

1-1-2016

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### Recommended Citation

Bataineh, Ahmed Saleh; Mizouni, Rabeb; El Barachi, May; and Bentahar, Jamal, "Monetizing Personal Data: A Two-Sided Market Approach" (2016). *All Works*. 2436.  
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The 7th International Conference on Ambient Systems, Networks and Technologies  
(ANT 2016)

## Monetizing Personal Data: A Two-Sided Market Approach

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### Abstract

Mobile phone-based sensing is a new paradigm that aims at using smartphones to answer sensing requests and collect useful data. Nowadays, a wide variety of domains ranging from health-care applications to pollution monitoring are benefiting from such collected data. However, despite its increasing popularity and the huge amount of data provided by users, there is no platform where mobile phone owners can effectively sell their data. In this paper, we propose the idea of a data monetization platform using two-sided market theory. In this platform, the data is viewed as an economic good and the data sharing activity is considered as an economic transaction. The proposed platform considers the case of abundant data. An experimental analysis is conducted to compare our approach against the peer-to-peer model using a real case study from the health care domain. We show that our proposed platform has the potential to generate higher profit for both data providers and data consumers.

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Peer-review under responsibility of the Conference Program Chairs

**Keywords:** Personal data monetization, Data quality, Data pricing, Two-sided market, Demand curve, Supply curve, Mobile phone sensing

### 1. Introduction and Motivation

The widespread adoption of the Internet and smartphones led to the production of huge amounts of data that can be used in a wide variety of domains including targeted marketing, credit and loan evaluation, medical research, and crime analysis. This opens the door for multi-billion dollar businesses involving buying and selling customer data<sup>18</sup>. Companies like Google and Facebook are earning much of their revenues by enabling marketers to target a specific audience, based on the audience characteristics. According to<sup>3</sup>, Facebook earned a total revenue of \$3.85 billion in the fourth quarter of 2014 from ads - a fact that allows marketers to reach the personal data of their users. Credit bureaux, such as Equifax, Experian and TransUnion sell their consumers' personal data to retailers, banks, insurance firms, and government agencies. The federal agency for Medicare and Medicaid Services, another class of organizations that are engaged in the business of buying and selling personal data, sells medical claims that include medical, demographic, and geographic personnel data to third parties<sup>6</sup>. However, instead of being sold directly by their owners, data is being

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sold by organizations that embed terms in the agreements with their customers to take the permission to use their personal data.

Mobile applications have also taken advantage of the widespread adoption of the Internet and smartphones. According to the International Data Corporation (IDC), the number of smartphone users is expected to reach 982 million users by the end of 2015<sup>7</sup>. This degree of market penetration, combined with the capabilities of phones' embedded sensors have revolutionized the methods of collecting and analyzing sensed data far beyond the scale of what was possible by traditional sensing methods (i.e. wireless sensor networks). This has led to the collection of huge amounts of personal data that could have a monetary value<sup>4</sup>. However, despite the huge demand for mobile sensed data, the development of mature and efficient platforms that enable individuals to trade their data has not been adequately addressed. Existing proposals such as<sup>13</sup> primarily focus on the trading of data from the perspective of organizations without involving individuals - the actual data owners. Some existing organizations, such as<sup>1,5</sup>, offer data services, which collect and aggregate personal data from individuals for specialized applications. Those services usually reward individuals with non-monetary rewards. Mobile phone sensing<sup>14</sup> applications still suffer from the same problem; the vast majority are based on volunteering despite the various costs incurred by individuals participating in sensing tasks.

In addition, current collected data vary in type and quality and their monetary value should also vary depending on the need and the requirements of the data consumers. In fact, most of the collected data using mobile phone sensing can be seen as personal, a data type that has been successfully used in many domains such as target marketing. However, from data consumers point of view, acquiring data is not an easy task as they: 1) need to target the right providers, those who can provide the required data quality; 2) usually have a limited budgets for data acquisition; and 3) need to collect a specific amount of data to satisfy their needs. Things are not better when it comes to data providers. They also need to 1) find consumers interested in their data; 2) know the monetary value of their data based on the "market need"; and 3) maximize their profit.

**Contributions:** Currently, the data market is suffering from the following problems: 1) There is no platform for monetizing data that involves a wide range of primary data providers; 2) Individuals (primary data owners) are either not compensated for sharing their personal data or are compensated by non-monetary rewards; 3) There is a lack of platforms that enable individuals to sell their personal data directly. Usually, secondary data owners like organizations are controlling this operation and benefiting from it; and 4) There is a lack of clear classification of data types and data quality levels; a classification that is required by a wide range of domains such as the health care domain, but also required for estimating the monetary value of the data - a value that may change over time.

To resolve these issues, we propose a platform for personal data trading, using two-sided market theory. A two-sided market is defined as a trading platform dealing with two distinct user groups that provide each other with benefits<sup>16</sup>. The double-sided market trading platform we propose enables individuals (primary data owners) to offer their data as economic good - data that is then classified into groups based on its type and quality. Furthermore, in order to determine the potential consumers for each data group, data consumers are classified based on the data quality they require. The trading platform determines both the purchasing price for data providers and the selling price for data consumers. The price of each data group is estimated based on the price that consumers are willing to pay. Data groups are ranked and separated by their prices. Obviously, consumers who are interested in higher quality data groups are charged a higher price. By using the power of two-sided market, our platform aims to help guarantee the trading of data by attracting more providers and consumers. Using a real-life data set from the health care domain, an experimental analysis to compare our proposed platform with a peer-to-peer model, from the perspective of data costs and the payoff for data providers, is conducted. The comparison shows that when using the two-sided market model, the data cost for consumers is much lower and the data payoff for providers is much higher.

## 2. System Description

### 2.1. Background : The Two-Sided Market Concept

A two-sided market, also called two-sided network, is an economic platform having two distinct user groups that provide each other with mutual benefits<sup>16</sup>. The benefits to each group exhibit demand economies of scale. Credit card holders, for instance, favor credit cards accepted by more merchants, while merchants favor cards carried by more holders. Two-sided market platforms choose the right price to charge each group and considers the fact that adoption on one side drives adoption on the other side. Demand curves on both sides are not fixed: they shift inward

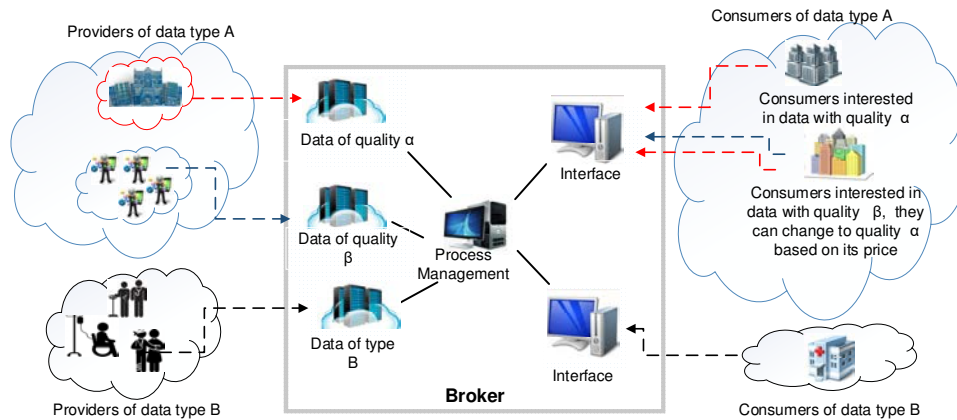


Fig. 1: Personal Data Monetization Platform

(negative network effects) or outward (positive network effects) in response to growth on either sides. Two-sided market Platforms charge the side whose demand increases more strongly in response to growth on the other side and subsidizes the side whose price is sensitive. Two-sided markets are found in many industries including credit card platforms, recruitment sites (job seekers and recruiters) such as Monster, search engines (advertisers and users) such as Google, Internet auctioneers (buyers and sellers) such as E-Bay, social networks (users and advertisers) such as Facebook and Twitter, video-game consoles (gamers and game developers) such as Sony game, and yellow pages (advertisers and consumers) such as daily newspapers.

## 2.2. Platform Description

The proposed platform, as shown in **Figure 1**, consists of three parties: data providers, a data broker, and data consumers. The **broker** is an online platform equipped with the needed infrastructure to store, process, and share data. The broker provides services that enable data providers and data consumers to perform data selling and buying transactions. Using those services, data providers are able to upload their data, set different pricing preferences, as well as accept or reject offers provided by the broker. Data consumers are able to request data and set different pricing preferences, amounts, types and qualities of required data, as well as accept or reject offers provided by the broker. The broker works rationally. This implies that data pricing and the data buying and selling mechanisms are determined based on a number of factors, such as: the number of providers; the number of consumers; the data types offered; the data quality parameters; and other economics factors. **Data consumers** are organizations whose business often requires huge amounts of data with particular specifications. Consumers' requirements vary in terms of the type, quality, and amount of data based on their scope and their applications' needs. We classify data consumers into groups based on the data quality they require. Each consumer group is interested in a particular group of data quality; however, the interest of consumers may change during the selling/buying process. **Providers** can be smartphone users, or individuals, having some personal data to sell. Most of them are not professionals and don't know how they can monetize their data. However, we assume that all data providers behave rationally and can calculate their utilities according to the type of the data they own. Since the provided data varies in type and quality, we propose to classify it accordingly into categories. The classification structure consists of two levels: data type and data quality. Data quality is defined by a vector of attributes which directly affects the data price. These attributes are dynamically defined based on the consumers' needs and may vary from one platform to another. For each data type, the related data quality groups have the same quality vector with different values for the defined attributes.

The proposed platform works as follows: The broker uses his knowledge of the market (further discussed at a later point) to calculate the optimal price for each group of data providers and data consumers. The broker then offers these prices. Providers may accept or reject this offer based on their utilities. Consumers may accept or reject the broker's offer, or they may change their interest and select a different data quality level with a different corresponding price. The broker then buys the data from providers and sells it to consumers.

### 2.3. Assumptions and Limitations

In this paper, we propose to study personal data monetization using two sided-market for cases in which there is no monopoly on either side of the market and in which there is relatively large supply and demand. The data of concern is not real-time data. In other words, the value of the data is not affected by time. The amount of data required by a consumer is much greater than the data provided by one provider, in the sense that consumers need many providers to satisfy the required amount of data. The same data can be sold more than once for different consumers. The broker is not able to discriminate the price among data providers providing the same quality of data or among data consumers requiring the same quality of data. In this scenario, we assume that the broker has complete knowledge about the supply size (number of providers), the demand size (number of consumers), the quality of the data needed by consumers, and the quality of data offered by providers. The broker dominates the entire process of buying and selling the data.

### 3. Model Description

Data providers are classified into  $n$  groups based on their data type.  $D = \{d^1, d^2, \dots, d^n\}$  is a set of groups where  $d^j \in D$  is a group of data producers, which provide the same data type. Each group  $d^j \in D$  is reclassified into  $m$  subgroups based on the quality of their data.  $d^j = \{d_1^j, d_2^j, \dots, d_m^j\}$ , where  $d_i^j$  is a set of data producers providing the same data type with the same quality.

Similar to providers, consumers are classified into  $n$  groups based on the data type they require.  $C = \{c^1, c^2, \dots, c^n\}$  is a set of groups where  $c^j \in C$  is a group of consumers interested in a data type provided by  $d^j \in D$ . Each group  $c^j \in C$  is reclassified into  $m$  subgroups based on the data quality needed.  $c^j = \{c_1^j, c_2^j, \dots, c_m^j\}$ , where  $c_i^j$  is a set of data consumers requiring the same data type with the same data quality. Consumers  $c_i^j$  are mainly interested in the data quality provided by the producers  $d_i^j$ .

#### 3.1. Demand

The broker offers different prices for each data quality group and reveals the available amount for each one. Consumers interested in the same data quality are charged the same price. Data consumer  $i$  has a utility function which is increases based on the amount and quality level of data and decreases based on the offered prices. Consumers calculate the optimal utility and then select a certain quality group with a corresponding price. Any consumer  $i \in c_i^j$  may therefore switch and become interested in a different data quality group such as  $d_k^j$ .

In economics, the demand curve is the graph depicting the relationship between the price of a certain commodity and the amount of that commodity that consumers are willing and able to purchase at that given price. It is a graphical representation of a demand schedule. Analyzing the history of the market is a powerful method of learning about demand and modeling relationships between its parameters, even in the absence of knowledge about the present market. We assume that a linear regression approach is applied by the broker on the history of the market and that the demand is a linear and continuously differentiable function.

The demand from the consumer group  $c_i^j$  on the data group  $d_i^j$ , denoted by  $q_{i(c_i^j)}^j$ , is a function of the amount of data  $s_i^j$  and its price  $p_i^j$  offered to consumers.  $q_{i(c_i^j)}^j$ , presented in **Figure 2a**, has an inverse relationship with the data price since consumers tend to buy data when its price falls. Also note that  $q_{i(c_i^j)}^j$  shifts to the right (has a positive relationship) when increasing the amount of data, since consumers who believed the data was too expensive will now be incited to buy it due to the increased amount available. The equation for the demand, depicted in **Figure 2a**, is as follows:

$$q_{i(c_i^j)}^j = \alpha_i^j + -\beta_i^j p_i^j + \gamma_i^j s_i^j \tag{1}$$

where  $\alpha_i^j$  is constant, and  $\beta_i^j$  and  $\gamma_i^j$  are slopes of the demand curve with respect to the price and amount of data. The total demand from all consumer groups on the data group  $d_i^j$ , denoted by  $q_i^j$ , is given by equation (2).

$$q_i^j = \sum_{k=1}^m \alpha_k^j + -\beta_k^j p_i^j + \gamma_k^j s_i^j \tag{2}$$

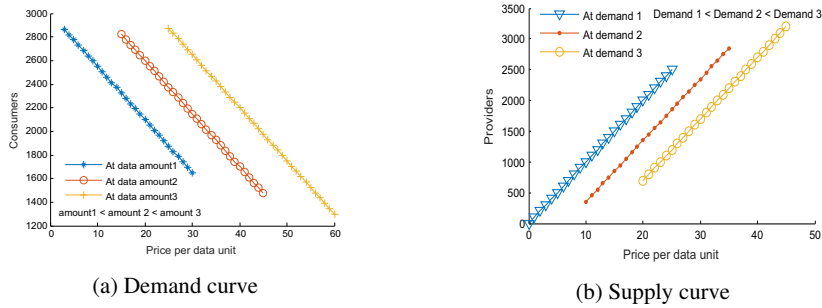


Fig. 2: Demand and Supply curves

### 3.2. Supply

The broker offers different prices for each data quality group and reveals the available demand for each one. Producers providing the same data quality are charged the same price. The provider calculates the optimal utility by calculating his data value and deducting its cost. The value of the data depends on many factors such as its quality, the competition among providers, and the demand size.

In economics, the supply curve is a graphical representation of the relationship between the product price and the number of sellers that are willing and able to supply this product. Similar to demand, we assume that a linear regression approach is applied by the broker on the history of the market and that supply is a linear and continuously differentiable function.

The supply from the data group  $d_i^j$ , denoted by  $s_i^j$ , is a function of the total demand  $q_i^j$  of the group and the price per data unit  $x_i^j$  offered by the broker.  $s_i^j$ , presented in **Figure 2b**, has a positive relationship with the price per data unit, since providers tend to sell the data when its price raises. Also note that  $s_i^j$  shifts to the right (has a positive relationship) when demand increases, since providers who thought the price was too low will be incited to sell to increase their revenues. The equation for the supply  $s_i^j$ , depicted in **Figure 2b**, is as follows:

$$s_i^j = \varepsilon_i^j + \delta_i^j x_i^j + \theta_i^j q_i^j \tag{3}$$

where  $\varepsilon_i^j$  is a constant, and  $\delta_i^j$  and  $\theta_i^j$  are slopes of the supply curve with respect to the price per data unit and the total demand, respectively.

### 3.3. Payoff

The broker’s net payoff is calculated by subtracting the total costs of collecting and selling the data from the total revenue. The cost of data for the broker, denoted by  $C_d$ , can be classified into two categories. The first is the cost of purchasing the data from providers, which is calculated by multiplying the quantity of data purchased by the price per data unit. The second is the cost of collecting the data, denoted by  $C$ , which includes infrastructures, staff and departments, licenses, advertisements, distributions, compensations, etc. The total cost can be written as:

$$C_d = \left( \sum_{j=1}^n \sum_{i=1}^m s_i^j * x_i^j \right) + C \tag{4}$$

The total revenue is calculated by multiplying the quantity of data sold by the price of the data unit. The broker’s net payoff is given by equation 5. Using equations 2 and 3, we can rewrite 5 as 6. The optimal solution of  $q_i^j$ ,  $s_i^j$ ,  $p_i^j$  and  $x_i^j$  can be obtained from the first order conditions given by the derivative of 6 with respect to all demands and supplies.

$$Payoff = \left( \sum_{j=1}^n \sum_{i=1}^m q_i^j * p_i^j \right) - \left( \sum_{j=1}^n \sum_{i=1}^m s_i^j * x_i^j \right) - C \tag{5}$$

$$Payoff = \sum_{j=1}^n \sum_{i=1}^m \frac{(q_i^j)^2 - \sum_{k=1}^m \alpha_k^j q_i^j - \sum_{k=1}^m \gamma_k^j s_i^j q_i^j}{\sum_{k=1}^m -\beta_k^j} + \frac{(s_i^j)^2 - \epsilon_i^j s_i^j - \theta_i^j q_i^j s_i^j}{\delta_i^j} - C \tag{6}$$

#### 4. Experimental Analysis

The interactions between the two sides of the market can easily yield multiple equilibria. For example, an equilibrium may exist at which neither providers nor consumers adopt the interaction via the broker. In the following analysis, we will focus on an equilibrium with positive interaction via the broker. We show that there exist threshold values of prices offered to consumers and prices per data unit above which providers and consumers accept the interactions via the broker. We will use a case study using real-life medical data to conduct our experimental analysis.

In our experiments, we adopt the parameters of the case study presented in<sup>20</sup>. In this case study, a broker collects data from diabetics and disseminates the data to interested organizations. The data is classified into three groups, as shown in table 1, based on the values of certain medical attributes. Table 1 shows the average cost of 200 records for each group.

Table 1: Costs of Diabetics’ Data with Different Quality Levels<sup>20</sup>

Group No	Quality level (NP, PA, RN)	Implementation costs	Data costs of 200 records	Price per diabetic	Total costs
Group1	31-100,29-200,yes	13000\$	12000\$	60\$	25000\$
Group2	100-101,200-400,No	13000\$	5163\$	25.815\$	18163\$
Group3	101-201,400-500,yes	13000\$	12479\$	62.395\$	25479\$

We performed an analysis on a fixed amount of data records (200 records) from group 1. The total cost of data as shown in the table is 25000\$, which includes 13000\$ in implementation costs and 12000\$ to purchase the data of 200 diabetics at a cost of 60\$ per diabetic. In our terms,  $x_1^1 = 60\$$  and  $s_1^1 = 200$ . According to<sup>2</sup>, the selling price of such data ranges in the market ranges from 40\$-80\$, which means 20-40 cents per record. We made the assumption that the number of consumers interested in the data of group 1 is 2000, and the demand curve, given by the equation 7, is defined over prices range from 20-40 cents. The supply,  $s_1^1$ , is neglected in equation 7 since it is fixed in our analysis. Using equation 5 and the calculation shown in section 3.3, the maximum broker’s payoff occurs at  $q_1^1 = 2000$  and  $p_1^1 = 40\$$ .

$$q_1^1 = 4000 - 50 * p_1^1 \tag{7}$$

Consider the first scenario, where interested organizations decide to purchase the data directly from diabetics (i.e. without broker). Since the broker pays 60\$ per diabetic, diabetics will not accept any lower price. However, the organizations also need 13000\$ in implementation costs. In this scenario, the organizations’ costs is 25000\$. **Figure 3a** explains the relationship between the costs when interacting via the broker and the price offered by the broker. As depicted in **Figure 3a**, costs of buying data from the broker is much less than the cost of collecting the data without the broker. Thus, organizations decide to interact with the broker.

In the second scenario, diabetics decide to bypass the broker and sell their data directly to interested organizations. Since the broker charges the organizations 20 cents per record, organizations will not accept paying a higher price. Diabetics need 600\$ to access the contact information of interested organizations (Exact Data website<sup>2</sup> sells organizations’ contact details at 30 cents per record). In this case, the diabetics’ payoff is -200 after deducting the cost of access to organizations’ contact information, and if we assume that all organizations are interested in buying their data directly from diabetics. **Figure 3b** illustrates the diabetics’ payoff over the price offered by the broker when they decide to bypass the broker. As depicted in **Figure 3b**, the providers’ payoff is negative as long as the total revenues, after deducting the cost of collecting organizations’ contact information is less than the price offered by the broker. Because of their negative payoffs, diabetics decide to rely on the broker for selling their medical data.

This results’ analysis can be formalized as follows: 1) Providers of group  $d_i^j$  decide to interact without the broker and offer a price of  $x_p < p_i^j$  at which a certain number of consumers, denoted by  $q_x$ , are willing to purchases the data if the condition  $q_x * x_p - z_c > x_i^j$  is satisfied, where  $z_c$  is the cost of access to consumers. 2) Consumers of group  $c_i^j$

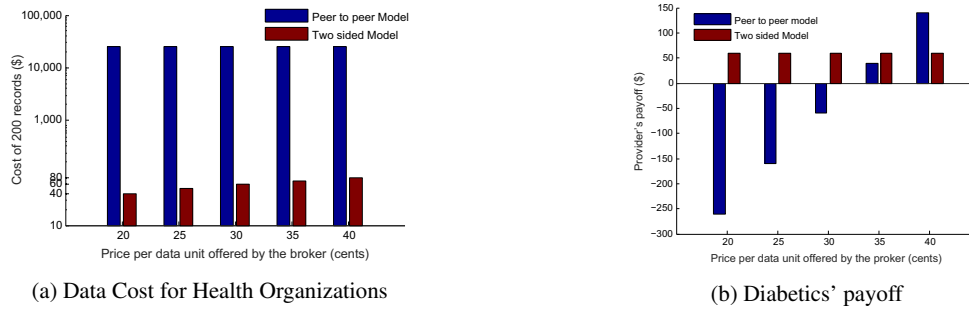


Fig. 3: Two-Sided Market Model Vs. Peer-to-Peer Model

decide to interact without the broker and offer a price of  $x_c > x_i^j$  at which a certain number of providers, denoted by  $s_x$ , are willing to sell their data if the condition  $s_x * x_c + C_d < p_i^j$  is satisfied, where  $C_d$  is the cost of contact details collection.

## 5. Related Work Review

To the best of our knowledge, Personal data monetization has not been studied extensively. Only few proposals<sup>11,13,8,10</sup> have studied the relationship between privacy concerns and data marketing, with a focus on organizations as data owners. Authors in<sup>13</sup> adopted an economics-based approach that addresses the privacy issue facing organizations and how to disseminate sensitive data to a third party data user. However, this work focuses on organizations as data owners, and it doesn't provide any platform for personal data monetization.

The problem of designing mechanisms for pricing data in mobile phone sensing applications has been addressed using different models and techniques. Reddy et al<sup>15</sup> designed a recruitment framework identifying well-suited participants for data sensing based on spatial-temporal availability as well as participation habits.<sup>17</sup> proposed pricing mechanisms for crowdsourcing markets based on the bidding model in which the requester bargains with participants to minimize the cost of data collection. The authors focused on designing a mechanism for buying items (rather than selling) from strategic agents which requires different machinery. Yang et al.<sup>21</sup> proposed Two types of incentive mechanisms using game theory to motivate users to participate in mobile sensing applications: a platform-centric incentive mechanism that is modeled as a Stackelberg game, and a user-centric incentive mechanism that is modeled as a reverse auction game. Lee et al. and Huangfu et al.<sup>12,9</sup> used auction mechanisms to motivate and reward truthful contributions. However, those proposals do not provide sufficient monetization/pricing mechanisms to reward high quality data contributors and are complex to implement in a fully distributed and highly dynamic settings.

To the best of our knowledge, this work is the first economics-based platform that addresses the monetization of data from the perspective of individuals and consumers, and that uses the two-sided market concept. While we have presented some research projects that have a direct link (e.g. selling personal data) or indirect link (e.g. motivating people to participate in crowdsensing, which will generate personal data) with data monetization, the work we are presenting in this paper differs in many ways: 1) We provide a platform for trading data rather than incentives for providers that focus on achieving a particular level of participation. Obviously, generating a high profit is a fact that will automatically attract and encourage users to participate; 2) None of the mentioned studies considered the classification of data based on its type and quality; and 3) The use of two-sided mechanisms for data monetization. Such mechanisms attract more data providers and data consumers and, as a consequence, increase the quality of data as well as the providers' payoff, and guarantee the availability of adequate data amounts.

## 6. Conclusion and Future Work

In this paper, we proposed a novel trading platform for personal data monetization, using two-sided market theory. This platform allows individuals (primary data owners) to trade and monetize their data. It also applies an economic approach to determining both purchasing and selling prices. In this platform, we classified the data into groups based on its type and quality. Moreover, consumers are classified based on the quality they require in order to determine



the potential consumers of each data group. As shown by the experimental analysis, the platform increases the data providers' payoff and decreases the cost of data collection for data consumers. It also guarantees an adequate level of quality and a suitable amount of data for consumers.

Our platform is limited to the cases in which there is no monopoly on either sides of the market and in which there is a relatively large supply and demand. In addition, the value of the sold data in the platform is not affected by time. Our platform can be extended to include more types of data and address different possible scenarios such as the cases in which there is monopoly on provider's side or relatively low demands from consumer's side. In addition, this platform, as it stands, is not able to deal dynamically with changes on consumer and providers sides. For example, when few consumers accept the offered price by the broker. However, extending the platform to include more types of data and considering more scenarios may move the control from the broker to the market sides, which requires further investigation using different techniques, particularly game theory<sup>19</sup>.

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