Incentivizing Data Quality in Blockchain-Based Systems—The Case of the Digital Cardossier

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Inspired by an industry initiative to address the celebrated market for lemons (poor-quality used cars), we investigate how incentives for a permissioned blockchain-based system in the automobile ecosystem can be designed to ensure high-quality data storage and use by different stakeholders. The peer-to-peer distributed ledger platform connects organizations and car owners with disparate interests and hidden intentions. While previous literature has chiefly examined incentives for permissionless platforms, we leverage studies about crowdsensing applications to stimulate research on incentives in permissioned blockchains. This article uses the action design research approach to create an incentive system featuring a rating mechanism influenced by data correction measures. Furthermore, we propose relying on certain institutions capable of assessing data generated within the system. This combined approach of a decentralized data correction and an institutionalized data assessment is distinct from similar incentive systems suggested by literature. By using an agent-based model with strategy evolution, we evaluate the proposed incentive system. Our findings indicate that a rating-based revenue distribution leads to markedly higher data quality in the system. Additionally, the incentive system reveals hidden information of the agents and alleviates agency problems, contributing to an understanding of incentive design in inter-organizational blockchain-based data platforms. Furthermore, we explore incentive design in permissioned blockchains and discuss its latest implications.

CCS Concepts: • **Networks → Network economics**; • **Computer systems organization → Reliability;**

Additional Key Words and Phrases: Blockchain, peer-to-peer market, incentives, data quality, action design research

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1 INTRODUCTION

Many industries struggle to improve processes that involve interrelationships (in some cases not apparent) between different, untrusted, and heterogeneous organizations. In many sectors (e.g., education, healthcare, and the automotive industry), there is no way an individual organization (including governmental bodies) can resolve emerging problems of high complexity by acting alone [20]. Nowadays, organizations establish relationships with others in nearly every business transaction stage [38]. Consequently, organizations build up inter-organizational relationships to address emerging problems and profit from improved performance (e.g., efficiency gains and new business models) and cooperation (e.g., innovations and knowledge sharing). To resolve trust issues, mechanisms such as legal contracts, regulations, and incentive alignment are usually established.

Blockchain technology is a distributed ledger allowing for decentralized peer-to-peer transactions. Participants can securely establish agreements on shared states for transactional data without the need for a central point of control. Recently, with the emergence of blockchain technology [48, 52], organizations have started experimenting and building up specific consortia, which are a popular means of working cooperatively to attain business goals [16]. More than 400 such consortia are now in existence [14]. Though the potential of blockchain technology for inter-organizational relationships has not been fully explored yet, it claims to be an enabler of business relationships in many fields (the financial sector and logistics currently being the most prominent). Blockchain technology may also alter established governance models [67]. Organizations involved in blockchain consortia opt for secure and transparent data exchange and storage, which this technology promises. This creates a new peer-to-peer disintermediated data market in which organizations can profit directly from buying and selling data to each other and other interested parties. However, to generate value from this exchange and storage (which is the goal of such inter-organizational relationships), these consortia must achieve stored data of high quality. As no individual organization governs this data market, new modes of governance are needed. One of the critical dimensions of blockchain governance lies in incentives [9]. Incentives motivate agents (network participants) to act so that their behavior remains aligned to the system goals [9]. These incentives may be monetary (e.g., earnings) or non-monetary (e.g., reputation, opportunities for new business models, or beneficial cooperation). While incentives are widely explored in research streams on organizational governance and, to some extent, on permissionless blockchains, there is a breadth of questions that remain open for permissioned blockchain technology.

Recently, [9] began to explore incentive mechanisms in blockchain-based systems and proposed a related research agenda. We focus on an incentive mechanism placed in a permissioned blockchain-based platform for the automobile ecosystem, which ensures a high quality of exchanged, stored, and traded data. By "data quality," we mean the correctness of the stored data (i.e., the data are accurate, valid, and error-free) as well as complete (no relevant data are missing) [43, 45]. In the car ecosystem, many different agents have various incentives to provide incorrect data or conceal data, such as car owners exaggerating the condition of their vehicles. While there are many approaches for incentivizing participants to contribute data, e.g., in crowdsensing applications [33], no mechanism has yet been proposed to incentivize data quality for permissioned blockchain applications in the car ecosystem to account for the diverse interests of (possibly external) agents.

The problem of poor-quality input data ("garbage in, garbage out") is widely known, but it becomes even more important to ensure high data quality in the context of blockchains. This is because—once recorded—data cannot be changed owing to the immutability of blockchains. So far, the literature suggests that internet-ofthings solutions (sensors for tracking physical measurements) combined with oracles (third-party services to verify data) may be a feasible solution [36]. However, these solutions usually have tradeoffs between efficiency gains and technology cost [5]. This problem is exacerbated since there is no central authority in a blockchain system to safeguard data quality. We argue that to achieve high-quality data, participant interests must be aligned towards this goal. Therefore, to ensure that a consortium can extract value from data exchanged and stored in a permissioned blockchain-based system, data quality must first be assured by correctly incentivizing the participant—in particular if agent interests are orthogonal to this goal. Consequently, in this article, we address the following research question:

RQ: How can we incentivize data quality in blockchain-based systems for the car ecosystem?

Furthermore, we discuss and generalize our results to incentive systems for permissioned blockchains. We use an **action design research** (**ADR**) [46] approach to understand the problem space and develop an incentive system. As part of the ADR, we use agent-based modeling [13, 31] to formalize the system and evaluate design choices. The contributions of this study are two-fold. First, we look at an instance problem based on findings from an existing blockchain project (referred to here as "Cardossier") to cope with the lack of quality data. Then, we combine the literature on crowdsensing applications and blockchain incentives to propose a hybrid incentive system including a rating mechanism impacting the payoff for participants to resolve incentivization problems related to the quality of data provided and exchanged. To evaluate this model, we ran extensive simulations to show what effects this has on the blockchain-based data market. In so doing, we contribute to solving the problem of data quality for blockchain-based systems for the car ecosystem.

Second, starting from the general problem setting of designing incentives for the blockchain economy introduced by [9], we abstracted our instance problem and solution with the help of agency theory [12] to discuss what implications the results of our study have in terms of incentive design for permissioned blockchains. This is an initial step towards understanding the mechanisms of incentive systems in permissioned blockchains.

The article is structured as follows: In the following section, we provide an overview of the consortium and the Cardossier project, i.e., the instance setting, and formulate its problems. In the methodology section, we describe the ADR approach taken in this study, and in the related work section, we review the relevant literature on blockchain in the car-related ecosystems, blockchain governance, and principal-agency theory. Next, we present our design goal and requirements, and in the model section, we introduce the Cardossier incentive system. The following section describes how we evaluate the incentive system by simulation, and in the results section, we present the simulation data. Our discussion reflects on the findings, their meaning, and the implications for blockchains in the car ecosystem, governance and incentives for permissioned blockchains, and principal-agency theory. Finally, we draw conclusions from our study, outline its limitations, and propose future research directions.

2 CARDOSSIER

A 2017 consumer study conducted in Germany reported that the automotive sector was among the least trusted consumer markets (only surpassed by banking/insurance and the telecommunication industry) [24]. In particular, the second-hand car market suffers from issues such as the car being in worse condition than advertised, having undisclosed accident damage or limited documentation, or the object of fraudulent activity, and so on [23]. This problem was famously documented by George A. Akerlof and is known as the "Market for Lemons" [2].

2.1 Cardossier Project

In a consortium of companies from the automotive market, the Cardossier project seeks to resolve mistrust, non-transparency, and process inefficiency by creating a blockchain-based solution. The project began as a research and innovation project and involved organizations from the car-related ecosystem—companies (an insurance company, an importer and official car dealer, and a car-sharing company) and public authorities (the Road Traffic

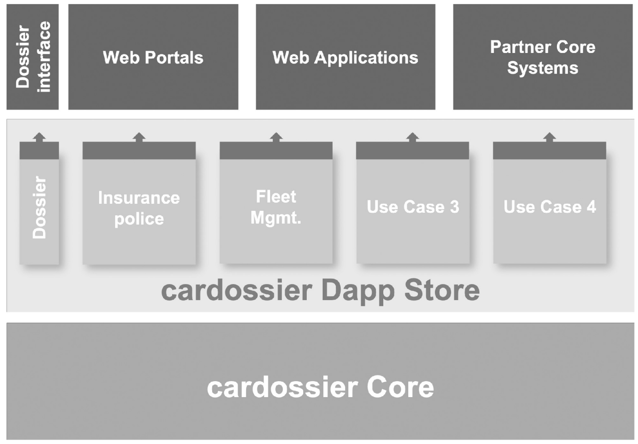

Fig. 1. The building blocks of the Cardossier platform.

Agency). The goal was to collect various data over a car's lifetime to create a valuable "Cardossier" and a shared platform for data exchange to increase the efficiency of operations. As multiple parties involved do not fully know or trust each other, the participants opted for a blockchain-based solution. Blockchain technology serves as an enabler for such inter-organizational relationships; from the technological perspective, centralized systems may address these issues, but they are legally and practically unviable. Legal issues (not least because of data protection and the limited scope of public administrations) prevent governments from running such systems. From an organizational point of view, participants do not trust any single provider to run a platform for them, so the distributed nature of blockchain governance is a significant driver for consortia to rely on blockchain technologies. In March 2019, a non-profit association was founded to prepare for market entry, foster expansion of the blockchain ecosystem, and establish Cardossier as a standard for car-related data in Switzerland.

The Cardossier solution is built on top of Corda,[1] a modular open-source platform providing a permissioned blockchain infrastructure. The permissioned framework is ideal for a business application in which participants require some means of identification but do not necessarily fully trust one another [55]. Such a system creates an inter-organizational relationship among companies which calls for well-established governance mechanisms. One of the governance mechanisms is an incentive system, ensuring consistency and a self-sustaining operation. These include the quality of data provided, gains and losses experienced by participants, and their behavior (e.g., how active participants are and how to identify and avoid malicious behavior).

The blockchain stores data records associated with vehicles—accidents, servicing, technical issues, and ownership transfer. The complete set of records for a specific vehicle is the Cardossier. The data are saved, linked on the blockchain, and customers (e.g., private or organizations) can purchase access to relevant data within the Cardossier platform. A system based on smart contracts, ensuring payment for data suppliers or payment of a fee for data consumers on fulfillment of certain conditions, provides a financial incentive for participation. Such a data market motivates data exchange in the Cardossier system, and its building blocks are depicted in Figure 1. The Cardossier core is blockchain-based storage for data exchange, which contains data records for vehicles, as mentioned above. The Cardossier's Dapp store offers a framework to create decentralized applications (the so-called Dapps). Dapps access the stored car-related data and execute business logic (e.g., creating an insurance policy, fleet management, or other use cases). These Dapps are connected to external applications or systems,

[1]See https://www.corda.net. Prior publication [64] reported on the Cardossier being implemented on Hyperledger Fabric. The project reconsidered the design decision for the blockchain platform in the course of the project and changed from Hyperledger Fabric to Corda due to privacy requirements.

such as web portals (e.g., an online portal for used cars), web applications, or the core systems of consortium partners. In essence, this is a system in which multiple parties can do business together without necessarily trusting one another.

2.2 Cardossier Problem Formulation

As the ADR team was actively involved in creating the system, problem analysis was highly iterative. It included feedback from the project partners (the Cardossier project) in interviews and project meetings (as described in the methodology section). The cars registered on the platforms may have undesirable features that a car owner or an organization would prefer to conceal. The organizations are internal to the platform, i.e., they participate in the consensus mechanism and write data to the blockchain. However, the data written to the blockchain by the organizations depend on external parties, namely the car owners. The car owners may have incentives to conceal their actions [17], such as having their car repaired externally to avoid documenting the accident in the Cardossier. The external repair shop which could provide the necessary data is not a part of the Cardossier system, so it does not contribute. In such a case, it depends on whether the car owner decides to report the external repair shop data; otherwise, there is a missing record in the car's service history.

Clearly, not all agents act dishonestly, but we can safely assume that not all their intentions are disclosed, and the overall quality of the data provided is difficult to control. Blockchain technology—thanks to its immutability characteristic—ensures that entered data cannot be altered, although it is still unclear how to ensure the initial input of data is correct (i.e., there are no unintentional errors or deliberate falsification) and supply is constant. Furthermore, since there is no central authority to guarantee the data inserted in the ledger (and/or the agent's accuracy), it is also a challenge to identify the agents that behave dishonestly. However, a clear identification of malicious agents enables measures to be taken (e.g., fines, declined services, or exclusion).

Several issues may hinder data quality: technology (e.g., incorrect manual input of data, no visual interface, or insufficient competence to use the system), strategic considerations (e.g., an organization does not wish to reveal any critical business information, and manipulates the data), data protection and privacy (e.g., how to deal with the private data of car owners in such a distributed system, and clarity over who owns the data records), and regulations (e.g., in cases when state organizations such as the Road Traffic Agency need to be enabled by law to use such systems as the basis for car registration checks). Moreover, organizations may act dishonestly, deliberately providing incorrect data. In such a case, the agent may even claim ex-post that they added incorrect data unintentionally, i.e., moral hazard [3]. Organizations and car owners may even collude to hide data or provide false data to the platform. These two factors (incorrect or missing data) decrease overall data quality and threaten the accuracy of a platform whose goal is to exchange high quality data. Inaccurate data undermines the platform's goal to rid the market for lemons [2] problem by reducing information asymmetries. The formation phase of the consortium is particularly problematic. Here, the Cardossier platform needs to offer the potential to resolve the lemons problem in the used car market by providing high-quality data [65]. In turn, agents need to have an incentive to provide high-quality data, even though the market activity and the revenues on the platform might be low at the beginning. Thus, an incentive system that involves the relevant external agents and is effective even with low revenues is needed to ensure data quality on the Cardossier platform.

3 METHODOLOGY

3.1 Action Design Research and Project Setting

For the entire project, we followed the ADR approach [46]. ADR allows for the design of an IT artifact embedded in an organizational context, encompassing proven methods from both design science research and action research. In our case, the IT artifact consists of an agent-based model of an incentive system designed to become part of the overarching IT artifact—the Cardossier platform. To create a valuable solution for blockchain-based

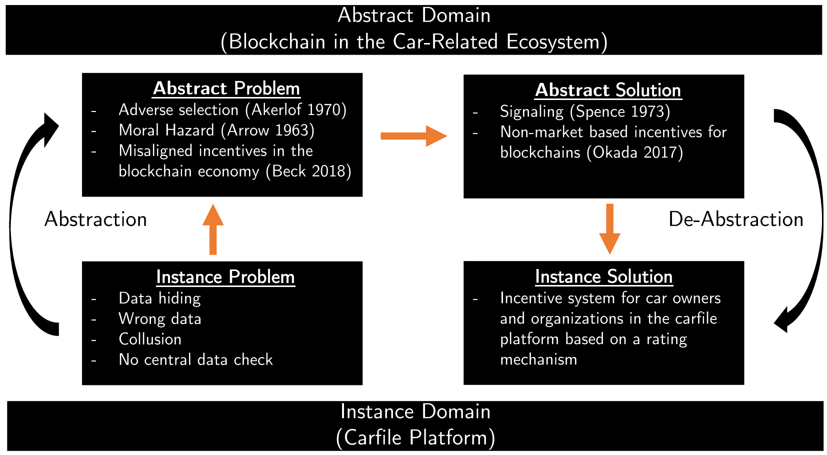

Fig. 2. Abstract and instance domain (illustration inspired by [25]).

data markets in the car sector, we operated in an abstract and an instance domain, as [25] suggest. We looked at an instance problem in the Cardossier platform. Due to the hidden actions of the participants, car owners and organizations have incentives and opportunities to hide certain data records, add incorrect data, and collude. Given the collaborative nature of the Cardossier platform, there is no single central authority checking data, which impairs the effectiveness of the peer-to-peer car data market by reducing data quality in the system. We abstracted these problems with the help of literature to general blockchain systems in the automotive sector. Principal-agency theory identifies the abstract problem of adverse selection [2] and moral hazard [3] while [9] describe misaligned incentives in the blockchain economy. Using solution concepts from the abstract domain such as signaling [47] and incentives for blockchains [37], we developed an incentive system as an instance solution. Figure 2 illustrates our approach.

The problem and the proposed solution addressed in this study call for close collaboration with a consortium of companies that build up a blockchain-based data market. This requires continuous examination of the specific organizational setting by intervening and evaluating [46]. The ADR methodology is the proper means not only by which to design and build an innovative IT artifact [19] but also to embed it into and learn from the organizational context while addressing a problematic situation [46]. The ADR project is conducted within the Cardossier project described above. Figure 3 summarizes how ADR was set up for this study regarding its stages, methods, and artifacts.

Stage 1: Problem formulation: To gain an overview of the state of the art in the field, extensive literature research was conducted as a starting point [54]. We focused on existing incentive models in current blockchain implementations as well as in other peer-to-peer networks. Four semi-structured interviews [34] with each of the business project partners in the Cardossier, conducted between April and July 2017, were analyzed to understand the organizations' business activities. Furthermore, the group of researchers involved in the project attended tri-weekly project meetings between August and November 2017. These meetings and discussions served as targeted observation sessions to determine specific problems regarding data quality and incentives. Finally, we used concepts from principal-agent theory to embed the problems theoretically.

Stage 2: Building, intervention, and evaluation: We formulated the early requirements for the incentive system, and these were verified on 5 October 2017 in a focus group [27] with the project partners. The scenario-based design [41] approach helped us form a link from abstract examples, where incentive mechanisms are needed, to provide more specific examples. Two scenarios were identified—car birth and logging in the blockchain, and

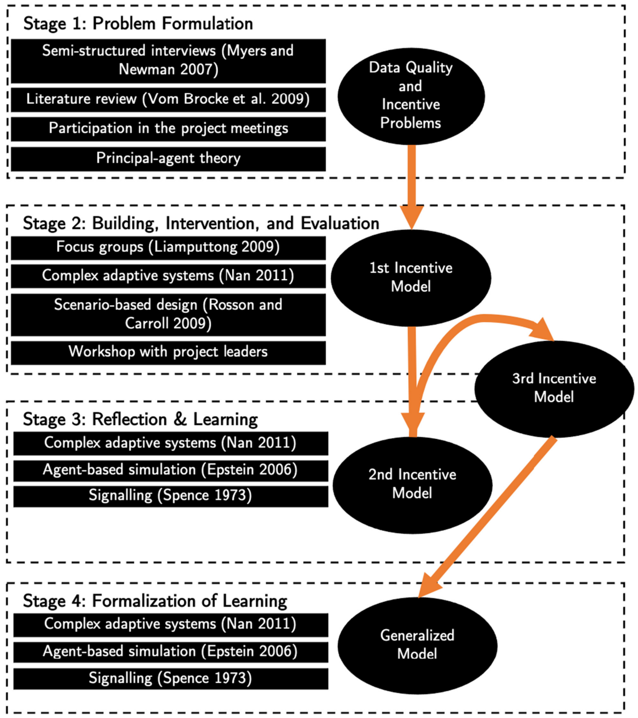

Fig. 3. The ADR process: Rectangular boxes are the methods used, round boxes are the artifacts.

car usage and the case of an accident. Following this, inspired by the modeling approach for **complex adaptive systems (CAS)** [35] (for a more detailed description, we refer to the modeling approach section), we designed the initial version of the model for the incentive system.

Stage 3: Reflection and learning: The model was evaluated in the follow-up focus group on 16 November 2017. The focus group provided constraints for the model. Furthermore, several rounds of workshops within the ADR team, conducted between February and April 2018, helped refine the model (e.g., including specific roles in the model). A simple version of the model was published in the peer-reviewed International Conference on Information Systems 2018 [63]. After receiving a lot of helpful feedback and following in-depth discussions within the ADR team, we improved the model by including the car owners in the incentive system and running further simulations. We conducted the second iteration of Stage 2 by creating an updated version of the incentive system. We verified the design and assumptions in a workshop with the vice-president of the Cardossier association on 29 November 2019. Furthermore, we refined the model within the ADR team based on the results of agent-based simulations embedded in signaling theory [47]. The inclusion of the car owners and the signaling aspect led to a third version of the incentive model.

Stage 4: Formalization of learning: In 2020, we generalized our Cardossier specific model to demonstrate how such an incentive model might be designed in heterogeneous blockchain-based systems in a car ecosystem. We conducted additional simulations to test the model under a variation of the cost for providing data, the probability that a data bundle is sold, and the probability that a car owner would consult an external organization. In this article, the abstract concepts from the model are presented for blockchain data markets together with the instance solution for the Cardossier project. We further elaborate implications from our model for the literature regarding incentive systems in blockchain, blockchain systems in the car ecosystem, and principal-agency theory.

3.2 Modeling Approach

One way to describe an inter-organizational network of high complexity and changing dynamics is to treat it as a CAS [11]. CAS describes "interplay between a system and its environment and the co-evolution of both the system and the environment" [11]. CAS can be referred to as "a system that emerges over time into a coherent form and adapts and organizes itself without any singular entity deliberately managing or controlling it" [11]. One important characteristic of CAS is that there is no central governance mechanism in place. This type of system is controlled by different distributed interacting parts with little or no central control. Each of these parts has its own governance rules, but together they influence the system by various means, enabling CAS to be highly adaptive to its surroundings [21]. This property closely resembles the spirit of decentralized blockchain-based systems. Consequently, we argue that it is a natural fit for designing and analyzing an incentive system for a blockchain-based data market. Furthermore, originating from studies on biological systems and later applied to numerous socio-economic systems, "CAS have the ability to self-organize and dynamically reorganize their components in ways better suited to survive and excel in their environments, and this adaptive ability occurs, remarkably, over an enormous range of scales" [30]. These factors—self-organization and adaptation—correspond to the requirements for designing the incentive system we propose in this study. Although there is no single definition that researchers agree on, since the concept is still developing and changing depending on the research field [35], three components of CAS are established and commonly recognized, namely agents, environment, and interactions [35]. We used the three basic concepts of CAS as a tool to describe the building blocks of the incentive system we designed. First, agents are actors or single entities in the system and may have specific attributes that reflect an agent's internal state and behavior according to specific rules. Second, the environment is a medium for agents to operate and interact and may be characterized by its structure. Third, interactions are the behaviors of agents characterized by connections between agents and flows of resources between them. During the modeling process, activities within the ADR project provided input to define specific attributes of agents (such as their roles and behavior). Beyond this, the activities helped define agent interactions in the systems aligned to creating a data market within the Cardossier project.

To analyze agent interactions in the environment of a CAS on a particular set of rules, researchers used agent-based modeling [13, 31] as a powerful tool for computational simulation. We kept the modeling approach parsimonious, intending to reduce the set of parameters to a bare minimum, which allowed us to disentangle their role in the overall system properties. Then, following the approach of [35], we conducted extensive simulations to measure global properties and the influence of certain parameters in the system. More specifically, we measured data quality with and without the incentive system, its capability to identify hidden intentions of agents, their strategic actions due to changed incentives, and the effectiveness of the proposed system.

4 RELATED WORK

4.1 Blockchain in the Car-Related Ecosystem

In recent years, an increasing number of publications have discussed blockchain-based systems in the automotive sector. For example, [36] outlined the idea of a "trust-free" transaction history of cars to address the "market for lemons" [2]. While the need for trust is not eliminated altogether, interpersonal trust is replaced by trust in the platform [64]. Other studies suggest that blockchain-related trust shifts to other (sometimes newly created) market participants [4]. This endangers business models based on interpersonal trust, such as in the case of used car dealers [8], and creates new data-driven business models [6]. These data-driven business models rely on the quality of the data and, most importantly, the data need to be correct and complete [58]. Though blockchain technology is often used to create a "single source of truth" for data, the problem of "garbage in, garbage out" remains, and this requires additional mechanisms to achieve and maintain high data quality. There are two approaches to this: (i) By collecting data with trustworthy "oracles" [32]; here, [10] propose trusted sensors to collect car usage data, and (ii) by incentivizing participating agents to provide the correct and complete data. A shared market for car data can provide the necessary funding to make it attractive for partners to provide high-quality data [7]. In addition, agents from the public sector may penalize those who deliver incorrect or incomplete information for official purposes, e.g., during regular checks for car roadworthiness [44]. While pointing to the essential building blocks of an incentive system, this research leaves it open to see how a comprehensive incentive system for improving data quality in the blockchain-based system for the car ecosystem should be designed.

4.2 Governance and Incentive Systems for Blockchains

Reasonable and well-aligned incentives play an important role not only in the digital economy, but also in the blockchain economy [9]. The blockchain economy consists of smart contracts enforcing pre-defined rules constituting a new governance paradigm for organizations. Without a consistent and self-sustaining incentive mechanism, a blockchain economy would not be possible. Though [9] do not define an incentive system for blockchain economy, they identify three levels on which incentives should be aligned, namely digital processes in peer-to-peer exchanges for value creation of blockchain-based digital goods; incentives to create private goods, club goods, and public goods; and new network-based processes that incentivize the peer-to-peer nodes to reach consensus. Also, [53] consider incentives a fundamental dimension in blockchain governance to motivate the agents. Indeed, there has been an ongoing debate about *on-chain* vs. *off-chain* blockchain governance [60]. While *on-chain* governance refers to rules directly encoded in the blockchain infrastructure, *off-chain* governance refers to all other rules and decision-making processes that might affect a blockchain system. For incentives, it is not clear whether they should be implemented *on-chain* or *off-chain*.

Incentive systems have been extensively studied within crowdsensing applications in which people voluntarily use their mobile devices to collect and share data with a platform. A good overview of existing approaches is given by [33], and usually, the incentive system takes the form of reputation, barter, or monetary rewards [18]. However, traditional crowdsensing applications rely on a centralized server that controls data flow. Recently, researchers have begun to study incentive systems for peer-to-peer networks based on blockchains. The objective of the incentive system differs depending on the application. For example, [18] incentivize data transmission in a distributed peer-to-peer system by a blockchain reward paid by the sender.

Similarly, [39] propose rewarding nodes in a blockchain system for storing data with a digital currency. Once stored, participants should share these data to reduce redundant work in the system. [62] construct a smart-contract-based approach that dynamically adjusts rewards for data sharing based on the cost of the participants. Besides these objectives, data quality in blockchain-based crowdsensing systems has also been addressed. Generally, the approaches are structured along the following lines: A data requester posts a task to the network stating the exact data quality parameters, after which miners check the data provided by the participating users. Both the miners and the users receive a reward [57] paid by the requester for their task. However, purely monetary rewards may have crowding-out effects on user-contribution behavior, as [28] demonstrate. It can either demotivate altruistic users or drive out low-contribution users due to intensified competition. As an alternative, an approach based on reputation, in which the requester checks the data quality and feedback affects the contributing user's reputation score can be used. [66]. Many permissionless platforms use a token for incentivizing their users, such as Steemit [26].

All these approaches are implemented within permissionless blockchains. In permissioned blockchains, there is no need for participants to engage in energy-consuming and competitive processes (such as mining), and they can instead agree on an appropriate mechanism [37]. Blockchain systems can have market- and non-market-based incentives. Market-based incentives are tightly bound to a token or cryptocurrency, pricing mechanisms, and market price. Therefore, they are more suited to permissionless blockchains, while in contrast, consortium blockchain systems need non-market-based incentives. [61] found that for systems where a permissioned blockchain is a more feasible solution than a permissionless one, and some data may be stored *off-chain* (e.g., for maintaining privacy), "an additional economic incentive is required for the participants to be honest." This incentive may include security deposits, reputation, or rating mechanisms. Furthermore, in these situations, there should be additional incentive mechanisms (e.g., legal measures, such as contracts or regulations), which will ensure the appropriate behavior of network participants. Beyond these participants, external parties should also be considered. [51] state that the internal participants of a blockchain platform and external parties such as the users, customers, and other partners should also be incentivized. Engaging external stakeholders is crucial for business model development in blockchain enterprise ecosystems. [37] conclude that there should be further exploration of how such incentive systems are designed, evolve, and change over time.

Recently, [59] suggested a hybrid incentive mechanism that integrates data quality, reputation, and monetary reward. Previous data quality and reputation scores influence the selection of a user for a specific task, and the updated reputation score affects the reward. The entire system runs on top of a permissioned blockchain platform. A useful benchmark for incentive systems is the concept of incentive compatibility [22]. In an incentive-compatible system, participants would gain no advantage by breaking the rules. In summary, the literature gives clear indications about how to design an incentive system to provide high-quality data in crowdsensing applications and, to some extent, in permissionless blockchains. In crowdsensing settings, users generally do not have an interest in providing false data, while in permissionless blockchains, there is usually a token that can be used to incentivize users with diverging interests. However, it remains unclear how to incentivize users in a permissioned blockchain who might profit by providing false data, or what part of the incentive system should be implemented *on-chain* and which part *off-chain*. Our study principally examines how an incentive system may be designed to overcome the challenge of insufficient data quality in a permissioned blockchain-based data platform with conflicting interests so that the creation of a public good, a valuable Cardossier, becomes possible.

4.3 Principal-Agency Theory

We speak of "agency" when an agent acts for, on behalf of, or as representative for another agent (the principal). Essentially all agreements between two or more parties involve agency relationships [40]. There are two issues in agency relationships [12]; first, the agent and the principal have conflicting goals or desires, and second, the principal does not have the necessary means to check whether the agent has behaved appropriately. Common to both issues is asymmetric information resulting in different outcomes to those predicted by neoclassical economics based on full information. The agents in such an environment cannot act entirely rationally but are bounded-rational owing to the lack of complete information [40]. If the principal cannot fully observe or understand the agents' actions, there is an incentive for moral hazard [3]. This occurs when an agent does not exert maximum effort, to the detriment of the principal. An agent can do this because they have hidden information or can take hidden actions [17]. A second important concept of principal-agency theory is adverse selection [42]. This happens when an agent claims to have specific characteristics, which are difficult for the principal to check, and as a result, the principal selects the wrong agent for a task. A classic example is the "market for lemons" [2]. In this situation, vendors can conceal information resulting in higher prices paid for poor-quality cars, potentially leading to a collapse of the entire market. Solutions to principal-agent theory often stem from contract design [17]. However, this requires a central party that sets up a contract and verifies compliance with pre-defined rules. Steps need to be taken beforehand by the principal in setting up a contract that gives the agent the correct incentives. Another solution in an asymmetric information context is signaling [47] that is a solution concept that starts with the agent rather than the principal. Signaling allows good agents to convey information to a principal about their intentions or qualifications in a way that bad agents cannot imitate. In the original model by [47], job applicants send a signal to future employers about their qualifications through educational certificates, enabling the identification of good agents before entering an agreement. In a dynamic setting, a signaling mechanism gives bad agents an incentive to improve.

5 DESIGN GOAL AND REQUIREMENTS

The Cardossier platform aims to (i) solve the problem of lemons in the used-car market and (ii) create an inter-organizational data market. For both objectives, high-quality data are fundamental, so the goal of the incentive systems is to improve the data quality of the Cardossier platform. To achieve this, the system needs to alleviate agency problems, and we require the system to be incentive-compatible by fulfilling three requirements:

- **Best response.** Adding correct data should be the best strategy for the agents.
- **Rewards.** Submitting complete and correct data should be rewarded.
- **Signaling.** Good agents should be able to identify themselves.

The best response requirement means that for a bounded-rational agent, adding correct data maximizes the payoff. Consequently, good agents that provide accurate data should also get a reward since they contribute to the platform's well-being. However, to reward the good agents, the platform needs to be able to identify them and, through signaling, they can demonstrate this to the platform.

Since the Cardossier platform is based on a blockchain and the agents act in a decentralized environment, some constraints need to be considered:

- **Fairness.** No organization or car owner may unfairly disadvantage other agents. If they do, the action must be justified, e.g., if the data delivered by the agent are of poor quality. In addition, agents may not harm one another for (unfair) reasons such as revenge, strategic considerations, or out of antipathy.
- **Decentralized Control.** Since the incentive system is implemented in a peer-to-peer blockchain system, agents should be incentivized to monitor each other. Consequently, participants should participate in the data quality assurance process, which can be either a few trusted notaries or possibly individual participants. However, no one central authority controls the data.
- **Capability.** Some agents in the system have special powers, e.g., the Road Traffic Agency making regular checks of the cars or the manufacturer collecting telemetry data. In an incentive system, these agents should occupy their unique role because they are better suited to the task.

These constraints ensure that an incentive system works in a decentralized setting and is not abused.

6 THE MODEL

This section explains the rules and building blocks of the proposed agent-based model, using superscripts for agents and subscripts for actions. All the parameters of the models are presented in Table 1.

6.1 Model Components

Principal. As suggested earlier, the Cardossier project is prone to both adverse selection [2] and moral hazard [3, 42]. The platform can solve the lemon problem by providing a transparent source of car-related data to reduce the information asymmetry currently present in the used-car trade. Beyond that, the platform provides a basis for data-driven business models and process improvements for participating agents. However, for the platform to provide this, high-quality data is critical. Low-data quality results in lower revenues generated *on* the platform by less-realized business models [6] and *through* the platform since the lemon problem is not resolved and many potential sales are not completed. In addition, the platform suffers from moral hazard as it incurs a cost in the form of lost revenues. Consequently, the platform is modeled as the principal in a principal-agent relationship.

Agents. In the Cardossier project, car owners and companies act for the platform by contributing data to the platform, i.e., the principal. Consequently, car owners and companies are modeled as agents in the principal-agent

Table 1. The Parameters of the Model and Their Categorization

Parameter	Description	Category	Determination
N	Number of car owners	Agent	Exogenous
M	Number of organizations	Agent	Exogenous
C	Number of cars	Car	Exogenous
d	Data entry	Data	Endogenous
p_d	Probability of a data event for a car	Data	Exogenous
ϕ	Fraction of cars checked	Data	Exogenous
Q	Quality of a car's data	Data	Endogenous
p_{ds}	Probability that a data bundle is sold	Market	Exogenous
p_{cs}	Probability that a car is sold	Market	Exogenous
p_{cb}	Probability that a new car is bought	Market	Exogenous
μ	Markup in car sale	Market	Endogenous
τ	Time when a car is sold	Market	Endogenous
θ	Type of agent	Strategy	Exo-/Endogenous
p_e	Probability of a car owner consulting an external organization	Strategy	Endogenous
K	Noise parameter of update rule	Strategy	Exogenous
ε	Update probability	Strategy	Exogenous
δ	Revenue share of the system	Payoff	Exogenous
γ	Revenue share of the car owner	Payoff	Exogenous
ω	Revenue share of the organizations	Payoff	Exogenous
Δ	Share of ω for an organization	Payoff	Endogenous
α	Cost of providing correct data for organizations	Payoff	Exogenous
π	Round payoff	Payoff	Endogenous
r_p	Provision rating	Provision rating	Endogenous
λ	Decay factor of provision rating	Provision rating	Exogenous
r_c	Correction rating	Correction rating	Endogenous
β_0	Intercept of correction rating	Correction rating	Exogenous
β_1	Reward intensity for reporting	Correction rating	Exogenous
β_2	Punishment intensity of misconduct	Correction rating	Exogenous
x_1	Number of reported errors	Correction rating	Endogenous
x_2	Number of confirmed misconducts	Correction rating	Endogenous
k	Sliding window size for reports/misconducts	Correction rating	Exogenous

relationship. Following the standard principal-agency theory, we assume that all agents are bounded-rational [40]. Within the Cardossier platform, N car owners posses one or more of the $C(t)$ cars registered at time t. Car owners buy, sell, and scrap cars over time. In line with [15], we set a fixed car life expectancy, and there are M car industry organizations that participate in the system. These organizations differ in size as well as the industry they operate in. The sizes of the organizations follow a Pareto law mirroring an empirical fact [29]. There are three types of agents $\theta^i \in$ {bad, mixed, and good}, whose type is unobservable to other agents and the Cardossier platform. We encoded the types with $\theta^i \in \{0, 0.5, 1\}$ representing probabilities for honest behavior.

Environment. The blockchain system acts as a common platform for car data provided by car industry organizations. A data event[2] (e.g., service, repair, renewed insurance policy, or accident) may appear at any point in time, and the data is collected for each car. Each car is connected to one organization per industry, where larger organizations naturally are connected to more cars than smaller ones, i.e., they have more customers. Thus, each data event involves one or many organizations affiliated with a car. The data entries are sold in each round with a probability p_{ds} and the revenues split among the car owner and the participating organizations. Once a car owner buys a new car, a car in the system is initiated and organizations add initial data[3] (again, larger organizations are more likely to be selected by owners).

[2]We call this kind of data *dynamic*.
[3]We call this data *static*.

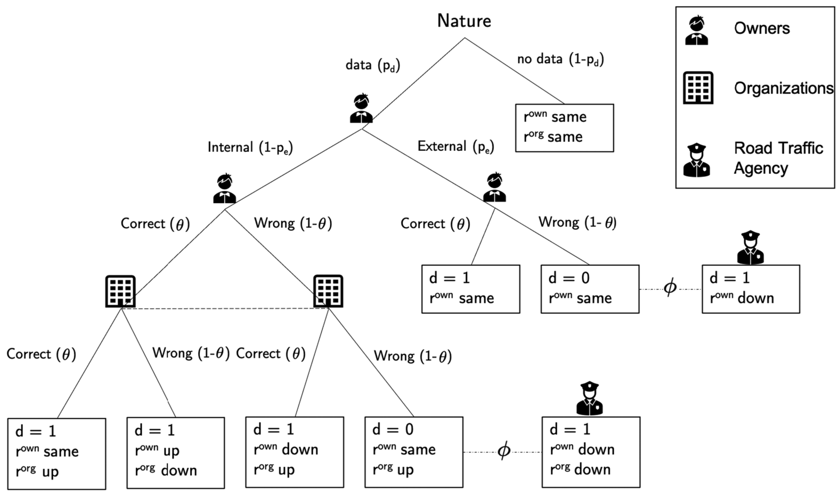

Fig. 4. The owners and organizations play with probability θ correct. Depending on the outcome, the rating of the owners (r^{own}) and the organizations (r^{org}) is adjusted. The road traffic agency routinely checks a fraction ϕ of cars' data and corrects inaccurate data.

Interactions. Once an event generating data for a car takes place, the owner is activated, i.e., starts making decisions. The data event for each vehicle is a Bernoulli process with parameter p_d, hence an owner i is activated at every time step with $1 - (1 - p_d dt)^{c^i}$, where c^i is the number of cars of owner i. If activated, the owner decides to consult an external organization with probability p_e^i (see Figure 4). For example, in case of a breakdown, they could decide to go to a repair shop that is not part of the Cardossier platform (external). In a second stage, they decide to act honestly with probability θ^i (see Figure 4). If they consult external organizations, being honest means adding this data entry to the blockchain. If they involve internal organizations, being honest means checking the entries of the organizations correctly. Being dishonest means trying to persuade the organization to add incorrect data to the blockchain. The organizations are activated if an owner selects them. Organization i acts honestly with probability according to its type θ^i. In particular, the organization does not collude with a dishonest owner if it acts honestly. If the organization is dishonest, it tries to add incorrect data to the blockchain, but it will only be successful if the owner is also dishonest, as shown in Figure 4. If both agents act dishonestly, the data entry in the blockchain is $d = 0$.

Data. The exact content of data provided by the organizations is not relevant for our purposes as we just model the quality of the data, i.e., correctness and completeness. In the model, we abstract the quality of the data in the simplest way possible: We denote high-quality data with $d = 1$ and low/quality data or missing data with $d = 0$. Such a binary representation is sufficient for all further analysis. In particular, it allows for an easy calculation of the average data quality for a car:

$$Q = \frac{1}{|d|} \sum^{|d|} d \quad \in [0, 1]. \tag{1}$$

6.2 Model Target

Payoffs. Since agents are bounded-rational, they try to maximize their payoffs. They can earn revenue if data in the blockchain market are bought. Data for car c are sold at a fixed price (w.l.o.g. assume a unit price), and the proceedings are split as follows:

$$\delta + \gamma + \omega = 1 \quad and \quad \delta, \gamma, \omega \geq 0, \tag{2}$$

where δ is the share that goes to the system e.g., for further development and maintenance, γ is the share of the car owner, and ω is distributed among the organizations providing data to this car. The car owners sell their cars at a rate p_{cs}. Once a car is sold, the car owner receives a fair price plus a markup μ. The fair price is the price with complete information, whereas the markup μ is inversely related to the data quality

$$\mu = f(Q), \qquad f'(Q) \leq 0. \tag{3}$$

In this study, we set $\mu = \gamma(1 - Q)$ to make the relative payoffs for the car owner comparable. If all data are added correctly, the markup μ equals zero. The buyer's knowledge depends on the car's information available in the system. If the seller can hide or falsify some information, we are in a situation of asymmetric information similar to [2]. The car owner's round payoff is given by

$$\pi^i = \sum_{j=1}^{c^i} \left(p_{ds}\gamma + \mathbb{E}[\mu^j(\tau^j)] \right) = c^i p_{ds}\gamma + \sum_{j=1}^{c^i} \mathbb{E}[\mu^j(\tau^j)], \tag{4}$$

where τ_j is the time car j is sold and not a priori known. As we use a fixed car sale probability p_{cs}, the holding time of a car follows a geometric distribution with the expected value $\frac{1}{p_{cs}}$. Using this and the fact that the process $\{\mu(t) : t \in T\}$ is a time-varying Markov chain with unknown transition probabilities, we crudely approximate the expectation with a weighted period-by-period problem:

$$\mathbb{E}[\mu(\tau)] \approx p_{cs} \sum_{s=0}^{\lfloor \frac{1}{p_{cs}} \rfloor} \mathbb{E}[\mu(s+1)|\mu(s)] \approx p_{cs} \sum_{s=0}^{\lfloor \frac{1}{p_{cs}} \rfloor} \mu(s). \tag{5}$$

Therefore, we can express the owners' round payoff as follows:

$$\pi^i \approx c^i p_{ds}\gamma + p_{cs} \sum_{j=1}^{c^i} \mu^j(t). \tag{6}$$

The organization's share ω is distributed among the m organizations that have contributed data to the car. Each organization receives an equal share Δ of ω of all cars c^i they process. We assume that the provision of one entry of correct data incurs an organizational marginal cost $\alpha \geq 0$. The round payoff for an organization i is therefore given by:

$$\pi^i = c^i p_{dc} \Delta\omega - \alpha^i \sum_{j=1}^{c^i} d^i_j. \tag{7}$$

6.3 The Cardossier Incentive System

Design Ideas. The incentive system needs to fulfill the requirements and constraints introduced in Section 5. The requirements *best response* and *rewards* can be satisfied by a system impacting agent payoffs. However, simply increasing the payoffs is not sufficient. Public information about how correctly an agent behaves must be universally available to allow for signaling and such an indicator should reflect the behavior of an agent. These design ideas hint towards a reputation or rating, so we suggest a rating mechanism that affects the agent payoff, as indicated in the literature [37] that affects the agents' payoff. Since the design goal of the incentive system is high-quality data, the better the quality of data provided (completeness and correctness), the higher the rating for an agent, and *vice versa.*

The constraints in Section 5 offer further guidance on how to shape such a rating mechanism. The *fairness* constraint prohibits a mechanism in which agents rate each other directly. Nevertheless, agents should monitor each other as stated by the *decentralized control* constraint. Therefore, we suggest that agents assessing each other can increase their ratings by reporting the misconduct of others. As the system must inherit the existing capabilities of agents, some Cardossier platform participants will acquire a unique role. They act as correction institutions and decide on reports from the agents; these could be governmental organizations, e.g., road traffic agencies or a pool of organizations. Institutions such as the Road Traffic Agency are suitable to conduct further quality checks, thereby contributing to high-quality data. However, no single correction institution should have the power to amend data in the *decentralized* platform.

The Rating Mechanism. Resulting from the design ideas above, we introduce a hybrid rating mechanism that influences the distribution of the revenues from the data sales, similar to [59]. This rating serves to signal the type of an agent publicly. The rating of a car owner and an organization should discourage them from providing incorrect data (incorrect data results in a lower rating, which subsequently leads to lower revenues) and incentivize quality control (reporting of incorrect data leading to a higher rating and thus to higher revenues). For the organizations, the ratings measure the organization's behavior as a data provider ("provision rating") and a reporter of incorrect data ("correction rating"). As outlined in Figure 4, there are two ways for the Cardossier platform to be made aware of incorrect data: (i) Owners and organizations check data entries and may report errors or (ii) an institution (e.g., the Road Traffic Agency) routinely checks a fraction ϕ of to detect wrong or missing data. The correction rating decreases if an organization makes a mistake (and is exposed). Both ratings are part of the payoff function for the organizations. For car owners—since they do not provide data—there is only a correction rating, which also influences their payoff.

The provision rating for each organization reflects the completeness of the data supply from this organization to the car in question. The provision rating is calculated per car and takes both the dynamic and static data (see Section 6.1) into account. Previous research has selected a Gompertz distribution to model a rating function [33], which is a generalization of the exponential distribution. Similarly, we select a functional form closely resembling an exponential distribution given by

$$r_p^i(t) = \left(\frac{1+d_s}{2}\right) \times \exp\left[-\lambda\left(\frac{t-t_{last}}{1+|d_d|}\right)\right] \in (0,1), \tag{8}$$

where λ is the decay factor of the provision rating (the higher it is, the more data the agent needs to provide), d_s is the static data, which the agent provides; t is the current time; t_{last} is the timestamp of the last data unit added; and $|d_d|$ is the total number of dynamic data units, which the agent provides. The correction rating for each organization and car owner reflects their activities in the correction mechanism depending on whether they highlight incorrect data. This rating increases if the reported data is corrected (meaning that it has now be reported correctly). This is a part of the correction mechanism that helps to maintain a better quality of data. The functional form of the correction rating is inspired by random utility models [56] and is determined as follows:

$$r_c^i(t) = \frac{\exp(\beta_0 + \beta_1 x_1(t) + \beta_2 x_2(t))}{1 + \exp(\beta_0 + \beta_1 x_1(t) + \beta_2 x_2(t))} \in (0,1), \tag{9}$$

where x_1 is the number of reported errors, x_2 the number of confirmed misconducts of the agent i over a period $[t-k, t]$, β_0 is the intercept parameter which defines the initial value of the correction rating, β_1, β_2 are consequently the reward and penalty intensity of the correction mechanism.

Rating-Based Payoffs. To incentivize a car owner i to behave honestly, the payoff is corrected by the rating r_c^i

$$\pi^i \approx c^i p_{ds}(r_c^i \times \gamma) + p_{cs} \sum_{j=1}^{c^i} \mu^j(t). \tag{10}$$

The payoff for the organizations is determined by taking the average r of the two ratings r_p and r_c to calculate their relative share Δ_c of a car's data sale

$$\Delta_c^i = \frac{r^i}{\sum_{j=1}^R r_j}, \tag{11}$$

where the sum is taken over all organizations that have provided data for this car. The payoff for an organization i is then corrected by the rating-adjusted Δ_c^i and is given by

$$\pi^i = \sum_{j=1}^{c^i} p_{ds}\Delta_j^i\omega - \alpha^i \sum_{j=1}^{c^i} d_j^i = \sum_{j=1}^{c^i}\left(p_{ds}\Delta_j^i\omega - \alpha^i d_j^i\right). \tag{12}$$

7 EVALUATION

7.1 Goal Achievement Measures

The **goal achievement measures** (**GAM**) for the incentive system measure whether the design goal and the three incentive compatibility requirements have been fulfilled:

GAM I: Data quality is high.
GAM II: Adding correct data is the best strategy.
GAM III: Good agents receive highest payoff.
GAM IV: Signaling is possible.

The subsequent simulation evaluates the fulfilment of these GAMs.

7.2 Simulation Setting

In this subsection, we explain how agents can update their strategy, outline the simulation dynamics, and determine the parameter set.

Strategy Update. We consider ε-greedy agents [49]: On activation and following data provision, the owner and the organization consider changing their type (hence strategy) with probability $\varepsilon > 0$. We use a simple rule for imitating the type of another agent [1, 50]. They randomly select one of their peers and use the Fermi-rule for updating their types:

$$P(\theta^i \to \theta^j) = \frac{1}{1 + \exp\left((\pi^i - \pi^j)/K\right)}, \tag{13}$$

where we normalize the organizations' payoff by their sizes and the car owner payoff by the number of cars owned. Parameter K is a measure for the level of randomness in the decision that may reflect the errors at measuring the payoffs of the other agents. We set $K = 0.1$ as is usually done in the literature to account for some noise in the system.

Simulation Dynamics. Before running the simulation, we initialized the M organizations with ten different roles, N car owners, and we allocated $C(0)$ cars to the owners (where N does not have to be equal to $C(0)$). We draw the type of an agent uniformly and the agents may update their strategy after a burn-in period.

The dynamics of the simulation is now as follows:

(1) For $c(t) \leq C(t)$ cars, a data event is generated.
(2) The owners are activated and play out their strategies. The activated organizations also play out their strategies.
(3) The payoffs for all agents are calculated.
    (3.1) Once the burn-in period is over, an agents considers updating its type with probability $\varepsilon > 0$.
(4) The owners sell, buy or scrap cars.

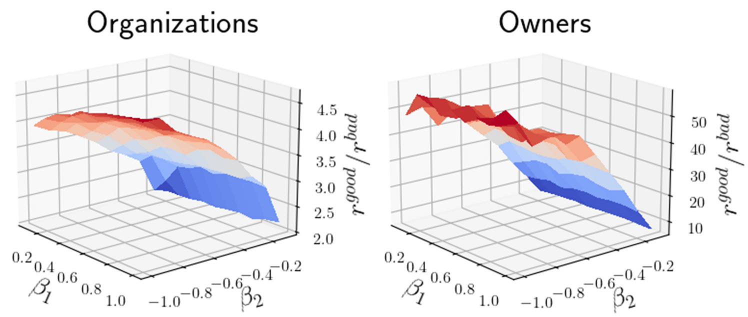

Fig. 5. The left plot shows the ratio between the rating for organizations of the good type and the bad type for different parameter combinations of β_1 and β_2. The right plot shows the rating ratios for the owners.

Table 2. The Parameters Values Selected for the Experiments

Parameter	Description	Value
N	Number of car owners	500
M	Number of organizations	100
C	Number of cars	1,000
p_d	Probability of a data event for a car	0.2
ϕ	Fraction of cars checked	0.5
p_{ds}	Probability that a data bundle is sold	0.1
p_{cs}	Probability that a car is sold	1/16
p_{cb}	Probability that a new car is bought	p_{cs}
p_e	Probability of a car owner consulting an external organization	0.2
K	Noise parameter of update rule	0.1
ε	Update probability	0.05
δ	Revenue share of the system	0.1
γ	Revenue share of the car owner	0.45
ω	Revenue share of the organizations	0.45
α	Cost of providing correct data for organizations	0.01
λ	Decay factor of provision rating	0.25
β_0	Intercept of correction rating	3
β_1	Reward intensity for reporting	1
β_2	Punishment intensity for reporting	−1
k	Sliding window size for reports/misconducts	20

Parameters. The larger the ratio between the rating for good types and bad types, the better the incentive system distinguishes the two. To determine the rating parameters β_1 and β_2 that maximize this ratio, Figure 5 explores different parameter combinations. The ratio for owners is about ten times higher than for organizations. As the maximum for both parties is close to a absolute value of one, we selected $\beta_1 = 1$ and $\beta_2 = -1$. All simulation parameters are shown in Table 2. For the choice of the other parameters, we closely followed [63].

Table 3. The Simulation Experiments to Measure the Four GAMs I (Data Quality), II (Best Strategy), III (Highest Payoff), and IV (Signaling)

Experiment	Description	Purpose	Figure
1	$T = 500$ timesteps without strategy updating	Model check	6, 7, 8 + 9
2	$T = 500$ timesteps with strategy updating	Measure GAMs	10, 11 + 12

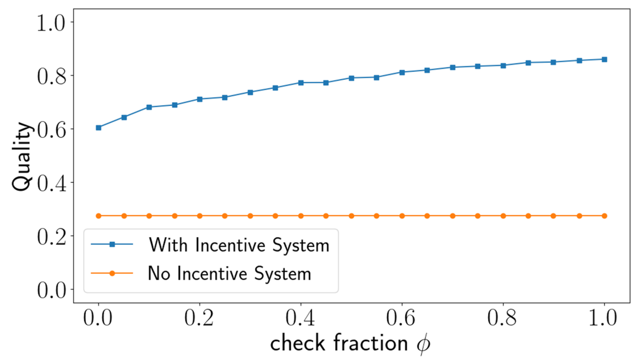

Fig. 6. The average data quality Q for different implementations of the incentive system for $N = 500$, $M = 100$, and $C = 1000$. The Road Traffic Agency checks one data entry of ϕ cars in each round.

8 RESULTS

8.1 Experiments

We conducted two numerical simulation experiments averaged over 50 runs summarized in Table 3. The first experiment serves as a model checker for the incentive system. The agents cannot change their strategy θ. We checked the basic results of the incentive systems such as the average data quality, the revenue of the agents, and the signaling mechanism. In the second experiment, agents could change their strategies. They imitate the type of a randomly selected peer according to the update rule in Equation (13). We measured GAM I-IV under different parameter settings.

8.2 Model Check

This section tests whether the incentive system can generate the basic desired effects. For this, we considered a setting in which agents could not update their strategies. In Figure 6, we varied the check fraction ϕ and plotted the average data quality with and without the incentive system introduced in Section 6.3, where data quality is defined as in Equation (1). Without the incentive scheme, less than 30 percent of all data were correct on average. With the incentive system, we achieved more than 60 percent within the Cardossier platform—even when the Road Traffic Agency does not check any data. Even though one-third of the agents are of the bad type and one-third of the mixed type, the data quality is high since the agents monitor each other and correct the data. This indicates that an incentive system can improve data quality, thereby contributing to the design goal of high-quality data.

Figure 7 shows the payoff for owners and organizations as a function of ϕ. Good organizations and good owners receive a higher payoff in the system on average. This is a direct result of the rating-weighted payoff functions in Equations (10) and (12). While the bad organizations profit from a more intense checking by the Road Traffic Agency, the owner payoff declines. Since more data are corrected, they cannot earn large markups μ on their cars anymore and the lemon problem is reduced. In short, the incentive system rewards good behavior.

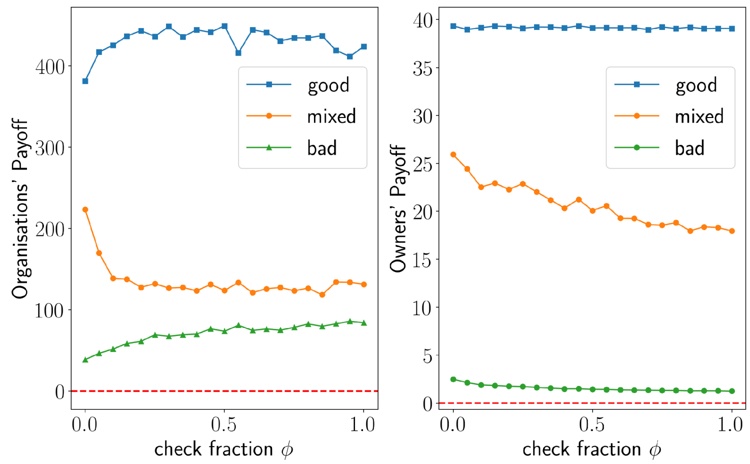

Fig. 7. The incentive system results on average in higher payoffs π for the good agents for all values of the check fraction ϕ.

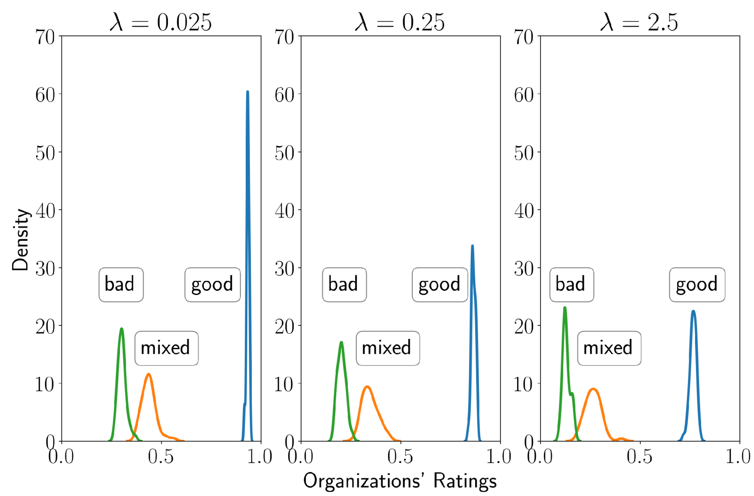

Fig. 8. The rating distribution using the correction rating with $\beta_1 = 1, \beta_2 = -1$. The $M = 100$ organizations can be distinguished by their rating r. The agents can use the rating r to signal their type θ.

Figure 8 plots the ratings for the organizations on the x-axis and the density of the distribution for the different types for three different values of λ on the y-axis. The distributions show that organizations can use the rating to signal their type. A choice of $\lambda = 0.25$ results in a good trade-off between a too-high rating for bad agents ($\lambda = 0.025$) and a too-low rating for good agents ($\lambda = 2.5$). The distributions are narrow enough to identify the hidden types of agents. The incentive system provides a means to signal the types for the organizations.

Similarly, Figure 9 plots the ratings for the owners on the x-axis and the density of the distribution for the different types over 50 simulation runs on the y-axis. The incentive system provides owners with the ability to signal their type. In particular, good owners are identified with high precision; consequently, the incentive system also enables signaling also for owners.

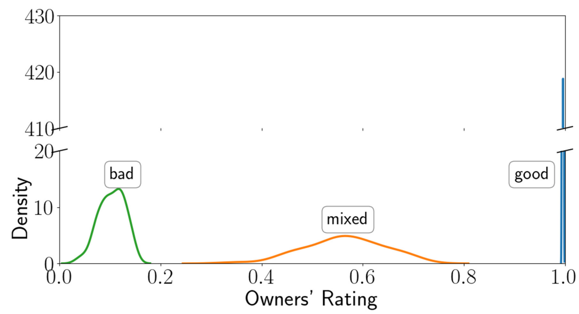

Fig. 9. The distributions of the correction ratings r_c with $\beta_1 = 1, \beta_2 = -1$ for the car owners. The agents can use the rating r_c to signal their type θ.

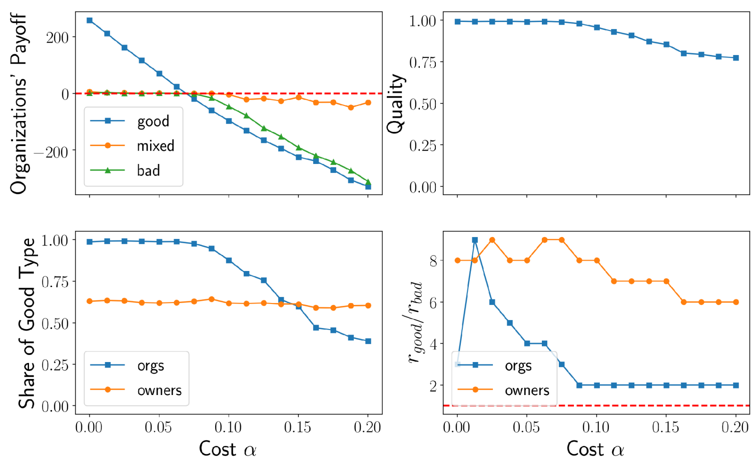

Fig. 10. The payoff of the organizations, the quality, share of good types, and the ratio between the ratings of the good types and bad types under a variation of the cost α.

In summary, these findings demonstrate that the incentive system generates the desired effects in a static setting.

8.3 Measurements

Figure 10 measures GAM I-IV under the variation of cost α. The more expensive it becomes to add correct data for the organizations, the worse the performance of the incentive system. At the cost of 0.08, it is no longer profitable for an organization to add data to the blockchain. Furthermore, the quality decreases sharply after this point, and with low costs, most organizations choose to behave well. Therefore, the cost of correctly adding data is a crucial parameter in the model that directly affects the incentive system's effectiveness. With low cost, the incentive system is highly effective in attaining a high data quality.

Figure 11 measures GAM I-IV under the variation of the data bundle sale probability p_{ds}. With increasing sale probability, the payoffs for good organizations increases linearly. The quality quickly converges close to 100 percent. A high sale probability creates a strong incentive to act well. Even owners will behave well since they can profit greatly from the increased dossier sales. If every dossier is sold in every round ($p_{ds} = 1$), it is not profitable for any agent to deviate from being good. A low-sale probability impairs the effectiveness of the

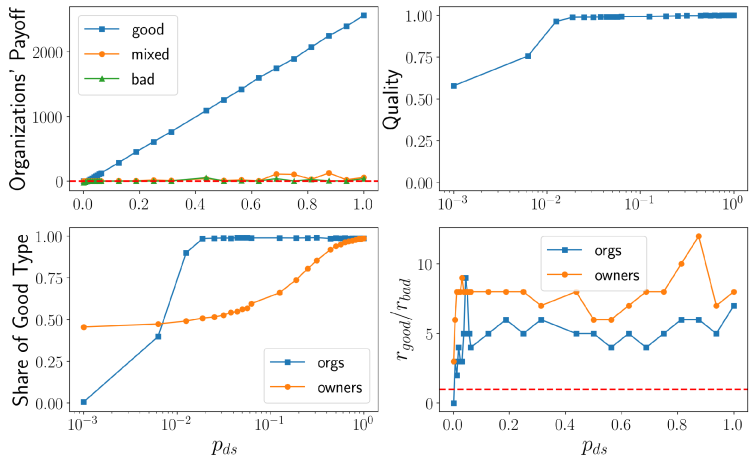

Fig. 11. The payoff of the organizations, the quality, share of good types, and the ratio between the ratings of the good types and bad types under a variation of p_{ds}.

incentive system, since good behavior is translated into lower profits. However, in an active system, the incentive system leads to high data quality.

Figure 11 measures GAM I-IV under the variation of the external rate p_e. While good agents benefit in any regime, the bad owner's payoff is increasing in p_e. Nevertheless, even if the owners decide to consult only external organizations ($p_e = 1$), the quality remains high. The ratings for the good agents are higher than the ratings for the bad agents, even though the signaling effect decreases when the owners consult external organizations more frequently.

To summarize, the incentive system is able to generate high data quality in the system, but its effectiveness depends on the cost of adding data, the activity of the system, and the rate of external consultancies by the agents.

9 DISCUSSION

9.1 Incentivizing Data Quality in Blockchain-Based Systems for the Automotive Sector

High-quality datasets are of great importance for blockchain-based systems in the automotive sector as the correctness and completeness of the data is a prerequisite for new data-driven business models [6]. To achieve this high data quality, incentives can be placed in the system to motivate agents to contribute correct and complete data. The current literature on blockchain applications in the car ecosystem does not give guidance on incentive systems. Therefore, we draw on the literature for crowdsensing applications to introduce a rating function for incentivizing the participants [33]. Even though a rating is an effective way to make agent behavior visible, we argue that a stand-alone rating function is not sufficient to incentivize agents do the right thing. Consequently, we connect rating with reward, in line with [59]. However, their rating system relies on a requester-worker architecture that is typical for crowdsensing applications. While for most incentive systems in crowdsensing applications, a requester needs to pay users for the data provision [18, 66], the function of a requester who pays a direct reward to the data provider does not exist in blockchain-based systems for the car ecosystem. Since no overarching authority exists to assume this role, the only available reward to incentivize agents is revenue from the sale of data bundles. Our system incentivizes agents by varying their relative revenue shares, thereby showing how to create incentives for data quality if resources are limited. It is surprising how effective a simple

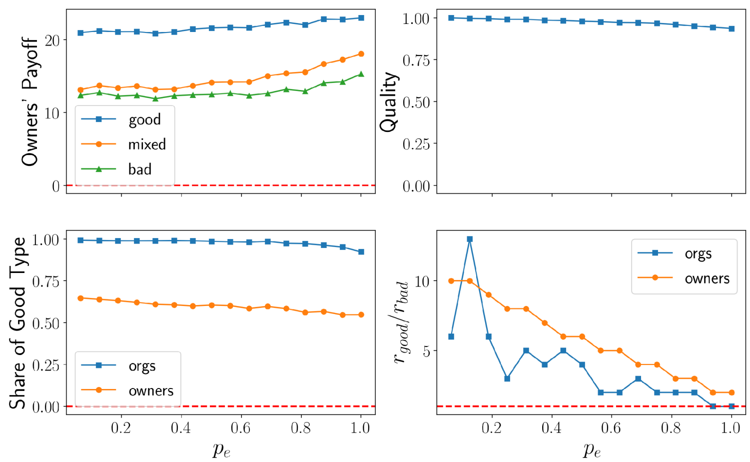

Fig. 12. The payoff of the owners, the quality, share of good types, and the ratio between the ratings of the good types and bad types under a variation of p_e.

redistribution of the available rewards can be. As shown in Figure 11, the larger the total amount of the reward, the more effective the incentive system.

Our study provides further significant understanding of incentive systems for blockchain-based platforms in the car ecosystem. For such an incentive system to be effective, the organization's cost for adding correct data to the blockchain platform must be low, as shown in Figure 10. In practice, this means that all participants should have easy access to the system. This can be attained by easy-to-use interfaces, integrated IT tools, and automated data input. We also demonstrate that the incentive system works better if more data are sold (Figure 11). However, even with low market activity, introducing an incentive system leads to markedly higher data quality and substantially affects agent behavior. As pointed out by [65], this is critical during the formation phase of a blockchain consortium to guarantee the soundness of the business approach. Later, the incentive system becomes even more effective; the higher the platform's market share, the higher the incentive for the participants to act correctly since the data sale is a more significant part of their income. Figure 12 shows that even when car owners are in a position to conceal data by consulting external entities, it only has a tiny impact on data quality. This alleviates the problem of car owners trying to evade the system by consulting external organizations (e.g., repair shops) to hide data. The incentive system is effective enough to guarantee high-quality data even in these cases.

An important difference to similar approaches is that since some institutions in the car ecosystem can be assigned a unique role in the car ecosystem [44], the data quality within a blockchain-based platform can be increased even more (Figure 6). Additionally, they may penalize agents during regular checkups, in addition to the incentive system. However, the incentive system leads to higher data quality even without relying on a specific institution. The existence of such a correction mechanism encourages organizations and car owners to behave with integrity due to the threat of a possible penalty (such as a decrease in rating and revenue and any legal measures integrated in the system). The incentive system not only fosters data quality; it enables the identification of agent type by giving them an option (or obligation) to signal their type [47]. Such an identification would barely be possible within a decentralized system since no umbrella party exists to identify malicious agents. Identifying the different types (Figures 8 and 9) offers additional possibilities; e.g., the incentive system could include mechanisms that exclude bad agents or reward good agents [61].

We are proposing an incentive system that introduces a powerful mechanism to increase data quality in blockchain-based platforms for the car ecosystem. By adapting the literature for crowdsensing applications and literature on blockchains in the car-related ecosystem, we offer an initial solution to the incentivization problem for data quality in blockchain-platform for the car ecosystem that is distinct to other approaches by including agents and institutions.

9.2 Blockchain Governance and Incentives

In recent years, IS researchers have started to approach topics such as design, adoption, governance, and use of blockchain-based systems [48, 52]. Indeed, an important aspect of blockchain governance is incentives placed in the system [9]. The design of incentive mechanisms for blockchain systems is not a trivial task because it depends on design properties (such as public or private, permissioned or permissionless [37]); the purposes of participants in the network, their activity and behavior, business context, and exogenous factors such as regulation. In permissionless blockchain data markets, incentive systems are often based on a token rewarded to miners [39, 57]. In permissioned blockchains, no such token exists, so other mechanisms need to be employed [37]. Until now, incentives in permissioned blockchains have been poorly researched, and as an initial step towards the exploration of incentive systems in permissioned blockchains, we propose a rating-based incentive mechanism tied to revenues. This incentive mechanism acts as a robust immune system for the blockchain as it penalizes bad behavior and encourages the correction of errors.

While everyone can participate in permissionless blockchains, participants in permissioned blockchains belong to one of two distinct groups. There are the entities that participate directly (by writing data to the blockchain), and there are other entities that are external to the system (data readers). The inclusion of the car owner shows that in a decentralized blockchain-based system in the car market, all parties involved should be included to take all (possibly hidden) incentives into account [51]. The inclusion of external stakeholders into the incentive system leads to markedly higher data quality. If car owners are part of the incentive system, self-monitoring in the system is more robust. As the lemon problem [2] demonstrates, car owners have the greatest incentive to abuse the system as they have a strong impact on the data quality and the well-being of the system, even though they are in some sense external to the system. As the incentive system shows, including external parties in incentive systems for permissioned blockchains is essential.

Permissioned blockchains consist of known participants who usually form a consortium. In contrast to permissionless blockchains, this involves governance mechanisms that are somewhat tilted towards the *off-chain* dimension [67] due to the absence of tokens and explicitly known participants. Reference [44] suggests that agents from the public sector might assume an essential role in penalizing agents who supply incorrect or incomplete information. Consequently, we do not need to reinvent institutions or governments in our incentive system. Instead, we benefit from their daily activities (e.g., security checks), leading to efficiency gains, trust, and information quality for the Cardossier platform (Figure 6). We believe that this realistic approach strengthens our model and calls for hybrid forms of governance. Such hybrid governance should incorporate existing governance mechanisms (e.g., those set by the government) in combination with blockchain-related incentives (e.g., to operate the network), as [9] suggest. Therefore, concerning the *on-chain*/*off-chain* governance debate [60], we argue that an incentive system should be placed *on-chain* and incorporate and profit from already established *off-chain* institutions and mechanisms. Such mechanisms can be incorporated into the design in the form of the proposed correction mechanism.

The design of incentive systems for permissioned blockchains needs to consider two critical factors: (i) external parties are highly relevant for permission blockchain networks, and (ii), they should be explicitly considered in the incentive design as the consortium interacts with many of these. Furthermore, since a permissioned blockchain network involves known organizations and institutions, their competencies can be naturally integrated into the incentive mechanism, strengthening the platform's *off-chain* governance aspect.

9.3 The Platform as a Principal

Modeling a blockchain platform as the principal has some exciting implications since the platform represents the community consisting of the organizations and owners who are themselves the agents. However, an important distinction must be made; organizations and owners are indeed agents, but only in terms of isolated actions while pursuing their interests. Through the platform, they collectively build up the community and assume the role of the principal. Here, they may impose incentives and other mechanisms to prevent the individual agents (and themselves) from deviating from a strategy beneficial to the entire platform. As a result, a situation emerges in which the agents and the principal overlap and differ only in their respective roles. Although some may question whether this is a proper agency relationship, we argue that it is since both the issues introduced by [12] are present—the agents have conflicting goals in their different roles, and the community does not have the appropriate means to check whether every agent has behaved appropriately. The second issue arises since all the individual agents have an incentive to hide their actions from the community. This setting has not yet been explicitly explored or modeled in the literature, but it is highly relevant to the blockchain economy.

10 CONCLUSION

This study reports on an ADR project conducted in collaboration with a consortium forming a blockchain-based inter-organizational data marketplace for the car ecosystem. The contributions of this study are two-fold: First, we provide an explicit incentive mechanism to resolve the crucial issue of insufficient data quality in a blockchain-based system for the car ecosystem. This mechanism combines a decentralized data correction mechanism with an institutionalized data assessment in a unique way. Such an incentive mechanism helps both car owners avoid the "lemon problem" and organizations to monetize their data. Additionally, this knowledge is valuable for blockchain practitioners in early and mature design and development phases—from the initial idea of creating such a system to actual use and operation. Second, we add to research on incentive systems for permissioned blockchains by outlining a specific incentivization problem based on a real-world case and discussing the implications of such a system. Incentive systems for permissioned blockchains require an intensive examination of *on-chain* and *off-chain* elements. The proposed system and the derived insights can be used to design incentives for other inter-organizational relationships based on blockchains when agents with conflicting interests participate, e.g., the healthcare, education, or construction sectors. Our results show that the proposed system is a potential solution of the garbage-in, garbage-out problem that blockchain-based systems suffer from. High data quality is a pre-condition for the proper functioning of blockchain-based systems and only then, they can realize their full potential. Therefore, the incentive system improves the efficiency of blockchain systems.

Furthermore, we outline an instance of the principal-agent problem in which agents act collaboratively as the principal once they work together as a community. This principal-agent problem provides fertile ground for researchers to develop agency theory further and offers practitioners a framework to structure the design of blockchain platforms.

This study has several limitations, which also suggest directions for future research. First, the dynamics of the participants; we did not consider whether agents (organizations) might enter and leave the system dynamically. This leads to additional data gaps due to missing partners and variable rates of information in the blockchain. Consequently, future studies should take account of temporal changes in system participants. Second, although mathematical modeling and simulations are an effective means of studying complex problems, it is still necessary to observe such systems operating in real-world situations. We assume here that agents would act bounded-rationally and no external factors would influence the system. However, real-world situations could bring both additional requirements for organizations to act and for the system to function. For example, further study of the payments provided as one of the incentives and their influence on the behavior and trustworthiness of players (e.g., a mechanic checking the technical qualities of a car) is necessary. Additional observation is also needed to give a more practical insight into the operation of such a platform. Third, we did not simulate the complexity of market-based pricing for datasets as this would call for the extension of the model in terms of data supply and demand (to incentivize agents to provide the data most needed). Further stages ought to check multiple incentive mechanisms to discover the optimal ones, either by delivering formal proof or investigating existing schemes. In addition, a comparison of the proposed system with the status quo—or with a system controlled centrally—both in terms of cost and percentage of correct information would be insightful. Finally, the principal-agent problem, relevant to all blockchain-based systems governed by a community, could be further examined and analyzed.

Beyond this, we call for more research in the new field of incentives for permissioned blockchains. The range of applications of blockchain-based systems has continuously grown in recent years, but the design and effect of incentives in these economies are under-researched, although they are fundamental to the growth of this technology. This study sheds light on the design of incentives for blockchain-based inter-organizational systems and, hopefully, will inspire follow-up studies in the growing research field on blockchain technology.

REFERENCES

[1] Christoph Adami, Jory Schossau, and Arend Hintze. 2016. Evolutionary game theory using agent-based methods. *Physics of Life Reviews* 19 (2016), 1–26.

[2] George A. Akerlof. 1970. The market for 'Lemons': Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics* 84, 3 (1970), 488–500.

[3] Kenneth J. Arrow. 1963. Uncertainty and the welfare economics of medical care. *The American Economic Review* 53, 5 (1963), 941–973.

[4] Andreas Auinger and René Riedl. 2018. Blockchain and trust: Refuting some widely-held misconceptions. In *Proceedings of International Conference of Information Systems*. Associaton of Information Systems. AIS Electronic Library), 1–9.

[5] Yannis Bakos and Hanna Halaburda. 2021. Blockchains, smart contracts and connected sensors: Substitutes or complements? (2021). Retrieved 10 March, 2022 from https://ssrn.com/abstract=3394546.

[6] Ingrid Bauer, Liudmila Zavolokina, Fabian Leisibach, and Gerhard Schwabe. 2020. Value creation from a decentralized car ledger. *Frontiers in Blockchain* 2, 30 (2020), 30. DOI: https://doi.org/10.3389/fbloc.2019.00030

[7] Ingrid Bauer, Liudmila Zavolokina, and Gerhard Schwabe. 2020. Is there a market for trusted car data? *Electronic Markets* 30, 2 (2020), 211–225. DOI: https://doi.org/10.1007/s12525-019-00368-5

[8] Joachim Baumann, Liudmila Zavolokina, and Gerhard Schwabe. 2021. Dealers of peaches and lemons: How can used car dealers use trusted car data to improve their value proposition? In *Proceedings of the 54th Hawaii International Conference on System Sciences*.

[9] Roman Beck, Christoph Müller-Bloch, and John King. 2018. Governance in the blockchain economy: A framework and research agenda. *Journal of the Association for Information Systems* 19, 10 (Oct. 2018), 1020–1034.

[10] Mathieu Chanson, Andreas Bogner, Dominik Bilgeri, Elgar Fleisch, and Felix Wortmann. 2019. Blockchain for the IoT: Privacy-preserving protection of sensor data. *Journal of the Association for Information Systems* 20, 9 (2019), 1274–1309. Retrieved from https://www.alexandria.unisg.ch/259820.

[11] Thomas Y. Choi, Kevin J. Dooley, and Manus Rungtusanatham. 2001. Supply networks and complex adaptive systems: Control versus emergence. *Journal of Operations Management* 19, 3 (2001), 351–366.

[12] Kathleen M. Eisenhardt. 1989. Agency theory: An assessment and review. *The Academy of Management Review* 14, 1 (1989), 57–74.

[13] Josuha M. Epstein. 2006. *Generative Social Science: Studies in Agent-based Computational Modeling*. Princeton University Press.

[14] Intelligence ESG. 2021. Blockchain Consortia, Companies, Leaders, Use Cases, and Resources. Retrieved 11 March, 2021 from https://esg-intelligence.com/access-enterprise-blockchain-intelligence/list-of-all-blockchain-consortia/.

[15] Alessandro Gavazza, Alessandro Lizzeri, and Nikita Roketskiy. 2014. A quantitative analysis of the used-car market. *American Economic Review* 104, 11 (2014), 3668–3700.

[16] Peter Gratzke, David Schatsky, and Eric Piscini. 2018. *Banding Together for Blockchain*. Technical Report. Deloitte.

[17] Oliver Hart and Bengt Holmström. 1987. *The Theory of Contracts*. Cambridge University Press, 71–156.

[18] Yunhua He, Hong Li, Xiuzhen Cheng, Yan Liu, Chao Yang, and Limin Sun. 2018. A blockchain based truthful incentive mechanism for distributed P2P applications. *IEEE Access* 6 (2018), 27324–27335. DOI: https://doi.org/10.1109/ACCESS.2018.2821705

[19] Alan R. Hevner, Salvatore T. March, Jinsoo Park, and Sudha Ram. 2004. Design science in information systems research. *MIS Quarterly* 28, 1 (2004), 75–105.

[20] Susan Hoberecht, Brett Joseph, Jan Spencer, and Nancy Southern. 2011. Inter-organizational networks: An emerging paradigm of whole systems change. *OD Practicioner* 43, 4 (2011), 23–27.

[21] John H. Holland. 1992. Complex adaptive systems. *Daedalus* 121, 1 (1992), 17–30.

[22] Leonid Hurwicz. 1972. On informationally decentralized systems. In *Proceedings of the Decision and Organization*.

[23] Justice and Consumers. 2014. *Study on the Second Hand Cars Market*. Technical Report. European Union.

[24] Sandra Lades. 2017. *Vertrauen der Deutschen in Sicherheitskräfte wächst weiter - Automobilbranche mit starken Verlusten*. Technical Report. GfK Verein.

[25] Jong Seok Lee, Jan Pries-Heje, and Richard Baskerville. 2011. Theorizing in design science research. In *Proceedings of the Service-Oriented Perspectives in Design Science Research*. Springer Berlin, Berlin, 1–16.

[26] Chao Li and Balaji Palanisamy. 2019. Incentivized blockchain-based social media platforms: A case study of steemit. In *Proceedings of the 10th ACM Conference on Web Science*. Association for Computing Machinery, New York, NY, 145–154. DOI: https://doi.org/10.1145/3292522.3326041

[27] Pranee Liamputtong. 2013. *Qualitative Research Methods, 4th Edition*. Oxford University Press.

[28] Yuewen Liu and Juan Feng. 2021. Does money talk? The impact of monetary incentives on user-generated content contributions. *Information Systems Research* 32, 2 (2021), 394–409. https://doi.org/10.1287/isre.2020.0971 arXiv:https://doi.org/10.1287/isre.2020.0971

[29] Robert E. Lucas. 1978. On the size distribution of business firms. *The Bell Journal of Economics* 9, 2 (1978), 508–523.

[30] Charles M. Macal and Michael J. North. 2007. Agent-based modeling and simulation: Desktop ABMS. In *Proceedings of the 2007 Winter Simulation Conference* (2007), 95–106.

[31] Charles M. Macal and Michael J. North. 2010. Tutorial on agent-based modelling and simulation. *J. Simulation* 4, 3 (Sep. 2010), 151–162.

[32] Kamran Mammadzada, Mubashar Iqbal, Fredrik Milani, Luciano García-Bañuelos, and Raimundas Matulevičius. 2020. Blockchain oracles: A framework for blockchain-based applications. In *Proceedings of the Business Process Management: Blockchain and Robotic Process Automation Forum*, Aleksandre Asatiani, José María García, Nina Helander, Andrés Jiménez-Ramírez, Agnes Koschmider, Jan Mendling, Giovanni Meroni, and Hajo A. Reijers (Eds.). Springer International Publishing, Cham, 19–34.

[33] Hayam Mousa, Sonia Ben Mokhtar, Omar Hasan, Osama Younes, Mohiy Hadhoud, and Lionel Brunie. 2015. Trust management and reputation systems in mobile participatory sensing applications: A survey. *Computer Networks* 90, C (2015), 49–73. https://doi.org/10.1016/j.comnet.2015.07.011 Crowdsourcing.

[34] Michael Myers and Michael Newman. 2007. The qualitative interview in IS research: Examining the craft. *Information and Organization* 17, 1 (12 2007), 2–26.

[35] Ning Nan. 2011. Capturing bottom-up information technology use processes: A complex adaptive systems model. *MIS Quarterly* 35, 2 (6 2011), 505–532.

[36] Benedikt Notheisen, Jacob Benjamin Cholewa, and Arun Prasad Shanmugam. 2017. Trading real-world assets on blockchain. *Business & Information Systems Engineering* 59, 6 (2017), 425–440.

[37] Hitoshi Okada, Shigeichiro Yamasaki, and Vanessa Bracamonte. 2017. Proposed classification of blockchains based on authority and incentive dimensions. In *Proceedings of the 2017 19th International Conference on Advanced Communication Technology*. 593–597.

[38] Walter W. Powell, Kenneth W. Koput, and Laurel Smith-Doerr. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly* 41, 1 (1996), 116–145.

[39] Yongjun Ren, Yepeng Liu, S. Ji, A. K. Sangaiah, and J. Wang. 2018. Incentive mechanism of data storage based on blockchain for wireless sensor networks. *Mobile Information Systems* 2018 (2018), 6874158:1–6874158:10.

[40] Stephen A. Ross. 1973. The economic theory of agency: The principal's problem. *The American Economic Review* 63, 2 (1973), 134–139.

[41] Mary Beth Rosson and John M. Carroll. 2007. Scenario-based design. In *The Human-Computer Interaction Handbook*. CRC Press, 1067–1086.

[42] Michael Rothschild and Joseph Stiglitz. 1976. Equilibrium in competitive insurance markets: An essay on the economics of imperfect information. *The Quarterly Journal of Economics* 90, 4 (1976), 629–649.

[43] Jan Schemm and Christine Legner. 2008. Toward the inter-organizational product information supply chain - evidence from the retail and consumer goods industries. *Journal of the Association for Information Systems* 9, 4 (2008), 120–152.

[44] Gerhard Schwabe. 2020. The role of public agencies in blockchain consortia: Learning from the Cardossier. *Information Polity* 24, 4 (2020), 437–451.

[45] Gerhard Schwabe and Marco Prestipino. 2005. How tourism communities can change travel information quality. In *Proceedings of the 13th European Conference on Information Systems*. 1685–1696.

[46] Maung Sein, Ola Henfridsson, Sandeep Purao, Matti Rossi, and Rikard Lindgren. 2011. Action design research. *MIS Quarterly* 35, 1 (March 2011), 37–56.

[47] Michael Spence. 1973. Job market signaling. *The Quarterly Journal of Economics* 87, 3 (1973), 355–374.

[48] Florian Spychiger, Paolo Tasca, and Claudio J. Tessone. 2021. Unveiling the importance and evolution of design components through the "tree of blockchain". *Frontiers in Blockchain* 3 (2021), 60. DOI: https://doi.org/10.3389/fbloc.2020.613476

[49] Richard S. Sutton and Andrew G. Barto. 1998. *Reinforcement Learning: An Introduction*. The MIT Press.

[50] György Szabó and Gábor Fáth. 2007. Evolutionary games on graphs. *Physics Reports* 446, 4 (2007), 97–216.

[51] Mohan Tanniru, Jianyu Niu, Chen Feng, Claudio Gottschalg Duque, Chang Lu, and Harish Krishnan. 2021. Incentives to engage blockchain and ecosystem actors. In *Proceedings of the Building Decentralized Trust : Multidisciplinary Perspectives on the Design of Blockchains and Distributed Ledgers*, Victoria L. Lemieux and Chen Feng (Eds.). Springer International Publishing, Cham, 35–61. DOI: https://doi.org/10.1007/978-3-030-54414-0

[52] Paolo Tasca and Claudio Tessone. 2019. A taxonomy of blockchain technologies: Principles of identification and classification. *Ledger* 4, 0 (2019), 1–39.

[53] Rowan van Pelt, Slinger Jansen, Djuri Baars, and Sietse Overbeek. 2021. Defining blockchain governance: A framework for analysis and comparison. *Information Systems Management* 38, 1 (2021), 21–41. DOI: https://doi.org/10.1080/10580530.2020.1720046 arXiv:https://doi.org/10.1080/10580530.2020.1720046

[54] Jan vom Brocke, Alexander Simons, Björn Niehaves, Kai Riemer, Ralf Plattfaut, and Anne Anne Cleven. 2009. Reconstructing the giant: On the importance of rigour in documenting the literature search process. In *Proceedings of the 17th European Conference on Information Systems*. 2206–2217.

[55] Marko Vukolić. 2017. Rethinking permissioned blockchains. In *Proceedings of the ACM Workshop on Blockchain, Cryptocurrencies and Contracts*. 3–7.

[56] Joan Walker and Moshe Ben-Akiva. 2002. Generalized random utility model. *Mathematical Social Sciences* 43, 3 (2002), 303–343. Random Utility Theory and Probabilistic measurement theory.

[57] Jingzhong Wang, Mengru Li, Yunhua He, Hong Li, Ke Xiao, and Chao Wang. 2018. A blockchain based privacy-preserving incentive mechanism in crowdsensing applications. *IEEE Access* 6 (2018), 17545–17556.

[58] Richard Y. Wang and Diane M. Strong. 1996. Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems* 12, 4 (1996), 5–33.

[59] Lijun Wei, Jing Wu, and Chengnian Long. 2020. A blockchain-based hybrid incentive model for crowdsensing. *Electronics* 9, 2 (2020), 215. DOI: https://doi.org/10.3390/electronics9020215

[60] Reijers Wessel, Wuisman Iris, Mannan Morshed, De Filippi Primavera, Wray Christopher, Rae-Looi Vienna, Cubillos Vélez Angela, and Orgad Liav. 2018. Now the code runs itself: On-chain and off-chain governance of blockchain technologies. *Topoi* 40, 4 (2018), 821–831. DOI: https://doi.org/10.1007/s11245-018-9626-5

[61] Xiwei Xu, Cesare Pautasso, Liming Zhu, Vincent Gramoli, Alexander Ponomarev, An Binh Tran, and Shiping Chen. 2016. The blockchain as a software connector. In *Proceedings of the 13th Working IEEE/IFIP Conference on Software Architecture*. 182–191.

[62] Shichang Xuan, Li Zheng, Ilyong Chung, Wei Wang, Dapeng Man, Xiaojiang Du, Wu Yang, and Mohsen Guizani. 2020. An incentive mechanism for data sharing based on blockchain with smart contracts. *Computers & Electrical Engineering* 83 (2020), 106587. DOI: https://doi.org/10.1016/j.compeleceng.2020.106587

[63] Liudmila Zavolokina, Florian Spychiger, Claudio J. Tessone, and Gerhard Schwabe. 2018. Incentivizing data quality in blockchains for inter-organizational networks - Learning from the digital car dossier. In *Proceedings of International Conference of Information Systems*.

[64] L. Zavolokina, Noah Zani, and Gerhard Schwabe. 2020. Designing for trust in blockchain platforms. *IEEE Transactions on Engineering Management* (2020), 1–15. DOI: https://doi.org/10.1109/TEM.2020.3015359

[65] Liudmila Zavolokina, Rafael Ziolkowski, Ingrid Bauer, and Gerhard Schwabe. 2020. Management, governance and value creation in a blockchain consortium. *MIS Quarterly Executive* 19, 1 (2020), 1–17.

[66] Ke Zhao, Shaohua Tang, Bowen Zhao, and Yiming Wu. 2019. Dynamic and privacy-preserving reputation management for blockchain-based mobile crowdsensing. *IEEE Access* 7 (2019), 74694–74710.

[67] Rafael Ziolkowski, Gianluca Miscione, and Gerhard Schwabe. 2018. Consensus through Blockchains: Exploring Governance across inter-organizational Settings. In *Proceedings of the International Conference of Information Systems*.

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