IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received May 6, 2019, accepted May 30, 2019, date of publication June 10, 2019, date of current version June 27, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2922035

Multi-Level Two-Sided Rating Protocol Design for Service Exchange Contest Dilemma in Crowdsensing

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This work was supported in part by the National Natural Science Foundation of China under Grant 61872323, Grant 61751303, Grant 61672468, and Grant 61602418, in part by the Social Development Project of Zhejiang Provincial Public Technology Research under Grant 2017C33054, in part by the Zhejiang Provincial Natural Science Foundation of China under Grant LD19A010001 and Grant LQ19F030010, and in part by the MOE (Ministry of Education in China) Project of Humanities and Social Science under Grant 19YJCZH056.

ABSTRACT Strategic users in a service exchange application of crowdsensing are apt to exhibit malicious behaviors such as greed, free-ride, and attack, resulting in the phenomenon that no user is willing to serve others and low social utility is obtained in myopic equilibrium, which is considered as a service exchange contest dilemma. To address this issue, we propose a game-theoretic framework of multi-level two-sided rating protocol using all-pay contests to balance service request and service provision between users, in which a user is tagged with a multi-level rating to represent her social status, and she is encouraged to take the initiative to be a server and provide high-quality services to increase her rating. The two-sided rating update rule updates the ratings of both service requesters and service providers, and thus no one can always get services without providing services. By quantifying necessary and sufficient conditions for a sustainable multi-level two-sided rating protocol, we formulate the problem of selecting the optimal design parameters to maximize the social utility among all sustainable multi-level two-sided rating protocols, and design a low-complexity algorithm to select optimal design parameters via a two-stage procedure in an alternate manner. Finally, the extensive evaluation results demonstrate how intrinsic parameters impact on recommended strategies, design parameters, as well as the performance gain of the proposed rating protocol.

INDEX TERMS All-pay contests, crowdsensing, game theory, incentive mechanism, rating protocol, service exchange.

I. INTRODUCTION

Crowdsensing has evolved as a compelling data-gathering and problem-solving paradigm by leveraging human intelligence and soliciting contributions from a large group of undefined people [1], [2]. With the rise and prevalence of crowdsensing, a new medium called service exchange application was catalyzed, where each user was willing to provide her service in order to receive in exchange the service of someone else. Numerous platforms of service exchange, such as Amazon Mechanical Turk [3], Peer-to-peer (P2P) [4], IoT-Cloud (IoT) [5], [6], Sensor-Cloud System (SCS) [7], [8], Yahoo! Answers [9], and CSDN [10], etc., have been widely and successfully developed in a broad range of domains. The interaction process in a service exchange application generally can be modeled as an asymmetric three-stage sequential game using all-pay contests. As shown in Figure 1, a typical transaction in a service exchange of crowdsensing takes the following stages: (i) A user chooses her role and selects to be either a client or a server. A client can publicize a task to a crowdsensing platform with its associated reward, and two servers randomly matched by the platform

The associate editor coordinating the review of this manuscript and approving it for publication was Xuxun Liu.

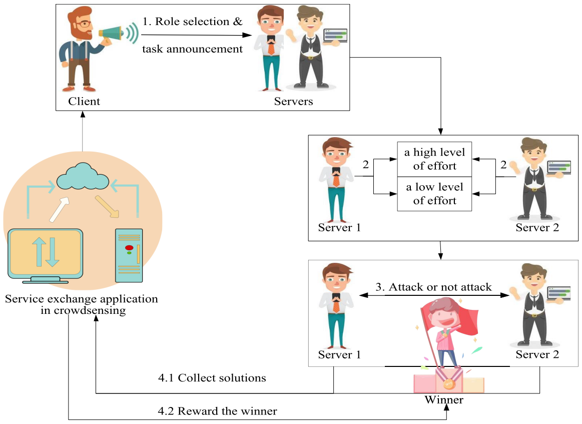

FIGURE 1. A general service exchange application in crowdsensing.

compete with each other to obtain a better solution. (*ii*) Each server chooses to devote a high level of effort or a low level of effort for her participating task. (*iii*) A server has the option of attacking or not attacking her opponent depending on whether the attack allows her to get ahead. (*iv*) After collecting solutions from servers, the platform selects a subset of servers as the winners and pays them the promised reward.

The success of service exchange applications often depends on the active participation of a large number of users and high quality of services contributed by them. However, providing services may not have a direct and immediate benefit for a user to be a server, and devoting a high-level effort often consumes a high cost in terms of time, resource, effort, etc. Under such a circumstance, strategic users in the first stage are more apt to seek services from others as a client rather than as a server (i.e., greed). In the second stage, servers find in their self-interest to devote a low-level effort to provide the requested service to the client (i.e., free-ride). While in the third stage, attacking is the normal regardless of any choice of intrinsic parameters (i.e., attack). These malicious behaviors result in a situation in which no user has the willingness to cooperate with each other and low social utility is obtained in myopic equilibrium. Such a situation is considered as a service exchange contest dilemma. Hence, efficient incentive mechanisms are needed to compel strategic users to contribute good behaviors in crowdsensing tasks.

In the literature, a variety of research efforts have been devoted to designing incentive mechanisms to incentivize users to contribute good behaviors in crowdsensing [11]–[15]. However, there exist five major reasons that prevent these works from being readily extended to deal with the service exchange contest dilemma in crowdsensing: (*i*) A user has the freedom to choose to be either a client (i.e., service requester) or a server (i.e., service provider), and thus it is necessary to balance the service request and service provision [27]. (*ii*) Although a rating protocol with two-level rating is simple to be designed, it often requires a multi-level one to overcome the inefficiency of the socially undesirable equilibrium [19]. (*iii*) Competitions exist not only among servers, but also between servers and clients, and hence, incentive mechanisms not only need to provide sufficient incentives to compel servers to devote high-level effort, but also to avoid malicious competition among them [26], [29]. (*iv*) Users in a crowdsensing platform are not sufficiently patient, especially when those users with bad ratings attempt to leave and rejoin the application as new members to avoid punishments (i.e., whitewashing) [19]. (*v*) In the presence of imperfect monitoring, individuals' rating labels may be inaccurate, which will impact on rating protocol design, as well as social welfare loss [32]. Therefore, it is of great importance to design satisfactory incentive mechanisms by taking the above features into consideration.

In this paper, we aim to develop a game-theoretic design of incentive mechanism to address the service exchange contest dilemma. The main topic of this paper is to design a multi-level two-sided rating-protocol, where *multi-level* means that the rating label used in this paper is discrete multivariate rather than simply binary, and *two-sided* means that the update of rating is applied on both the clients and the servers matched in the service exchange contest game. To the best of our knowledge, few prior works have investigated multi-level two-sided rating protocols based incentive mechanisms with the aim of maximizing the social utility in crowdsensing.

A. MAIN CONTRIBUTIONS

The main contributions of this paper are summarized as follows:

- We model the interaction process in service exchange applications using all-pay contests as an asymmetric sequential game consists of three-stage. Equilibrium analysis results show that strategic users are apt to exhibit malicious behaviors such as greed, free-ride and attack in the first, the second and the third stage, respectively, and thus low social utility is obtained at myopic equilibrium, which is a service exchange contest dilemma.
- We propose a game-theoretic framework of multi-level two-sided rating protocol to stimulate users to cooperate with each other. A user is tagged with a multi-level rating label to represent her social status, and she is encouraged to take the initiative to be a server and provide high-quality services to increase her rating. The two-sided rating update rule updates the ratings of both service requesters and service providers, and thus no one can always get services without providing services.
- By quantifying necessary and sufficient conditions of a sustainable multi-level two-sided rating protocol, we formulate the problem of selecting the optimal design parameters to maximize the social utility among all sustainable multi-level two-sided rating protocols, and design a low-complexity algorithm to select optimal design parameters via a two-stage procedure in an alternate manner.
- Extensive evaluation results demonstrate how intrinsic parameters impact on recommended strategies, design

parameters, as well as the performance gain of our proposed multi-level two-sided rating protocol.

B. RELATED WORK

In the literature, there exist many popular types of incentive mechanisms, such as pricing [16]–[18] and reputation [5], [7], [20]. Incentive mechanisms based on pricing incentivize users to cooperate with each other relying on monetary or matching rewards in the form of micropayments [21], [22]. In some sense, the pricing scheme is the easiest and most effective way to promote cooperation between users. The reputation-based incentive mechanisms, on the other hand, use users' reputation (similar concepts include credit, trust, rank, etc.) as a summary record of a user to indicate their social status according to their historical behaviors in a crowdsensing system, and hence a user with high/low reputation will be rewarded/punished by other users in the system who have not had past interactions with her [23].

Although both of the pricing and the reputation schemes have a potential to form a basis for successful incentive mechanisms for service exchange in crowdsensing, neither of them being used separately may be efficient in a service exchange contest in crowdsensing, in which users are part of a community and repeatedly interact. This is because users' behaviors are influenced by incurred costs and designed payment, as well as their long-term utilities, which cannot be solely determined by a pricing scheme [29]. Moreover, if an inefficient pricing-based incentive mechanism is applied, "free-riding" happens when rewards are paid before a task starts, a server always has the incentive to take the reward but refuse to devote efforts, whereas if rewards are paid after the task is completed, "false-reporting" arises since the client has the incentive to lower or refuse the reward to servers by lying about the outcome of the task [24]. Besides, users choose to crowdsource and devise solutions in exchange for payment, increasing users' reputation without differential payment cannot decrease their malicious behaviors [19].

Recently, a considerable amount of efforts have been devoted using game theory to mathematically analyze how to maximize the social welfare while enforcing cooperation among users under a designed incentive mechanism [30], [31]. One of the most successful employed incentive is based on rating schemes, which was originally proposed by Kandori [25]. In a rating-based incentive mechanism, each user is assigned with a rating label which will go up (resp. come down) when the user complies with (resp. deviate from) the social norm [27], [28]. To implement incentive mechanisms in crowdsensing, it is very important to share as little as possible but enough amount of information about historical interactions in a crowdsensing platform. The use of rating labels as a summary record of a user requires significantly less amount of information being maintained. Hence, the rating based incentive mechanism has a potential to form a basis for successful incentive mechanisms in service exchange contest in a crowdsensing platform.

In our previous works [29], a rating protocol integrating the pricing and the reputation schemes was proposed to address the crowdsourcing contest dilemma. However, it only stood at the server's point view, and explored the strategies of servers aiming to maximize their utilities on all tasks and provide servers sufficient incentives of contributing good behaviors in order to sustain high-performance crowdsourcing. As the requesters' utilities are ignored, they may not have sufficient incentive to post tasks via a crowdsourcing platform if they cannot earn enough benefit. In our another previous work [19], the first game-theoretic design of optimal two-sided rating protocol was developed from a different angel, and the role of each user was allowed to be switched in the next transaction. Nevertheless, the rating labels were denoted by a binary set $\{0, 1\}$, i.e., a user's social status is simply described as good or bad. Although the binary rating is simple to be designed, the multi-level rating is closer to the actual situation, and can achieve a more desirable incentive effect. Additionally, the crowdsourcing process was modeled in a uniform random matching manner, that is, in every period a client interacted with a server. Competition among servers was ignored, but they may attack each other to maximize their own utilities. Hence, it is crucial to design a multi-level two-sided rating protocol, and consider competitive relations not only among servers, but also between servers and clients, and hence, rating protocols not only need to provide sufficient incentives to compel servers to devote high-level effort, but also to avoid malicious competition among them.

C. PAPER ORGANIZATION

The remainder of this paper is organized as follows. In Section II, we propose a multi-level two-sided rating protocol to address the service exchange contest dilemma. In Section III, we formulate the problem of selecting the optimal design parameters to maximize the social utility among all sustainable rating protocols. Section IV designs a low-complexity algorithm to select optimal design parameters via a two-stage procedure in an alternate manner. Section V presents evaluation results to demonstrate key features of the proposed rating protocol. Finally, conclusions and future works are discussed in Section IV.

II. SYSTEM MODEL

A. SERVICE EXCHANGE CONTEST DILEMMA GAME

We model the service exchange contest process in crowdsensing as a sequential game consisting of three-stage. In the first stage, a user's strategy is chosen from the set $\{C, S\}$, where C stands for "choosing to be a client", and S stands for "choosing to be a server". In the second stage, the matched two servers have a binary choice from the set $\{H, L\}$, where H stands for "high-level effort", L stands for "low-level effort", while the client has no choice but to wait. In the third stage, servers have the option of attacking or not attacking her opponent, which is denoted by the set of $\{A, N\}$.

There are eight intrinsic parameters in a service exchange contest game, i.e., $b, s, c_1, c_2, d, \mu_1, \mu_2$ and ω. A client posts a task on a crowdsensing platform, she needs to pay a service charge s and one unit reward for the task, and when the task is completed (i.e., a server devotes a high-level effort), she will earn a profit b, otherwise she will get nothing. The costs $c_1 \in (0, 1)$ and $c_2 \in (0, 1)$ are related with the adopted choices H and A in the second stage and the third stage, respectively, while choosing L in the second stage and N in the third stage is free. The damage inflicted by an attack is denoted as $d \in (0, 1)$. Finally, we denote μ_1 and μ_2 as imperfect monitoring factors about severs' strategies in the second stage and the third stage, respectively. Conveniently, Table 1 lists the main notations used in this paper.

TABLE 1. Summary of variables in this paper.

Notations	Physical Meanings
s	charge cost for crowdsource a task as a client
b	service benefit for the client if the service is fulfilled
c_i	cost caused by the $(i+1)_{th}$-stage game for servers
d	damage inflicted by attack from the server
μ_i	probability that errors occur in the $(i+1)_{th}$-stage game
ω	discount factor to denote servers' patience
$\mathcal{P}$	rating protocol
θ, Θ	rating label, set of rating labels
σ	social strategy
π	recommended strategy
τ	rating update rule
$\mathcal{K}$	size of the set of rating labels
κ	threshold of the selected rating label
$\eta_{\mathcal{P}}(\theta)$	stationary distribution of rating labels
v,v^{∞}	expected one-period, lone-term utility of a user
$u_{\mathcal{P}}$	the social utility

In the all-pay contests model, the server with a higher productivity and choosing H in the second stage will be selected as the winner. The winner will take all the reward, while the loser receive nothing. Of course, if both of the two servers choose H and their productivities are the same, the total reward will be divided equally between them. As the reward of a task is given to the platform ex-ante and the platform won't return the reward to the client even both servers devoted low-level efforts, and thus the client has no incentive to intentionally provide false reports. We call such a payment scheme as ''winner takes all based on service quality''.

According to the payment scheme, servers choosing L in the second-stage game leads to zero or negative utility, (H, H) is a unique strategy equilibrium in the second stage. The pay-off matrix of servers for the third-stage game under the strategy (H, H) is first computed and depicted in Table 4, where the expected number of attacking is 1. Then we turn back to compute the expected utilities of servers in the second-stage game when both servers choose their strategies in the third-stage before knowing their productivities. Finally, we derive the expected pay-off matrices of users in the first-stage game, which are depicted in Table 2. Let λ be the rate that a user chooses to be a client, and then the unique mixed equilibrium is possessed if and only if $\lambda = 1 - (\mathcal{X} + \sqrt{(\mathcal{X}+s)^2 + \mathcal{Y}s})/(2\mathcal{X} + s + \mathcal{Y})$ (here, we set $\mathcal{X} = \frac{1}{2} - c_1/2 - c_2\ d + (c_2\ d^2)/2$ and $\mathcal{Y} = 2b - s - 1$). When $\lambda = \frac{1}{3}$, service request and service provision will be balanced. The detailed computation process for Table 2 is shown in Appendix A.

TABLE 2. The expected pay-off matrices for the first-stage.

user3: C

user1 \ user2	C	S
C	$-s, -s, -s$	$-s, 0, -s$
S	$0, -s, -s$	$\mathcal{X}, \mathcal{X}, \mathcal{Y}$

user3: S

user1 \ user2	C	S
C	$-s, -s, 0$	$\mathcal{Y}, \mathcal{X}, \mathcal{X}$
S	$\mathcal{X}, \mathcal{X}, \mathcal{Y}$	$0, 0, 0$

Through the equilibrium analysis of the game model, we found that the expected number of attacks is 1 in the third stage for any choice of intrinsic parameters. Moreover, greed in the first stage and free-ride in the second stage resulting in no user willing to cooperate with each other and low social utility is obtained in myopic equilibrium, which is considered as a service exchange contest dilemma.

B. MULTI-LEVEL TWO-SIDED RATING PROTOCOLS

In order to balance service request and service provision, and incentivize a user to devote a high level of effort when providing services as a server, we design a game-theoretic multi-level two-sided rating protocol that consists of a recommended strategy and a two-sided rating update rule. A formal definition of such a rating protocol is given as follows:

Definition 1: A multi-level two-sided rating protocol $\mathcal{P}$ is represented as a 5-tuple $(\theta, \sigma, \rho, \pi, \tau)$: a rating label θ, a social strategy σ, a client/server ratio ρ, a recommended strategy π, and a two-sided rating update rule τ.

- $\theta \in \Theta$ represents the rating label for a user, where $\Theta = \{0, \cdots, \mathcal{K}\}$ is the set of multi-level rating labels, 0 and $\mathcal{K}$ are the minimum and the maximum rating labels, respectively.
- $\sigma \in \mathcal{A}$ denotes the social strategies adopted by a user, where $\mathcal{A} = \{\{C, S\} \times \{H, L\} \times \{A, N\}\}$, $\sigma_C = \{C\}$ and $\sigma_S = \{\{S\} \times \{H, L\} \times \{A, N\}\}$ denotes the social strategies can be adopted by a client and a server, respectively.
- $\rho : \Theta \to R^+$ is the proportion of the a user with rating θ who chooses to be a client and a server.
- $\pi : \Theta \times \Theta \to \mathcal{A}$ defines the recommended strategy $\sigma \in \mathcal{A}$ which a server should adopt

$$\pi(\theta_S, \theta_C) = HN, \quad \text{if } \theta_C \geq \kappa \tag{1}$$

where κ is the selected threshold of rating label.
- τ updates the rating labels of a server and a client to θ'_S and θ'_C based on servers' adopted strategies σ_S, current ratings θ_S and θ_C, the recommended strategy $\pi(\theta_S, \theta_C)$, as well as the ratio ρ according to the following

conditional distribution:

$$Pr[(\theta_S', \theta_C')|(\theta_S, \theta_C, \sigma_S, \rho)] = \begin{cases} \alpha, & \text{if } \theta_S' = \min\{\theta_S+1, \mathcal{K}\},\ \theta_S \geq \kappa, \\ & \text{and } \sigma_S = HN \\ 1-\alpha, & \text{if } \theta_S' = \theta_S - 1,\ \theta_S > \kappa, \\ & \text{and } \sigma_S = HN;\ \text{or} \\ & \text{if } \theta_S' = 0,\ \theta_S = \kappa, \\ & \text{and } \sigma_S = HN \\ 1-\beta, & \text{if } \theta_S' = \min\{\theta_S+1, K\},\ \theta_S \geq \kappa, \\ & \text{and } \sigma_S \neq HN \\ \beta, & \text{if } \theta_S' = \theta_S - 1, \theta_S > \kappa, \\ & \text{and } \sigma_S \neq HN;\ \text{or} \\ & \text{if} \theta_S' = 0,\ \theta_S = \kappa, \\ & \text{and } \sigma_S \neq HN \\ \gamma, & \text{if } \theta_C' = \min\{\theta_C+1, \mathcal{K}\}, \theta_C \geq \kappa, \\ & \text{and } \rho \leq \frac{1}{2} \\ 1-\gamma, & \text{if } \theta_C' = \theta_C - 1,\ \theta_C > \kappa, \\ & \text{and } \rho \leq \frac{1}{2};\ \text{or} \\ & \text{if } \theta_C' = 0,\ \theta_C = \kappa, \\ & \text{and } \rho \leq \frac{1}{2} \\ 1-\delta, & \text{if } \theta_C' = \min\{\theta_C+1, \mathcal{K}\},\ \theta_C \geq \kappa, \\ & \text{and } \rho > \frac{1}{2} \\ \delta, & \text{if } \theta_C' = \theta_C - 1,\ \theta_C > \kappa, \\ & \text{and } \rho > \frac{1}{2};\ \text{or} \\ & \text{if } \theta_C' = 0,\ \theta_C = \kappa, \\ & \text{and } \rho > \frac{1}{2} \\ 1, & \text{if } \theta_S' = \theta_S + 1,\ \text{and } \theta_S < \kappa;\ \text{or} \\ & \text{if } \theta_C' = \theta_C + 1,\ \text{and } \theta_C < \kappa \end{cases} \quad (2)$$

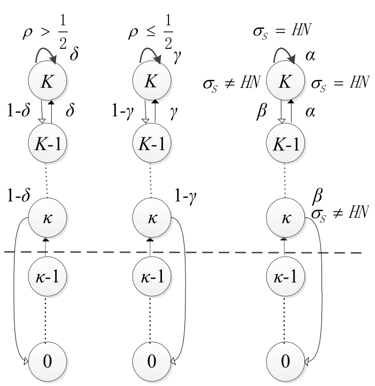

FIGURE 2. Schematic representation of a rating protocol $\mathcal{P}$.

Remark: A schematic representation of a proposed two-sided rating protocol $\mathcal{P}$ according to Definition 1 is provided in Figure 2. Given a rating protocol $\mathcal{P}$, the rating of a user is denoted by $\theta \in \Theta$ and updated based on her adopted strategy as well as her current rating label. According to the rating update rule, if a user's rating is lower than the threshold κ, she will be isolated by the platform, i.e., she will be forbidden to choose to be either a client or a server. And the isolated user's rating will be increased by 1 with probability 1 in the next period. As for the non-isolated users with rating $\theta \geq \kappa$, a server's rating θ_S will be increased by 1 while not exceeding $\mathcal{K}$ with probability α, and will be decreased by 1 with probability $1-\alpha$ after a period, if the server follows the recommended strategy π; otherwise, it will be increased by 1 while not exceeding $\mathcal{K}$ with probability $1-\beta$ and dropped by 1 with probability β. A client's rating θ_C will be increased by 1 while not exceeding $\mathcal{K}$ with probability γ and will be decreased by 1 with probability $1-\gamma$, if her ratio $\rho \leq \frac{1}{2}$; otherwise, it will be increased by 1 while not exceeding $\mathcal{K}$ with probability $1-\delta$ and will be dropped by 1 with probability δ. In particular, if a user's current rating is $\theta = \kappa$, it will be decreased to 0 in order to achieve punishment for her excessive request for services (i.e., greed) as a client or her malicious behaviors (i.e., free-ride and attack) as a server. Hence, α and β can be referred to as the strength of reward and punishment imposed on severs when they follow or deviate from the recommended strategy π, respectively. While γ and δ can be referred to as the strength of reward and punishment imposed on clients when they contribute good behaviors and ask for services from others too much, respectively.

C. UTILITIES

We check the incentive for a server when her opponent follows the recommended strategy under the law of majority wins. The pay-off matrix showing the utility of each non-isolated user (i.e., $\theta \geq \kappa$) in one transaction under perfect monitoring is given in Table 3. Without loss of generality, we assume that a server adopting strategy $\sigma_S = LA$ wins when her opponent takes strategy $\sigma_S = HN$. In such a scenario, no one could take the reward according to the "winner takes all based service quality" scheme. Then we derive the utility array V_S and V_C from Table 3, and A, B, C and D denote the imperfect monitoring factors when the server adopts the strategy HN, HA, LN and LA, respectively. For example, the client may report HN with probability $(1-\mu_1)(1-\mu_2)$, HA with probability $(1-\mu_1)\mu_2$, LN with probability $\mu_1(1-\mu_2)$ and LA with probability $\mu_1\mu_2$ given the server's actual strategy HN. As the client has no choice but to wait in the second stage and the third stage, for the sake of simplicity, the strategy adopted by servers such as $\sigma_S = HN$ is abbreviated as HN.

The expected one-period utility of a sever v_S according to her adopted strategies under the imperfect monitoring factors μ_1 and μ_2 can be derived as follows:

$$\begin{cases} v_S(HN) = A \times V_S \times A^T \\ v_S(HA) = B \times V_S \times A^T \\ v_S(LN) = C \times V_S \times A^T \\ v_S(LA) = D \times V_S \times A^T \end{cases} \quad (3)$$

TABLE 3. The utility matrix of one period under perfect monitoring.

		server 1			
		HN	HA	LN	LA
server 2	HN	$\frac{1}{2}-c_1, \frac{1}{2}-c_1,$ $2b-s-1$	$-c_1-d, 1-c_1-c_2,$ $2b-s-1$	$1-c_1, 0,$ $b-s-1$	$-c_1-d, -c_2,$ $-s-1$
	HA	$1-c_1-c_2, -c_1-d,$ $2b-s-1$	$\frac{1}{2}-c_1-c_2-d, \frac{1}{2}-c_1-c_2-d,$ $2b-s-1$	$1-c_1-c_2, -d,$ $b-s-1$	$1-c_1-c_2-d, -c_2-d,$ $b-s-1$
	LN	$0, 1-c_1,$ $b-s-1$	$-d, 1-c_1-c_2,$ $b-s-1$	$0, 0,$ $-s-1$	$-d, -c_2,$ $-s-1$
	LA	$-c_2, -c_1-d,$ $-s-1$	$-c_2-d, 1-c_1-c_2-d,$ $b-s-1$	$-c_2, -d,$ $-s-1$	$-c_2-d, -c_2-d,$ $-s-1$
		client			

while a client's expected one-period utility v_C associated with servers' strategies under the imperfect monitoring factors μ_1 and μ_2 can be derived as follows:

$$\begin{cases} v_C(HN) = A \times V_C \times A^T \\ v_C(HA) = B \times V_C \times A^T \\ v_C(LN) = C \times V_C \times A^T \\ v_C(LA) = D \times V_C \times A^T \end{cases} \quad (4)$$

where

$$V_S = \begin{bmatrix} \frac{1}{2}-c_1 & -c_1-d & 1-c_1 & -c_1-d \\ 1-c_1-c_2 & \frac{1}{2}-c_1-c_2-d & 1-c_1-c_2 & 1-c_1-c_2 \\ 0 & -d & 0 & -d \\ -c_2 & -c_2-d & -c_2 & -c_2-d \end{bmatrix} \quad (5)$$

$$V_C = \begin{bmatrix} 2b-s-1 & 2b-s-1 & b-s-1 & -s-1 \\ 2b-s-1 & 2b-s-1 & b-s-1 & b-s-1 \\ b-s-1 & b-s-1 & -s-1 & -s-1 \\ -s-1 & b-s-1 & -s-1 & -s-1 \end{bmatrix} \quad (6)$$

and

$$\begin{aligned} A &= [(1-\mu_1)(1-\mu_2), (1-\mu_1)\mu_2, \mu_1(1-\mu_2), \mu_1\mu_2] \\ B &= [(1-\mu_1)\mu_2, (1-\mu_1)(1-\mu_2), \mu_1\mu_2, \mu_1(1-\mu_2)] \\ C &= [\mu_1(1-\mu_2), \mu_1\mu_2, (1-\mu_1)(1-\mu_2), (1-\mu_1)\mu_2] \\ D &= [\mu_1\mu_2, \mu_1(1-\mu_2), (1-\mu_1)\mu_2, (1-\mu_1)(1-\mu_2)] \end{aligned} \quad (7)$$

Obviously, the expected one-period utility of a client depends on the strategies adopted by her matched servers, which has its maximum at $\sigma_S = HN$ or $\sigma_S = HA$. Through simple calculations, the following inequalities $v_S(HA) > v_S(HN)$, $v_S(HA) > v_S(LN)$, and $v_S(HA) > v_S(LA)$ hold. Hence, in the remainder of this paper, we just need to check whether a server can gain by a unilateral deviation from the recommended strategy and adopt strategy $\sigma_S = HA$. What's more, users are more inclined to choose to be a client as the expected one-period utility of a client is no less than the server's.

Given a multi-level two-side rating protocol $\mathcal{P}$, the expected one-period utility of a θ-user with a chosen rate λ and the strategy σ before she is matched can be expressed as

$$v_\lambda(\theta|\sigma) = \begin{cases} 0, & \text{if } \theta < \kappa \\ \lambda v_C(HN) + (1-\lambda)v_S(HN), & \text{if } \theta \geq \kappa \text{ and } \sigma_S = HN \\ \lambda v_C(HA) + (1-\lambda)v_S(HA), & \text{if } \theta \geq \kappa \text{ and } \sigma_S = HA \end{cases} \quad (8)$$

Let $p_{\mathcal{P}}(\theta'|\theta, \sigma)$ be the transition probability that a θ-user becomes a θ'-user in the next period when her adopted strategy is σ, and her chosen rate is λ under protocol $\mathcal{P}$, which is given by

$$p_{\mathcal{P}}(\theta'|\theta, HN) = \begin{cases} \lambda\gamma + (1-\lambda)\big[\alpha(1-\mu_1)(1-\mu_2) + (1-\beta)(\mu_1 + \mu_2 - \mu_1\mu_2)\big], & \text{if } \theta' = \min\{\theta+1, \mathcal{K}\}, \theta \geq \kappa \\ \lambda(1-\gamma) + (1-\lambda)\big[(1-\alpha)(1-\mu_1)(1-\mu_2) + \beta(\mu_1+\mu_2-\mu_1\mu_2)\big], & \text{if } \theta' = 0 \text{ and } \theta = \kappa; \text{ or} \\ & \text{if } \theta' = \theta - 1 \text{ and } \theta \geq \kappa + 1 \\ 1, & \text{if } \theta' = \theta + 1 \text{ and } \theta < \kappa \end{cases} \quad (9)$$

$$p_{\mathcal{P}}(\theta'|\theta, HA) = \begin{cases} \lambda\gamma + (1-\lambda)\big[\alpha(\mu_2 - \mu_1\mu_2) + (1-\beta)(1-\mu_2 + \mu_1\mu_2)\big], & \text{if } \theta' = \min\{\theta+1, \mathcal{K}\} \text{ and } \theta \geq \kappa \\ \lambda(1-\gamma) + (1-\lambda)\big[(1-\alpha)(\mu_2-\mu_1\mu_2) + \beta(1-\mu_2+\mu_1\mu_2)\big], & \text{if } \theta' = 0 \text{ and } \theta = \kappa; \text{ or} \\ & \text{if } \theta' = \theta - 1 \text{ and } \theta \geq \kappa + 1 \\ 1, & \text{if } \theta' = \theta + 1 \text{ and } \theta < \kappa \end{cases} \quad (10)$$

The expected long-term utility of a θ-user is the infinite horizon discounted sum of her expected one-period utility with her expected future payoff multiplied by a common discount factor ω, which can be expressed as:

$$v_\lambda^\infty(\theta|\sigma) = \begin{cases} v_\lambda(\theta|\sigma) + \omega \sum_{\theta' \in \Theta} p_\lambda(\theta'|\theta, \sigma) v_\lambda^\infty(\theta'|\sigma), & \theta \geq \kappa \\ \omega v_\lambda^\infty(\theta+1|\sigma), & 0 \leq \theta < \kappa \end{cases} \quad (11)$$

Proposition 1: Given a multi-level two-sided rating protocol $\mathcal{P}$, the marginal long-term utility of a user is denoted as

$\Delta v_{\lambda}^{\infty}(\theta) \triangleq v_{\lambda}^{\infty}(\theta+1) - v_{\lambda}^{\infty}(\theta)$, which satisfies the following properties:

(i) $\Delta v_{\lambda}^{\infty}(\theta|HN) > 0, \forall\theta \in [0, \mathcal{K})$;

(ii) $\Delta v_{\lambda}^{\infty}(\theta|HN) > \Delta v_{\lambda}^{\infty}(\theta+1|HN), \forall\theta \in [\kappa, \mathcal{K})$.

Proof: See Appendix B. ■

From Proposition 1, it is easy to find that the expected long-term utility of a user monotonically increases with her rating label, but the growth rate will gradually decrease. In addition, the marginal long-term utilities $\Delta v_{\lambda}^{\infty}(\theta)$ can be referred as incentives enforced on users who comply with the social norm, and thus users with rating $\theta = \mathcal{K}$ have the smallest incentives.

III. PROBLEM FORMULATION

A. SUSTAINABLE MULTI-LEVEL TWO-SIDED RATING PROTOCOLS

Rational and selfish users always adjust their strategies to maximize their own utilities, and they have the incentive to comply with the social norm under a given multi-level two-sided rating protocol $\mathcal{P}$, if and only if they cannot benefit in terms of their long-term utilities upon deviations. Such a rating protocol is called a sustainable multi-level two-sided rating protocol, and its formal definition is given as follows:

Definition 2: (Sustainable Multi-level Two-sided Rating Protocols) A multi-level two-sided rating protocol $\mathcal{P}$ is sustainable if and only if $v_{\lambda=\frac{1}{3}}^{\infty}(\theta|HN) \geq v_{\lambda'}^{\infty}(\theta|\sigma')$ for all $\lambda' \neq \frac{1}{3}$, $\sigma' \neq HN$, and $\theta \in [0, \mathcal{K}]$.

The service exchange contest process can be formulated as a Markov decision process under a multi-level two-sided rating protocol [29], where the state is the user's rating label θ, and the action is her social strategy σ. We compare the long-term utilities of whether users follow the recommended strategy π, in order to check whether a multi-level two-sided rating protocol is sustainable in the second stage and the third stage. As shown in Lemma 1, we derive the one-shot deviation principle.

Lemma 1: (One-Shot Deviation Principle) A multi-level two-sided rating protocol $\mathcal{P}$ satisfies the one-shot deviation principle if and only if

$$\Delta v_{\lambda=\frac{1}{3}}^{\infty}(\mathcal{K}-1|HN) \geq \frac{\frac{1}{2}\left[v_C(HA) - v_C(HN)\right] + v_S(HA) - v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)(\alpha+\beta-1)} \tag{12}$$

Proof: See Appendix C. ■

Under the service exchange contest dilemma, the optimal strategy of a user in the first stage is to choose to be a client and hope that her matched servers will follow the recommended strategy π. However, the social utility is maximized if and only if the ratio of clients to servers is balanced to 1:2 (i.e., $\lambda=\frac{1}{3}$), which is named as the principle of fairness [19]. Then we derive a necessary and sufficient condition for a multi-level two-sided rating protocol to be sustainable in the first stage, as shown in Lemma 2.

Lemma 2: (The Principle of Fairness) A multi-level two-sided rating protocol $\mathcal{P}$ satisfies the principle of fairness if and only if

$$\Delta v_{\lambda=\frac{1}{3}}^{\infty}(\mathcal{K}-1|HN) \geq \frac{\frac{2}{3}[v_C(HN) - v_S(HN)]}{\omega\left\{\frac{1}{3}\gamma+\frac{2}{3}[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)]+\delta-1\right\}} \tag{13}$$

Proof: See Appendix D. ■

By integrating the one-shot deviation principle and the principle of fairness, we can derive the following necessary and sufficient conditions for a multi-level two-sided rating protocol to be sustainable.

Theorem 1: A multi-level two-sided rating protocol $\mathcal{P}$ is sustainable if and only if

$$\Delta v_{\lambda=\frac{1}{3}}^{\infty}(\mathcal{K}-1|HN) \geq \max\left\{\frac{\frac{1}{2}\left[v_C(HA) - v_C(HN)\right] + v_S(HA) - v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)(\alpha+\beta-1)}, \frac{\frac{2}{3}[v_C(HN)-v_S(HN)]}{\omega\left\{\frac{1}{3}\gamma+\frac{2}{3}\left[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\right]+\delta-1\right\}}\right\} \tag{14}$$

Proof: This proof can be directly obtained from Lemma 1 and 2, and is omitted here. ■

B. STATIONARY RATING DISTRIBUTION

Given a sustainable multi-level two-sided rating protocol $\mathcal{P}$, suppose that each user is a "compliant user", who always follows the recommended strategy π and keeps her own $\rho \leq \frac{1}{2}$ in any period. Then the transition probabilities $p_{\mathcal{P}}(\theta'|\theta, HN)$ in Eq.(9) can be rewritten as follows

$$p_{\mathcal{P}}(\theta'|\theta, HN) = \begin{cases} \mathcal{M}, & \text{if } \theta \geq \kappa \text{ and } \theta' = \min\{\theta+1, \mathcal{K}\} \\ 1-\mathcal{M}, & \text{if } \theta > \kappa+1 \text{ and } \theta' = \theta-1;\ \text{or} \\ & \text{if } \theta = \kappa \text{ and } \theta' = 0 \\ 1, & \text{if } \theta < \kappa \text{ and } \theta' = \theta+1 \end{cases} \tag{15}$$

Here we set $\mathcal{M} = \frac{1}{3}\gamma+\frac{2}{3}\left[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\right]$ for simplicity. The stationary distribution $\left\{\eta_{\mathcal{P}}(\theta)\right\}_{\theta=0}^{\mathcal{K}}$ can be derived in the following expressions, the detailed computation process is in Appendix E.

$$\eta_{\mathcal{P}}(\theta) = \begin{cases} \dfrac{1}{\kappa-1+\frac{1}{1-\mathcal{M}}\left\{1+\frac{\mathcal{M}}{1-2\mathcal{M}}\left[1-(\frac{\mathcal{M}}{1-\mathcal{M}})^{\mathcal{K}-\kappa}\right]\right\}}, & \theta \in [0, \kappa-1] \\ \dfrac{1}{1-M}(\frac{\mathcal{M}}{1-\mathcal{M}})^{\theta-\kappa}\eta_{\mathcal{P}}(0), & \theta \in [\kappa, \mathcal{K}] \end{cases} \tag{16}$$

It is easy to find that the stationary distribution is independent of the recommended strategy that users should follow, as Eq.(16) is independent of the recommended strategy.

C. OPTIMIZATION PROBLEM WITH CONSTRAINTS

Given a sustainable multi-level two-sided rating protocol $\mathcal{P}$, each user is motivated to take the initiative to serve others as a server and devote a high level of effort. We aim to design such a protocol to maximize the expected one-period utility of a user, which is denoted as the social utility $u_{\mathcal{P}}$ in this paper. The problem of designing a multi-level two-sided rating protocol that maximizes the social utility $u_{\mathcal{P}}$ can be formulated as:

Definition 3: The multi-level two-sided rating protocol design problem can be formulated as follows:

$$\begin{cases} \max u_{\mathcal{P}} \triangleq \sum_{\theta\geq\kappa} \eta_{\mathcal{P}}(\theta)v_{\lambda}(\theta|\sigma) \\ s.t. \Delta v^{\infty}_{\lambda=\frac{1}{3}}(\mathcal{K}-1|HN) \geq \\ \quad \max\left\{\frac{\frac{1}{2}\big[v_C(HA)-v_C(HN)\big]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)(\alpha+\beta-1)}, \right. \\ \quad \left. \frac{\frac{2}{3}\big[v_C(HN)-v_S(HN)\big]}{\omega\Big\{\frac{1}{3}\gamma+\frac{2}{3}\big[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]+\delta-1\Big\}}\right\} \end{cases} \tag{17}$$

IV. OPTIMAL DESIGN OF MULTI-LEVEL TWO-SIDED RATING PROTOCOLS

In this section, we investigate the problem of designing an optimal multi-level two-sided rating protocol $u_{\mathcal{P}}$ that maximizes the social utility $u_{\mathcal{P}} \triangleq \sum_{\theta\geq\kappa} \eta_{\mathcal{P}}(\theta)v_{\lambda}(\theta|\sigma)$, i.e., selecting the optimal design parameters (α^*, β^*, γ^*, δ^*, κ^*, $\mathcal{K}^*$) to meet the constraints in Eq. (17), and maximize the social utility $u_{\mathcal{P}}$.

A. EXISTENCE OF THE OPTIMAL DESIGN

We first investigate whether there exists a sustainable multi-level two-sided rating protocol, i.e., checking whether there exists a feasible solution for the design problem of Eq.(17).

Theorem 2: A sustainable multi-level two-sided rating protocol $\mathcal{P}$ under the recommended strategy π exists if and only if

$$\omega \in \Big[\max\left\{\frac{\frac{1}{2}\big[v_C(HA)-v_C(HN)\big]+v_S(HA)-v_S(HN)}{(1-\mu_1)(1-2\mu_2)\Delta v^{\infty}_{\lambda=\frac{1}{3}}(\mathcal{K}-1|HN)}, \frac{\frac{2}{3}\big[\,v_C(HN)-v_S(HN)\big]}{\big[\frac{1}{3}+\frac{2}{3}(1-\mu_1)(1-\mu_2)\big]\Delta v^{\infty}_{\lambda=\frac{1}{3}}(\mathcal{K}-1|HN)}\right\}, 1\Big) \tag{18}$$

Proof: For the "if" part: By maximizing reward factors and punishment factors, the incentives for users to follow the recommended strategy would be maximized. Substituting $\alpha=\beta=\gamma=\delta=1$ and $\kappa=\mathcal{K}=1$ into Eq.(14), we have

$$\Delta v^{\infty}_{\lambda=\frac{1}{3}}(\mathcal{K}-1|HN)\Big|_{\alpha=\beta=\gamma=\delta=1,\kappa=\mathcal{K}=1} \geq \max\left\{\frac{\frac{1}{2}[v_C(HA)-v_C(HN)]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)}, \frac{\frac{2}{3}[v_C(HN)-v_S(HN)]}{\frac{1}{3}\gamma+\frac{2}{3}(1-\mu_1)(1-\mu_2)}\right\} \tag{19}$$

By solving Eq.(19), the lower bound of ω is obtained. Therefore, if a user has a sufficient patience as shown in Eq.(18), the design problem of Eq.(17) always has a feasible solution.

For the "only if" part: Suppose Eq.(18) hold, it is easy to check whether constraints in the design problem of Eq.(17) are satisfied. And thus, the "only if" part can be proved. ■

B. OPTIMAL VALUES OF THE DESIGN PROBLEM

Under the assumption that Eq.(18) holds, we analyze how these design parameters ($\alpha, \beta, \gamma, \kappa, \mathcal{K}$) impact on the social utility $u_{\mathcal{P}}$, as summarized in Proposition 2.

Proposition 2: Social utility $u_{\mathcal{P}}$ monotonically increases with $\alpha, \gamma, \mathcal{K}$, and $\mathcal{K}-\kappa$, and monotonically decreases with κ and β.

Proof: See Appendix F. ■

We now focus on selecting the largest α, γ and $\mathcal{K}$, and the smallest κ and β such that $\mathcal{K}-\kappa$ is maximized, by supposing that constraints (12) and (13) are satisfied. With this idea, as shown in Theorem 3, we first give the optimal value of α, γ, δ for any sustainable multi-level two-sided rating protocols.

Theorem 3: Given a sustainable multi-level two-sided rating protocol $\mathcal{P}$, $\alpha^* = \gamma^* = \delta^* = 1$ is always the optimal solutions of Eq.(17).

Proof: $u_{\mathcal{P}}$ monotonically increases with reward factors α and γ according to Proposition 2, and they have its maximum values at 1. Furthermore, $u_{\mathcal{P}}$ is not determined by punishment factor δ, we maximize the penalty by setting $\delta = 1$, and the smallest β and κ, and the largest $\mathcal{K}$ can be obtained. Hence, this statement follows. ■

Social utility $u_{\mathcal{P}}$ is proportional to the non-isolated users' distribution $\sum_{\theta\geq\kappa} \eta_{\mathcal{P}}(\theta)$, then we transform the problem of maximizing $u_{\mathcal{P}}$ into the problem of minimizing $\sum_{\theta=0}^{\kappa-1} \eta_{\mathcal{P}}(\theta)$ for simplicity. According to the stationary distribution as shown in Eq.(16), we fix $\alpha = \gamma = \delta = 1$ and rewrite the design problem *w.r.t* β, κ and $\mathcal{K}$ in Eq.(17) as follows:

$$\begin{cases} \min\limits_{(\beta,\kappa,\mathcal{K})} \kappa\eta_{\mathcal{P}}(\theta) \\ s.t. \Delta v^{\infty}_{\lambda=\frac{1}{3}}(\mathcal{K}-1|HN) \geq \\ \max\left\{\frac{\frac{1}{2}\big[v_C(HA)-v_C(HN)\big]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)\beta}, \frac{\frac{2}{3}\big[v_C(HN)-v_S(HN)\big]}{\omega\big[1+(\frac{1}{3}-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]}\right\} \end{cases} \tag{20}$$

Given $\alpha^* = \gamma^* = \delta^* = 1$, there are still three unsolved design parameters β, κ and $\mathcal{K}$, We regard $\mathcal{K}$ as a constant, and then calculate the smallest values of β and κ in the remainder of this section. Obviously, Eq.(20) is a non-convex optimization problem, now we design a low-complexity two-stage two-step algorithm to achieve the optimum as shown in Algorithm 1. In stage (i), we first fix $\beta = 1$ and compute the smallest κ (i.e., κ^+) with given Eq.(21), and then giving κ^+,

Algorithm 1 Alternate Optimal Design Parameters β and κ

Input: $b, c_1, c_2, s, d, \mu_1, \mu_2, \omega$ and $\mathcal{K}$.
Output: β^* and κ^*.

1: Initialize $\beta^0 = 1$ and $t = 1$.
2: **repeat**
3: Update $(\kappa^+)^t$ by solving Eq.(21) with given $(\beta^+)^{t-1}$.
4: Update $(\beta^+)^t$ by solving Eq.(22) with given $(\kappa^+)^t$.
5: $t = t + 1$
6: **until** $(obj^{t-1} - obj^t)/obj^t \leq \mu_1\mu_2$
7: $obj_1 = \min obj^t((\beta^+)^t, (\kappa^+)^t)$.
8: Set $\kappa^0 = \mathcal{K}$ and $t = 1$.
9: **repeat**
10: Update $(\beta^-)^t$ by solving Eq.(23) with given $(\kappa^-)^{t-1}$.
11: Update $(\kappa^-)^t$ by solving Eq.(24) with given $(\beta^-)^t$.
12: $t = t + 1$
13: **until** $(obj^{t-1} - obj^t)/obj^t \leq \mu_1\mu_2$
14: $obj_2 = \min obj^t((\beta^-)^t, (\kappa^-)^t)$.
15: $(\beta^*, \kappa^*) = \arg\min\{obj_1, obj_2\}$

we compute the smallest β, (denoted as β^+) with given Eq.(22). Stage (ii) is symmetric with stage (i), but we first fix $\kappa = \mathcal{K}$ and then update the smallest β (denoted as β^-) and κ (denoted as κ^-) with given Eq.(23) and Eq.(24), respectively. The above observations are summarized in Definition 4 and Theorem 4.

Definition 4: The variables κ^+, β^+, κ^- and β^- are defined as follows:

(i) Given $\alpha^* = \gamma^* = \delta^* = 1$ and $\beta = 1$, κ^+ is the smallest value such that the following inequality holds

$$\begin{cases} \min \kappa \\ s.t.\ \Delta v^{\infty}_{\substack{\lambda=\frac{1}{3} \\ (\alpha=\gamma=\delta=1,\beta=1)}}(\mathcal{K}-1|HN) \geq \\ \max\left\{\frac{\frac{1}{2}\left[v_C(HA)-v_C(HN)\right]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)},\right. \\ \left.\frac{\frac{2}{3}\left[v_C(HN)-v_S(HN)\right]}{\omega\left[1-\frac{2}{3}(\mu_1+\mu_2-\mu_1\mu_2)\right]}\right\} \end{cases} \tag{21}$$

(ii) Given $\alpha^* = \gamma^* = \delta^* = 1$ and $\kappa = \kappa^+$, β^+ is the smallest value such that the following inequality holds

$$\begin{cases} \min \beta \\ s.t.\ \Delta v^{\infty}_{\substack{\lambda=\frac{1}{3} \\ \alpha=\gamma=\delta=1,\kappa=\kappa^+}}(\mathcal{K}-1|HN) \geq \\ \max\left\{\frac{\frac{1}{2}\left[v_C(HA)-v_C(HN)\right]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)\beta},\right. \\ \left.\frac{\frac{2}{3}\left[v_C(HN)-v_S(HN)\right]}{\omega\left[1-(\frac{1}{3}-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\right]}\right\} \end{cases} \tag{22}$$

(iii) Given $\alpha^* = \gamma^* = \delta^* = 1$ and $\kappa = \mathcal{K}$, β^- is the smallest value such that the following inequality holds

$$\begin{cases} \min \beta \\ s.t.\ \Delta v^{\infty}_{\substack{\lambda=\frac{1}{3} \\ (\alpha=\gamma=\delta=1,\kappa=\mathcal{K})}}(\mathcal{K}-1|HN) \geq \\ \max\left\{\frac{\frac{1}{2}\left[v_C(HA)-v_C(HN)\right]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)\beta},\right. \\ \left.\frac{\frac{2}{3}\left[v_C(HN)-v_S(HN)\right]}{\omega\left[1-(\frac{1}{3}-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\right]}\right\} \end{cases} \tag{23}$$

(iv) Given $\alpha^* = \gamma^* = \delta^* = 1$ and $\beta = \beta^-$, κ^- is the smallest value such that the following inequality holds

$$\begin{cases} \min \kappa \\ s.t.\ \Delta v^{\infty}_{\substack{\lambda=\frac{1}{3} \\ (\alpha=\gamma=\delta=1,\beta=\beta^-)}}(\mathcal{K}-1|HN) \geq \\ \max\left\{\frac{\frac{1}{2}\left[v_C(HA)-v_C(HN)\right]+v_S(HA)-v_S(HN)}{\omega(1-\mu_1)(1-2\mu_2)\beta^-},\right. \\ \left.\frac{\frac{2}{3}\left[v_C(HN)-v_S(HN)\right]}{\omega\left[(1-\frac{1}{3}-\beta^-)(\mu_1+\mu_2-\mu_1\mu_2)\right]}\right\} \end{cases} \tag{24}$$

Theorem 4: Given a multi-level rating protocol $\mathcal{P}$ and $\alpha^* = \gamma^* = \delta^* = 1$, the output of (β^*, κ^*) by Algorithm 1 is an optimal solution to Eq.(20).

Proof: Algorithm 1 consists of two stages, lines 1-7 are the first stage, and the rest of the algorithm (lines 8-14) is the second stage. In stage (i), for a given value of $\mathcal{K}$, we first fix $\beta = 1$ and repeat line 3, 4 and 5 to update $(\kappa^+)^t$ and $(\beta^+)^t$ by solving Eq.(21) and Eq.(21) until the termination condition in line 6 of Algorithm 1 is satisfied. Then we can derive a solution and denote it as (β^i, κ^i), and the local optimal value of Eq.(20) based on stage (i) is denoted by obj_1. Similarly, we can obtain another solution $(\beta^{ii}, \kappa^{ii})$ and the local optimal value obj_2 based on stage (ii). Comparing obj_1 with obj_2, and the minimum value between obj_1 and obj_2 is the global optimum, meanwhile, the optimal design parameters (β^*, κ^*) are obtained.

Assume that there exists another solution (β^x, κ^x) such that $obj(\beta^x, \kappa^x) < \min\{obj_1(\beta^i, \kappa^i), obj_2(\beta^{ii}, \kappa^{ii})\}$. And it is easy to find that $\kappa^{ii} \geq \kappa^i$ and $\beta^i \geq \beta^{ii}$. Assume that $\kappa^x \notin (\kappa^i, \kappa^{ii})$ or $\beta^x \notin (\beta^{ii}, \beta^i)$, which contradicts the termination condition in line 6 of Algorithm 1. This proves that $\kappa^x \in (\kappa^i, \kappa^{ii})$ and $\beta^x \in (\beta^{ii}, \beta^i)$. We now assume that $obj_1(\beta^i, \kappa^i) > obj_2(\beta^{ii}, \kappa^{ii})$, which means that $(\beta^{ii}, \kappa^{ii})$ is a better solution than (β^i, κ^i). According to line 11 of Algorithm 1, $(\kappa^-)^t$ is updated by solving Eq.(23) with given $\beta^x > \beta^{ii}$, and a smaller value of $obj(\beta^x, \kappa^x)$ will be obtained by decreasing β^x to β^{ii}. This proves that there does not exist another better solution (β^x, κ^x). As for the case $obj_1(\beta^i, \kappa^i) < obj_2(\beta^{ii}, \kappa^{ii})$, it can

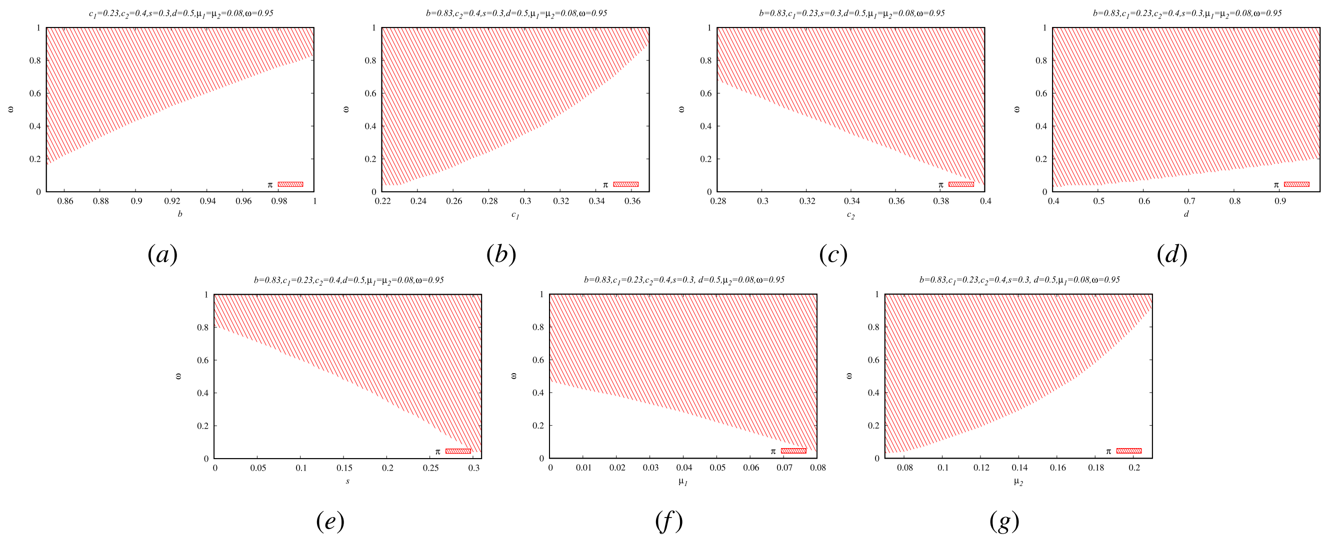

FIGURE 3. Optimal recommended strategy against intrinsic parameters intrinsic parameters (a) b; (b) c_1; (c) c_2; (d) d; (e) s; (f) μ_1; (g) μ_2.

be proved that (β^x, κ^x) is no better than (β^i, κ^i) in a similar way, and it is omitted here.

Therefore, given a value of $\mathcal{K}$, the output of (β^*, κ^*) by Algorithm 1 is an optimal solution to Eq.(20). ■

After that, we can derive the optimal value of the rating size $\mathcal{K}$, which is further formalized in Theorem 5.

Theorem 5: Given a multi-level rating protocol $\mathcal{P}$, $\alpha^* = \gamma^* = \delta^* = 1$, and $\beta = \beta^*, \kappa = \kappa^*$ derived by Algorithm 1, the optimal value of $\mathcal{K}^*$ that maximizes the social utility can be designed as $\widetilde{\mathcal{K}}$, where $\widetilde{\mathcal{K}}$ is the largest value with which the sustainable constraints in Eq.(18) are satisfied.

Proof: According to Proposition 2, it is easy to find that $\widetilde{\mathcal{K}}$ is the largest value such that $\kappa^* \in [1, \widetilde{\mathcal{K}}]$ and $\widetilde{\mathcal{K}} - \kappa^*$ is maximized. And social utility $u_{\mathcal{P}}$ is monotonic increasing with $\mathcal{K}$ and $\mathcal{K} - \kappa$, which gives the conclusion that $\mathcal{K}^* = \widetilde{\mathcal{K}}$. ■

V. SIMULATION RESULTS

In this section, we present simulation results to illustrate key features of the proposed multi-level two-sided rating protocol $\mathcal{P}$ for the service exchange contest dilemma in crowdsensing. First, we show how intrinsic parameters impact on the recommended strategy. Second, we further investigate how design parameters change when intrinsic parameters vary. Finally, we examine the performance gain of the proposed rating protocol against intrinsic parameters.

A. RECOMMENDED STRATEGY AGAINST INTRINSIC PARAMETERS

Figure 3 illustrates how the recommended strategy is impacted by intrinsic parameters: (a) b, (b) c_1, (c) c_2, (d) d, (e) s, (f) μ_1, and (g) μ_2. In Figure 3 (a), when b is sufficiently large, a user with a higher ω has a higher probability to comply with the social norm. This is because users with smaller ω find it enticement to deviate from the principle of fairness as b increases. A similar phenomenon can be found in Figure 3(b) and Figure 3(e), which plot the region of ω and c_1, and the region of ω and s. In Figure 3(c) and Figure 3(d), a larger c_2 or a smaller d make the recommended strategy π easier to be sustainable. This is due to the fact that as the cost of attack increases or the damage caused by an attack decreases, users will find that her best option is to follow the one-shot deviation principle. As shown in Figure 3(f), as μ_1 increases, the recommended strategy π is sustainable with a lower ω. The main reason behind this phenomenon is that a larger μ_1 leads to a less deviation gain, and thus users are apt to comply with the recommended strategy. Figure 3(g) is contrary to Figure 3(f) as a larger μ_2 leads to a less deviation gain.

B. THE IMPACT OF INTRINSIC PARAMETERS ON DESIGN PARAMETERS

Figure 4 plots the impact of design parameters against intrinsic parameters:(a) b, (b) c_1, (c) c_2, (d) d, (e) s, (f) μ_1,(g) μ_2, and (h) ω. As shown in Figure 3, we know that a larger b, c_1, d, μ_2 or a smaller c_2,s, μ_1, ω require an increasing strength of punishment to provide sufficient incentive to compel users to comply with the social norm. In Figure 4(a), higher punishment factors are needed to sustain the recommended strategy π as b increases. Though a smaller β^* reduces the strength of punishment, a narrower $\mathcal{K}^*$-κ^* offsets this impact. Similar phenomena can be found in Figure 4(b), 4(d), and 4(g). Different from Figure 4(a), 4(b), 4(d) and 4(g), a weaker punishment factor can sustain a rating protocol as intrinsic parameters increase, as shown in Figure 4(c), 4(e), 4(f), and 4(h). For example, as ω increases (when $\omega \leq 0.85$ as shown in Figure 4(h)), $\mathcal{K}^*$-κ^* keeps unchanged, a smaller β^* reduces the strength of punishment. Afterwards, an increasing β^* and $\mathcal{K}^*$-κ^* together sustain the rating protocol.

C. PERFORMANCE EFFICIENCY

In Figure 5, we compare the performance of the proposed rating protocol $u_{\mathcal{P}}$ and the social optimum $u_{\mathcal{C}} \triangleq v_{\lambda=\frac{1}{3}}(HN)$

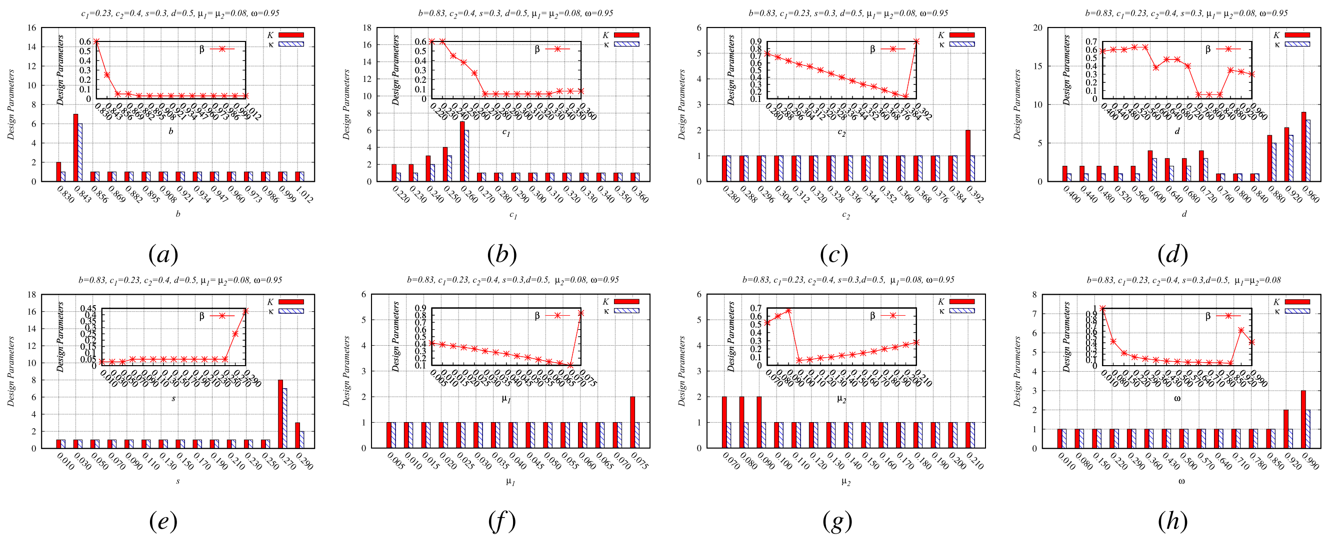

FIGURE 4. The impact of design parameters against intrinsic parameters (a) b; (b) c_1; (c) c_2; (d) d; (e) s; (f) μ_1; (g) μ_2; (h) ω.

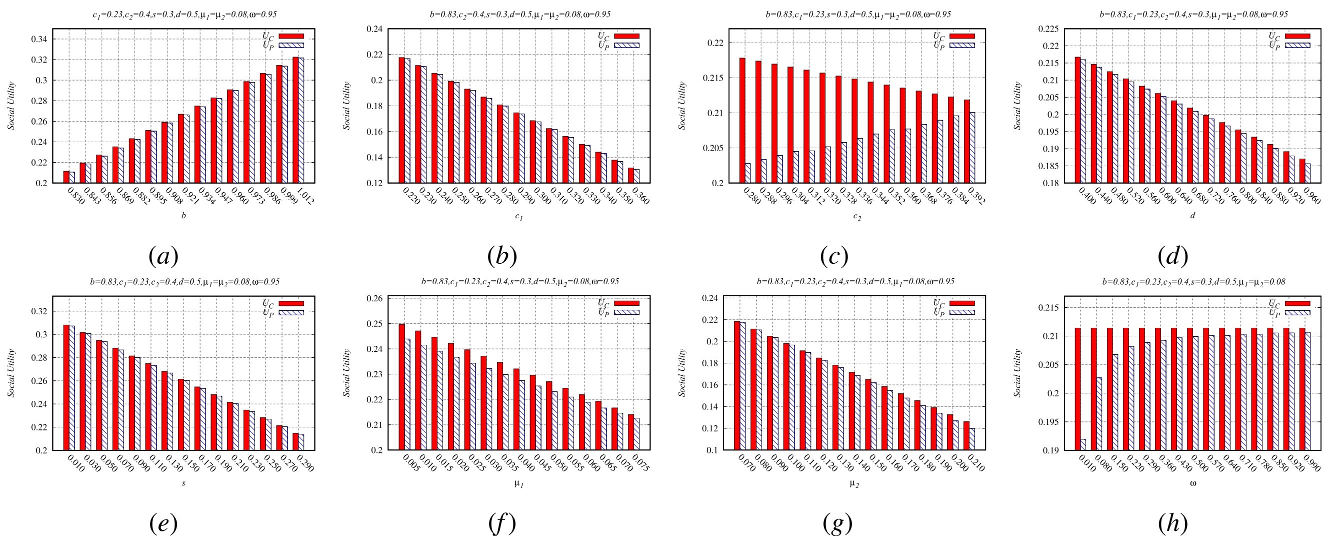

FIGURE 5. Normalized performance against intrinsic parameters (a) b; (b) c_1; (c) c_2; (d) d; (e) s; (f) μ_1; (g) μ_2; (h) ω.

on the premise that users always follow the recommended strategy and keep $\lambda = \frac{1}{3}$ in any period. First of all, it is easy to find that both $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$ monotonically increase with b, but monotonically decrease with c_1, d, s, μ_1, and μ_2. The main difference is that the social optimum $u_{\mathcal{C}}$ is only determined by these intrinsic parameters and is independent of ω. And a larger ω leads to an increase in social utility $u_{\mathcal{P}}$ and a narrower gap between $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$, as shown in Figure 5(h). Specifically, in Figure 5(c), the gap between $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$ becomes more significant, as $u_{\mathcal{P}}$ monotonically increases with c_2, in other words, $u_{\mathcal{P}}$ increases as punishment factors decrease. While $u_{\mathcal{C}}$ is independent of design parameters and only monotonically decreases with c_2. What's more, as shown in Figure 5(a), 5(b), 5(d) and 5(e), the gap between $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$ is almost unchanged. The reason can be traced back to Figure 4, where the impact of b, c_1, d and s on design parameters ($\mathcal{K}^*$, κ^*, β^*) are almost offset. Hence, both $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$ are influenced by b, c_1, s and d, respectively. However, a decreasing and an increasing punishment strength in Figure 4(f) and Figure 4(g) will result in a narrower and a wider gap between $u_{\mathcal{P}}$ and $u_{\mathcal{C}}$ as shown in Figure 5(f) and Figure 5(g), respectively.

VI. CONCLUSION

In this paper, we developed a game-theoretic design of multi-level two-sided rating protocol using all-pay contests to address the service exchange contest dilemma in crowdsensing. By rigorously analyzing how intrinsic parameters impact on recommended strategies, design parameters, as well as users' valuation of their individual long-term utilities, we first fix the optimal design parameters that $\alpha^* = \gamma^* = \delta^* = 1$, then another design parameter of the optimum κ^*, $\mathcal{K}^*$, and β^*

can be obtained via a two-stage alternate algorithm. Under the proposed optimal protocol, service request and service provision are balanced, and servers are motivated to always contribute good behaviors.

There are a few directions for the future work. (i) Considering designing differential recommended strategies based on the rating of the matched client and the server, which is more realistic and complicated. (ii) It is a challenging task to consider the general case with multi-client multi-server. The multiple levels of rating labels with multi-client multi-server will undoubtedly increase the difficulty of the optimal design problem.

TABLE 4. The pay-off matrix of each server for the third-stage game under the (H, H) case.

		server 2: A	server 2: N
server 1	A	$1-c_1-c_2, -c_1-c_2$	$1-c_1-c_1, -c_1$
	N	$-c_1, 1-c_1-c_2$	$1-c_1, -c_1$

APPENDIX A
COMPUTATION PROCESS FOR TABLE II

In our system model, HH is a unique strategy equilibrium in the second-stage game, then we first derive the pay-off matrix of each server for the third-stage game under the (H, H) in Table 4. Let φ_1,φ_2 denote the probabilities that server 1 and 2 choose A, respectively. we know that the game possesses a unique mixed equilibrium where

$$\begin{cases} \varphi_1 = 1 - c_2 \\ \varphi_2 = c_2 \end{cases} \tag{25}$$

It is obvious that the expected number of attacks is 1. We now take a step back and compute expected utilities when both servers choose H in the second stage. The ex-ante utility of server 1 (and symmetrically of server 2) is

$$\begin{aligned} u_1(u_2) &= P_r(P_2 < P_1 < P_2 + d)(1 - c_1 - c_2) \\ &\quad + P_r(P_1 > P_2 + d)(1 - c_1 - c_2) \\ &= \frac{1}{2} - c_1/2 - c_2 d + (c_2 d^2)/2 \end{aligned} \tag{26}$$

After the expected utilities of servers in the second stage is concluded, we derive the computation process for Table 2 in four cases as follows:

Case I: (C, C, C), i.e., all users choose to request services as clients. Each user consumes a cost of s to request a service, but receives zero benefit as there is no server providing service. We describe this in the CCC cell of the pay-off matrix in Table 2.

Case II: (S, S, S), i.e., all users choose to provide services as servers. The expected utility of each user is zero as no user requests service. The SSS cell of the pay-off matrix in Table 2 describes such a case.

Case III: (S, C, C), (C, S, C), (C, C, S), i.e., two users choose to request services as a client and only one user chooses to provide services as a server. Such situations are not satisfied with our system model, so the expected utilities of each client and the server are $-s$ and 0, respectively. The SCC, CSC and CCS cells of the pay-off matrices in Table 2 describes such cases.

Case IV: (S, S, C), (C, S, S), (S, C, S), i.e., two users choose to provide services as a server and only one user choose to request services as a client. According to the "winner takes all based service quality" scheme, when servers choose HN or HA, the utility of a client is $2b-s-1$ (denoted as $\mathcal{Y}$). And the utility of a server in the first-stage game is $\frac{1}{2} - c_1/2 - c_2 d + (c_2 d^2)/2$ (denoted as $\mathcal{X}$) according to Eq.(26). The pay-off matrices show utilities of SSC, CSS and SCS cases appear in Table 2.

Let $\lambda_1, \lambda_2, \lambda_3$ denote the probabilities that user 1, 2 and 3 choose C, respectively, we find that the game possesses a unique mixed equilibrium, and

$$\lambda_1 = \lambda_2 = \lambda_3 = 1 - \frac{\mathcal{X} + \sqrt{(\mathcal{X}+s)^2 + s\mathcal{Y}}}{(2\mathcal{X} + \mathcal{Y} + s)} \tag{27}$$

APPENDIX B
PROOF OF PROPOSITION 1

(i) We prove this statement by contradiction. Suppose, for the sake of contradiction, that $\Delta v_\lambda^\infty(\theta|HN) \le 0, \forall\theta \in [0, \mathcal{K})$ is true. According to Eq.(9), Eq.(10), and Eq.(11), when a user with rating $\theta \in [\kappa+1, \mathcal{K}]$ adopts strategy $\sigma_S = HN$, she will receive expected long-term utility $v_\lambda^\infty(\theta|HN)$, whereas her expected long-term utility is $v_\lambda^\infty(\theta|HA)$ if $\sigma_S = HA$, as shown in Eq.(28) and Eq.(29), respectively.

$$\begin{aligned} v_\lambda^\infty(\theta|HN) &= v_\lambda(\theta|HN) + \omega\Big\{\lambda\gamma + (1-\lambda)\big[\alpha + (1-\alpha \\ &\quad - \beta)(\mu_1 + \mu_2 - \mu_1\mu_2)\big]\Big\} v_\lambda^\infty(\theta+1|HN) \\ &\quad + \omega\Big\{\lambda(1-\gamma) + (1-\lambda)\big[1 - \alpha - (1-\alpha-\beta) \\ &\quad \times (\mu_1 + \mu_2 - \mu_1\mu_2)\big]\Big\} v_\lambda^\infty(\theta-1|HN) \end{aligned} \tag{28}$$

$$\begin{aligned} v_\lambda^\infty(\theta|HA) &= v_\lambda(\theta|HA) + \omega\Big\{\lambda\gamma + (1-\lambda)\big[1 - \beta + (\alpha \\ &\quad + \beta - 1)(\mu_2 - \mu_1\mu_2)\big]\Big\} v_\lambda^\infty(\theta+1|HN) \\ &\quad + \omega\Big\{\lambda(1-\gamma) + (1-\lambda)\big[(1-\alpha-\beta) \\ &\quad \times (\mu_2 - \mu_1\mu_2) + \beta\big]\Big\} v_\lambda^\infty(\theta-1|HN) \end{aligned} \tag{29}$$

By comparing (28) and (29), we have

$$\begin{aligned} & v_\lambda^\infty(\theta|HN) - v_\lambda^\infty(\theta|HA) \\ & = v_\lambda(\theta|HN) - v_\lambda(\theta|HA) \\ & \quad + \omega(1-\gamma)(1-\mu_1)(1-2\mu_2)(\alpha+\beta-1)\big[v_\lambda^\infty(\theta+1|HN) \\ & \quad - v_\lambda^\infty(\theta-1|HA)\big] \end{aligned} \tag{30}$$

It is easy to find that the first term $v_\lambda(\theta|HN)$–$v_\lambda(\theta|HA) < 0$, while the second term $\omega(1-\gamma)(1-\mu_1)(1-2\mu_2)(\alpha+\beta-1)\big[v_\lambda^\infty(\theta+1|HN) - v_\lambda^\infty(\theta-1|HN)\big] < 0$, since $\Delta v_\lambda^\infty(\theta|HN) \le 0$. Therefore, $\sigma_S = HA$ is the optimal strategy when $\theta \in [\kappa+1, \mathcal{K})$. Under such a rating protocol, users are encouraged to adopt malicious behavior $\sigma_S = HA$ without being punished, which contradicts the original intension of the proposed protocol.

For the isolated users, their expected long-term utilities can be expressed as $v_\lambda^\infty(\theta) = \omega v_{P,\lambda}^\infty(\theta+1), \theta < \kappa$ and $v_\lambda^\infty(0) = \omega v_{P,\lambda}^\infty(\kappa)$, it is easy to find that $\Delta v_\lambda^\infty(\theta|HN) > 0$. Hence, this statement follows.

(*ii*) For the non-isolated user's rating $\theta \in [\kappa+1, \mathcal{K})$, we have

$$\begin{aligned}
&\Delta v_\lambda^\infty(\theta|HN)\\
&\quad= v_\lambda(\theta+1|HN) - v_\lambda(\theta|HN)\\
&\qquad+\omega\Big\{\lambda\gamma+(1-\lambda)\big[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}\\
&\qquad\Delta v_\lambda^\infty(\theta+1|HN)+\omega\Big\{\lambda(1-\gamma)+(1-\lambda)\big[1\\
&\qquad-\alpha-(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}\Delta v_\lambda^\infty(\theta-1|HN)
\end{aligned} \tag{31}$$

It is easy to find that the first term $v_\lambda(\theta+1|HN) - v_\lambda(\theta|HN) = 0$, here we set $\mathcal{M} = \lambda\gamma + (1-\lambda)\big[\alpha + (1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]$ for simplicity, so Eq.(31) can be rewritten as

$$\begin{aligned}
\Delta v_\lambda^\infty(\theta|HN) &= \omega\mathcal{M}\Delta v_\lambda^\infty(\theta+1|HN)\\
&\quad+\omega(1-\mathcal{M})\Delta v_\lambda^\infty(\theta-1|HN)
\end{aligned} \tag{32}$$

For the sake of contradiction, we suppose that $\Delta v_\lambda^\infty(\theta|HN) \le \Delta v_\lambda^\infty(\theta+1|HN), \forall\theta \in [\kappa+1,\mathcal{K})$ is true. Then we can derive that the higher the user's rating θ, the more incentive the user is to follow the social norm, which contracts statement (ii). The proof of $\Delta v_\lambda^\infty(\kappa|HN) > \Delta v_\lambda^\infty(\kappa+1|HN)$ follows the same idea and is omitted here. Hence, this statement follows.

APPENDIX C
PROOF OF LEMMA 1

For the "if" part: By substitution $\lambda=\frac{1}{3}$ and $\theta=\mathcal{K}$ into Eq.(28) and Eq.(29), the expected long-term utility of a user when she complies with the recommended strategy π=*HN* and unilaterally deviates from *HN* to *HA* can be expressed as follows:

$$\begin{aligned}
&v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)\\
&\quad=\frac{1}{3}v_C(HN)+\frac{2}{3}v_S(HN)\\
&\qquad+\omega\Big\{\frac{1}{3}\gamma+\frac{2}{3}\big[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}\\
&v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)+\omega\Big\{\frac{1}{3}(1-\gamma)+\frac{2}{3}\big[1-\alpha-(1-\alpha\\
&\qquad-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}-1|HN)
\end{aligned} \tag{33}$$

$$\begin{aligned}
&v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HA)=\frac{1}{3}v_C(HA)+\frac{2}{3}v_S(HA)\\
&\qquad+\omega\Big\{\frac{1}{3}\gamma+\frac{2}{3}\big[1-\beta+(\alpha+\beta-1)(\mu_2-\mu_1\mu_2)\big]\Big\}\\
&\qquad v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)+\omega\Big\{\frac{1}{3}(1-\gamma)+\frac{2}{3}\big[(1-\alpha-\beta)(\mu_2\\
&\qquad-\mu_1\mu_2)+\beta\big]\Big\}v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}-1|HN)
\end{aligned} \tag{34}$$

By solving the following inequality then we can have the inequality Eq.(12):

$$v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN) \ge v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HA) \tag{35}$$

For the "only if" part: According to statement (*ii*) in Proposition 1, users with $\theta = \mathcal{K}$ have the weakest motivation to comply with the recommended strategy. That is, if $\sigma_S = HN$ when $\theta = \mathcal{K}$, then $\sigma_S = HN, \forall\theta \in [\kappa, \mathcal{K}]$.

APPENDIX D
PROOF OF LEMMA 2

For the "if" part: As the expected one-period utility of a client is no less than a server, users cannot benefit from deviating from $\lambda = \frac{1}{3}$ to $\lambda' < \frac{1}{3}$, which leads to the same rewards and a higher probability $1-\lambda'$ to be a server. Hence, we just need to focus on the case that $\lambda' > \frac{1}{3}$. The expected long-term utility of a user with $\theta = \mathcal{K}$ deviating from $\lambda = \frac{1}{3}$ to $\lambda' \in (\frac{1}{3}, 1]$ only in the current period and following $\lambda = \frac{1}{3}$ afterwards, which is given by

$$\begin{aligned}
&v_{\lambda'}^\infty(\mathcal{K}|HN)\\
&=\lambda' v_{C(HN)}+(1-\lambda')v_{S(HN)}+\omega\Big\{\lambda'\\
&\quad(1-\delta)+(1-\lambda')\big[\alpha+(1-\alpha-\beta)(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}\\
&\quad\times v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)+\omega\Big\{\lambda'\delta+(1-\lambda')\big[1-\alpha-(1-\alpha-\beta)\\
&\quad\times(\mu_1+\mu_2-\mu_1\mu_2)\big]\Big\}v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}-1|HN)
\end{aligned} \tag{36}$$

Then we analyze how λ' impact on the expected long-term utility

$$\begin{aligned}
\frac{\partial v_{\lambda'}^\infty(\theta|HN)}{\partial\lambda'}&=v_C(HN)-v_S(HN)+\omega\big[\gamma-\alpha-(1-\alpha-\beta)\\
&\quad\times(\mu_1+\mu_2-\mu_1\mu_2)\big]\Delta v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)
\end{aligned} \tag{37}$$

It is obvious that $\frac{\partial v_{\lambda'}^\infty(\theta|HN)}{\partial\lambda'}, \forall\lambda' \in (\frac{1}{3}, 1]$ is a constant value which is determined by these intrinsic parameters, as well as design parameters. As a result, $v_{\lambda'}^\infty(\theta|HN), \forall\lambda' \in (\frac{1}{3}, 1]$ is a monotonic increasing function, which is the only one case that we need to check, otherwise no user has an incentive to deviate from $\lambda = \frac{1}{3}$. By submitting $\lambda' = 1$ into Eq.(36), we have

$$\begin{aligned}
v_{\lambda'=1}^\infty(\mathcal{K}|HN)&=v_C(HN)+\omega(1-\delta)v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN)\\
&\quad+\omega\delta v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}-1|HN)
\end{aligned} \tag{38}$$

By solving the following inequality, we can obtain the inequality (13):

$$v_{\lambda=\frac{1}{3}}^\infty(\mathcal{K}|HN) \ge v_{\lambda'=1}^\infty(\mathcal{K}|HN) \tag{39}$$

For the "if" part: According to statement (*ii*) in Proposition 1, if $\lambda = \frac{1}{3}$ is satisfied for $\mathcal{K}$-user, then we have $\lambda = \frac{1}{3}$ for all θ-user, where $\theta \in [\kappa, \mathcal{K}]$. With this mind, we can compute the region of design parameters in (13), where a multi-level two-sided rating protocol is satisfied with the principle of fairness.

APPENDIX E
COMPUTATION PROCESS FOR STATIONARY RATING DISTRIBUTION

Given the transition probability as shown in (15), we have

$$\begin{cases} \eta_{\mathcal{P}}(0) &= (1-\mathcal{M})\eta_{\mathcal{P}}(\kappa) \\ \eta_{\mathcal{P}}(\theta) &= \eta_{\mathcal{P}}(\theta-1), \theta \in [1, \kappa-1] \\ \eta_{\mathcal{P}}(\kappa) &= \eta_{\mathcal{P}}(\kappa-1) + (1-\mathcal{M})\eta_{\mathcal{P}}(\kappa+1) \\ \eta_{\mathcal{P}}(\theta) &= \eta_{\mathcal{P}}(\theta-1) + (1+\mathcal{M})\eta_{\mathcal{P}}(\theta+1), \\ & \quad \theta \in [\kappa+1, \mathcal{K}-1] \\ \eta_{\mathcal{P}}(\mathcal{K}) &= \mathcal{M}\big[\eta_{\mathcal{P}}(\mathcal{K}-1) + \eta_{\mathcal{P}}(\mathcal{K})\big] \end{cases} \tag{40}$$

Since $\eta_{\mathcal{P}}(0) = (1-\mathcal{M})\eta_{\mathcal{P}}(\kappa)$ and $\eta_{\mathcal{P}}(\kappa) = \eta_{\mathcal{P}}(\kappa-1) + (1-\mathcal{M})\eta_{\mathcal{P}}(\kappa+1)$, we have

$$\eta_{\mathcal{P}}(\kappa-1) - \eta_{\mathcal{P}}(\kappa) = \frac{2\mathcal{M}-1}{(1-\mathcal{M})^2}\eta_{\mathcal{P}}(0) \tag{41}$$

For the case that $\kappa + 1 \leq \theta < \mathcal{K}$:

$$\begin{aligned} \eta_{\mathcal{P}}(\theta) &= \eta_{\mathcal{P}}(\theta-1) + (1+\mathcal{M})\eta_{\mathcal{P}}(\theta+1) \\ &\Rightarrow \frac{\eta_{\mathcal{P}}(\theta+1) - \eta_{\mathcal{P}}(\theta)}{\eta_{\mathcal{P}}(\theta) - \eta_{\mathcal{P}}(\theta-1)} = \frac{\mathcal{M}}{1-\mathcal{M}} \\ &\Rightarrow \eta_{\mathcal{P}}(\theta) = \eta_{\mathcal{P}}(\kappa) + \big[\eta_{\mathcal{P}}(\kappa+1) - \eta_{\mathcal{P}}(\kappa)\big] \\ &\quad \sum_{t=0}^{\theta-\kappa-1} (\frac{\mathcal{M}}{1-\mathcal{M}})^t \\ &= \frac{1}{1-\mathcal{M}}(\frac{\mathcal{M}}{1-\mathcal{M}})^{\theta-\kappa}\eta_{\mathcal{P}}(0) \end{aligned} \tag{42}$$

Then we have

$$\eta_{\mathcal{P}}(\mathcal{K}) = \frac{\mathcal{M}}{1-\mathcal{M}}\eta_{\mathcal{P}}(\mathcal{K}-1) = (\frac{\mathcal{M}}{1-\mathcal{M}})^{\mathcal{K}}\eta_{\mathcal{P}}(0) \tag{43}$$

Finally, the stationary distribution $\left\{\eta_{\mathcal{P}}(\theta)\right\}_{\theta=0}^{\mathcal{K}}$ can be derived.

APPENDIX F
PROOF OF PROPOSITION 2

It is easy to find that $u_{\mathcal{P}}$ monotonically increases with the reward factors α and γ, while monotonically decreases with the punishment factor β. As increasing $\mathcal{K}$ or decreasing κ enlarges the length of warning window, less users will be punished to be isolated. Hence, this statement follows.

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