and 490 thousand released projects and generates over 400 million dollars of total rewards. The crowdsourcing projects in the data set ranged from September 7th, 2006, and January 24th, 2017.

This study focused on the fraudulent behaviors of sponsors in contest projects on the platform. The data contained 380,393 contest projects and 198,961 related sponsors. Before preprocessing the data, we excluded unfinished projects still in progress and obtain a total of 82,500 projects. Then, we extracted project identifiers and winning bidders’ usernames from the bulletin board on which the platform announces projects confirmed to be fraudulent. After that, we identified each sponsor by matching each project identifier in the project table and extract each winning bidder by matching the bidder’s username in the user table. As some projects in the bulletin board table are duplicates or do not have the winning bidder’s username, we included only 569 fraudulent projects with complete and valid information. Finally, we used these 569 fraudulent projects officially confirmed by the platform as positive samples.
We randomly sampled 569 non-fraudulent projects from the original unbalanced datasets to form a new balanced data set. We wrote a python script to perform these tasks automatically. Finally, we constructed a dataset of 1,138 instances for our research questions. The data pre-processing flow is illustrated in Figure 1.

According to the classification of cues in the hypothesis, descriptions of important extraction features of each dimension of the online information on crowdsourcing platforms are listed in Table 6.

Table 6. Important features of four dimensions

|                   | Verbal                          | Nonverbal                      |
|-------------------|---------------------------------|--------------------------------|
| **Static**        | affect_ratio_static             | Year                           |
|                   | pos_affect_ratio_static         | Province                       |
|                   | neg_affect_ratio_static         | winner_has_truename            |
|                   | avg_sentenceLength_static       | winner_sex                     |
|                   | avg_wordLength_static           | winner_has_introduction        |
|                   | pausality_static                | winner_hits                   |
|                   | lexical_diversity_static        | winner_has_group               |
|                   | group_reference_ratio_static    | winner_projects_quantity       |
|                   | individual_reference_ratio_static| friends_winner_quantity       |
|                   | self_reference_ratio_static     | sponsor_has_truename           |
|                   | sentence_quantity_static        | sponsor_sex                    |
|                   | verb_quantity_static            | sponsor_has_introduction       |
|                   | total_words_quantity_static     | sponsor_hits                  |
|                   | perceptron_ratio_static         | sponsor_has_group              |
|                   |                                 | sponsor_projects_quantity      |
|                   |                                 | friends_sponsor_quantity       |

Table 6 continued on next page
DATA MINING METHODS

Predictive analytics includes empirical methods that generate data predictions and methods for assessing predictive power, which not only assist in creating practically useful models but also play an important role alongside explanatory modeling in theory building and theory testing (Shmueli & Koppius, 2011). As a predictive analytics tool, machine learning can automatically learn hidden knowledge or patterns from training data or previous experience. To detect fraudulent crowdsourcing projects, we utilize several widely used machine learning models: k-nearest neighbors (KNN), logistic regression (LR), support vector machines (SVM), artificial neural networks (ANN), and random forest (RF).

To classify an instance, KNN uses the most frequent label of its k-nearest neighbors as the label of the instance. Our study assigned the hyperparameter k to 3 and uses Euclidean distance as the distance metric (Martin, 1995). SVM was proposed for solving two-class classification problems (Vapnik, 2013). As the data in this study are not linearly separable, we use the radial basis function kernel (RBF). The hyperparameter C is assigned a value of 10; C is a penalty parameter to avoid over-fitting. We also considered the RF classifier, a kind of ensemble model that consists of dependent decision tree classifiers and takes the most-selected label as the label of the instance (Breiman, 2001).

ANN consists of interconnected artificial neurons that are connected with different weights. Each neuron takes in inputs, proceeds through activation functions to justify the weight of the input, and finally gives outputs (Han & Kamber, 2005). The implementation of the ANN model was based on the open-source machine-learning python package, scikit-learn. In this study, we used the default setting of the number of neurons, which shows good performance on both training and testing sets. We performed the one hidden layer ANN model with 100 neurons to get nice classification measures and avoid over-fitting at the same time. We also utilized a sigmoid activation function and a classic neural network training process, that is, forward propagation to compute the cost function and weights and backpropagation by gradient descent to minimize the cost (Fuller et al., 2009).

| Verbal                          | Nonverbal                     |
|--------------------------------|-------------------------------|
| affect_ratio_dynamic           | in_last10per                  |
| pos_affect_ratio_dynamic       | in_last15per                  |
| neg_affect_ratio_dynamic       | in_last20per                  |
| avg_sentenceLength_dynamic     | in_last25per                  |
| avg_wordLength_dynamic         | in_last30per                  |
| pausality_dynamic              | pro_total_amount              |
| lexical_diversity_dynamic      | pro_duration                  |
| group_reference_ratio_dynamic  | pro_has_extraintro            |
| individual_reference_ratio_dynamic | msg_amount                |
| self_reference_ratio_dynamic   | msg_reply                     |
| sentence_quantity_dynamic      | regist_after_releasetime      |
| verb_quantity_dynamic          | is_same_province              |
| total_words_quantity_dynamic   |                               |
| perceptron_ratio_dynamic       |                               |
| pro_buchong_length             |                               |
MACHINE LEARNING EVALUATION METHODOLOGY

In this study, we utilized 10-fold cross-validation to generate training and validation sets since the volume of data is not large enough. There were two steps when different classifiers using k-fold cross-validation (k = 10) do classification tasks. First, the whole data set was split into k subsets with the same class distribution. Second, the classifier used the remainder k–1 subsets to train the classifier and uses the remaining subset for testing.

The two-by-two confusion matrice (shown in Table 7) was mainly used to evaluate binary classification performance. TP refers to the number of true positives, which, in the fraud detection context, are equal to the number of projects that are correctly predicted to be fraudulent. Similarly, FP (False Positive) is the number of projects that are predicted to be fraudulent but are non-fraudulent. Finally, FN (False Negative) is the number of projects predicted to be non-fraudulent but fraudulent. Further, we can calculate comparable measures, such as recall, precision, F1-score, and accuracy, based on the confusion matrix (Hotho et al., 2005; Kotsiantis et al., 2007). The F1 score and accuracy measures are used to evaluate the overall power of classification models.

\[
Recall = \frac{TP}{TP + FN} \\
Precision = \frac{TP}{TP + FP} \\
F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \\
Accuracy = \frac{TP + TN}{TP + TN + FP + FN}
\]

More specifically, if a crowdsourcing project is predicted as fraudulent by a classifier and it is a fraudulent project, then it is a true-positive project. As mentioned above, TP refers to the number of projects that are correctly predicted to be fraudulent. Therefore, higher precision means a higher percentage of true fraudulent projects in the projects that are predicted as fraudulent by a classifier. Recall refers to the power of a classifier to detect fraudulent projects in the set of all fraudulent projects. Higher recall indicates that the classifier will identify more truly fraudulent projects.

EMPIRICAL RESULTS

Descriptive Statistics

We describe various characteristics of the data set. In total, we consider 1,138 projects, half of which are fraudulent. According to Table 8, the maximum reward amount of the non-fraudulent projects
is almost eight times as large as that of the fraudulent ones. In contrast, the mean project reward amount is two times as large for the non-fraudulent projects as for the fraudulent projects. On average, fraudulent projects have longer durations and more specifications than non-fraudulent projects.

According to the statistics in Table 9, fraudulent sponsors have fewer average clicks, more project participation, and fewer friends than non-fraudulent sponsors. In addition, there is a difference in the message quantity between fraudulent and non-fraudulent sponsors, which vary significantly in response time. That is, fraudulent sponsors have longer response times than non-fraudulent sponsors.

According to Table 10, the number of clicks on non-fraudulent winning bidders is about 200 times that of fraudulent winning bidders. Similarly, the non-fraudulent winning bidder’s project participation average is nearly 150 times that of the fraudulent winning bidder, while the number of friends is about 50 times. Therefore, it can be stated that the winning bidder of the fraudulent project is relatively inactive on the platform.
We also conducted a one-way ANOVA to compare fraudulent and non-fraudulent projects. We found that most of the variables in Tables 8–10 were significantly different except for sponsor_projects_quantity (F value = 1.425, p value = 0.233 > 0.001). This data set is suitable for our forecasting work.

**EVALUATION OF MACHINE LEARNING CLASSIFIERS**

Tables 11–13 list the prediction scores of different machine learning classifiers with ten-fold stratified cross-validation. Table 15 reports the results of McNemar’s test (Everitt, 1992), which compares the performance of different classifiers. We build different classifiers based on static and dynamic contexts, combining nonverbal and linguistic cues. We evaluate the model performance by precision, recall, F1-score, and accuracy for each classifier. As the labels are distributed equally in our data, we use random guessing as our baseline, for which all measures are 0.5. Concerning machine learning techniques applied, the RF classifier is the best-performing classifier, which might be explained by the RF classifier’s good performance in structured data.

Table 11 presents the testing results using ten-fold cross-validation method. Linguistic cues extracted from the static context refer to features extracted from textual descriptions of projects. In contrast, linguistic cues extracted from the dynamic context are features extracted from the textual information of messages between sponsors and workers. Most of the predictive measures of linguistic cues extracted from the static context are higher than 0.9, which is much better than random guessing. Thus, with static linguistic cues, automated deception detection techniques can provide promising solutions for detecting fraudulent crowdsourcing projects (H1a). Meanwhile, the predictive value of linguistic cues extracted from the dynamic context is no better than that of the static context, as almost all measures are below 0.9 (H1b). In line with the previous research (Zhou et al., 2004a; Zhou & Zhang, 2008), verbal information in online fraud detection is indeed very effective.

| Classification Algorithms | Static linguistic cues | Dynamic linguistic cues |
|---------------------------|-----------------------|------------------------|
| KNN                       | Precision 0.8537 Recall 0.9211 F1 0.8861 Accuracy 0.8816 | Precision 0.8468 Recall 0.8246 F1 0.8356 Accuracy 0.8377 |
| LR                        | Precision 0.8934 Recall 0.9561 F1 0.9237 Accuracy 0.9211 | Precision 0.8947 Recall 0.7456 F1 0.8134 Accuracy 0.8289 |
| SVC                       | Precision 0.9123 Recall 0.9123 F1 0.9123 Accuracy 0.8796 | Precision 0.8796 Recall 0.8333 F1 0.8559 Accuracy 0.8596 |
| ANN                       | Precision 0.9286 Recall 0.9123 F1 0.9204 Accuracy 0.9211 | Precision 0.8829 Recall 0.8596 F1 0.8711 Accuracy 0.8728 |
| RF                        | Precision 0.9381 Recall 0.9298 F1 0.9339 Accuracy 0.9342 | Precision 0.8525 Recall 0.9123 F1 0.8814 Accuracy 0.8772 |
Table 12 presents testing results using the ten-fold cross-validation. Nonverbal cues extracted from the static context refer to nonverbal features extracted from the information of sponsors, projects, and winning bidders. Nonverbal cues from the dynamic context equate to typical behaviors or sponsors’ information in the crowdsourcing process, such as the bidding time. We compare classifiers based on nonverbal cues extracted from the static context versus the dynamic context. Most predictive measures listed in Table 10 are above 0.80, which supports the assertion that nonverbal cues extracted from static and dynamic contexts provide value capable of detecting the fraudulent behavior of crowdsourcing sponsors (H2a, H2b). The findings conclude that nonverbal cues are powerful predictors for detecting fraudulent projects. Consistent with the study’s conclusion on detecting fake online reviews (Zhang et al., 2016), nonverbal information is also very effective in crowdsourcing, which is noteworthy.

Table 12. Result with nonverbal cues extracted from static vs. dynamic context

| Classification Algorithms | Static nonverbal cues | | Dynamic nonverbal cues | |
|---------------------------|-----------------------|---------------------|------------------------|------------------------|
|                           | Precision  | Recall  | F1     | Accuracy  | Precision | Recall | F1     | Accuracy  |
| KNN                       | 0.7769     | 0.8860  | 0.8279 | 0.8158    | 0.8073    | 0.7719 | 0.7892 | 0.7939    |
| LR                        | 0.8571     | 0.9474  | 0.9000 | 0.8947    | 0.8390    | 0.8684 | 0.8534 | 0.8509    |
| SVC                       | 0.8321     | 0.9561  | 0.8898 | 0.8816    | 0.8319    | 0.8684 | 0.8498 | 0.8465    |
| ANN                       | 0.8425     | 0.9386  | 0.8880 | 0.8816    | 0.8174    | 0.8246 | 0.8210 | 0.8202    |
| RF                        | 0.9643     | 0.9474  | 0.9558 | 0.9561    | 0.8362    | 0.8509 | 0.8435 | 0.8421    |

We performed machine learning classification methods using verbal and nonverbal features separately and examine the difference between the predictive performance of features extracted from the static context (static features) and the dynamic context (dynamic features). The results shown in Table 13 indicate that classifiers using verbal cues have higher performance measures than those using nonverbal cues. The results shown in Table 15 suggest that classifiers considering static features have higher performance measures than those considering dynamic features. To test the difference in performance between models using nonverbal and verbal cues, as well as dynamic and static features, we perform McNemar’s test, which compares the predictive accuracy of two binary classifiers. Table 15 shows no significant difference between features extracted from the dynamic context and those extracted from the static context among all classifiers, except when using the RF classifier (p-value = 0.099<0.1). On the contrary, the difference between models using nonverbal and verbal cues is significant among the KNN, LR, and ANN classifiers, for which the p-values of McNemar’s test are all significant at the level of 0.1. The results provide evidence for H3a and H3b. Inconsistent with our expectations, verbal information is more valuable than nonverbal information for detecting fraudulent crowdsourcing projects, while dynamic information is no more valuable than static information. Although the measures of F1 and accuracy in models using static features are higher than in models using dynamic features, the difference is not significant.
To summarize, the above results show that nonverbal and verbal information in static and dynamic contexts are valuable for detecting fraudulent contest projects on crowdsourcing platforms. Further, we find that verbal information is especially valuable and that classifiers taking verbal cues as inputs outperform classifiers based on nonverbal cues (Table 16).
To validate our results in a more realistic platform environment, we performed the tests with the original unbalanced data set, in which the ratio of fraudulent projects is only 0.69 percent. We apply the five classifiers again, and the measures are indicated below (Tables 17–21). As the majority label may influence the accuracy measure in the unbalanced distribution, it is unsuitable for model evaluation. Instead, the AUC (Area Under the ROC Curve) is calculated to measure the overall performance. The ROC curve is used to visualize the performance of a binary classifier (Bradley, 1997).

Table 16. Summary of results

| Dynamic context | Nonverbal cues | Verbal cues |
|-----------------|----------------|-------------|
| Static context  | H1a: Valuable  | H1b: Valuable| H3b: Dynamic not outperform static |
|                 | H2a: Valuable  | H2b: Valuable| H3a: Verbal outperforms nonverbal |

Table 17. Result with linguistic cues extracted from static vs. dynamic context

| Classification Algorithms | Static linguistic cues | Dynamic linguistic cues |
|---------------------------|------------------------|-------------------------|
|                           | Precision | Recall | F1    | Auc    | Precision | Recall | F1 | Auc  |
| KNN                       | 0.9844    | 0.5040 | 0.6667| 0.7520 | 0.4194    | 0.1040 | 0.1667| 0.5515|
| LR                        | 0.1724    | 0.0800 | 0.1093| 0.5385 | 0.3913    | 0.2880 | 0.3318| 0.6423|
| SVC                       | 0.9857    | 0.5520 | 0.7077| 0.7760 | 0.5429    | 0.1520 | 0.2375| 0.5755|
| ANN                       | 0.6720    | 0.6720 | 0.6720| 0.8347 | 0.4793    | 0.4640 | 0.4715| 0.7301|
| RF                        | 0.7981    | 0.6640 | 0.7249| 0.8314 | 0.4188    | 0.3920 | 0.4050| 0.6939|

Table 18. Result with nonverbal cues extracted from static vs. dynamic context

| Classification Algorithms | Static nonverbal cues | Dynamic nonverbal cues |
|---------------------------|------------------------|-------------------------|
|                           | Precision | Recall | F1    | Auc    | Precision | Recall | F1 | Auc  |
| KNN                       | 0.4464    | 0.2000 | 0.2762| 0.5991 | 0.2500    | 0.0800 | 0.1212| 0.5391|
| LR                        | 0.0000    | 0.0000 | 0.0000| 0.5000 | 0.5333    | 0.1280 | 0.2065| 0.5636|
| SVC                       | 0.0000    | 0.0000 | 0.0000| 0.5000 | 0.7778    | 0.0560 | 0.1045| 0.5279|
| ANN                       | 0.0000    | 0.0000 | 0.4999| 0.4681 | 0.4681    | 0.1760 | 0.2558| 0.5872|
| RF                        | 0.6435    | 0.5920 | 0.6167| 0.7947 | 0.3529    | 0.1920 | 0.2487| 0.5947|
As shown in Tables 17 and 18, verbal and nonverbal cues in static and dynamic contexts are valuable for detecting fraud in crowdsourcing projects, which is consistent with the results in the balanced data set. Besides, classifiers based on verbal cues have higher AUC measures than those based on nonverbal cues. The McNemar’s test shows a significant difference between the models using verbal and nonverbal cues. However, unlike the results in the balanced data set, in which measures using static features are not significantly better than those using dynamic features, static features in the original unbalanced data set are more valuable than dynamic features. Although the accuracy/AUC measures of models using static verbal cues are higher than those using nonverbal cues in both data sets, the difference in classification performance when using different cues is not significant in the balanced data. As the fraudulent projects are the same in the balanced and unbalanced data sets, the possible reason for the change in the results (H3b) is that as the volume of data increases, the distribution of the values of the features changes in the non-fraudulent projects of the unbalanced data set.

Table 19. Testing data with nonverbal features vs. verbal features

| Classification Algorithms | Nonverbal features | Verbal features |
|---------------------------|--------------------|----------------|
|                           | Precision | Recall | F1 | Auc   | Precision | Recall | F1 | Auc   |
| KNN                       | 0.4167    | 0.0800 | 0.1342 | 0.5396 | 0.8116    | 0.4480 | 0.5773 | 0.7236 |
| LR                        | 0.4390    | 0.1440 | 0.2169 | 0.5713 | 0.6075    | 0.5200 | 0.5603 | 0.7587 |
| SVC                       | 0.8000    | 0.0320 | 0.0615 | 0.5160 | 0.8911    | 0.7200 | 0.7965 | 0.8597 |
| ANN                       | 0.4595    | 0.2720 | 0.3417 | 0.6348 | 0.8972    | 0.7680 | 0.8276 | 0.8837 |
| RF                        | 0.9490    | 0.7440 | 0.8341 | 0.8718 | 0.9500    | 0.7600 | 0.8444 | 0.8798 |

Table 20. Testing data with static features vs. dynamic features

| Classification Algorithms | Static features | Dynamic features |
|---------------------------|-----------------|------------------|
|                           | Precision | Recall | F1 | Auc   | Precision | Recall | F1 | Auc   |
| KNN                       | 0.8923    | 0.4640 | 0.6105 | 0.7318 | 0.7838    | 0.2320 | 0.3580 | 0.6158 |
| LR                        | 0.4900    | 0.3920 | 0.4356 | 0.6944 | 0.5842    | 0.4720 | 0.5221 | 0.7347 |
| SVC                       | 0.9733    | 0.5840 | 0.7300 | 0.7919 | 0.8889    | 0.4480 | 0.5957 | 0.7238 |
| ANN                       | 0.8070    | 0.7360 | 0.7699 | 0.8673 | 0.6535    | 0.6640 | 0.6587 | 0.8307 |
| RF                        | 0.9429    | 0.7920 | 0.8609 | 0.8958 | 0.7453    | 0.6320 | 0.6840 | 0.8152 |

Table 21. McNemar’s test on classifiers

| Classification Algorithms | Nonverbal vs. Verbal | Dynamic vs. Static |
|---------------------------|----------------------|--------------------|
|                           | chi2     | p-value |       | chi2     | p-value |
| KNN                       | 24.322    | 0.000   | 10.782 | 0.001    |
| LR                        | 5.608     | 0.018   | 2.064  | 0.151    |
| SVC                       | 57.398    | 0.000   | 6.300  | 0.012    |
| ANN                       | 62.791    | 0.000   | 7.692  | 0.006    |
| RF                        | 0.018     | 0.894   | 18.824 | 0.000    |
data. As a result, the insignificant difference in model performance between classifiers using static and dynamic features in the balanced data set becomes significant in the unbalanced data set.

**DISCUSSION**

The results show that the proposed classifiers can help address the fraud detection problem in crowdsourcing contests. Static linguistic cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests (H1a). In terms of predictive strength, all the methods yield outstanding accuracy, with the lowest accuracy resulting from the KNN model (88%). In particular, the highest accuracy is 94 percent, achieved by the RF model, which means 94 percent of all projects predicted to be fraudulent are indeed fraudulent projects. Meanwhile, the accuracy of all classifiers is above 80 percent, which suggests that dynamic linguistic cues are of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests (H1b). The value is obvious, but it can be seen that the accuracy is not very high, which should be attributed to the characteristics of the crowdsourcing platforms. One of the most important reasons is that sponsors and workers can communicate outside the platform, such as by mobile phone and other instant messaging tools, where the information is unavailable for our analysis. Furthermore, the sponsors’ desire for excellent work ensures the authenticity of most of their verbal information, which to some extent reduces the leakage of available linguistic cues. Therefore, if the dynamic communication between the sponsor and workers can be captured more thoroughly, it will be constructive in improving the accuracy of the prediction. Consistent with the findings of Siering et al. (2016), verbal information is of value in fraud detection. Various verbal cues, such as the number of words and sentences, the affect, and the perceptual information within an online environment, can be helpful indicators (Hancock et al., 2009; Zhou & Zhang, 2004). Although we did not consider the content of verbal information, given that the sponsors’ purpose is to obtain a satisfactory solution, the linguistic cues leaked by sponsors’ fraudulent intentions are enough to enable us to distinguish their differences.

Static and dynamic nonverbal cues are also of significant value in detecting the fraudulent behavior of sponsors in crowdsourcing contests (H2a, H2b). As can be seen from Table 12, the prediction accuracy is reasonable, whether based on static or dynamic nonverbal information, which indicates that the characteristics of sponsors and winning bidders are very effective indicators. Workers’ information and submission behaviors will impact their chances of winning (Bockstedt et al., 2015). Yang et al. (2011) found that workers who submit early or late in a task’s duration tend to win more than other workers; they also found a worker’s experience to be a good predictor of future winning probability. Therefore, if the sponsor chooses a winning bidder whose information is not within the expected range, it will likely be suspected of fraud. One of the main reasons is that in the crowdsourcing context, if the sponsor has committed fraud, the winning bidder is typically a participant in a conspiracy or the sponsor himself. As can be seen from Table 10, the winning bidders of fraudulent projects are indeed less experienced and less active workers. At the same time, the sponsors of fraud projects are relatively active and experienced, which means that the sponsors may have found vulnerabilities within the platform in the participation process and seek to profit from them. Consequently, nonverbal cues should not be ignored in online fraud detection, and online behaviors can be as effective as expressions, gestures, and actions in indicating fraud.

Nonverbal cues do not provide more value in detecting fraudulent behavior of crowdsourcing sponsors than linguistic cues (H3a). Dynamic cues do not provide more value in detecting fraudulent behavior of crowdsourcing sponsors than static cues (H3b). Neither hypothesis 3a nor hypothesis 3b was supported. Although the difference between the comparison results is insignificant, it contradicts our expectations. It is also inconsistent with the fake review detection study of Zhang et al. (2016). The possible reason is that reviewers often use the same account for frequent fraud operations in the fake review context. In contrast, in the crowdsourcing context, due to the infrequent demand for fraud, the fraudulent behavior of an account may not be repeated. There is little significant difference between
the predictive value of static and dynamic information, which may be due to the incomplete acquisition of dynamic information in crowdsourcing. In contrast, richer dynamic information is available in the interactive online experiment (Hancock et al., 2007b). In addition, it confirms why previous studies (Ho et al., 2016; Newman et al., 2003) pay more attention to linguistic cues—that is, in the context of the Internet, verbal information is indeed a richer form of expression and is not easy to disguise. Meanwhile, although we cannot obtain the traditional nonverbal information, such as expression and gesture, as is possible in face-to-face interaction, the Internet has historical memory. Online behavior also provides a sufficient basis for the discrimination of fraudulent behavior. Therefore, regardless of verbal or nonverbal information in the Internet environment, whether in a dynamic or static context, any information, as long as it can be captured, should be fully acquired and effectively utilized.

Furthermore, we also considered the class distribution with 0.69 percent suspicious projects and calculated the predictive performance index to analyze the capability of the classifier under the original unbalanced class distribution. The outcomes show that the developed classifiers are significantly better than naive classifiers that classify each item as suspicious or nonsuspicious, which is consistent with the results in the balanced data set. Therefore, our fraud detection models can play an influential role in the practical application of crowdsourcing platforms.

CONCLUSIONS
As one of the most celebrated and successful new business models of the emerging knowledge economy, crowdsourcing has roused many concerns in the academic world, inciting research on sponsors, platforms, and workers. Compared to platforms and workers, there is not much research on sponsors, and the existing research mainly focuses on the performance and strategy of sponsors while ignoring fraud detection and risk control. With this study, we contribute to the crowdsourcing literature by conducting empirical research on detecting sponsors’ fraudulent behaviors. This study also contributes to the literature on fraud detection by conducting a contrastive analysis of verbal and nonverbal information in static and dynamic contexts to detect suspicious behaviors via data mining techniques and machine learning methods, which enrich the application and popularization of deception theory. Traditional linguistic cues are effective in online non-money-driven fraud, and online nonverbal cues (i.e., user basic characteristics and behavior characteristics), such as response latency and past participation, are also necessary and meaningful. Through various classifiers based on the balanced and the original unbalanced data, we find that verbal information is more valuable than nonverbal information, and static information is more valuable than dynamic information. However, all four types of information are highly effective, and we should not ignore any of them. The results can be applied to international contest-based crowdsourcing platforms, such as 99designs, and DesignCrowd. These platforms collect solutions from global knowledge-based workers and pay close attention to intellectual property protection. In addition to verbal information analysis, we suggest that it is a good perspective to monitor the risk with the sponsor’s behavioral cues.

In practice, our results benefit the various stakeholders in crowdsourcing markets. Firstly, the platform can spend less workforce on these fraudulent projects, and conflicts are resolved in a timelier manner. Secondly, potential workers benefit from a reduced risk of being deceived and avoiding unpaid labor losses. Thirdly, sponsors of non-fraudulent crowdsourcing projects will benefit from the fact that their projects will receive more attention if fraudulent projects are detected and terminated. Finally, the platform benefits from the increased trust of the sponsors and workers, encouraging sponsors to pay more for high-quality solutions and workers to provide higher-quality work on the platform. In general, a precise fraud detection mechanism will help crowdsourcing workers and platforms detect fraudulent projects more conveniently and scientifically, increasing user engagement and promoting the development of global crowdsourcing markets.

This study also has several limitations. First, our analysis focuses on the contest-based crowdsourcing platform in China. Our work can be generalized to crowdsourcing platforms in other...
countries to a certain extent since the language and cultural differences need further examination. Second, this paper examines the effectiveness of different cues, but the model cannot make predictions and provide early warning of fraudulent behavior. Since cues appear over time and not simultaneously in practice, we could make a time series model achieve an early warning function and deepen the practical significance. In addition, we can also consider the characteristics of the relationship network among users, which may further improve the prediction accuracy.

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REFERENCES

Akerlof, G. A. (1978). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *Uncertainty in Economics*, 84(3), 235–257.

Albors, J., Ramos, J. C., & Hervas, J. L. (2008). New learning network paradigms: Communities of objectives, crowdsourcing, wikis and open source. *International Journal of Information Management*, 28(3).

Arrow, K. J. (1972). Economic welfare and the allocation of resources for invention. In *Readings in industrial economics* (pp. 219–236). Springer. doi:10.1007/978-1-349-15486-9_13

Behl, A., Sheorey, P., Chavan, M., Jain, K., & Jajodia, I. (2021). Empirical investigation of participation on crowdsourcing platforms: A gamified approach. *Journal of Global Information Management*, 29(6), 1–27. doi:10.4018/JGIM.20211101.oa14

Bockstedt, J., Druhl, C., & Mishra, A. (2015). Problem-solving effort and success in innovation contests: The role of national wealth and national culture. *Journal of Operations Management*, 36(1), 187–200. doi:10.1016/j.jom.2014.12.002

Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recognition*, 30(7), 1145–1159. doi:10.1016/S0031-3203(96)00142-2

Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32. doi:10.1023/A:1010933404324

Burgoon, J. K., & Buller, D. B. (1996). Interpersonal Deception Theory. *Communication Theory*, 6(3), 203–242. doi:10.1111/j.1468-2885.1996.tb00132.x

Callaway, D. S., Newman, M. E. J., Strogatz, S. H., & Watts, D. J. (2000). Network robustness and fragility: Percolation on random graphs. *Physical Review Letters*, 85(25), 5468–5471. doi:10.1103/PhysRevLett.85.5468 PMID:11136023

Caruana, R., Munson, A., & Niculescu-Mizil, A. (2006). *Getting the Most Out of Ensemble Selection*. Paper presented at the International Conference on Data Mining. doi:10.1109/ICDM.2006.76

Chang, W. H., & Chang, J. S. (2012). An effective early fraud detection method for online auctions. *Electronic Commerce Research and Applications*, 11(1-6), 346–360. doi:10.1016/j.elerap.2012.02.005

Chen, Y., & Zhang, W. (2020). Effect of user involvement in supply chain cloud innovation: A game theoretical model and analysis. *Journal of Global Information Management*, 28(1), 23–28. doi:10.4018/JGIM.2020010102

Cheng, L. C., Hu, H. W., & Wu, C. C. (2021). Spammer group detection using machine learning technology for observation of new spammer behavioral features. *Journal of Global Information Management*, 29(2), 61–76. doi:10.4018/JGIM.2021030104

Deng, X., Joshi, K., & Galliers, R. D. (2016). The duality of empowerment and marginalization in microtask crowdsourcing: Giving voice to the less powerful through value sensitive design. *Management Information Systems Quarterly*, 40(2), 279–302. doi:10.25300/MISQ/2016/40.2.01

Drouin, M., Miller, D., Wehle, S. M., & Hernandez, E. (2016). Why do people lie online? “Because everyone lies on the internet.” *Computers in Human Behavior*, 64, 134–142. doi:10.1016/j.chb.2016.06.052

Eickhoff, C., & de Vries, A. (2011). How crowdsourcable is your task. *Proceedings of the workshop on crowdsourcing for search and data mining (CSDM) at the fourth ACM international conference on web search and data mining (WSDM).*

Ekman, P., & Friesen, W. V. (1969). Nonverbal leakage and clues to deception. *Psychiatry*, 32(1), 88–106. doi:10.1080/00332747.1969.11023575 PMID:5779090

Estellés-Arolas, E., & González-Ladrón-De-Guevara, F. (2012). Towards an integrated crowdsourcing definition. *Journal of Information Science*, 38(2), 189–200. doi:10.1177/0165551512437638

Everitt, B. S. (1992). *The analysis of contingency tables*. Chapman & Hall. doi:10.1201/b15072
Frieder, L., & Zittrain, J. L. (2007). Spam Works: Evidence from Stock Touts and Corresponding Market Activity. *Hastings Comm. & Ent. LJ, 30*, 479. doi:10.2139/ssrn.920553

Fuller, C. M., Biros, D. P., & Delen, D. (2011). An investigation of data and text mining methods for real world deception detection. *Expert Systems with Applications, 38*(7), 8392–8398. doi:10.1016/j.eswa.2011.01.032

Goel, S., Williams, K., & Dincelli, E. (2017). Got phished? Internet security and human vulnerability. *Journal of the Association for Information Systems, 18*(1), 2. doi:10.17705/1jais.00447

Hancock, J., Birnholtz, J., Bazarova, N., Guillory, J., Perlin, J., & Amos, B. (2009). Butler lies: awareness, deception and design. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. doi:10.1145/1518701.1518782

Hancock, J., Toma, C., & Ellison, N. (2007a). The truth about lying in online dating profiles. *Proceedings of the SIGCHI conference on human factors in computing systems*. doi:10.1145/1240624.1240697

Hancock, J. T., Curry, L. E., Goorha, S., & Woodworth, M. (2007b). On Lying and Being Lied To: A Linguistic Analysis of Deception in Computer-Mediated Communication. *Discourse Processes, 45*(1), 1–23. doi:10.1080/01638530701739181

Hao, L., Hou, W., & Liu, M. (2014). *The game analysis of enterprises’ R&D innovation strategy under crowdsourcing contest mode*. Science Research Management.

Harhoff, D., Henkel, J., & Hippel, E. V. (2003). Profiting from voluntary information spillovers: How users benefit by freely revealing their innovations. *Research Policy, 32*(10), 1753–1769. doi:10.1016/S0048-7333(03)00061-1

Hirth, M., Hoffeld, T., & Tran-Gia, P. (2010). Cheat-Detection Mechanisms for Crowdsourcing. *Mathematical and Computer Modelling, 57*, 2918–2932. doi:10.1016/j.mcm.2012.01.006

Ho, S. M., Hancock, J. T., Booth, C., & Liu, X. (2016). Computer-Mediated Deception: Strategies Revealed by Language-Action Cues in Spontaneous Communication. *Journal of Management Information Systems, 33*(2), 393–420. doi:10.1080/07421222.2016.1205924

Hotho, A., Nürnberg, A., & Paaß, G. (2005). *A brief survey of text mining*. Paper presented at the Ldv Forum.

Howe, J. (2006). The rise of crowdsourcing. *Wired Magazine, 14*(6), 1-4.

Howe, J. (2008). *Crowdsourcing: Why the power of the crowd is driving the future of business*. Crown Business.

Huang, C.-L., Chung, C. K., Hui, N., Lin, Y.-C., Seih, Y.-T., Lam, B. C., & Pennebaker, J. et al. (2012). The development of the Chinese linguistic inquiry and word count dictionary. *Chinese Journal of Psychology, 54*(2), 185–201.

Humpherys, S. L., Moffitt, K. C., Burns, M. B., Burgoon, J. K., & Felix, W. F. (2011). Identification of fraudulent financial statements using linguistic credibility analysis. *Decision Support Systems, 50*(3), 585–594. doi:10.1016/j.dss.2010.08.009

Johnson, P. E., Grazioli, S., Jamal, K., & Berryman, R. G. (2001). Detecting deception: Adversarial problem solving in a low base-rate world. *Cognitive Science, 25*(3), 355–392. doi:10.1207/s15516709cog2503_2

Kotsiantis, S. B., Zaharakis, I., & Pintelas, P. (2007). Supervised machine learning: A review of classification techniques. *Emerging Artificial Intelligence Applications in Computer Engineering, 160*, 3-24.

Kurup, A. R., & Sajeel, G. P. (2020). A task recommendation scheme for crowdsourcing based on expertise estimation. *Electronic Commerce Research and Applications, 41*, 100946. doi:10.1016/j.elerap.2020.100946

Leung, G. S. K., Cho, V., & Wu, C. H. (2021). Crowd Workers’ Continued Participation Intention in Crowdsourcing Platforms: An Empirical Study in Compensation-Based Micro-Task Crowdsourcing. *Journal of Global Information Management, 29*(6), 1–28. doi:10.4018/JGIM.20211101.oa13

Li, G., Wang, J., Zheng, Y., & Franklin, M. J. (2016). Crowdsourced Data Management: A Survey. *IEEE Transactions on Knowledge and Data Engineering, 28*(9), 2296–2319. doi:10.1109/TKDE.2016.2535242

Liu, Z., Sakulyeva, T., Mikheev, A., & Stepanova, D. (2021). Management Problems in Global Crowdsourcing. *Journal of Global Information Management, 30*(3), 1–15. doi:10.4018/JGIM.20220701.oa3
Liu, Z. J., Panfilova, E., Mikhaylov, A., & Kurilova, A. (2022). Assessing Stability in the Relationship Between Parties in Crowdfunding and Crowdsourcing Projects During the COVID-19 Crisis. *Journal of Global Information Management, 30*(4), 1–18. doi:10.4018/JGIM.297905

Mahr, D., Rindfleisch, A., & Slotegraaf, R. J. (2015). Enhancing Crowdsourcing Success: The Role of Creative and Deliberate Problem-Solving Styles. *Customer Needs and Solutions, 2*(3), 1–13. doi:10.1007/s40547-015-0038-z

Massanari, A. L. (2012). DIY design: How crowdsourcing sites are challenging traditional graphic design practice. *First Monday, 17*(10). Advance online publication. doi:10.5210/fm.v17i10.4171

McCornack, S. A. (1992). Information manipulation theory. *Communication Monographs, 59*(1), 1–16. doi:10.1080/03637759209376245

McCornack, S. A., Levine, T. R., Solowczuk, K. A., Torres, H. I., & Campbell, D. M. (1992). When the alteration of information is viewed as deception: An empirical test of information manipulation theory. *Communication Monographs, 59*(1), 17–29. doi:10.1080/03637759209376246

Natalicchio, A., Messeni Petruzzelli, A., & Garavelli, A. C. (2014). A literature review on markets for ideas: Emerging characteristics and unanswered questions. *Technovation, 34*(2), 65–76. doi:10.1016/j.technovation.2013.11.005

Newman, M. L., Pennebaker, J. W., Berry, D. S., & Richards, J. M. (2003). Lying words: Depicting deception from linguistic styles. *Personality and Social Psychology Bulletin, 29*(5), 665–675. doi:10.1177/0146167203029005010 PMID:15272998

Qi, G., Hou, L., Chen, J., Liang, Y., & Zhang, Q. (2021). How does user social network improve innovation outcomes on a virtual innovation platform?: Evidence from LEGO ideas platform. *Journal of Global Information Management, 29*(3), 188–211. doi:10.4018/JGIM.2021050108

Siering, M., Koch, J. A., & Deokar, A. V. (2016). Detecting Fraudulent Behavior on Crowdfunding Platforms: The Role of Linguistic and Content-Based Cues in Static and Dynamic Contexts. *Journal of Management Information Systems, 33*(2), 421–455. doi:10.1080/07421222.2016.1205930

Twitchell, D. P., & Fuller, C. M. (2019). Advancing the assessment of automated deception detection systems: Incorporating base rate and cost into system evaluation. *Information Systems Journal, 29*(3), 738–761. doi:10.1111/isj.12231
Wang, J., Li, Y., & Rao, H. R. (2016). Overconfidence in phishing email detection. *Journal of the Association for Information Systems, 17*(11), 1. doi:10.17705/1jais.00442

Wang, L., Jian, T., & Liu, D. (2014). Research on factors influencing the performance of innovation contest based on network community. *Science Research Management, 35*(2), 17–24.

Yanchun, Z., Wei, Z., & Changhai, Y. (2011). Detection of feedback reputation fraud in taobao using social network theory. Paper presented at the 2011 International Joint Conference on Service Sciences. doi:10.1109/IJCSS.2011.44

Yang, Y., Chen, P.-y., & Banker, R. (2011). Winner determination of open innovation contests in online markets. Paper presented at the International Conference on Information Systems, Icis 2011, Shanghai, China.

You, W., Lu, L., Mu, X., & Lv, C. (2011). Reputation inflation detection in a Chinese C2C market. *Electronic Commerce Research and Applications, 10*(5), 510–519. doi:10.1016/j.elerap.2011.06.001

Zahedi, F. M., Abbasi, A., & Chen, Y. (2015). Fake-Website Detection Tools: Identifying Elements that Promote Individuals’ Use and Enhance Their Performance. *Journal of the Association for Information Systems, 16*(6), 448–484. doi:10.17705/1jais.00399

Zhang, D., Zhou, L., Kehoe, J. L., & Kilic, I. Y. (2016). What Online Reviewer Behaviors Really Matter? Effects of Verbal and Nonverbal Behaviors on Detection of Fake Online Reviews. *Journal of Management Information Systems, 33*(2), 456–481. doi:10.1080/07421222.2016.1205907

Zhong, W., & Lin, L. (2015). Optimal Fee Structures of Crowdsourcing Platforms. *Decision Sciences, 47*(5), 820–850.

Zhou, L., Burgoon, J. K., Nunamaker, J. F., & Twitchell, D. (2004a). Automating Linguistics-Based Cues for Detecting Deception in Text-Based Asynchronous Computer-Mediated Communications. *Group Decision and Negotiation, 13*(1), 81–106. doi:10.1023/B:GRUP.0000011944.62889.6f

Zhou, L., Burgoon, J. K., Twitchell, D. P., Qin, T., & Nunamaker, J. F. Jr. (2004b). A comparison of classification methods for predicting deception in computer-mediated communication. *Journal of Management Information Systems, 20*(4), 139–166. doi:10.1080/07421222.2004.11045779

Zhou, L., & Zhang, D. (2004). Can online behavior unveil deceivers? An exploratory investigation of deception in instant messaging. Paper presented at the 37th Annual Hawaii International Conference on System Sciences, Hiciss 2004, Hawaii.

Zhou, L., & Zhang, D. (2008). Following linguistic footprints: Automatic deception detection in online communication. *Communications of the ACM, 51*(9), 119–122. doi:10.1145/1378727.1389972

Zuckerman, M., DePaulo, B. M., & Rosenthal, R. (1981). Verbal and nonverbal communication of deception. *Advances in Experimental Social Psychology, 14*(1), 1–59.

Zuckerman & Miron. (1981). Verbal and nonverbal communication of deception. *Advances in Experimental Social Psychology, 14*, 1-59.

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