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An Empirical Analysis of an Evolutionary Game Theory Model for Trustworthy Information Collection and Distribution

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ABSTRACT

This paper analyzes the honest-dishonest behavior of cloud data collection and dissemination system users, employing evolutionary game theory. It's very important to study evolutionary game theory application in cloud data collection and dissemination systems. It tends to describe the trends of honest-dishonest behavior of system stakeholders based on their strategic choices during the game rounds. This study employs involvement and character as criterion to incentivize or reprimand stakeholders. The truthful stakeholder is incentivized while the untruthful stakeholder is penalized. The system is coded using MATLAB software, and several experiments carried out. The system user's behavior is analyzed using replicator dynamics. The discoveries indicated that regardless of the number of stakeholders selecting an untruthful approach at beginning of the game, the mainstream of stakeholders is encouraged to select a truthful strategy after numerous game rounds. According to a comparative investigation of the evolution dynamics simulation outcomes for information suppliers and users indicated that, ultimately they select honest strategy, and the proportion of honest stabilizes. Consequently, the incentive approach can effectively encourage stakeholders to use the system honestly. The empirically analyzed evolutionary game theory model supports stakeholders' efficient participation and guarantee truthful use of the information collection and dissemination system.

Key words: Honest, Dishonest, Evolutionary, Replicator Dynamics, Stable State

I. INTRODUCTION

Jeff Howe first used the term "crowdsourcing" in a 2006 article that appeared in Wired Magazine [1]. Howe defined crowdsourcing as the practice of delegating an employee's task to a sizable, unclear group of people who are not affiliated with the organisation [2]. Ever since, a number of academic and commercial academics have articulated interest in the conception. According to [3], crowdsourcing is a tactic employed by businesses to entice and persuade people to provide provisions in terms of amount and excellence that are often fulfilled by traditional commercial establishments and procedures. Howe and Brabham mutually emphasised that crowdsourcing uses members of the public to finish tasks instead of corporate staff. Crowdsourcing can be described as an online participatory project in which a person or organisation offers a group of people or organisations with different backgrounds and levels of heterogeneity the voluntary undertaking of a task through a flexible open request [4]. According to [5], crowdsourcing is made easier by the usage of ICT to access the knowledge, labour, and abilities of a universal population. Moreover, Sanga defined crowdsourcing as a process of attaining services by way of an online request for hand-outs from individuals who may or may not be compensated [5]. Crowdsourcing offers many benefits, including access to a large worldwide pool of people with exceptional ideas, skills, knowledge, and solutions [6][7][8].

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Candidate, supportive, and competitive [9] [10] [11] and crowdsourcing [12] are the three core categories of crowdsourcing information systems. Consumers can cooperate to submit responsibilities and concepts through supportive crowdsourcing [10]. Howe and Di recommended that interactions should take place on intermediary platforms and should be ongoing between users and the organization as well as between users and one another [1] [13]. These intermediary platforms, which function as information systems, enable companies to establish user networks and collect information on knowledge, technology, solutions, and other relevant subjects [12]. Users are welcome to offer suggestions and assist in creating tasks for new products. They take part because they care about the brand, not because they want to make money. Users that engage in this process get enjoyment, a sense of personal fulfilment, interest-related information and abilities, and produces and services that are enhanced meet their requirements [14]. These payments are the core drivers of user motivations in cooperative crowdsourcing. One instance of a cooperative platform is Dell's Idea Storm [10].

Competitive crowdsourcing gives people the freedom to choose projects and submit ideas as they see fit. The greatest proposal, which may be from a single submission or a collaborative effort, can then be chosen and awarded by the organization [15]. According to [16], some organizational challenges can be addressed more quickly, effectively, and affordably by competitive crowdsourcing than businesses can handle them internally. Users may communicate with organizational agents, but they seldom work together or interact with others. Information systems that use crowdsourcing help organizations assign jobs to users and select the best submission among a number of users. It guarantees that each user submits a proposal freely and without influence from others [12]. Payments are the primary motivators for consumers in cooperative crowdsourcing. One example of a collaborative platform is Dell's Idea Storm [10]. People are allowed to select projects and contribute ideas as they see fit using competitive crowdsourcing. The organization may then pick out and award the superlative idea, which may be from a single tender or a team effort [15]. Competitive crowdsourcing can solve some organizational problems faster, cheaper, and more efficiently than companies can do it themselves [16]. Although users rarely collaborate or engage with others, they can converse with organizational agents. Crowdsourcing-based information systems assist organizations in assigning tasks to consumers and choosing the superlative submission from a pool of consumers. It ensures that every user makes a proposal voluntarily and independently of other people [12]. According to [17], the main incentive for users to participate in crowdsourcing activities is the possibility of winning financial rewards. Using candidate crowdsourcing platforms, organizations can choose candidates and collaborate closely with them to do the obligatory tasks [18] [19]. Systems that demand tight and ongoing cooperation between an organization and certain partners are good candidates for crowdsourcing [12]. Employers can select candidates with these kinds of platforms, connect with them, and share information with them over the network. Organizations are advised, nevertheless, to devote extra time and funds to encouraging cooperation and information distribution between rivals and themselves. For rivals, the prime incentive is the potential for financial gain. Crowdsourcing has found uses in a range of disciplines through the use of numerous technologies, including mobile phones [20] and the World Wide Web [21]. According to [22], three smartphone

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applications that are utilized for crowdsourcing are "Ushahidi," "fashism," and "askus," all of which were created and are currently in use in Kenya.

II. RELATED WORK

Two Correlated Works [23], categorized crowdsourcing applications into three categories based on their intended uses: entertainment, services, and financial gain after looking at a variety of incentive programs that enticed users to participate. Three incentive systems were presented by [24], namely; TBA (Threshold-Based Auction), TOIM (honest online incentive), and TOINZ-AD (Truthful Online Incentive Non-Zero Arrival-Departure). The TBA technique aimed to exploit the user's utility, but TOIM-AD and TOIM tried to strike a stability between utility intensification and veracity. Study by [25] proposed an honest and economical mechanism that emphasizes the severe budget constraint. To boost user participation [26] suggested a quality-driven auction-based reward mechanism. In order to incentivize system users, they suggested an incentive scheme and established criteria for data quality. Nevertheless, in their anticipated contrivance, these studies did not account for collaboration and honest of both suppliers and requesters. While crowdsourcing offers numerous benefits across diverse domains, scholars have recognized several pragmatic challenges. Among the challenges comprise consumer management, data quality maintenance, quality and abuse control [21], privacy concerns, and prioritization [22]. The majority of crowdsourcing systems charge individual users a fee to participate, which is another issue. The amount of a user's resources, such as dispensation speed, airtime, battery life, or an internet bundle, may be used to establish these charges. However, the users' personal data may be exposed if the system requests specific sensitive private information from them. If there aren't enough incentives to offset the expenses of participation, people won't practice such systems. The common of innovation platforms in use currently rely on voluntary consumer participation without appropriate incentive structures. The study by [27] introduced a participation-reputation based reward system where incentives were derived from participation and reputation. However, their work did not conduct an empirical analysis of their evolutionary game theory model. In most cases, a user cannot use a crowd-based system for free. These costs might cover the amount of processing power, batteries, airtime, internet bundles, and other resources that the user uses. However, it's possible that the system will ask certain users to provide sensitive personal data, which could jeopardize their privacy. Therefore, unless there is a justifiable incentive that pays for participation costs, consumers will not use such systems. However, most state-of-the-art systems now in operation lack robust incentive structures and depend on voluntary user participation. This paper provides an empirical analysis of an evolutionary game theory model that encourages users of crowdsourcing platforms to use the system and submit reliable information through an incentive structure based on participation and reputation. The study used the dynamic replicator idea to analyze the dynamics of stakeholder approach selection and offer evolutionary stable solutions for the stakeholders.

III. SYSTEM MODELLING

This study utilised sigmoid function to calculate the consumer's reputation and participation score. The sigmoid function output varies from zero to one. When mimicking the idea of human behaviour, the sigmoid function, which has been

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utilised a lot; is a better fit than other functions [28]. Equations (1) and (2) define the utilised sigmoid function to record the weighted total amount of logs and the amount of accurate information or response provided on the system by a particular stakeholder over a time epoch t.

$$\boldsymbol{g_{i,t}} = \frac{\boldsymbol{2tan^{-1}(u_i)}}{\boldsymbol{\pi}}; \qquad 0 \leq \boldsymbol{g_{i,t}} \leq 1 \tag{1}$$

$$\boldsymbol{m_{i,t}} = \frac{\boldsymbol{2tan^{-1}(h_i)}}{\boldsymbol{\pi}}; \qquad 0 \leq m_{i,t} \leq 1 \tag{2}$$

Where;

$\boldsymbol{u_i}$ is the aggregated amount of logs of a specific stakeholder during an epoch of time t.

$\boldsymbol{h_i}$ is the aggregated amount of correct information or comments of a specific stakeholder during an epoch of time t.

In the system model, the number of players, or users, is depicted by S= {s1, s2, s3, s4….s_n}. Every actor's (Users') strategy complies with Contributing Honesty (T) and Contributing Dishonestly (F). As a outcome, the two types of tactics that each user (player) will have are honest and dishonest, denoted by the letters M= {T, F}. The symbols and notations used in this model are demarcated in Table 1. The reputation score, represented by $\mathbf{S_{i,t}}$, is a numerical value ranging between zero and one that can be calculated using equation (3).

$$\boldsymbol{S_{i,t}(m_{i,t}, g_{i,t}) = a * g_{i,t} * m_{i,t} * e^{b * e^{c * m_{i,t} * g_{i,t}}}} \tag{3}$$

The result $\mathbf{S_{i,t}}$ of equation (3) gives the reputation score for a particular stakeholder Zi at time t. If $\mathbf{m_{i,t} \geq 0}$ and $\mathbf{S_{i,t} \geq 0}$, then the stakeholder is deemed dishonest; otherwise, the stakeholder is deemed honest.

Table 1: Terminology and Notations Definition

SYMBOL	DEFFINITION
Zi, Zj	Users and providers of information, respectively
Cr	Incentive percentage rate
Dr	Penalty percentage rate
Si,t	Reputation Score of Users *Zi* at period *t*
Sj,t	Reputation Score of Providers *Zj* at period *t*
Vi,t (x,y)	When the information supplier does action x and the information user executes action y, anticipated Utility for user Zi at period t
Vj,t (x,y)	When an information supplier makes action x and an information user does action y, anticipated Utility for Provider Zj at period t
u_i	The quantity of times a user uploads or retrieves data
h_i	The quantity of helpful data or honest reviews that users upload at period t
$m_{i,t}$	Users at time t weighted prehistoric system logs they had accumulated
$m_{j,t}$	Weighted prehistoric system logs gathered by providers at time t
$g_{i,t}$	Users Z_i weighted total amount of helpful data or honest reviews uploaded at period t
$g_{j,t}$	Providers Z_j weighted total amount of helpful data or sincere reviews uploaded at time t
K	Amounts due for fees and taxes at a specific time t
B	Scored incentive a time t.
A	Scored Penalty at period t.

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Equations (5) and (6) produce the incentive score (denoted by B) and penalty score (denoted by A) of a single shareholder that participates dishonestly and honestly, correspondingly.

$$B = S_{i,t} * \mathrm{Cr} \tag{5}$$

$$A = g_{i,t} * \mathrm{Dr} \tag{6}$$

Information supplier Zi and information consumer Zj are both anticipated to act rationally throughout the evolutionary game. As a result, we present the following estimated payoff for information consumer Zj and information supplier Zi for each strategy profile:

When information consumer and information supplier embrace strategy honest (T) during their system collaboration at period t, information supplier Zi receives Vi,t (T,T). When the information consumer takes the dishonesty approach, Vi,t (T, F) indicates the disbursement for the information supplier Zi (F). However, at period t, the information supplier selects an honest approach (T) when interacting with the system. Throughout their system collaboration at period t, when the information consumer chooses Honest approach (T) and the information supplier chooses Dishonest approach (F), Vi,t (F,T) represents the payoff for information provider Vi. When information consumer and information supplier choose dishonest approach (F) during their system interaction at period t, the reward for information supplier Zi is shown by Vi,t (F, F). The reward for information provider Zi are summed up in Table 2.

Table 2: Providers of Information *Zi* Payoff Matrix

		User of Information	
		T	F
Provider Information ***Z_i***	T	$V_{i,t}$ (T, T)	$V_{i,t}$ (T, F)
	F	$V_{i,t}$ (F, T)	$V_{i,t}$ (F, F)

The expected reward for information user Zj was defined as follows in each approach profile: The Uj,t denotes the payment to information user Zj (T,T). Users and information providers select honest strategy when the system is activated at time t (T). If the information provider selects strategy dishonest (F) and the information user selects honest (H) during their system interaction at time t, Vj,t (T, F) represents the reward for information user Zj. During their system interaction at time t, if the information user (Zj) chooses the dishonest (F) strategy and the information provider (Zi) chooses the honest (T) approach, Vj,t (F,T) represents the reward for information user Zj. When both the information provider and the information user choose the dishonest (F) approach during their system interaction at time t, the information user Zj receives Vj,t (F, F). These rewards are summarized up for information provider Zj in Table 3.

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Table 3: Information users Zj Payoff Matrix

		Provider of Information	
		T	F
User of Information Z_j	T	$V_{j,t}$ (T,T)	$V_{j,t}$ (T,T)
	F	$V_{j,t}$ (F,T)	$U_{j,t}$ (F,F)

After every play, the model adjusts the user's reputation and degree of engagement based on the strategy they chose during each iteration of the evolutionary game. After a set period of time, t, the algorithm calculates each user's involvement and reputation score. Then, based on this score, one may determine if an individual is honest or not. Table 4 depicts the user's participation status at time t: honest or dishonest. The user is either rewarded or penalised based on this data.

Table 4: Penalized or Rewarded.

		Users of Information Zj	
		T	F
Provider of Information Z_i	T	(1,1)	(1,-1)
	F	(-1,1)	(-1,-1)

When information providers and users are both truthful at time t, the expected incentives for each participant in the strategy profile are described by equations (7) and (8)

$$\{V_{i,t}(T,T) = K - S_{i,t} * Cr \tag{7}$$

$$\{V_{j,t}(T,F) = K - S_{j,t} * Cr \tag{8}$$

Equations (9) and (10) define the predicted incentive or penalty for each player in the strategy profile at time t, where information suppliers are honest and information users are dishonest.

$$\{V_{i,t}(T,F) = K - S_{i,t} * Cr \tag{9}$$

$$\{V_{j,t}(T,F) = K + m_{j,t} * Dr \tag{10}$$

Equations (11) and (12) define the expected reward or penalty for each participant in the strategy profile when information providers are dishonest and information users are truthful at time t.

$$\{V_{i,t}(F,T) = K + m_{i,t} * Dr \tag{11}$$

$$\{V_{j,t}(F,T) = K - S_{j,t} * Cr \tag{12}$$

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Equations (13) and (14) specify the projected penalty for each actor in the strategy profile when both information suppliers and information users are dishonest at time t.

$$\{V_{i,t}(F,F) = K + m_{i,t} * Dr \tag{13}$$

$$\{V_{j,t}(F,F) = K + m_{j,t} * Dr \tag{14}$$

3.1 Replicator Dynamics

When players in evolutionary games come upon a dynamic situation with unpredictable results due to other players' actions, they will adapt their plans in each tragedy and learn from previous exchanges. The evolutionary stable strategy (ESS) is a steady equilibrium approach that is often used in evolutionary game theory. If all individuals in the population embrace ESS, then natural selection will not be able to suppress the population through any twisted tactics. The replicator dynamic equations were used to depict the distribution of strategies among the residents in order to investigate the evolution of participant tactics. The decision to transfer the practical ESSs if the prerequisites were satisfied was made. In the proposed paradigm, there are two types of participants: information providers and information users. Since information providers may switch from being information providers to information users in the next interaction while the model is running, we assume that all of them will select the same honest course of action. Ui's utility function was used to simulate the strategy selection dynamics of information users, whereas Uj's utility function was used to characterize the strategy selection dynamics of information providers.

3.1.1 Information users' Replicator Dynamics

The study defined 1-x_t as the proportion of stakeholders choosing dishonest strategy at time t and x_t as the proportion of stakeholders choosing an honest strategy at the same moment. When users select the honest strategy, they will receive the following information as a reward, per the game grid:

$$P_u^H = x_t * V_{i,t}(T,T) + (1 - x_t) * V_{i,t}(T,F) \tag{15}$$

$$= x_t * \left(K - S_{i,t} * C_r\right) + (1 - x_t) * (K - S_{i,t} * C_r)$$

$$P_u^H = K - S_{i,t} * C_r \tag{16}$$

The payoff of information users opting for dishonest approach are given as;

$$P_u^D = x_t * V_{i,t}(F,T) + (1 - x_t) * V_{i,t}(F,F) \tag{17}$$

$$= x_t * \left(K + m_{i,t} * P_r\right) + (1 - x_t) * (K + m_{i,t} * D_r)$$

$$P_u^D = K + m_{i,t} * D_r \tag{18}$$

Consequently, the average payoff of information users will be calculated as follows;

$$P_u = x_t * P_u^H + (1 - x_t)P_u^D \tag{19}$$

$$= x_t * \left(K - S_{i,t}D_r\right) + (1 - x_t) * \left(K + m_{i,t}D_r\right)$$

$$P_u = -x_t\left(S_{i,t}C_r + m_{i,t}D_r\right) + (K + m_{i,t}D_r) \tag{20}$$

The replicator dynamic equation of the projected game for the information users can be derived as follows;

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$$\frac{dx_t}{dt} = x_t * (P_u - P_u^H) \tag{21}$$

$$= x_t * [\left(-x_t\left(S_{i,t}C_r + m_{i,t}D_r\right) + \left(K + m_{i,t}D_r\right)\right) - \left(K - S_{i,t}C_r\right)]$$

$$\frac{dx_t}{dt} = (x_t - x_t^2)(S_{i,t}C_r + m_{i,t}D_r) \tag{22}$$

The circumstance for ESS is that $\frac{dx_t}{dt} = 0$

$$x_t(1 - x_t)\left(S_{i,t}C_r + m_{i,t}D_r\right) = 0$$

The results are $x_t = 0$ or $x_t = 1$

3.1.2 Information provider's replicator dynamics

This study defined y_t as the percentage of stakeholders selecting the honest strategy at time t, and 1-y_t as the percentage of stakeholders selecting the dishonest strategy at time t. The subsequent is the payout for information providers who select the honest approach, rendering to the game matrix:

$$P_p^H = y_t * V_{j,t}(T,T) + (1 - y_t) * V_{j,t}(T,F) \tag{23}$$

$$= y_t * \left(K - S_{j,t} * C_r\right) + (1 - y_t) * (K - S_{j,t} * C_r)$$

$$P_p^H = K - S_{j,t} * C_r \tag{24}$$

The payoff of information providers selecting dishonest strategy is calculated by the following formula;

$$P_p^D = y_t * V_{j,t}(F,T) + (1 - y_t) * V_{j,t}(F,F) \tag{25}$$

$$= y_t * \left(K + m_{j,t} * D_r\right) + (1 - y_t) * (K + m_{j,t} * D_r)$$

$$P_p^D = K + m_{j,t} * D_r \tag{26}$$

Consequently, the average payoff of information providers will be determined by the following formula;

$$P_p = y_t * P_u^H + (1 - y_t)P_p^D \tag{27}$$

$$= y_t * \left(K - S_{j,t}C_r\right) + (1 - y_t) * \left(K + m_{j,t}D_r\right)$$

$$P_u = -y_t\left(S_{j,t}C_r + m_{j,t}D_r\right) + (K + m_{j,t}D_r) \tag{28}$$

The replicator dynamic equation of the proposed game for the information providers can be calculated as follows;

$$\frac{dy_t}{dt} = y_t * (P_p - P_p^H) \tag{29}$$

$$= y_t * [\left(-y_t\left(S_{j,t}C_r + m_{j,t}D_r\right) + \left(K + m_{j,t}D_r\right)\right) - \left(K - S_{j,t}C_r\right)]$$

$$\frac{dy_t}{dt} = (y_t - y_t^2)(S_{j,t}C_r + m_{j,t}D_r) \tag{30}$$

The circumstance for ESS is that $\frac{dy_t}{dt} = 0$

$$y_t(1 - y_t)\left(S_{j,t}C_r + m_{j,t}D_r\right) = 0$$

The results are $y_t = 0$ or $y_t = 1$

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3.3 Analysis of evolutionary stable strategies (ESS)

The evolutionary stable strategy is the collection of stable fixed points in a system of differential equations (Zhu et al., 2010).). However, for the evolutionary game of information producers and users, respectively, not all of the two solutions given in equations (22) and (30) are necessarily ESSs. Using the suggested evolutionary participation reputation-based game model, study investigated the evolutionary stable strategies (ESSs) for both information providers and information consumers, abiding to ESSs rules.

3.2.1 Information users Stability Analysis

If and only if a strategy meets the requirements of equilibrium and stability, then it is the ESS. That means H(x) should fulfil the following circumstances;

$$\begin{cases} H(x_t) = 0 \\ H'(x_t) < 0 \end{cases} \tag{31}$$

Both of the solutions satisfy the first criterion based on the replicator dynamics analysis for the information users. In order to maintain a unique ESS, study identified and discarded the solutions that did not meet the second requirement condition $H(x_t) < 0$ as follows;

Let $H(x_t) = \frac{dx_t}{dt}$; Thus from (22) we get,

$$H(x_t) = (x_t - x_t^2)(S_{i,t}C_r + m_{i,t}D_r)$$

$$H'(x_t) = (1 - 2x_t)\left(S_{i,t}C_r + m_{i,t}D_r\right)$$

Consequently, $H'(x_t = 1) = -\left(S_{i,t}C_r + m_{i,t}D_r\right)$ (32)

$$H'(x_t = 0) = (S_{i,t}C_r + m_{i,t}D_r) \tag{33}$$

Hence, $H'(x_t = 0) > 0$ and $H'(x_t = 1) < 0$

Consequently, only $x_t = 1$ satisfy the second condition in the evolutionary game for information users and is the only ESS in the evolutionary game for information users. The results of the analysis demonstrate that every information user will ultimately decide on a moral path of action in order to reach an evolutionary stable state. This implies that regardless of the population of information users' starting choice (honest or dishonest), after a certain amount of development, all information users will select the clean approach (honest). Consequently, EPRIGM is able to ensure the dependability of information users in the collection and sharing of data on the cloud.

3.2.2 Information provider's Stability Analysis

If and only if a strategy meets the requirements of equilibrium and stability, then it is the ESS. That means H(y) should satisfy the following conditions;

$$\begin{cases} H(y_t) = 0 \\ H'(y_t) < 0 \end{cases} \tag{34}$$

Thus, H(y) ought to meet the subsequent requirements. Both of the solutions satisfy the first criterion based on the replicator dynamics analysis for the information providers. In order to maintain a unique ESS, the study identified and discarded the solutions that did not meet the second requirement $H(y_t) < 0$ as follows;

Let $H(y_t) = \frac{dy_t}{dt}$; Thus from (30) we get,

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$$H(y_t) = (y_t - y_t^2)(S_{j,t}C_r + m_{j,t}D_r)$$

$$H'(y_t) = (1 - 2y_t)\left(S_{j,t}C_r + m_{j,t}D_r\right)$$

Therefore, $H'(y_t = 1) = -\left(S_{j,t}C_r + m_{j,t}D_r\right)$ (35)

$$H'(y_t = 0) = (S_{j,t}C_r + m_{j,t}D_r) \quad (36)$$

Consequently, $H'(y_t = 0) > 0$ and $H'(y_t = 1) < 0$

Consequently, in the evolutionary game of information providers, only one $y_t = 1$ satisfy the second requirement. Regardless of whether the population of information users first selects the honest or dishonest course of action, this stability study for information providers demonstrates that over time, all information providers will embrace the honest strategy. Thus, the proposed participation-reputation-based incentive mechanism can ensure that data contributors offer accurate information to ensure the system's operation.

IV. EXPERIMENTAL SIMULATION

The model was coded using MATLAB software, and several experiments were carried out with it. The results of the experiment demonstrated that the incentive structure in place can influence participants to make moral decisions. If stakeholders choose an unethical approach, they will immediately suffer the repercussions, which will discourage them from doing so in the future. The dynamic of the proportion of reputation ratings ($x_t$and y_t) and honesty scores ($S_{i,t}$ and $S_{j,t}$) for information providers and users, respectively, is presented by the experimental findings. The study further analyzed the significance of initialized values of the honest proportion (x_0 and y_0) on the time to grasp ESSs. To attain satisfiable outcomes, parameters a, b, and c was set between 0.1 and 0.9. The subsequent setup; $x_0 = 0.7$, $y_0 = 0.7$, $a = 0.9$, $b = 0.6$, $c = 0.9$, $C_r = 0.6$, $D_r = 0.3$, and $K = 100$ was used in experiment.

V. EXPERIMENTAL RESULTS AND DISCUSSION

5.1 The dynamics evolution for information users

When $x_0 = 0.7$, the dynamic evolutions of x_t and $S_{i,t}$ for information users are depicted in Fig.1. The value of x_t will rise until it reaches the steady state as demonstrates by the simulation results in Fig.1. Information users start the game by selecting the honest approach, and their reputations increase in tandem with their decisions. But if information users pick a dishonest approach for any reason, their reputations will suffer and they will be penalised right away, as shown by $(t = 1,7,10,27,36,38\ etc.)$ in Fig. 1. After a while, the penalised information users will observe that their fees and taxes have gone up from what was initially agreed upon. Thus, in the following iteration, they will attempt to select a honest approach and track the outcomes. The information users will notice cheaper costs and taxes during this iteration when compared to the fees and taxes that were first set. Information user will thus decide on a honest course of action to save costs associated with fees and taxes. Ultimately, information user will only select honest courses of action, and the proportion of honest user will stabilize. The simulation's conclusion demonstrates how information users adjust their strategies to maximise their payoffs (discounts) based on what they learn from the payoffs they receive for each strategy they select throughout a game round.

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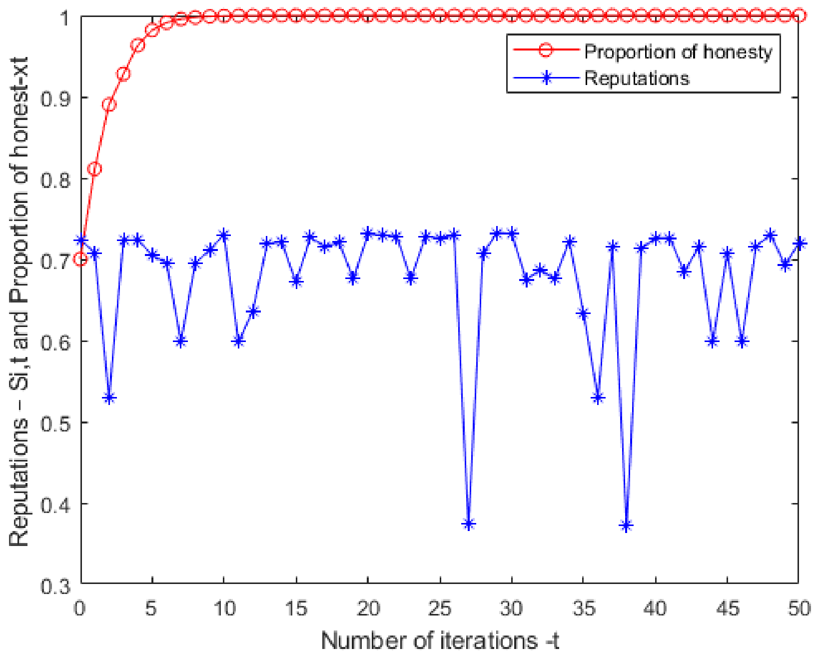

Figure 1: The evolution of x_t and $S_{i,t}$ for initialized value $x_0 = 0.7$

5.2 The outcome of initialized values of x_0 (honest proportion of information users)

As seen in Fig. 2, the group ESS expands more quickly the more honest people are there at the beginning of the evolutionary game. The fundamental clarification is that, as the game goes on, there is a good chance that those information users who initially chose the dishonest approach will eventually change to the honest strategy if a higher percentage of information users choose the honest strategy. Because of this, individuals who utilise dishonest strategy are likely to move to a more honest strategy in order to get additional tax and fee discount. Information providers will therefore swiftly adjust their methods to attain a steadier state.

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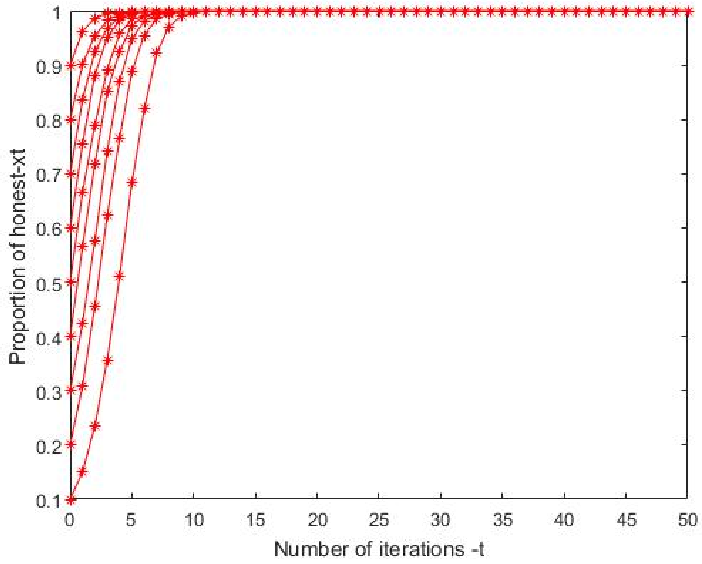

Figure 2. The effect of initialized value x_0 on information users

5.3 Information provider' s dynamics evolution

The dynamic evolutions of y_t and $S_{j,t}$ of providers for information are portrayed in Fig.3 when $y_0 = 0.7$. Figure 3 shows the simulation results, where y_t increase until they reach the steady state. Information providers opt for the honest approach at the start of the game, and their reputations increase in tandem with their decisions. However, as shown in Fig. 3, information providers' reputations would suffer and they will be penalised right away if they pick honest technique for any reason as described by $(t = 2,5,24,29,37, etc.)$ in Fig.3. After a while, the penalised information providers will observe that their fees and taxes have gone up from what was first agreed upon. Thus, in the following iteration, they will attempt to select honest approach and track the outcomes. The information providers will notice lower costs and taxes during this iteration in comparison to the first established fees and taxes. Information providers will therefore pick the honest approach in order to receive additional tax and charge discounts. Ultimately, information providers will only select honest strategy, and only a portion of honest strategies will succeed in reaching a stable state. This finding suggests that players keep learning from the rewards received for each strategy they select in a round of the game and modify their tactics to maximise their rewards (discount).

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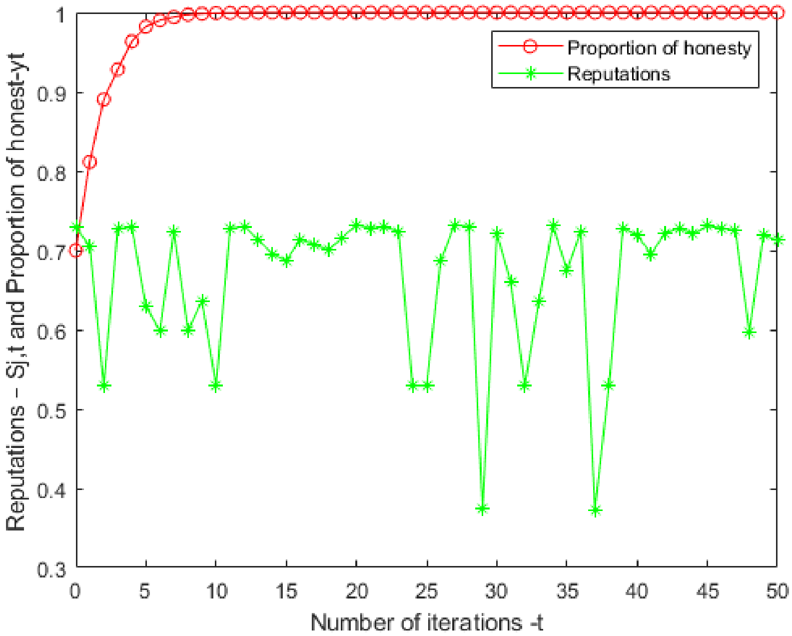

Figure 3: The evolution of y_t and $S_{j,t}$ for initialized value $y_0 = 0.7$

5.4 The outcome of initialized values of y_0 (honest proportion for information providers)

As depicted in Fig. 4, the ESS group arises more quickly the larger the fraction of honest individuals at the beginning of the evolutionary process. The basic argument is that as the game goes on, there is a good chance that the dishonest information providers will eventually switch to honest strategy if more of them embrace honest strategy within their community. Because of this, there's a significant likelihood that dishonest information providers may move to a honest strategy to save more money on taxes and fees (discount). Information providers will therefore swiftly adjust their strategy to attain a steadier state.

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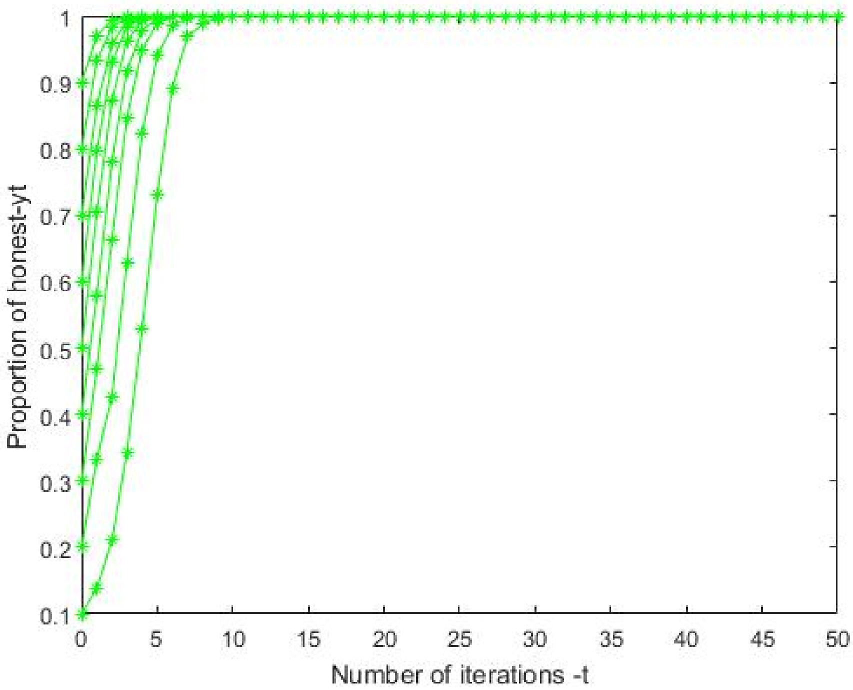

Figure 4. The effect of initialized value y_0 on information users

Regardless of the population of stakeholders or the high number of stakeholders choosing a dishonest strategy at the beginning of the game, the majority of stakeholders will be motivated to choose an honest strategy after multiple game rounds. According to a comparative analysis of the dynamics evolution simulation results for both information providers and users. Consequently, the approach can effectively encourage stakeholders to use the system, provide accurate data, and offer candid feedback.

5.5 Conclusive Theoremon Convergence of Strategy Selection in Evolutionary Games for Information Providers and Users

Given an evolutionary game where information users and providers start with an initial proportion of honest individuals, the strategies of both groups (honest or dishonest) evolve over time based on the feedback from their respective payoffs (taxes, fees, etc.). Under the assumption that each player adapts their strategy to maximize their individual payoffs, the proportion of honest individuals will stabilize at a steady state, eventually leading to a cooperative (honest) equilibrium for both information providers and users.

Proof:

I. **Initial Setup and Dynamics**: Let the proportion of honest information users at time *t* be denoted by x_t and the proportion of honest information providers by y_t. Initially, both x_0 and y_0 are set to a value x_0=y_0=0.7, representing the fraction of honest individuals in the population at the start of the game.

II. **Strategy Evolution for Information Users**: Information users begin by selecting the honest strategy. If they continue to play honestly, their reputation increases and they receive rewards in the form of lower taxes and fees, as illustrated in Fig. 1. However, if an information user selects the dishonest strategy, their reputation

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suffers, and they are penalized (increased fees and taxes), as observed in various time steps (e.g., t=1,7,10,27,36,38 in Fig. 1). The penalized users, upon observing the increased costs, are incentivized to return to the honest strategy in subsequent rounds. Over time, this feedback loop leads to a gradual increase in the proportion of honest users, ultimately stabilizing at a point where the majority of users adopt the honest strategy.

III. **Strategy Evolution for Information Providers**: Similarly, information providers also begin by selecting the honest strategy. If they deviate to dishonesty, their reputation is penalized, leading to higher taxes and fees, as shown in Fig. 3. This penalty acts as a deterrent, prompting the dishonest providers to return to the honest strategy in subsequent rounds. The feedback mechanism (penalization followed by incentive to choose honesty) encourages providers to adopt honest strategies over time. As the simulation progresses, the proportion of honest providers, y_t, stabilizes at a point where most providers select the honest strategy.

IV. **Effect of Initial Conditions**: As shown in Figs. 2 and 4, the rate at which the Evolutionarily Stable Strategy (ESS) group expands depends on the initial proportion of honest individuals in both user and provider populations. The larger the initial fraction of honest individuals (either x_0 or y_0), the faster the ESS group reaches its steady state. This can be attributed to the positive feedback effect, where more honest players encourage others to adopt the honest strategy to avoid the penalties associated with dishonesty.

V. **Convergence to Stable Equilibrium**: Regardless of the initial proportion of dishonest players, the evolutionary process leads to the convergence of both information users and providers toward a stable state in which the majority select the honest strategy. This outcome is driven by the self-interested behavior of each player, who adjusts their strategy to maximize their payoff (i.e., tax and fee discounts). The dynamics suggest that, after sufficient rounds, the system reaches a stable state where honesty is the dominant strategy.

IV. CONCLUSION AND RECOMMENDATION

The study aim was to empirically analyse an evolutionary game-theoretical framework for trustworthy data collection and distribution. The concept employed reputation and involvement (participation) as criteria to reward honest users and penalise dishonest ones. The dynamics of information providers and users were empirically simulated. The simulation results demonstrate that both information users and providers will eventually converge to a state where the majority adopt the honest strategy, regardless of initial conditions. This convergence is a direct result of the payoff-driven evolutionary dynamics, where the feedback loops of penalties for dishonesty and rewards for honesty incentivize players to adapt their strategies. Thus, the system effectively encourages stakeholders to adopt honest behavior, ensuring the accuracy of data and the provision of candid feedback, which is essential for the success and stability of the information exchange system.

The implementation of an incentive scheme based on participation-reputation necessitates the creation of regulations that facilitate private-public partnerships in the areas of system development, channel acquisition, and system management. All data formats supporting the ICT tools owned by stakeholders should be supported by the designed information management system.

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