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Market Dynamics and Regulation of a Crowd-Sourced AI Marketplace

PRACHI DHAMANGE[1], SARTHAK SONI[2], V. SRIDHAR[3], AND SHRISHA RAO[3], (Senior Member, IEEE)
[1]Microsoft Corporation (IDC), Bengaluru 560103, India
[2]MathWorks Bangalore, Bengaluru 560103, India
[3]International Institute of Information Technology-Bangalore, Bengaluru 560100, India

Corresponding author: V. Sridhar (vsridhar@iiitb.ac.in)

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ABSTRACT As usage of artificial intelligence (AI) technologies across industries increases, there is a growing need for creating large marketplaces to host and transact good-quality data sets to train AI algorithms. Our study analyzes the characteristics of such an oligopsony crowdsourced AI Marketplace (AIM) that has a large number of producers and few consumers who transact data sets as per their expectations of price and quality. Using agent-based modeling (ABM), we incorporate heterogeneity in agent attributes and self-learning by the agents that are reflective of real-world marketplaces. Our research augments the existing studies on the effect of and reputation systems in such market places. Extensive simulations using ABM indicate that ratings of the data sets as a feedback mechanism plays an important role in improving the quality of said data sets, and hence the reputations of producers. While such marketplaces are evolving, regulators have started enacting varying rules to oversee the appropriate functioning of such marketplaces, to minimize market distortions. In one of the first such studies, we integrate regulatory interventions in a marketplace model to analyze the impacts of various types of regulations on the functioning of an AIM. Our results indicate that very stringent regulatory measures negatively affect the production of quality data sets in the marketplace. On the other hand, regulatory oversight along with a ratings-based feedback mechanism improves the functioning of an AIM, and hence is recommended for governments and policy makers to adopt.

INDEX TERMS Crowd-sourced, oligopsony, quality sensitivity, regulation, reputation systems, trust, agent-based modeling.

I. INTRODUCTION

Artificial intelligence (AI) and machine learning (ML) technologies have made inroads into several domains including agriculture, healthcare, transportation, finance and commerce recently. It is estimated that AI technologies will contribute to about 1.2 percent additional GDP growth per year, thus contributing to about USD 13 trillion worth of economic activity by the year 2030 [1]. To achieve these targets, model builders and application developers need to train their algorithms using large numbers of appropriately annotated data sets from multiple sources for building operational predictive systems [2]. It is envisioned that an AI Marketplace (AIM) can enable the development and distribution of such data sets. Such an AIM facilitates the matching of the data sets produced, typically by a "crowd" of data producers, to those needed by the customers as per their requirements [3]. In accordance with these concepts, some countries have envisioned the creation of national AIMs [4]. It is hypothesized that such marketplaces will increase the application and adoption of AI in certain critical sectors such as healthcare, education, and agriculture. The objective of an AIM is to democratize the availability of curated annotated content for testing and use in AI applications by academia, civil society organizations, small and large businesses, startups, and governments, in a sustainable way.

The AI community has often used crowdsourcing for the generation of high-quality labeled data, thus augmenting the development of superior and accurate ML algorithms [5]. There are two types of crowd-sourced marketplaces:

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- The first type is demand driven, as exemplified by marketplaces such as Amazon Mechanical Turk (AMT), CrowdFlower, Microworkers, and Shorttask [6]. In these, a requester posts a task (e.g., annotate an image with a set of related keywords), and workers are for the most part treated as replaceable commodities that can complete the task. Many crowdsourcing studies have been conducted that utilize Amazon Mechanical Turk, a popular demand-driven crowdsourcing marketplace platform that enables businesses and individuals to outsource tasks [7].
- The other type is a supply-driven marketplace where workers advertise their skills, special talents, and artifacts and portfolios, with the aim of differentiating from one another and induce buyers to procure and use their products and services. The AI community was early to embrace supply-driven crowdsourcing as a tool for quickly and inexpensively obtaining the vast quantities of labeled data needed to train ML systems [8].

In this paper, we analyze the characteristics and behavior of such a supply-driven crowdsourced marketplace using an agent-based modeling (ABM) approach. In such a marketplace, transactions between producers and consumers occur if there is a match both in price and quality expectations. Typically, in such marketplaces, consumers review and rate the producers and their artifacts, primarily based on their own past experiences of quality. These ratings in turn affect the reputations of the producers and future demand for their artifacts in the marketplace. Further, the producers can also learn through the ratings and improve the quality of the data sets they produce. While these are common characteristics in any marketplace, crowdsourced marketplaces often are *oligopsony* markets, where there are a large number of producers (the "crowd") and relatively few price- and quality-conscious consumers.

However, these marketplaces tend to exhibit some imperfections due to information asymmetry that exists between the producers and consumers [2], the *monopsony* power of the consumers [9], and the tendency of the producers to deviate from what they declare as the attributes of their artifacts [10]. When the "invisible hand" fails to correct such imperfections, regulation is one of the tools available to the government and policy-makers to correct market anomalies [11], [12]. While the ABM literature is sometimes criticized for not reflecting the behavior of the real world [13], we incorporate heterogeneity in the agent attributes and self-learning by agents, that are reflective of real-world marketplaces.

While such marketplaces continue to evolve, regulators are starting to enact various rules to oversee their appropriate functioning. Though there have been many studies on the functioning of these marketplaces [3], [6], [14], [15], the effect of regulations on such marketplaces is not well studied [12].

While the extant studies of regulatory interventions have looked at aspects of crowdsourced markets in the areas of employment and labor [16], political economy [17], and ethics [18], our research augments the literature by studying the regulator's role in governing the appropriate functioning of AI marketplaces.

Our results indicate that rating of the data sets as a feedback mechanism to build trust between consumers and producers plays an important role in encouraging production of high quality data sets in the AIM. We also show that stringent regulatory measures often adversely impact the effective working of the marketplaces, thereby decreasing the average quality of data sets in the AIM.

An integration of a market-based approach and regulations provides an effective toolkit for policy-makers to set appropriate quality standards and govern the appropriate functioning of the marketplaces through effective feedback mechanisms.

The rest of the paper is structured as follows. Section II describes the characteristics of the AI marketplace. In Section III we present the ABM and model parameters. The simulations of the AIM under various scenarios and the corresponding results are presented in Section IV. Section V presents the conclusions and directions for future research.

II. CHARACTERISTICS OF CROWDSOURCED AI MARKETPLACES

Digital marketplaces are common in transport, healthcare, e-commerce and other sectors where businesses enable value-creating interactions between two sets of users, typically producers and consumers. However, the type of market that exists in a crowdsourced setting is very different compared to those types of digital marketplaces. Typically, supply-driven crowdsourced marketplaces are imperfect markets, with a large number of producers and relatively few consumers. There are low entry barriers for producers, hence they are the crowd at large. However, the consumers of these crowdsourced goods and services are often far fewer, and are selective in terms of price and quality. Such a market is referred to as an *oligopsony* in the economics literature. The prevalence of oligopsonies in crowdsourced online marketplaces has been analyzed in prior research [9], [19]. The AIM is such a supply-driven crowdsourced online labor market with the following set of stakeholders:

- **Producers:** Content creators and annotators who generate curated and annotated data sets in a crowdsourced model.
- **Consumers:** Model builders and users who access these annotated data sets from the marketplace and use them to train their models, algorithms, and applications for specific uses.

A. THEORIES OF TRUST AND REPUTATION SYSTEMS

Crowdsourcing platforms are well suited to generating large amounts of data that are required to train AI algorithms. However, challenges arise since the data supplied by the crowd can be prone to errors and omissions. Technologies and processes have been developed to handle such quality issues by assigning tasks to multiple workers, and aggregating workers' responses with the help of algorithms [20]. Economic literature on crowdsourcing focuses on developing appropriate incentive mechanisms to elicit high-quality work and penalize bad behavior and poor quality [8], [21]. Much of such work builds on the literature on peer prediction, a framework in which crowdworkers' payments are a function of their own reported labels and the labels of other workers [22].

Another stream of research explores the trust relationship between consumers and producers that associates the probability that the consumer expects to receive a quality contribution from the crowdworker [10], [14]. Reputation systems seek to establish trust between parties to establish long-term relationships and foster trustworthy behavior [23].

It is pointed out that reputation systems indeed have the potenital to improve market quality [24]. Since, in a geographically dispersed crowdsourced marketplace, consumers often do not know producers personally, they can rely on the reputation of a producer, that can possibly indicate the community-wide judgment of a given worker's capabilities. In order to create trust among strangers that is a necessary requirement for the function of collaborative consumption marketplaces, almost every online platform uses some form of reputation system, typically consisting of a record of qualitative reviews and numerical ratings tied to the profile of a platform user [12]. Further, it has been pointed out that both positive and negative feedback ratings are important for an effective reputation system [15]

Such rating methods are also widely used in e-commerce for signaling the reputation of the data sets, and hence that of the producers towards maintaining the desired quality of said data sets in the marketplace [25]. We model such a reputation system, wherein consumers use a rating method to provide both positive and negative feedback about producers based on experiences with the data sets.

B. REGULATING DIGITAL MARKETPLACES

Though trust and reputation systems practised in digital marketplaces have evolved significantly, they are still far from perfect [15], [23]. Information asymmetry between producers and consumers, and producers' sophisticated capabilities to manipulate and game their ratings, have been reported as drawbacks of reputation systems [23]. From a regulatory perspective, reputation systems fulfil a role similar to more traditional means of market regulation. Some authors therefore claim that reputation systems are a way of creating self-policing communities which make traditional forms of consumer regulation superfluous [15]. However, economic studies suggest that there are some inherent weaknesses in the self-regulating model of online marketplaces [21], [26]. The concerns about the integrity of reputation mechanisms have recently prompted regulatory initiatives in a number of EU member states. The spectrum of policies include guidelines issued by national market watchdogs, legislative amendments to consumer laws, and use of standards drafted by national standardization bodies [12].

In general, there are regulatory guidelines governing platforms on aspects of privacy, data protection, trustworthiness, quality, price, market dominance, barriers to entry, and abuse of market power [27]. In this paper, we focus on quality regulation in a crowdsourced AI marketplace.

The AIM should, by its design, ensure that the market participants and the artifacts they produce and consume adhere to such regulatory requirements. A well-functioning marketplace with appropriate regulations can ensure that the data sets are exchanged between marketplace participants efficiently.

We consider in this paper three forms of regulatory responses as suggested by Sridhar [27]:

- **No Regulation:** As pointed out by many researchers, regulators normally do not intervene in technology markets so that innovation in technology and business models can be promoted. It is expected that the market corrects itself if there are any imperfections [11].
- **Passive Regulation:** The second category is that of passive regulation wherein a regulator continuously monitors the marketplace and red flags any negative effects. This is often observed in telecommunications [27]. It is hoped that this disapproval of certain artifacts or processes by the regulator acts as warnings to the market participants to alter their behavior suitably.
- **Active Regulation:** The third category is that of active regulation wherein the regulators red flags certain issues and also penalizes the corresponding stakeholders by actions such as levying fines, banning their activities, or removing them from the marketplace itself.

III. AGENT BASED MODEL OF THE AI MARKETPLACE

We use an agent-based modeling (ABM) approach to construct the different stakeholders and simulate their behaviors under varying regulatory regimes. Though the applications of ABM in producer-consumer markets is well documented [28], [29], our work analyzes a specific crowdsourced marketplace and the impact of various type of regulation on the effective functioning of such a marketplace.

While the agents are modeled as rational—seeking to maximize their respective utility functions, their behaviors under various regulatory environments provide us visibility of the emergent macro properties of the market dynamics. The goal is to identify, using ABM, a certain set of micro-level entities, together with mechanisms, parameters, and interaction rules, that jointly generate the target macro phenomenon in question—as some recent research has shown [30], [31].

Since AI marketplaces are still evolving in practise, our ABM and simulations provide a toolkit for governments and policy makers to influence the orderly functioning of such marketplaces.

It is typical in discrete event simulations that the designer of a simulation will pre-specify all possible transitions, to control the behavior of the events. However, agents in the real world such as business entities and individuals do have intelligence to adapt their behavior depending on the

TABLE 1. Attributes of producer agents.

Notation	Producer Agent Attribute
I	Set of all instances i of producer agent
N_i	Number of data sets produced by producer i
R_i	Reputation of producer i
S_i	Sales revenue of the Producer i
M_i	Market share of the Producer i

TABLE 2. Attributes of consumer agents.

Notation	Consumer Agent Attribute
J	Set of all instances j of Consumer agent
$\alpha_j \sim \mathcal{U}(0,1)$	Price sensitivity coefficient of Consumer j
$\beta_j \sim \mathcal{U}(0,1)$	Quality sensitivity coefficient of Consumer j
$\gamma_j \sim \mathcal{U}(0,1)$	Sensitivity coefficient of Consumer j towards reputation of the Producer
$\psi_j \sim \mathcal{U}(0,1)$	Sensitivity of the Consumer j towards regulatory decision
$\tau_j \sim \mathcal{U}(0,1)$	Tolerance level of the Consumer j for the quality of the data set
$V^j_{k(i)}$	Consumer j's valuation of data set $k(i)$

outcomes of the events, and take into account the temporal change in the environment. Hence, in this work, we have built a model with learning agents, in which intelligence can be constructed in the agents, rather than prescribed as in centralized control. With this approach, agents learn from their own observations about the simulation environment and from the experience of other agents and adapt to the situations.

A. THE MODEL SCHEMA

We formulate the AI marketplace as shown in Figure 1. There are two types of agents: producers and consumers of the date sets in the marketplace. There is also a regulator who enacts one of the three policy regimes as discussed in the previous section.

The following are the distinguishing characteristics of this AIM compared to a marketplace for any good or service:

- **Oligopsony market:** with the crowd as producers and a limited number of highly quality-sensitive consumers, as pointed out by Kumar, *et al.* [3].
- **Reputation system:** this incorporates consumers' ratings of the date sets, and consequently the reputation scores of the producers, as indicated in prior research [29], [32].
- **Self-learning producers:** the rating feedback from consumers is used by the producers in improving the quality of their data sets [10].

The interactions between producer and consumer agents are simulated based on various agent attributes. At any given iteration, every producer agent produces data sets with certain characteristics (e.g. price and quality), and posts them in the marketplace; consumers search the marketplace and select the data sets based on their valuations and use them. Consumers also post reviews about the quality of the data sets. The producers in turn adjust the quality of the data sets to promote them in the marketplace.

B. PRODUCER AGENT

Producers are important stakeholders in the AIM, who create annotated and curated data sets and post them in the marketplace. The properties of the producers are given in Table 1.

In our model, a producer creates data sets and sets the price and quality drawn from appropriate distributions with mean and standard deviation as given in Table 3. Each producer has a reputation score that is calculated and updated based on the interactions in the marketplace (as described in later sections). Further, depending on the type of regulation in force, the regulator can also flag the producers who produce low-quality data sets (also explained in later sections). The market share and sales revenue of the producers are updated after transactions take place in the AIM.

C. CONSUMER AGENT

The other type of agent is consumer. Consumers are defined to be of three types: (i) price sensitive; (ii) quality sensitive; and (iii) reputation sensitive, depending on the weights they assign to the price or quality of data sets, or to the reputation of the producer who has created the data set respectively. The properties of consumer agents are given in Table 2. The values of α, β, γ are respectively higher for price-, quality-, and reputation-sensitive consumer types.

We create equal numbers of price-, quality-, and reputation-sensitive consumer agents during the simulation in order not to introduce any bias in the consumer agent population. At any given iteration of the simulation, each consumer agent searches all the data sets in the AIM and selects the one that maximizes its valuation. Consumers also have loyalty toward certain producers from whom they avail their data sets regularly—consumer agents may prefer their preferred producers despite the presence of an economic incentive to change [33]. We accordingly include a loyalty coefficient l^i_j based on the purchase history between producer-consumer pair in the simulation. If the consumer is loyal, then it prefers a producer with whom it has a previous history.

Consumers may have varying degrees of tolerance towards the quality of the data sets—some are less tolerant and hence give poorer ratings even if the quality of the data sets deviates only slightly from their declared levels, while others are relatively more tolerant.

D. DATA SETS IN THE AIM

The crowd of producers create data sets and post them in the AIM with an indication of their quality, and associated offered price. The properties of the data sets are as given in Table 3. Every data set has price and quality that are declared by the producer, randomly drawn from normal distributions with certain means and standard deviations. Consumers choose data sets that maximize their valuations. While using a data

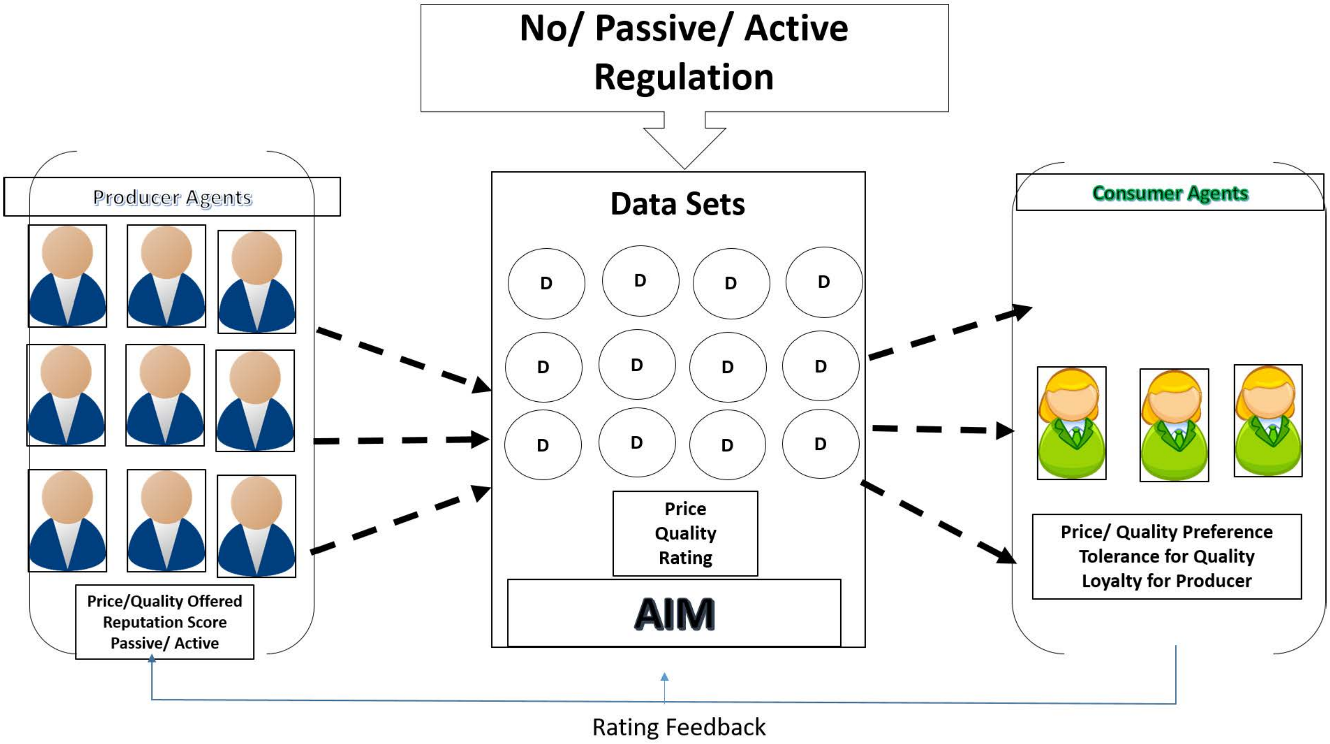

FIGURE 1. Schematic of the crowdsourced AI marketplace.

TABLE 3. Properties of the data sets.

Notation	Properties of the data sets
$k(i) \in K(i)$	data set k produced by producer i
$p_{k(i)} \sim \mathcal{N}(100, 10)$	Price of data set k offered by producer i
$q_{k(i)} \sim \mathcal{N}(100, 10)$	Quality of data sets of $k(i)$ offered by producer i
$n_{k(i)}$	Number of data sets produced by Producer i sold through the AIM
$n^j_{k(i)}$	Number of data sets produced by Producer i that are purchased by Consumer j
$q^j_{k(i)} \sim \mathcal{N}(100, 10)$	Quality as perceived by Consumer j of the data set k offered by producer i
$r^j_{k(i)} \in (0, 1)$	Rating provided by consumer j for data set $k(i)$

set, a consumer experiences its quality as per its distribution. Depending on whether the quality experienced meets expectations, consumers rate the data sets.

E. THE REPUTATION SYSTEM

We model a reputation system in which consumers rate the data sets that they have used to provide feedback to the producers. If after purchase, a consumer experiences quality that is as good or better than that declared by the corresponding producer (moderated by the tolerance level τ) then the consumer is satisfied with the data set and provides a positive feedback, increasing the rating of the data set. However, if the experienced quality of the data set is lower than the declared quality, then the consumer provides negative feedback that lowers the rating for that data set.

We use a Bayesian averaging method [25] to calculate the reputation score for each producer based on the rating of the corresponding data sets as given in equation (2) in Table 5. This is to avoid giving undue advantage to a producer $\bar{\imath}$ who produces a large number of data sets with average quality over another producer $\bar{\jmath}$ who produces fewer data sets but of higher quality. Though an exhaustive list of quality control approaches used in crowdsourcing systems exists [14], [20], it is known that challenges still remain for defining, measuring, and managing quality in crowdsourcing systems. In this work, we add to the existing literature by modeling how producers use the reputation score as a feedback mechanism to improve the quality of their data sets.

F. REGULATORS AND THEIR ROLES

As indicated in the earlier section, we study the behavior of the AI marketplace in the absence and presence of a regulator. Properties of the regulators are as in Table 4. Regulators, if they are present, can be either passive or active. Depending on the type of regulation, a regulator flags producers who produce data sets that do not meet minimum quality standards MQS_R set by them, and also penalize such producers by reducing their reputation scores. The consumers valuation function as given in equation (1) in Table 5 incorporates the regulator's penalty, and hence in turn affects the choices of the consumers in their purchase decisions.

TABLE 4. Attributes of regulator.

Notation	Attributes of the Regulator
$t_R \in \{None, Passive, Active\}$	Type of Regulation
$f_i \in \{0, 1\}$	Penalty flag set by the regulator for producer i
MQS	Minimum quality standard set by the Regulator

TABLE 5. Equations used in the model.

Equation	Number
$V^j_{k(i)} = (\alpha_j \times p_{k(i)}) + (\beta_j \times q_{k(i)}) + (\gamma_j \times R_i) + (\psi_j \times f_i)$	(1)
$R_i = \frac{\sum_{j \in J} \sum_{k(i) \in K(i)} r^j_{k(i)}}{\|J\|\|K(i)\|}$	(2)
$S_i = \sum_{k(i) \in K(i)} p_{k(i)} \times n_{k(i)}$	(3)
$m_i = \frac{\sum_{k(i) \in K(i)} n_{k(i)}}{\sum_{i \in I} N_i}$	(4)

G. THE INTERACTION BETWEEN PRODUCERS AND CONSUMERS IN AIM

Interactions between the consumers and producers in the marketplace are governed by equations given in Table 5, as described below:

- **Valuation of the data sets:** A consumer's valuation of the data set is based on the price and quality of that data set. The valuation is also adjusted for the reputation of the producer. The reputation of a producer tends to increase the valuation of the corresponding data set as perceived by the consumer [15], [23]. If the regulator penalizes a producer for non-compliance, this also affects the consumers' valuation. These are captured in equation (1) with appropriate weights.
- **Reputation of the Producer:** The reputation score for each producer is calculated using the method of Bayesian averaging of the individual rating of the data set in equation (2) [25]. This rating is used to adjust the consumer's calculation in equation (1).
- **Sales revenue of the Producer:** The sales revenue is calculated from the price of the data set and the number of instances sold. The accumulated revenue from all such data sets is the gross revenue of the producer, as defined in equation (3).
- **Market share of the Producer:** The market share of a producer is the number of data sets sold by that producer in the marketplace, compared to the total number of data sets in the marketplace, and is calculated as in equation (4).

H. MEASURING THE PERFORMANCE OF THE AIM

We describe the functioning of the AIM using the flowchart as shown in Figure 2. Note that there are feedback loops that guides the macro behavior of the marketplace. Our objective is to measure and test the following:

- **Average quality of the data sets:** As prior research indicates [2], quality of the data sets in the AIM is an important variable and is expected to improve as the market matures (as indicated by the number of iterations of the simulation).
- **Average reputation of the producers:** The reputation system that forms the basis for providing feedback to the producers is an important aspect of the AIM. The ratings which the consumers give also depend on their tolerance levels. It can be hypothesized that less-tolerant consumers tend to generate stronger negative feedback to data sets, and hence enable the AIM to clearly partition good quality data sets and the associated highly reputed producers from the others.
- **Effect of regulation:** In this paper, as one of the important contributions, we want to measure the effect of regulation on the functioning of the AIM. It can be hypothesized that stringent regulation to penalize the producers of poor quality data sets is likely to improve the quality of the data sets in the AIM and consequently the reputation of the producers. However, we want to test whether there is any threshold MQS, beyond which the producers' marginal benefits gained by increasing the quality of the data sets is lower compared to the cost and effort required to improve the same.

IV. SIMULATIONS AND RESULTS

Extensive simulations have been carried out with 3 consumers and 500 producers representative of an oligopsony marketplace. The parameters of the model are derived from uniform and Gaussian distributions as given in Tables 1, 2, 3, 4, and 5, to create the required heterogeneity and randomness in the agents' attributes. Each scenario with varying regulatory conditions was simulated over 1000 iterations to study the steady-state behavior of the AIM. The consumers are uniformly distributed across low, moderate and high quality sensitivity. The producers are also uniformly distributed to produce low-, moderate-, and high-quality data sets.

A. MARKET WITH PASSIVE REGULATOR

The first set of simulations have been carried out with no regulations in place and that the producers in AIM are passive. In the early stage of any technology innovation cycle, the regulators are not formed yet to formulate rules governing the adoption of the technology. Even if the regulators are present, they do not interfere with the market mechanisms and interrupt flow of innovation and entrepreneurship [27].

In this case, consumers purchase data sets through the AIM that meet their quality requirements, and which maximize their valuations. Since the regulator is either not present or is a passive one, its contribution to the valuation function is not present in equation (1) in Table 5. Results of the simulation are presented in Figure 3.

We observe that initially there is lot of variance in the reputations of the producers, as they try to optimize

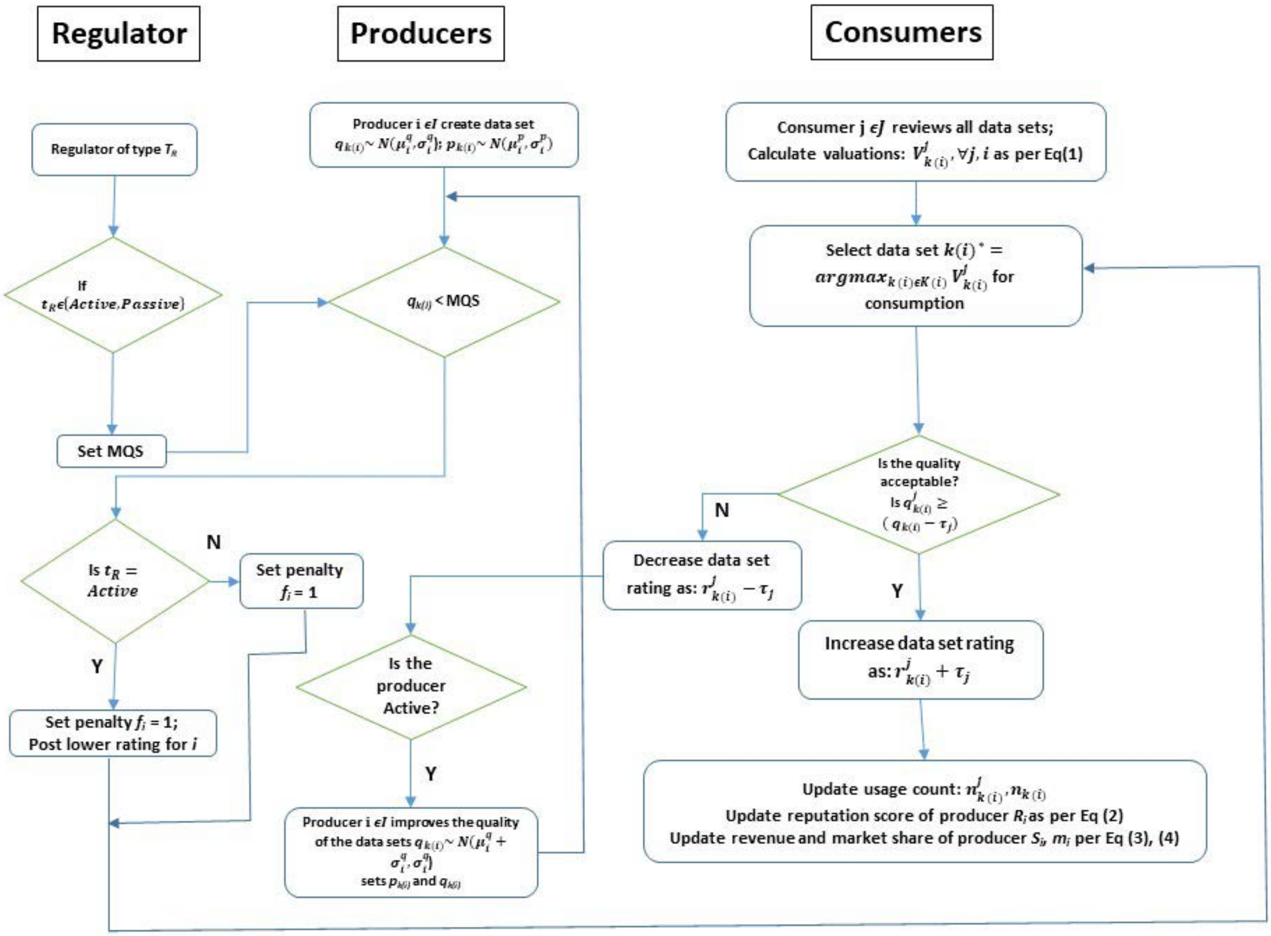

FIGURE 2. Interactions between Producers, Consumers and Regulators in the AIM.

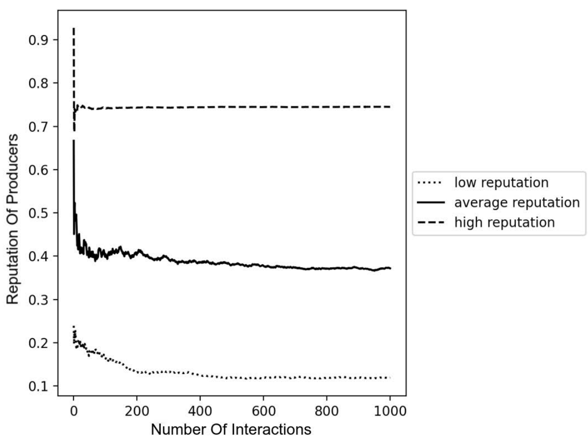

FIGURE 3. Reputation of passive producers with no regulation.

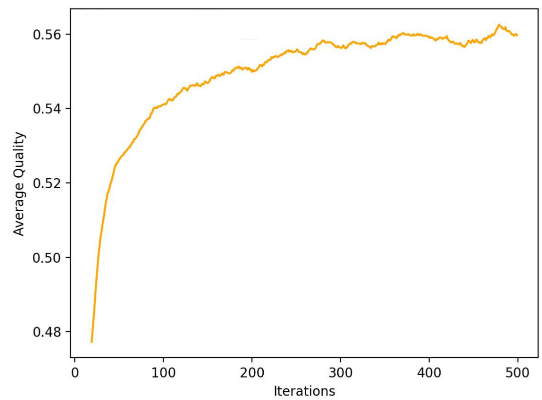

FIGURE 4. Quality of data sets in an AIM with no regulation.

the price-quality combinations of their data sets. However, as data sets get consumed and the consumer ratings start to flow through the marketplace, the producers find their optimal combination of price and quality that are suitable for their target consumers. Hence after the initial dynamics, the producers' reputations settle. High-quality producers always create better quality data sets and hence earn better reputation scores. Since the regulator is passive and does not intervene, moderate- and low-quality producers do not strive to improve the quality of their data sets, and hence are content to get reputation scores much lower than those of high-quality producers.

Correspondingly, the average quality of data sets in the AIM initially increases, but then stabilizes at a value that is neither high nor low in a range of 0-1, as illustrated in Figure 4.

It is typical that the market share m_i and sales revenue S_i of a producer are positively correlated. However, data sets

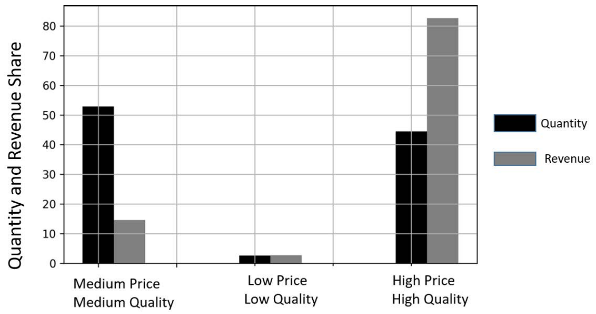

FIGURE 5. Market share of producers by quantity and revenue.

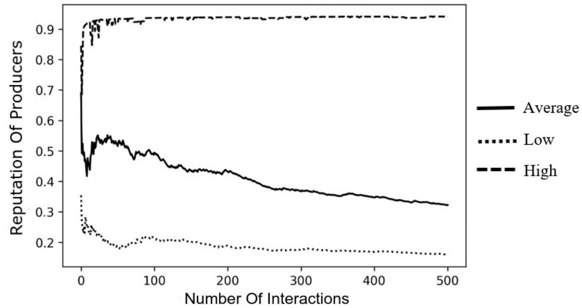

FIGURE 6. Reputation of the producers in the presence of consumers with low τ.

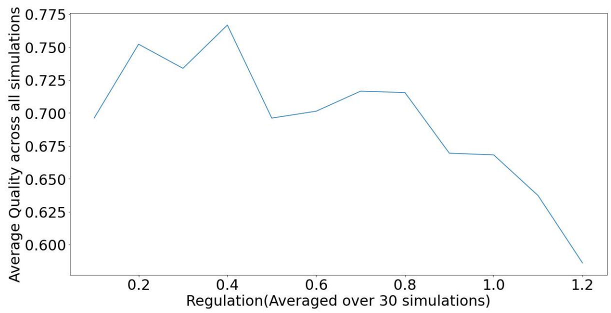

FIGURE 7. Average quality of data sets with varying MQS set by the passive regulator.

can vary both in terms of quality and price, ranging from low quality and low price, to high quality and high price.

Figure 5 illustrates how quantity and revenue market share of the producers vary across different levels of quality and price. Low-quality data sets are not preferred by consumers despite their low prices, showing lower values in both quantity sold and revenue generated. This indicates that the consumers are relatively inelastic with respect to price, meaning thereby that an increase in the price of the data sets does not reduce their consumption proportionately. However, they are relatively elastic with respect to quality, as low-quality data sets are not preferred for purchasing in the marketplace. This is due to minimum quality expected by the consumers while purchasing the data sets in the marketplace, as indicated in Figure 2. Due to this, we see that the marketplace encourages production of relatively good quality data sets that bring in more revenue to the producers.

The consumers experience the quality of the data sets after they procure them in the AIM and use them. If the perceived quality so experienced $q_k^j(i)$ is very different from that declared $q_{k(i)}$ by the producer, then the consumer responds by giving a poor rating for the data set that subsequently lowers the reputation of the corresponding producer. The effect is more pronounced in the case of consumers who are less tolerant (i.e. with lower τ) compared those with high tolerance levels.

In Figure 6, the variation of the reputation of the producers in the presence of consumers with low tolerance levels is illustrated. With low-tolerance consumers, high-quality producers with higher reputation scores stand out as their data sets get positive reviews. Producers who create data sets with medium and low quality are penalized with lower ratings, and their reputation scores show a continuous decline.

B. MARKET WITH ACTIVE REGULATOR

Regulators often step in once a market matures, and there are indications of market failure such as decreasing quality or increasing prices of artifacts. In this context regulators flag data sets if they do not meet their prescribed minimum quality standards (MQS) and also penalize the respective producers by reducing their reputation scores accordingly [26]. Nevertheless, in many industries, and in particular in marketplaces such as AIM, quality observability and enforceability are not perfect [26]. It is to be noted that the consumers' valuation function $V_{k(i)}^j$ in equation (1) in Table 5 captures the regulators' action. If the rating of a data set and the reputation score of its producer decrease due to regulators' penalties, the value of the data set also decreases, and consequently it will be consumed less. The self-learning active producers in turn will improve the quality of their data sets $q_{k(i)}$ so that they successfully pass the scrutiny of the regulator. Thus, the regulator after setting the MQS levels, leaves it for the market to self-correct [27].

We model and simulate this scenario to understand the dynamics of market equilibrium in such cases. Figure 7 shows how the average quality of the data sets in the AIM varies with varying levels of quality threshold levels in a range [0, 2] as set by a passive regulator. We also simulated the market under an active regulator that not only flags the data set, but also penalizes the corresponding producer by lowering its reputation score. Figure 8 shows the average quality variations in the AIM due to the presence of an active regulator.

In both cases, the average quality increases due to the intervention of the regulator. It attains a maximum and then starts deteriorating at higher MQS levels. When the MQS is made higher and higher, lower-quality producers find it difficult to comply. Due to the issues mentioned by Chen & Serfes [26], they along with moderate-quality producers tend to deviate from the set MQS and produce lower-quality artifacts. Noting this, even high-quality producers may get frustrated and start producing lower quality artifacts so that they can sell them at lower prices in the marketplaces to compete effectively.

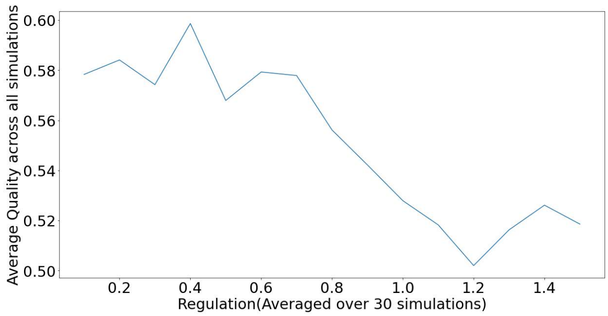

FIGURE 8. **Average quality of data sets with varying MQS set by the active regulator.**

Accordingly, the average quality of the data sets in AIM peaks at a moderate MQS, and then starts decreasing. In fact as observed in Figure 8, the deterioration is much steeper if the regulator is an active one. This clearly indicates that very stringent standards set by the regulator, that are diffiicult to comply with, should be avoided for the market to self-correct effectively.

V. CONCLUSION

Many nations have recently announced their intentions to adopt AI on a large scale for development benefits. Countries are developing national AI strategies for the judicious use of AI in various sectors [34]. The AIM is one of the proposed solutions to deal with data deficiency. Hence, simulation of AIM to understand the working and the shortcomings of such a marketplace is important, both as contributions to the research community, as well as providing a toolkit for regulators and policy-makers. Results from this study gives directions to policy-makers regarding the prospects and risks of their directives for making such a marketplace functional, efficient and equitable.

A. POLICY IMPLICATIONS

The modeling and the resultant behavior of the AIM we have described is in accordance with numerous crowdsourced digital marketplaces that are evolving in areas such gig economy [32] and sharing platforms [12]. While self-regulation is advocated by many researchers for the efficient functioning of such markets as pointed out by Sundararajan [35], there are instances of misuse and outright dishonesty, especially by the producers in such markets [15]. Accordingly, trust and reputation systems are being advocated by researchers to strengthen the quality of markets and associated communities [10], [21].

Our study augments the literature in this area by investigating the effect of varying forms of regulation [12]. Though regulatory researchers have looked at various aspects of crowdsourced markets such as employment and labor [16], political economy issues [17], and ethical dimensions [18], research on the regulator's role in the reputation systems of such markets is less well understood. It is in this context that our work provides an illustration of the emerging behavior of the market under varying regulatory conditions. The model provides a toolkit for the regulator to choose appropriate level of quality standards and feedback mechanisms for the orderly conduct of marketplaces.

Our research indicates that in a crowdsourced AI marketplace, ratings given by the consumers are vital to ensuring the quality of the data sets produced and sold in the marketplace. Further, the presence of regulator, whether passive or active, has the effect of increasing the quality of the data sets to some extent. When the regulator increases MQS beyond a threshold, it acts as binding constraint with producers not able to increase the quality of the data sets further. This often leads to non-compliance and failure of the marketplace. This provides important lessons for the regulators of such marketplaces to be vigilant and at the same time not to micromanage the functioning of the marketplace.

B. LIMITATIONS OF THE STUDY

There have been a number of economic studies in analyzing the reputation systems in crowdsourced markets. However, concerns have been raised by researchers that trust and reputation systems often have vulnerabilities and could often be less robust for the market to behave with efficiency and equity [21].

Our model does not take in to account the bargaining power of the consumers in Oligopsony markets as pointed out by Rogers and Sexton [36] and Bergman & Brännlund [37]. Further, same-side and cross-side network effects as experienced in such marketplaces may have some effect on its effective functioning as pointed out by Rochet and Tirole [38], but we have not included network effects in our model.

The ABM is characterized by a bottom-up approach, heterogeneous agents, bounded rationality of the agents, and the direct interaction between the agents. These have bothered the neoclassical economists as the ABM tends to produce unstable results and that the results are not always comparable to empirical data from the real world [13].

The other learned criticism of ABM is that it lacks the explanatory power of the real world. While simulations generate large quantities of synthetic data as per the model formulation, they may differ from the actual data of the real world. cIn this work, the model parameters are derived from the available empirical data, as cited throughout. However, we have not validated our model both at the micro- as well as at macro-levels with real world data. The branch of agent-based computational economics (ACE) models agents as active gatherers of data that can dynamically learn and alter their behavior and interactions [39]. Recently researchers have built simulators using ACE to investigate market dynamics [40], [41]. As and when the data localization regimes around the world mature, more data will be available from the real world for us to incorporate them into ACE models that blend nicely the abstract theoretical behavior of the model with the real world instances, for the results of the study to be more useful to practitioners and policy makers.

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PRACHI DHAMANGE received the Integrated M.Tech. (iMTech-bachelor's and master's) degree in electronics and communications engineering with a specialization in networking and communication from the International Institute of Information Technology-Bangalore, Bengaluru, India, in 2020.

She currently works as a Software Development Engineer at the Office Platforms Extensibility Team under Experience and Devices Group, Microsoft Corporation (IDC), Bengaluru. Her research interests include networking and ethical marketing practices.

SARTHAK SONI received the Integrated M.Tech. (iMTech) degree in computer sciences with a specialization in data science from the International Institute of Information Technology-Bangalore, Bengaluru, India, in 2021.

He is currently working at MathWorks Bangalore as a part of the Engineering Development Group (EDG). He is also working with customers who are using MATLAB and Simulink for accelerating the pace of engineering and science. He recently published his first paper "Interleaving Fast and Slow Decision Making" at IEEE International Conference on Robotics and Automation (ICRA 2021). His research interests include artificial intelligence and agent-based modeling.

V. SRIDHAR received the Ph.D. degree in management sciences from The University of Iowa, Iowa City, IA, USA, in 1994. He is currently Professor at the Centre for IT and Public Policy, International Institute of Information Technology-Bangalore, India. He was a Visiting Scholar at the Annenberg School for Communication and Journalism, University of Southern California, Los Angeles, CA, USA, from May 2021 to June 2021. He has taught at many Institutions in USA, Finland, New Zealand, and India. He has received funding from different sources, both national and international for his research projects, recent ones being from Facebook. He has published many peer-reviewed articles in *Telecom* journal and *Information Systems* journal. He has also written more than 300 articles in newspapers and magazines on telecom regulation in India. He is the author of three books, such as *The Telecom Revolution in India: Technology, Regulation and Policy* (2012), *The Dynamics of Spectrum Management: Legacy, Technology, and Economics* (2014), and *Emerging ICT Policies and Regulations: Roadmap to Digital Economies* (2019). His recently edited book *Data Centric Living: Algorithms, Digitization and Regulation*, (Routledge, 2022). He has been a member of Government of India committees on Telecom and IT.

SHRISHA RAO (Senior Member, IEEE) received the M.S. degree in logic and computation from Carnegie Mellon University, Pittsburgh, PA, USA, and the Ph.D. degree in computer science from The University of Iowa.

He is currently a Professor at the Graduate School of Information Technology, International Institute of Information Technology-Bangalore, Bengaluru, India. He works on algorithms and approaches for resource management in complex systems, such as used in cloud computing. He has interests in energy efficiency, computational sustainability, and intelligent transportation systems. His primary research interests include artificial intelligence and agent-based modeling, such as bioinformatics and computational biology.

Dr. Rao is a member of the Expert Committee on Technology for the National Spatial Data Infrastructure (NSDI) which comes under the Department of Science and Technology, Government of India. He is also a Life Member of the American Mathematical Society and the Computer Society of India. He is a Contributing Member of the LITD 14 "Software and Systems Engineering" Sectional Committee (a National Mirror Committee of the ISO/IEC Sub-Committees JTC 1/SC 7 Software and System Engineering and JTC 1/SC 38 Cloud Computing), Bureau of Indian Standards (BIS), and a member of the LITD 31 "Cloud Computing, IT and Data Centers" Sectional Committee, which mirrors ISO/IEC/JTC1/SC 38 "Cloud Computing and Distributed Platforms" and ISO/IEC/JTC1/SC 39 "Sustainability, IT and Data Centers." He was an ACM Distinguished Speaker, from 2015 to 2021.