*sustainability*

*Article*

# Using Reputation Scores to Foster Car-Sharing Activities

**Maria Nadia Postorino [1] and Giuseppe M. L. Sarnè [2,*]**

[1] Department of Civil, Chemical, Environmental and Materials Engineering (DICAM)—Alma Mater Studiorum University of Bologna, Viale Risorgimento 2, 40136 Bologna, Italy
[2] Department of Psychology, University of Milano Bicocca, Pz. dell'Ateneo Nuovo 1, 20126 Milano, Italy
* Correspondence: giuseppe.sarne@unimib.it; Tel.: +39-02-64483781

**Abstract:** In the near future, the growth of personal mobility is expected to continue all over the world and to cause impacts such as increased levels of traffic congestion and worsened quality of life, mainly in highly populated urban areas. Alternative solutions for individual mobility have been promoted to dissuade people from using private cars. Particularly, renting private vehicles scarcely used by their owners would result in several benefits, including environmental ones, and traffic reduction. This type of solution, based on the willingness of individuals to rent their own vehicles, is called Peer-to-Peer Car-Sharing (P2P-CS). This study proposes a methodological approach focused on the adoption of both a reputation system and blockchain technology to support P2P-CS activities. Reputation scores are introduced to meet CS actors' expectations of dealing with trusted partners, by allowing both access to service and the opportunity to customize CS fares, while the blockchain makes reputation scores publicly accessible and unchangeable and allows the P2P-CS transport solution to be managed without third parties. The effectiveness of the proposed approach has been verified by several tests carried out on real and simulated data. The obtained results are satisfactory and encourage the adoption of these further sustainable travel mode opportunities.

**Keywords:** car-sharing; mobility; sustainability; trustworthiness; reputation systems



**Citation:** Postorino, M.N.; Sarnè, G.M.L. Using Reputation Scores to Foster Car-Sharing Activities. *Sustainability* **2023**, *15*, 3295. https://doi.org/10.3390/su15043295

Received: 29 December 2022
Revised: 4 February 2023
Accepted: 7 February 2023
Published: 10 February 2023



## 1. Introduction

In recent decades, individual mobility has been growing all over the world, with increasing levels of traffic and environmental impacts [1,2], particularly in dense urban areas. Although this trend has been partially slowed down by the recent COVID-19 pandemic [3], the goal of providing people with sustainable and efficient mobility is still a challenge where both public and private actors are engaged. Currently, several policies are being implemented to support changes in users' habits by discouraging the use of private cars (e.g., by adopting restrictive and/or monetary policies such as road tolls, parking fees, and limited traffic zones) and by promoting alternative forms of mobility, mainly transit-based [4] (pp. 91–92), [5] (pp. 20–40).

However, many people still prefer the use of private cars which are considered more appealing in terms of comfort, privacy and flexibility, particularly if compared to discontinuity in both time and space that characterize transit systems [6,7]. Nevertheless, private car ownership requires a significant financial commitment in terms of initial, fixed (e.g., insurance and taxes) and operational (e.g., gas, oil, parking, and service) costs.

In this context, the focus is on developing sustainable mobility based on "being mobile" rather than "owning a car" [8]. This means moving from the current, no longer sustainable, linear economic model, based on the "extract, produce, use, and waste" scheme, to a circular economic model, based on the principles of "sustainable resources, products as services, sharing platforms, life extension, and new life cycles". This transition to a circular economy has all the characteristics of a virtuous system capable of realizing new opportunities for growth and development in terms of competitiveness, innovation, environment and employment [9,10].

Car-Sharing Systems (hereafter CS) is a sustainable mobility solution [11] that mitigates pollutant emissions, reduces individuals' needs for private car, parking demand [12], traffic in urban centers [13], as well as the impact of vehicles at the end of their useful life [14].

For these reasons, CS has gained increasing worldwide popularity because of the opportunity to adopt a "*Pay-As-You-Use*" approach [15] (p. 425). In this perspective, CS is a reasonable choice towards socially sustainable consumption [16] because it provides some people with opportunities for personal mobility by renting a car on demand (or on reservation), usually for local and short trips, while keeping the same benefits of a personal vehicle without costs and obligations of ownership [17]. CS is not a new phenomenon, but the first positive commercial results have been achieved only in the late 80s [18] (p. 27). Recent technological development and changes in people's economic and cultural behaviours [19], including a stronger "green attitude", have led CS to gain new relevance. Internet tools have increased CS opportunities and nowadays, most CSs are Web-oriented [20–22]. so that they can reach a wider audience and reduce transaction costs in matching trip demand and car offers by acting as trusted third parties [23].

Like other *Sharing-Economy* (SE) businesses that enable the renting of various assets, there are several CS business models, which may be: (*i*) *Not-For-Profit*, where the profit is not the primary goal of CS; (*ii*) *Peer-to-Peer* (P2P), where private users rent their cars for monetary compensation; (*iii*) *Business to Consumer* (B2C), managed by companies that make CS services available in order to obtain financial benefits [24,25] (for instance: (*i*) companies such as Getaround, and JustShareIt propose P2P CS; (*ii*) Manufacturers such as BMW and Peugeot, rental and CS brands such as Hertz, WeCar and Zipcar offer B2C CS; (*iii*) Cooperative or public initiative as City Car Share and Autolib are examples of NFP CS)

These business models are characterized by some common features [26]:

- *under-used capacity*—the existence of assets with high cost and limited owner's use is crucial to redistribute underutilized capacity;
- *critical mass*—an adequate amount of resources and users make the system self-sustainable; in fact CS activities usually require a high population density in the area where they are adopted;
- *confidence in strangers*—the attitude to trust strangers is crucial and should be supported by appropriate processes and tools.

By focusing on P2P models, a recent report states that in England, over the past 25 years, cars and vans were parked 96% of the time [27]. The willingness of private users to rent their vehicles, when they do not use them, offers the opportunity to develop P2P-CS services, based on the use of smartphones and social networks [28] similarly to other P2P systems. This CS system, first started in 2001 in Boulder, Colorado, U.S., makes it possible to offset ownership costs and to increase income together with consumers' expectations in terms of time, cost and environmental benefits [29], [30] (p. 8).

To be profitable P2P-CS requires fewer consumers per shared car than B2C-CS [31], so that it is not limited only to large urban scenarios. In addition, it is cheaper than B2C-CS since it does not require initial investments for new cars or their maintenance and it is flexible to market changes. Finally, some results show that the potentially positive environmental effects are strongly linked to the total per Passenger Kilometer Traveled (PKT) demand by car rather than to merely sharing cars [32]. However, P2P-CS is as "green" as traditional CS. In fact, although they are based on the use of existing vehicles, which could be more polluting than recent ones; however, the resources needed to produce new cars are saved.

The successful development of P2P-CS requires specific tax, legal and insurance rules and a positive trust atmosphere [33]. In particular, trust influences actors' behaviour and would help people to perceive risks and uncertainty in the right perspective when deciding to be engaged [34].

From this point of view, a *Reputation System* (RS) is a good tool for both fostering trust between the involved parties (i.e., car owners and customers/drivers) and promoting CS systems. Reputation is recognized to be a strong driver of social interactions [35]. In particular, it represents how someone is perceived by others and contributes to generating confidence in expected behaviours, which will influence future choices and perspectives [36]. For this reason, trust and reputation systems are becoming more and more popular, also due the opportunity to access a relevant amount of permanent, globally available and usable information.

Reputation measures based on available data have the advantage of examining human behaviours without prejudice or perception-related preferences, although the risk of continuous profiling activities there exists [37]. On the other hand, subjective evaluations of reputation may have impacts on the directly involved actors—i.e., drivers and car owners. As an example, misleading perceptions could lead to accepting unreliable drivers—or refusing reliable ones—with potential consequences on car maintenance costs. In addition, unreliable drivers may have impacts on road safety, which is a primary issue for the whole society. Reputation measures too cannot be considered completely error-free; however, their reliability may be strengthened by using both subjective evaluations and detected data. In addition, appropriate attention should be paid to the multifaceted nature of reputation, for avoiding misjudgments and mismanagement.

In our CS scenario, on the owners' side an RS should limit the risks of sharing their own cars, often considered one of the individual's most valued asset [38], with unreliable or unqualified drivers [39]. Among the possible parameters for identifying unreliable drivers, aggressiveness has a primary role [40], even though it is not the only one. Manifold evidence correlate an aggressive driving style with drivers' impatience, annoyance, hostility and desire to save time [41]. However, differently from other parameters, it can be automatically detected in a reliable way also from a simple sensing platform (as the one we adopted, see below). There is a general consensus that "aggressive" driving has many negative effects on aspects such as traffic safety hazards, breaking, tailgating and increased vehicle use [42–44]. It should be noted that the use of several parameters, on the one hand, would lead to more accurate profiling of drivers' and car owner's behaviours, but on the other hand, would require a more sophisticated sensing platform, greater computational load and RS fine-tuning. Similarly, the adoption of an RS also for computing the reputation score of car owners might limit for a driver the risks of renting a vehicle in poor, unsafe conditions.

In this perspective, the CS rent cost could depend on the trustworthiness of the involved actors (i.e., driver and car owner), which is expected to promote, on one hand, better driving behaviours (Monitoring drivers' habits with a sensing device, often connected to the vehicle via CAN-BUS, is already adopted by some insurance companies to reduce their costs [45,46]) and, on the other hand, to improve the quality of vehicle available for further sharing.

In general, the effectiveness of an RS depends mainly on the (*i*) quality of feedback, (*ii*) resilience against malicious behaviours and (*iii*) the way adopted to spread reputation scores in a community. Solutions to these issues come from technological advances in computing, electronic, control systems, signal processing and communications as well as from proposals for safety regulations making smart data recorders mandatory on every vehicle (e.g., UE proposal N.286/2018 [47]).

Given the above premises, the aim of this study is to contribute to making the P2P-CS more usable. Many aspects are involved in this complex rental process, such as legal, financial, economic, insurance, social, environmental, and cultural issues, as well as others more tightly related to the service, such as data access, finding reliable partners, web platforms, car reservation, vehicle status (before and after service), transfer of car keys, parking, and payments. Our proposal aims to provide a solution to some of the service instances listed above and is mainly focused on the adoption of a distributed reputation mechanism for P2P-CS scenarios (*Car-Sharing Reputation System*, CSRS), which would provide car owners and drivers with effective information to realize a good partner selection. The proposed CSRS relies on feedback to keep the actors' reputation scores up-to-date. In particular, the feedback about a driver is automatically computed by exploiting on-board detected kinematic measures, while the feedback about a car owner is directly released by their driver customer. Many studies have verified that driving habits can be automatically monitored in real time by using simple sensing platforms without introducing significant errors in terms of detected data. Furthermore, in the proposed framework a blockchain platform is considered to update and spread reputation scores by making them permanent, resistant to manipulations and publicly available in a decentralized approach that will avoid single points of failure [48]. Although some other aspects of the entire car rental process could be managed by means of blockchain technology, they are however out of the aim of this proposal and they will not be considered in the following.

To validate the proposed approach in terms of effectiveness and potential advantages for P2P-CS activities, some tests have been performed on real and simulated data.

The remainder of the paper is organized as follows. Section 2 gives an overview of the related literature. Section 3 introduces the proposed P2P-CS process and then focuses on the methodology adopted to compute driver feedback, the proposed reputation system and the added value provided by the adoption of smart contracts. Section 4 summarizes and discusses the results of the experiments. Finally, in Section 5 some conclusions are drawn.

## 2. Literature Review

A recent study has investigated the use of CS systems as a common urban mobility practice also based on digital technologies, by comparing data collected in some cities in Europe in order to understand the relevance of the respective CS systems [49]. The results have shown that digital technologies together with regulations are among the most important factors for business models. In addition, Auer et al. [50] have investigated blockchain and IoT technologies as key drivers for P2P shared mobility systems, whose effectiveness depends on many factors among which privacy, authenticity, traceability and reliability.

Satisfaction with current mobility options and the inherent uncertainty in car-sharing decisions play a relevant role in this context, particularly the guarantee of car availability is among the most important factors to be considered for developing a CS system [51].

As with other SE applications, P2P-CS systems are founded on the existence of trust and reputation relationships among the involved actors. Particularly, trust and reputation information is significant in almost every decision process and social interaction in human or virtual societies, and they help reduce both knowledge asymmetries among actors and risks of deception by predicting future behaviours based on own past experiences and/or those of others.

Such information can encourage the individual willingness [52] to share with strangers by alleviating uncertainty, which is a perturbing factor in this highly dynamic market [53]. In addition, trust and reputation criteria are closely linked to the role played by ICT and Web platforms for sharing goods [54], which influences consumers' willingness to be engaged in sharing. This implies that there exist two levels of trust, the first one occurring between car owners and customers and the second one among the actors and the Internet application, which needs to be trusted [55].

To fit different contexts, a wide variety of trust and RSs are needed, which are driven by (*i*) number, reliability and nature (e.g., direct or indirect experiences) of information sources, (*ii*) aggregation and inference rules (e.g., in a local or global way) and (*iii*) adopted architecture (e.g., centralized or distributed).

The role of RSs is particularly relevant in a large, sparse community where most part of the members is mutually unreferenced. Some desirable RS properties [56] are: (*i*) involving long-living entities to gather a number of information about their past behaviours; (*ii*) deciding to carry out a new interaction with an entity driven only by their past behaviours; (*iii*) releasing feedback about the own counterparts in order to compute a score for them, which will be spread into the community.

The importance of trust and reputation is detailed in an early study [39] that confirms the reluctance to share personal vehicles with other people for lack of trust, while the relevance of positive rating for users' choices was investigated with respect to the relationships users–CS mediators and users–car owners [55]. Reputation scores on CS consumers' driving habits were exploited in [57] by adopting a neural network approach tested on publicly available data.

One relevant tool to manage and disseminate reputation scores everywhere and anytime, as well as to make whitewashing strategies difficult to implement, is the blockchain [58], which is a decentralized, distributed and accessible ledger in form of interconnected permanent, unchangeable and chronologically ordered data blocks, validated and verified by a distributed consensus (typically, a consensus mechanism consists of (*i*) transaction endorsement, (*ii*) ordering and (*iii*) validation and commitment processes). The main blockchain applications are referred to criptocurrencies [58], smart-contracts [59–62] ("a computerized transaction protocol that executes the terms of a contract" [63], see Section 3.5) and data repositories). Data blocks are replicated on multiple hosts so that they cannot be deleted, disrupted, compromised or hacked by a single strike [64]. More in detail, the consensus protocol [65] provides the blockchain with robustness, latency, scalability and computational complexity placed on the ledgers. Lower computational complexity may be obtained if ledgers are mutually known, so that it is possible to relax some constraints by adopting a "permissioned" blockchain instead of a "permissionless" [66]. In the context of P2P-CS, the blockchain has the potential to make sure and reliable transactions for the involved actors.

More in general, the mobility ecosystem can benefit from blockchain technology to redefine roles and services in a variety of use-cases [67], e.g., insurances, sharing services, intermediary activities, keyless system management, data repository (e.g., maintenance, accidents and profiles of cars, owners and drivers) and payments [68]. Currently, a growing number of initiatives and proposals using blockchain technologies involve sharing activities. In fact, they easily enable trust between parties by generating smart contracts (with codified penalties for contract breaches) that are verified and terminated.

In this context, an early proposal to take advantage of Ethereum smart contracts was HireGo [69] based on two virtual tokens (HGO and ERC-721 car tokens), which can be purchased in Ether and act as meta-cryptocurrencies to rent a car. HireGo provides three types of contracts, the first two to acquire HGO and ERC-721 and the other one to conclude a rental contract. Helbiz [70] is another blockchain-based system for a scooter sharing system that employs ERC-20 tokens, called HBZ, to pay for the service. FFQuest [71] uses the proprietary Distributed FFQ Ledger blockchain, but it is based on the Ethereum Virtual Machine, which employs its own ERC-20 type FFC token to share transaction details, payments and images, vehicle availability and reservations among car companies, drivers and customers. Other proposals are Car Next Door [72], SC2Share [73] (derived from SePCar [74]), ARTICONF [75], where a decentralized approach is proposed.

In the above perspective, P2P-CS systems may be based on the combined use of RS procedures and blockchain to guarantee qualities such as trust among actors, reliability and security of transactions. However, RSs require that each participant assesses both the honesty and the behaviour of their counterpart through feedback. Consequently, the RS accuracy depends closely on the quality of the feedback because incorrect information or inaccuracies might compromise the trust-building mechanism. To this end, our approach proposes to remove the human factor in generating feedback on drivers' behaviour and the automatic analysis of their driving habits, skills, and abilities during CS rentals.

In the last few decades, the study of drivers' behaviours, including the level of drivers' aggressiveness, has received increasing attention in many fields (e.g., insurance, safety, traffic violations and so on), but their modelling is a complex and expensive process. In fact, it requires knowledge of detailed features on several parameters such as environment, dynamics and characteristics of the vehicle, sensing equipment and significant computational resources, so simplification is necessary to model the level of aggressiveness of drivers [76].

Usually, driving style has been studied by collecting data from questionnaires submitted to drivers [77], which allows to obtain both statistical and motivation viewpoints [43], although external factors, such as traffic flow and road type, may affect significantly drivers' behaviours [78]. After, vehicles (or simulators [79]) equipped with specialized, often expensive, tools and sensors were used to collect objective, more accurate data about drivers' style [80]. Currently, data may be obtained by lightweight, low-cost, not intrusive on-board sensing platforms often equipped with communication and storing capabilities (like common smartphones) and smart data recorders.

In the literature, there are several proposals to classify driver's aggressiveness, based on different computational models [40]; the simplest ones discriminate only between a normal or harsh driving-style [81,82], while the more structured models may recognize different degrees of aggressiveness [83,84]. Generally, such methods use information concerning acceleration on one or more axes, speed and steering data [85]. Information about the motion of vehicles in time and space may be provided by smartphones, which are reliable sensing platforms for collecting such data without introducing errors having relevance from a practical viewpoint [86–88]. This simple device may be used to identify risky manoeuvres and, based on their severity, drivers may be classified as aggressive or non-aggressive on the basis of the computation of a comprehensive risk index [89], or on some specific data, such as sudden changes in acceleration and unsafe turns [90].

Fuzzy-logic approaches have also been used to classify drivers based on the frequency of specific driving events [91], showing that braking and turning are more useful than acceleration events to classify drivers, while in SenseFleet they have been detected independently on the vehicle, route, weather conditions and mobile devices [81]. Other interesting proposals to classify drivers are in [92–95].

In the above perspective, the proposed approach, described in the next section, adds the benefits of a purpose-specific RS to a mechanism for computing automatic feedback on driving aggressiveness. Furthermore, the relationships between consumers and car owners are managed by a blockchain, which ensures the reliability and effectiveness of the involved operations, including feedback.

## 3. The P2P-CS Process and the Proposed Framework

In the proposed approach, a blockchain platform is assumed to manage: (*i*) the affiliation of CS actors, by recording their identities, aliases, financial data, and so on; (*ii*) the CSRS and the updating of the signed Digital Credential Certificates (DCCs) that confirm the identity (i.e., alias) and the current reputation score of each CS actor; (*iii*) the keyless system that enables the sharing of the car [96]; (*iv*) the payments by using a cryptocurrency (see Figure 1).

Furthermore, we assume that: (*i*) a *Booking* list of check cars is always available and kept updated based on information coming from the car owners and the blockchain; (*ii*) for each booked car: its rental cost, the reputation score of the car owner and the minimum consumer reputation score required by the car owner to rent their car are stored; (*iii*) all cars are equipped with on-board units to manage a keyless system and are equipped with communication, Global Positioning Systems (GPS) and inertial sensing capabilities. (*iv*) each actor is equipped with a pair of asymmetric cryptographic keys provided by the adopted blockchain platform (note that to avoid the use of improper accounts, further mechanisms should be adopted such as an authentication process at two levels).

It is worthwhile to note that P2P-CS processes generally involve a large number of legal, economic and management issues, such as privacy, payment, key management, withdrawal, insurance, and legal value. Since these activities are not the core of the paper, for them we will refer to other studies to write realistic smart contracts for car rental (see Section 3.5).

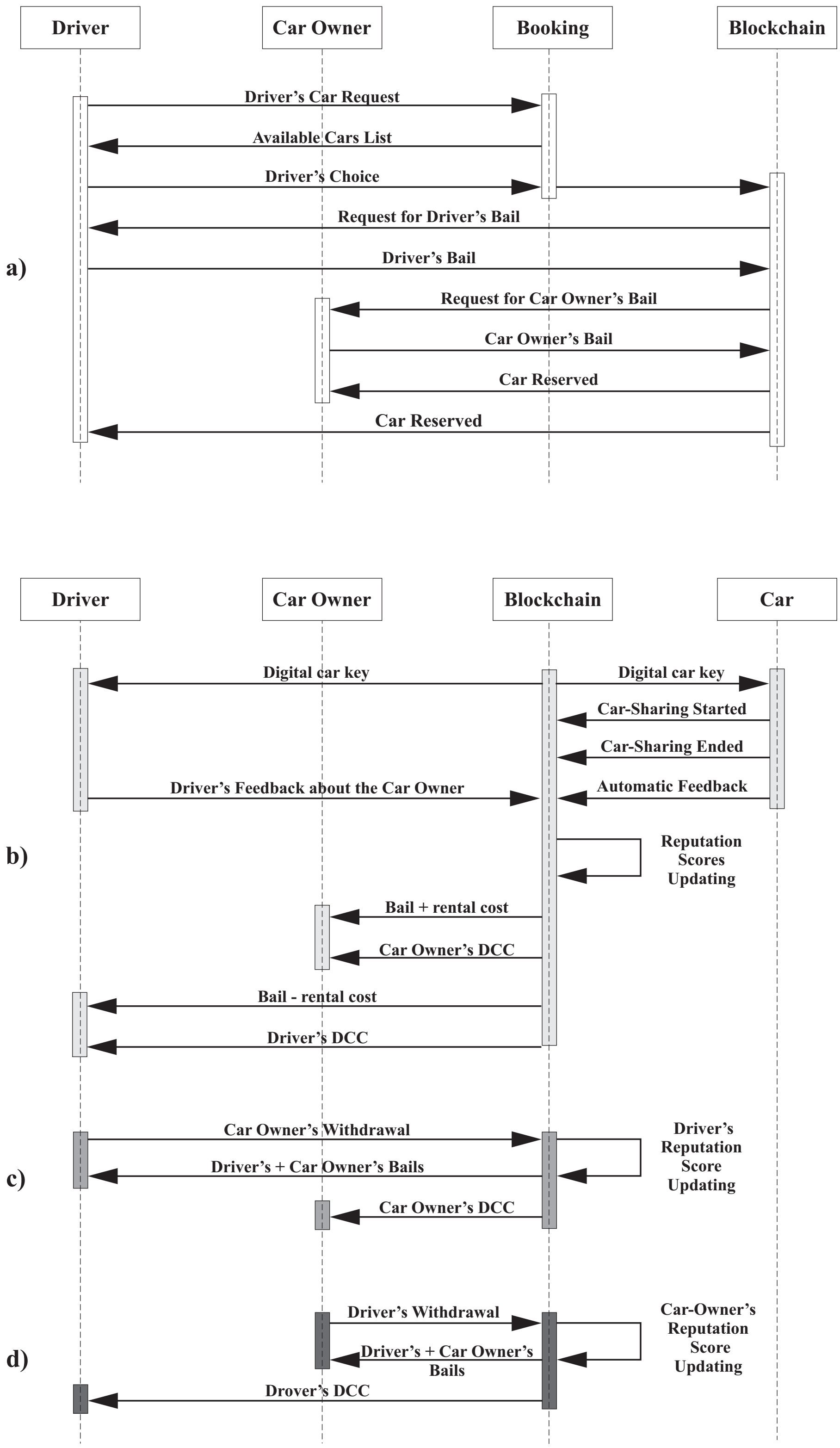


**Figure 1.** Main CS phases: (**a**) Booking; (**b**) CS service; (**c**) Car owner's withdrawal for car not available; (**d**) Driver's withdrawal for car not picked-up.

Booking and CS services are the two main steps that start the P2P-CS process accomplished by car owners and consumers. In particular:

- *Booking*—When consumers want to rent a car, they take advantage of the *Booking* service, which will offer them a list of available cars that meet their preferences and needs. The list may be empty (no match was found) or no choice is made by the consumer because none of the proposals satisfy them (e.g., because of the car model, the car owner's reputation, etc.), then the P2P-CS process ends. Otherwise, if a car is chosen from the list, then a smart contract will be activated on the blockchain before the rental process starts and the consumer picks-up the car. Through the use of cryptography, the smart contract can ensure both the confidentiality and authenticity of booking details as well as provide forensic evidence to the agreement. The smart contract will store the following data: (*i*) Actors' data (e.g., aliases); (*ii*) Car data (e.g., car plate, model); (*iii*) Renting data (e.g., renting time, renting and extra-time prices, pick-up and return car locations, deception penalty, withdrawal period to cancel without penalties). In addition, both parties will have to guarantee, by a deposit in cryptocurrency, the costs for both the rental and the possible deception; if the CS service ends regularly, the deposit minus the rental costs will be refunded. Note that multiple bookings for the same time interval can be easily precluded by the system.

- *CS service*—Close to the car rental scheduling, the smart contract will activate the process of generating and delivering the digital car key to the consumer in order to start the rent service [97]. When the CS service ends, the consumer receives feedback about their behaviour, which is automatically computed based on their driving aggressiveness (see Section 3.4). In turn, each consumer provides a feedback about the car owner based on the perceived "quality" of the rented car. If the reserved car is available, regularly picked up by the consumer and the CS service ends in accordance with the smart contract, then (*i*) the reputation scores of the consumer and the car owner is updated based on the actors' feedback received (see Section 3.4), (*ii*) the updated DCCs is sent, respectively, to the consumer and the car owner and (*iii*) the monetary assets (e.g., payments, deposits) fulfilled. Otherwise, if the reserved car is not available or the consumer does not pick up it, then the actor who has not honored the contract is penalized in their reputation score (a new updated DCC will be sent to them) and they will pay a penalty to the counterpart by leveraging their deposit. The reputation update process is depicted in Figure 2. To summarize, reputation scores are updated either when one of the two actors makes a withdrawal (cases a and b) or after the end of a CS service (case c) by exploiting the mutual feedback calculated as described above.

### 3.1. The Drivers' Aggressiveness Feedback

The detection of the driver's aggressiveness, which is used to compute their reputation score, is an important part of this process. Inattentive or inappropriate driving habits, also combined with road features (e.g., stone pavement, rough gravel, and so on) and traffic conditions (e.g., frequent stop-and-go sequences) can stress the mechanical components of vehicles and can lead to increased usage cost that causes accidents or requires maintenance. While road and traffic conditions generally are considered known factors, potentially aggressive drivers might generate concern in car owners and prevent them to share their cars with strangers, whose guide behaviour is not known a priori.

To encourage suitable driving style in a P2P-CS context, a convenient policy might be to reward "good" drivers with advantageous fares and deny access to CS services to more aggressive drivers.

As discussed in Section 2, to measure the degree of driving aggressiveness, a common smartphone can provide reliable measures about the guide style by recording on-board kinematic data without practical drawbacks [92,98]. Therefore, to collect data for computing driver's aggressiveness a smartphone has been used in this study.

To summarize, the proposed approach to manage P2P-CS, which has the blockchain at its core, is based on the following main elements:

- detection of the driver's guide style, particularly driver's aggressiveness;
- actor's feedback;
- reliability of each actor in the P2P-CS process, identified by a reputation score;
- smart contracts.

These aspects are presented and discussed in the following.

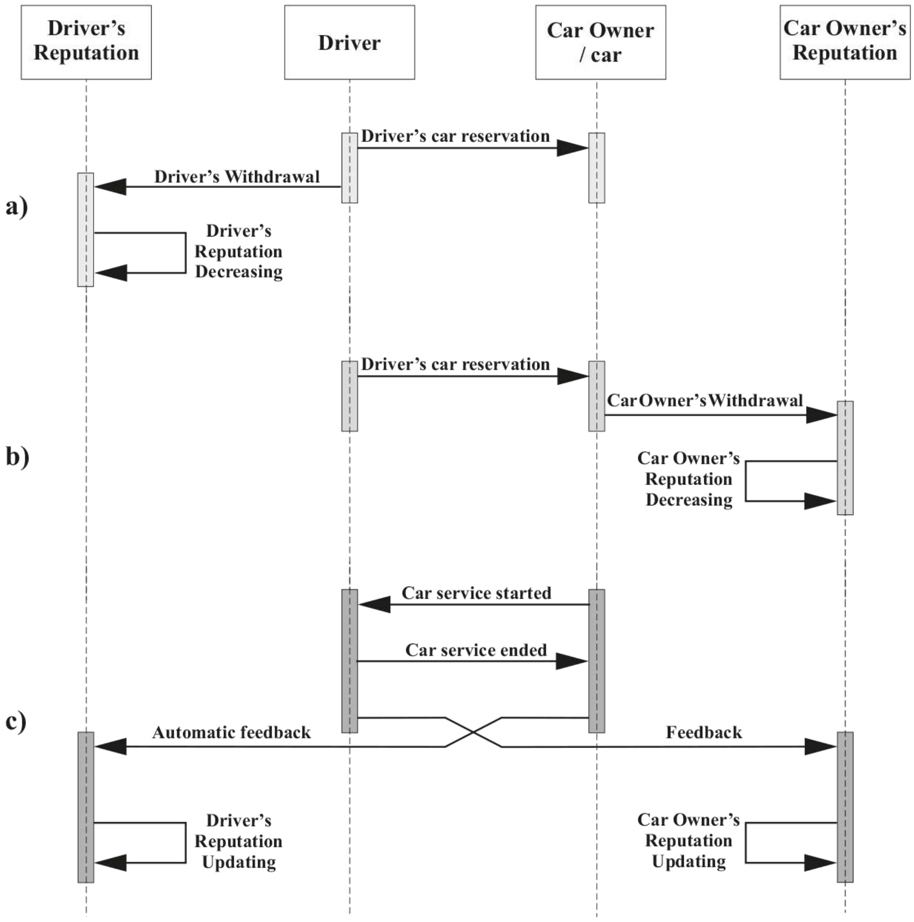


**Figure 2.** Reputation scores updating process: (**a**) Driver's withdrawal; (**b**) Car owner's withdrawal; (**c**) End of a CS service.

### *3.2. Detection of Driver's Aggressiveness*

We propose a simplified computational procedure, suitable for the adopted equipment and the conceived reputation system (see Section 3.4), based on:

- GPS sensor data to identify the vehicle position in space and time, including distance covered and speed computation;
- x, y, z-axis inertial sensors data to measure longitudinal, lateral and vertical accelerations.

During its motion, a vehicle can be assumed as a rigid body and its kinematic varies for each driving action. Variations in kinematic parameters during driving events, such as acceleration and breaking can be detected by a sensing platform (currently, vehicles can be equipped with at least 120 different types of on-board sensors, including those required for the autonomous vehicle driving, and their number is increasing quickly). Note that a correct classification of driving events might be difficult, particularly when the vehicle speed is lower than 10 km/h. At a very low speed, vehicle damages linked to aggressive guide style are often irrelevant; then, in order to simplify the data analyses without introducing a significant loss of accuracy, it is assumed that when the vehicle speed is lower than 10 km/h the sensor data are not processed.

Notwithstanding its simplicity, the procedure described below to compute the driver's feedback for a CS service is effective. More in details, it analyzes the kinematic data collected by the on-board sensing platform in real-time by splitting the entire trip of a CS service into a sequence of short time slices, each one of 20 s. Based on the number and the type of maneuvers considered as aggressive carried out in each slice, this latter will be classified as "aggressive" or "not aggressive" (by using suitable thresholds and weights, see Section 4). Finally, for that CS service, the driver's feedback computation will take into account the percentage of slice scores classified as aggressive.

Formally, let $T$ be the trip time of a CS service and let $N$ be a finite sequence of time slices $t_i$ such that:

$$T = \sum_{i=1}^{N} t_i \text{“aggressive”}$$

Let consider driving events grouped in classes and let $M$ be the total number of classes. Each class $m$ contains driving events such as acceleration, speed, breaking, steering, bump. For the $i$-th time slice, the *Aggressiveness* $A_i$ is computed as:

$$A_i = \sum_{m=1}^{M} \omega_m \cdot e_{m,i}$$

where:

- $\omega_m$ is the weight assigned to a driving event of type $m$;
- $e_{m,i}$ is the number of aggressive driving events of type $m$ occurred in the $i$-th slice. An event is classified as aggressive if the value measured by the on-board sensing platform is greater than a suitable threshold $\tau$ (see Table 1 in Section 4.1 for an example).

  If $A_i > \tau$ that slice is classified as "aggressive".

### 3.3. Actor's Feedback

Both drivers and car owners release feedback $F$ about CS services through the blockchain platform. Car owners receive information about the driving style of the consumers, while drivers provide information about the quality of the CS service, which includes car features and its conditions. In the following "driver's feedback" will identify the information about the driving style, while "car owner's feedback" will be used to identify the judgment provided by drivers about the CS service quality.

Driver's feedback is computed by using the aggressiveness index $A_i$ for each time slice of the CS service $s$ realized by driver $d$. Particularly, let $\Delta$ be the number of slices classified as aggressive for a CS trip. The following index $F_d$ ranging in $[0;1]$ is a measure of the driving style for the CS trip:

$$F_d = 1 - \frac{\Delta}{N} \qquad \forall s$$

High (low) values imply a not aggressive (aggressive) driving behaviour for that CS service. Note that the index $F_d$ is computed based on data detected automatically by the on-board device and it is used as a measure of the driver's feedback. This feedback is released automatically by the blockchain.

On the other hand, car owner's feedback $F_o$ provided by the drivers about the CS service is a score—still in the range $[0;1]$—that unlike $F_d$ is not released automatically, but it synthesizes the driver's assessment about the service.

### 3.4. The Car-Sharing Reputation System

The *Car-Sharing Reputation System* (CSRS) adopted to measure the reliability of each CS participant is based on the reputation score ($\rho$) associated with each actor and varies in $[0,1]$, where $\rho = 1$ identifies the best reputation and $\rho = 0$ the worst one. Note that those CS actors playing both the roles of consumer and car owner will be provided with two dedicated reputation scores. Moreover, each newcomer receives an initial reputation score of 0.75, in order to not be penalized too much when starting the renting service the first time.

The reputation scores are linked to the different types of behaviours adopted by the involved actors, which have been grouped in "alternate", "complaining" and "collusive":

- *Alternate*: behaviours are said alternate if actors adopt different behaviours for different CS services—e.g., more aggressive for some CS, less aggressive for some others CS—because they imagine that their bad (e.g., more aggressive) behaviours are balanced by good (e.g., less aggressive) behaviours. In other words, when driving without aggressiveness for a CS service, they gain reputation, which might be used to balance loss of reputation for aggressive driving during another CS service.
- *Complaining*: behaviours are said complaining if actors release negative feedback (i.e., $F_o < 0.5$) to the counterparts in a systematic manner regardless of their real behaviours. In the case of complaining behaviour, malicious people may adopt complaining strategies with the aim to decrease the reputation of honest actors.
- *Collusive*: behaviours are said collusive if actors agree for releasing suitable feedback in order to increase their respective reputation scores. In our system only car owners can benefit from collusive activities because drivers receive feedback automatically computed that cannot be influenced by malicious strategies.

In this context, *Alternate*, *Complaining* and *Collusive* behaviours may be adopted by drivers, while car owners can only perform *Collusive* behaviours.

The reputation scores depend on the CS *Freshness*—i.e., older CS services do not contribute to the current reputation of a CS actor—and the relationship between *Feedback* and *Relevance*. As for this latter, given a CS service $s$, the *Relevance* $R_s$ is defined such that the higher the fare of the CS service $s$ is, the higher $R_s$ is. $R_s$ is computed as:

$$R_s = \begin{cases} \dfrac{c_s}{C} & \text{if } c_s \leq C \\ 1 & \text{otherwise} \end{cases} \tag{1}$$

where $c_s$ is the rental cost and $C$ a cost threshold. Note that CS service fares might be customized based on driver's reputation score.

To compute the reputation score for a CS actor, the latest $h$ assessable CS service made by the CS actor $a$ will be considered. The concept of "assessable service" is linked to the actor's behaviour, as explained below. The reputation score of actor $a$, $\rho_a$, with respect to their latest $h$-th assessable CS services (ordered from the most recent to the $h$-th), is computed as:

$$\rho_a = K_a \cdot \frac{\sum_{i=1}^{h} \varphi_i \cdot R_{a,i} \cdot F_{a,i}}{\sum_{i=1}^{h} w_i} \tag{2}$$

where $\varphi_i = 1/i$ is the *Freshness* parameter, whose value decreases as much as the feedback received by $a$ for CS services is old; in other words, $\varphi_i$ weights recent feedback more than oldest ones. As a consequence, the contribution of older CS services will gradually become more and more irrelevant $K_a \in [0,1]$ is the *Complaining* parameter, which takes into account potential complaining behaviours. For car owners, $K_o = 1$ because they cannot release feedback about drivers, while for drivers $K_d$ is computed as:

$$K_d = \begin{cases} 1 & \text{if } \frac{NF}{TF} \leq 0.3 \\ 1 - \dfrac{NF}{TF} & \text{otherwise} \end{cases} \tag{3}$$

where $NF$ is the percentage of driver's released negative feedback and $TF$ is the total number of feedback.

To clarify the role of $K_a$ and the concept of "assessable service", some preliminary experiments have been carried out to identify values for $F$ and $R$ corresponding to the several behaviours.

Particularly, $F \geq 0.75 \bigvee R < F$ has been observed for alternate behaviours, while complaining strategies does not give a real advantage to malicious actors when the relevance of a CS service is $R < 0.5$. Therefore, to discourage dishonest actors, CS services that verify: $(F \geq 0.75 \bigvee R < F) \bigcup (R < 0.5)$ are considered not "assessable" to contribute to reputation. It is expected that the computation of reputation scores by taking into account assessable services will be effective in discouraging both alternate and complaining behaviours, and in promoting correct ones without penalizing actors too much.

Assessable CS services are represented in Figure 3 by gray and white areas, where the gray area includes all those CS services that received a negative feedback (i.e., $F < 0.75$) regardless of their relevance, while the white area identifies CS services that received a positive feedback (i.e., $F \geq 0.75$) but for which $R \geq F$. CS services in the black area are not assessable for contributing to the computation of the reputation score.

To limit collusive behaviours, each actor can contribute once to the reputation of another actor and with their more recent feedback.

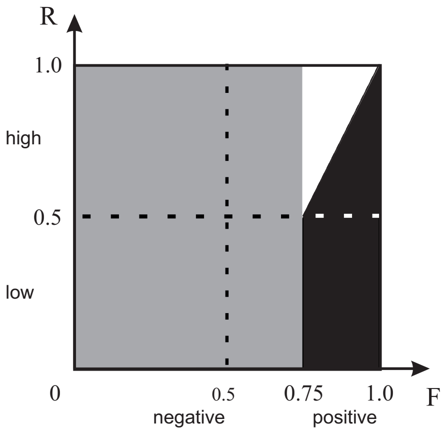


**Figure 3.** Assessable CS services (white and gray areas).

### *3.5. Cost of Smart Contracts for Car-Rental*

Smart contracts [63] are computerized transaction protocols (written in suitable scripting languages) not relying on trusted third parties. They execute the terms of immutable contracts between different entities when some predefined contractual conditions are satisfied. Coherently with [63], smart contracts should assure the properties of *observability* for monitoring the contractual behaviours of counterparts, *online enforceability* to ensure compliance with contract terms, *verifiability* for the auditability of the contract when a conflict occurs between participants and *privity* for a selective transparency of contract data that will be verifiable only for participants and encrypted for the other.

In the proposed P2P-CS framework, smart contracts could manage the entire rental process by enabling several fully decentralized services (e.g., car reservations, rental contracts, monetary deposits, payments and compensations, digital key and reputation system management among the others). They would ensure compliance with contractual obligations by preventing frauds and providing legal evidence without the assistance of trusted third parties [48] in a reliable, secure, permanent and confidential way. Consequently, the cost of a smart contract must be added to the CS fare.

To estimate this cost, the well known Ethereum [59] blockchain has been considered here, although it has to be noted that the proposed framework does not rely on a specific blockchain platform. In particular, test smart contracts (for different time horizons $h$) written in Solidity [99] (pp. 69–110) and compiled on the Ethereum Virtual Machine have been tested on a local Ethereum environment. In addition, the public JAVA scripting libraries for Ethereum and the open source Truffle Suite [100] have been used.

Transaction on the Ethereum blockchain take place in Ether ($ETH$), which is its cryptocurrency denoted by a high volatility, depending it on both gas and currency exchange markets. As a result of our tests, the estimated costs of Ethereum smart contracts managing a whole P2P-CS process range from 0.000855138 ETH (for $h = 4$) to 0.000996275 ETH (for $h = 10$). In other words, the contract will have minimal impact on the CS fare even in the worst case (i.e., for $h = 10$) for current exchange rates (1 ETH = 1104.30$ at 19 December 2022). Note that these costs do not consider the costs for developing smart contracts.

## 4. Experiments

To test the most relevant aspects of the proposed framework, the results of two experiments, carried out on real and simulated data. are presented and discussed in this section.

The first experiment focuses on the computation of reliable feedback about drivers' aggressiveness (see also Sections 3.2 and 3.3), while the second one verifies the effectiveness of the *Car-Sharing Reputation System* (see also Section 3.4).

### *4.1. Computation of the Drivers' Aggressiveness Feedback*

To assess the aggressiveness of drivers, the procedure described in Sections 3.2 and 3.3 was tested on real data. The experiment is based on a sample of 12 users (heterogeneous in age and gender) driving a fleet of personal vehicles belonging to different categories (note that some users have driven more vehicles) and equipped with common smartphones (used as sensing platforms).

Two tests have been considered. In the first one (Case A), drivers have been asked to maintain their usual driving habits, while in the second one (Case B) they have been asked to have a more aggressive driving style.

The accuracy of users' smartphones, equipped with the app *Physic Sensor Suite* (www.vieyrasoftware.net, accessed on 1 December 2021), were verified through a validation procedure (Figure 4) before being used as on-board sensing platforms. The measures provided by the sensors of the tested smartphones tested varied in a narrow interval which is suitable for our aims.


**Figure 4.** Smartphones used as sensing platform for detecting driving style: testing and validation (S1—Device to validate; S2—Reference device; D—Data acquisition).

Data have been collected both in real-time and in off-line modalitiesby smartphones with a sampling frequency of 500 Hz, recorded in csv format and analyzed, as described in Section 3.2, in order to compute driver feedback. The adopted parameters are shown in Table 1. Different values of the parameters listed in Table 1 will lead to different feedback values, but this does not limit the validity of the tests.

**Table 1.** Setting adopted for computing drivers' aggressiveness.

| Parameter | Values |
|---|---|
| Time slice (s) | 20 s |
| Speed threshold | 13.8 m/s |
| Acceleration threshold | 2.4 $m^2/s$ |
| Breacking threshold | 1.5 $m^2/s$ |
| Centrifugal acc. threshold | 3.1 $m^2/s$ |
| Speed weight | 1 |
| Acceleration weight | 1 |
| Breacking weight | 0.9 |
| Steering weight | 0.8 |
| Aggressive driving threshold ($\tau$) | 1.5 |

In Case A, users adopted their usual driving style on urban roads having different geometrical characteristics, medium traffic flow levels and under different weather conditions. A sample of 240 driving experiments (i.e., 20 experiments per user) ranging from approximately 6 to 25 min were collected. Each experiment was referred to a single trip and a single vehicle. The analyses showed that 292 slices on 11,133 were classified as "aggressive" (i.e., 2.62%), whereas the feedback value $F_d$ varied from 0.94 to 1.00 (see Table 2-A). In the second test (Case B) users adopted a more aggressive driving style on a restricted area and each user realized only one trip. The analyses lead to classify 671 slices on 4864 as aggressive (13.8%), while $F_d$ ranged from 0.89 to 0.96 (see Table 2-B), significantly less than in Case A.

**Table 2.** Drivers' aggressiveness results.

| Feedback | Number of Samples | |
|---|---|---|
| | Case A | Case B |
| 0.8900–0.8999 | - | 4 |
| 0.9000–0.9099 | - | 26 |
| 0.9100–0.9199 | - | 32 |
| 0.9200–0.9299 | - | 39 |
| 0.9300–0.9399 | - | 36 |
| 0.9400–0.9499 | 24 | 39 |
| 0.9500–0.9599 | 31 | 51 |
| 0.9600–0.9699 | 48 | 13 |
| 0.9700–0.9799 | 42 | - |
| 0.9800–0.9899 | 35 | - |
| 0.9900–0.9999 | 59 | - |
| 1.00–1.00 | 1 | - |

These results show that the procedure proposed to compute automatically drivers' feedback is able to recognize the degree of aggressiveness of different driving styles based on the kinematic data collected by the adopted sensing platform.

### *4.2. Effectiveness of the Car-Sharing Reputation System (CSRS)*

The effectiveness of the proposed CSRS has been tested by means of several simulations in which consumers and car owners (both malicious and honest) interacted for CS services. Simulated CS scenarios considered different numbers of assessable CS services (i.e., $h$) and different percentages of malicious actors performing collusive, complaining and alternate behaviours.

The first set of simulations focused on identifying malicious and honest actors (see Section 3.4), particularly malicious actors have been set to systematically perform some randomly selected malevolent activities with high frequency. Furthermore, the performance of the proposed CSRS has been compared with those of three main RSs proposed in the literature [101–103].

To test the proposed CSRS and its competitors, a simulated population of $10^3$ drivers and $10^3$ car owners has been considered. 120 simulations, each one arranged in $10^2$ epochs, where for each epoch 500 CS service have been requested from randomly selected drivers and car owners in the respective populations, have been carried out. Each simulated CS actor has been provided with a profile, $P_a(X)$, where $X$ is a vector of features referred to their default behaviour (e.g., honest or malicious), the minimum reputation score required by the counterpart to interact with them, the driving habits (necessary to determine the consumer's driving aggressiveness). In addition, (*i*) when the actor's reputation was inadequate to meet the counterpart's requirements, the simulated CS service was denied and (*ii*) part of the recognized malicious actors (who became inactive in the simulations due to their low reputation) was replaced by new malicious actors at each epoch in order to keep a suitable sample size. The percentage of malicious consumers and car owners with respect to their populations has varied from 5% to 15%, with a 5% step.

Finally, the cost threshold $C$ for a CS service $s$ has been set to €20.0. In order to reward reliable drivers, CS service fares are customized through a discount that will be proportional to the driver's reputation, the higher the reputation the greater the discount.

### *4.3. The RSs Competitors Tested against CSRS*

As for the three RSs used for comparison, the first one (RS1) is SPORAS, still considered one of the most effective multipurpose RS [104]. It over-penalises agents with low reputations by safeguarding those with high reputations. In SPORAS the reputation scores range in the domain $[0, 3000]$ and are updated as follows:

$$R_i = R_i^{old} + \frac{1}{\theta} \cdot \Phi(R_i^{old}) \cdot R_j \cdot (W_i - E_i)$$
$$\Phi(R_i^{old}) = 1 - \frac{1}{1 + e^{-(R_i^{old} - 3000)\sigma}} \qquad E_i = R_i^{old}/3000$$

where $R_i$ and $R_i^{old}$ are the updated and current reputation of $i$, $R_j$ is the reputation of $j$ that released the feedback $W_i$ about $i$, $\theta$ is the number of ratings exploited in updating $R_i$, $\Phi$ is the dumping function [101] while $\sigma$ is a parameter called "*accelerator*" empirically set equal to 0.11 [101].

The second competitor, RS2, described in [102], has been designed for IoT contexts. It is able to mitigate the effects of unfaithful feedback by assessing their *credibility* against collusive behaviours and *certainty* against malicious activities exploiting false identities. More in detail, let $L_S(\Delta t_k)$ be the *Local Objective Reputation* of the service $s$ (made available by a provider) computed on the basis of the feedback $F$, received in a time window $\Delta t_k$, weighted by credibility ($\Gamma$) and certainty ($\Lambda$) as:

$$L_s(\Delta t_k) = F(\Delta t_k) \cdot \Gamma(\Delta t_k) \cdot \Lambda(\Gamma(\Delta t_k)$$

Based on the $L_s$ scores, the *Global Objective Reputation* ($G_s(\Delta t_z)$) for a given service $s$, for $Z$ consecutive time windows and for each provider is computed as:

$$G_s(\Delta t_z) = \sum_{k=1}^{Z} (L_s(\Delta t_k \cdot v_k)$$

where the value $v_k$, ranging in $[0, 1]$, decreases as the age of knowledge increases. The computation of the weight $\Gamma$, $\Lambda$ and $v$ is described in [102]. The last step is the normalization of $G_s(\Delta_{t_z})$ in $[0, 1]$.

Finally, the last competitor, RS3, is eBay, a very popular and very basic RS [105] which computes the reputation of each user as the percentage of positive feedback received in a time window (Note that multiple feedback released by the same counterpart in a closed time and neutral feedback are not considered in the calculation). To tackle multiple identities, RS3, like RS1, assumes that newcomers receive a null reputation. This RS has been largely studied and, although some upgrades have occurred over time, it is not particularly resilient to malicious behaviours, in particular, if collusive.

The reputation scores of all RSs range in $[0.0, 1.0]$ excepted those of RS1 that ranges in the domain $[0.0, 3000.0]$ However, such scores have been normalized in $[0.0, 1.0]$ to make RS1 comparable with the other RSs; In addition, for RS2 the time window was assumed to equal the number of interactions used to compute individual reputation (i.e., the horizons in CSRS). These small changes have not degraded the performance with respect to the original proposal. Furthermore, coherently with RS descriptions, the initial reputation scores were set at 0 for RS1 and RS3, 0.5 for RS2 and 0.75 for CSRS.

Finally, the values of $h$ in CSRS, $\theta$ in RS1 (with $\theta \equiv h$), and the time windows $\Delta t$ in the RS2 (with $\Delta t \equiv h$) varied from 4 to 10 with step 3. Note that RS3 provided valuable results only by considering the entire previous history of each actor in terms of feedback.

### *4.4. Detection of Malicious Behaviours by CSRS and the Tested RSs*

Reputation systems are primarily used to identify the nature of the actors (i.e., honest or malicious) as early as possible. In our scenario, malicious drivers may perform alternate, collusive and complaining behaviours, while malicious car owners can perform only alternate behaviours. To select the most suitable RS among the considered ones— including the proposed CSRS—we tested their accuracy separately for drivers and car owners. Particularly, 120 simulations have been considered, in the worst case (i.e., for drivers in presence of concurrent malicious behaviours), for different percentages of malicious actors and different values of $h$. The results of this comparison among CSRS, RS1, RS2 and RS3 in recognizing the nature of drivers and car owners are depicted in Figures 5 and 6 and synthetically shown in Tables 3 and 4.

The results show that CSRS is the best RS among the tested ones in terms of both accuracy and responsiveness. In particular, CSRS performs better also if $h$ decreases and the number of malicious actors increases. As reported in Table 3, CSRS is right in recognizing car owner behaviours (honest or malicious) in 89.9 to 93.5 cases out of 100 just after 5 epochs, and in 93.7 to 97.4 cases out of 100 after 30 epochs. Even better results are obtained for drivers (see Table 4). Moreover, the results have shown that CSRS performances degrade only slightly as $h$ and the malicious percentage vary, thus proving a high resilience of CSRS to malicious activities (see Figures 5 and 6).

**Table 3.** Percentages of honest and malicious car owners correctly recognized (average results on 120 simulations).

| Epoch | CSRS | | RS1 | | RS2 | | RS3 | |
|---|---|---|---|---|---|---|---|---|
| | Min | Max | Min | Max | Min | Max | Min | Max |
| 5 | 89.9% | 93.5% | 79.2 | 86.5 | 83.2 | 89.8 | 66.7 | 75.1 |
| 30 | 93.7% | 97.4% | 81.0 | 89.5 | 87.3 | 93.5 | 88.7 | 90.9 |

**Table 4.** Percentages of honest and malicious drivers correctly recognized (average results on 120 simulations).

| Epoch | CSRS | | RS1 | | RS2 | | RS3 | |
|---|---|---|---|---|---|---|---|---|
| | Min | Max | Min | Max | Min | Max | Min | Max |
| 5 | 94.3% | 97.2% | 88.7 | 90.6 | 91.1 | 96.1 | 67.2 | 74.5 |
| 30 | 95.9% | 98.5% | 91.8 | 96.8 | 91.3 | 98.8 | 89.4 | 92.0 |

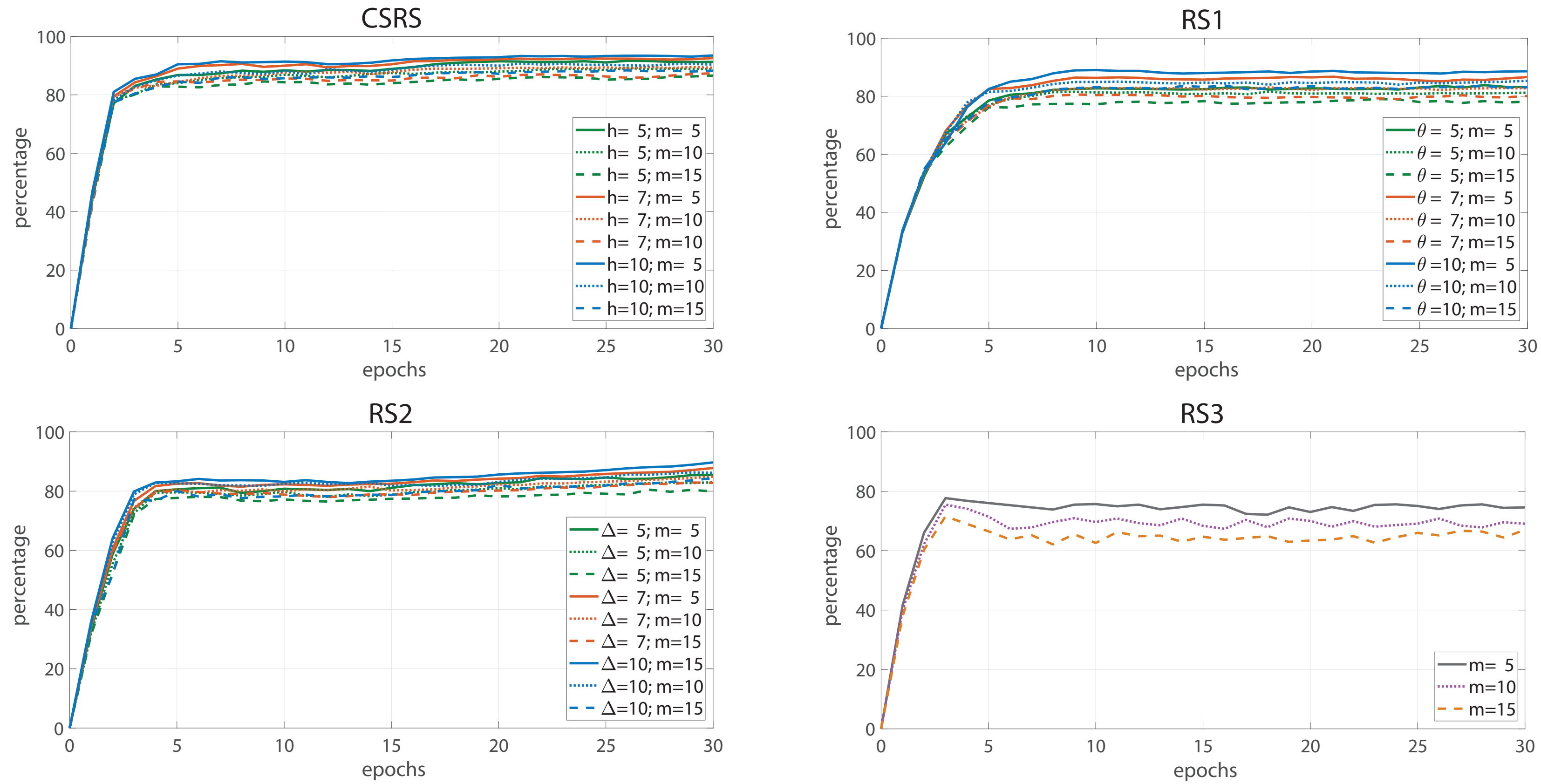


**Figure 5.** Effectiveness of tested RSs in recognizing the honest or malicious nature of drivers.

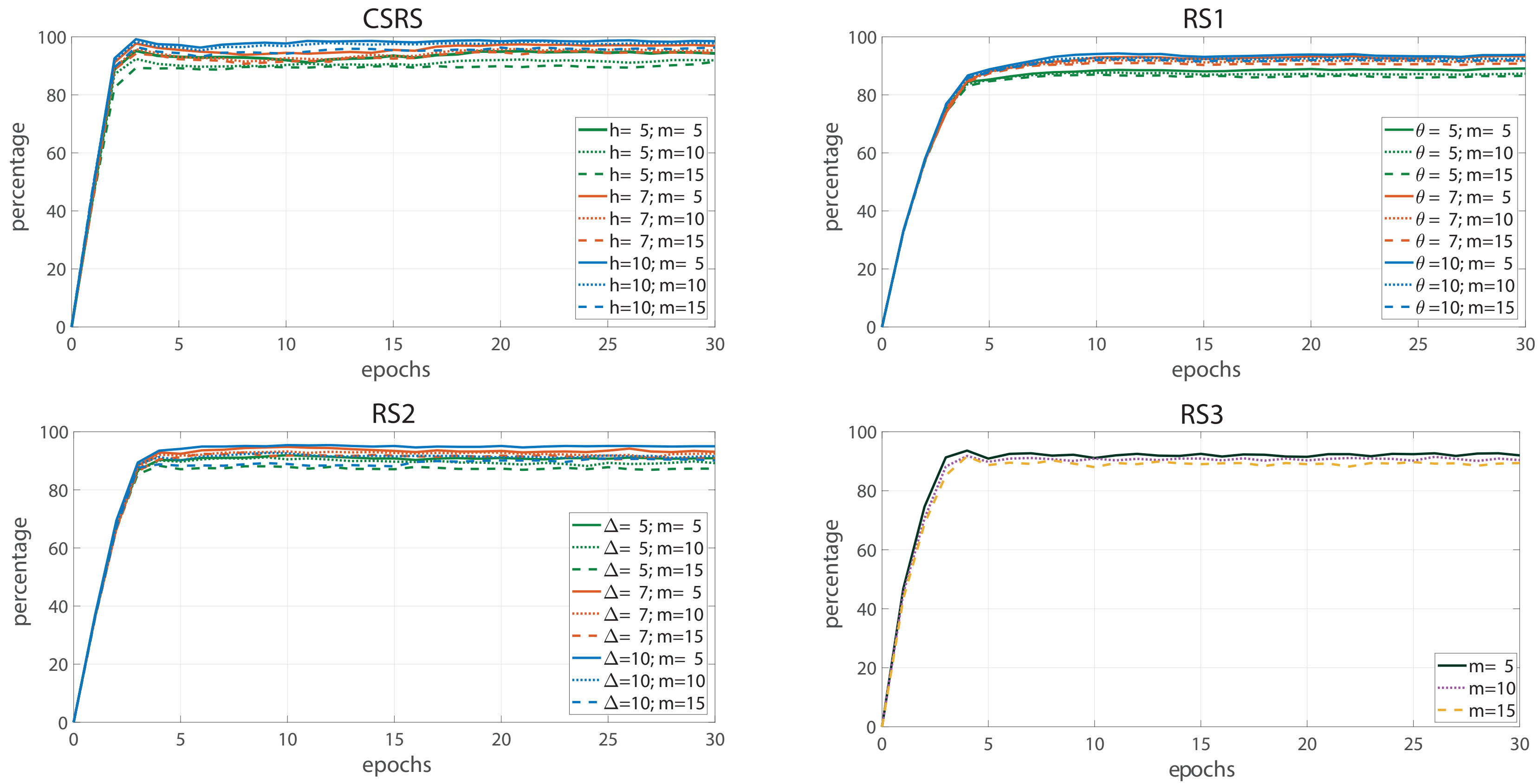


**Figure 6.** Effectiveness of tested RSs in recognizing the honest or malicious nature of car owners.

RS1 shows good performances too and it is quite stable over time, but not particularly fast in recognizing malicious actors. The performance of RS2 is slightly better than RS1, so it can be considered the best competitor of CSRS. However, it is less accurate in distinguishing between alternate and collusive activities, regardless of their relevance. Finally, RS3 is the worst among the tested RSs, mainly because it calculates reputation scores as simple averages of feedback, thus it is more affected by malicious behaviours, even the most common ones.

To summarize, the experimental results show that CSRS is the most performing RS among the selected competitors in recognizing the nature of both customers and car owners. Based on these preliminary tests, reputation score results will be presented only for CSRS. Figure 7 depicts how the average reputation score of malicious and honest CS actors varies across epochs for different percentages of malicious actors and horizons. In particular, starting from the initially assigned reputation score of 0.75, which is also the threshold adopted to differentiate honest from malicious actors, it can be seen that the reputation of honest consumers and car owners increases along epochs while one of malicious actors decreases at the same time. Figure 7 shows clearly how the reputation of these two groups diverge.

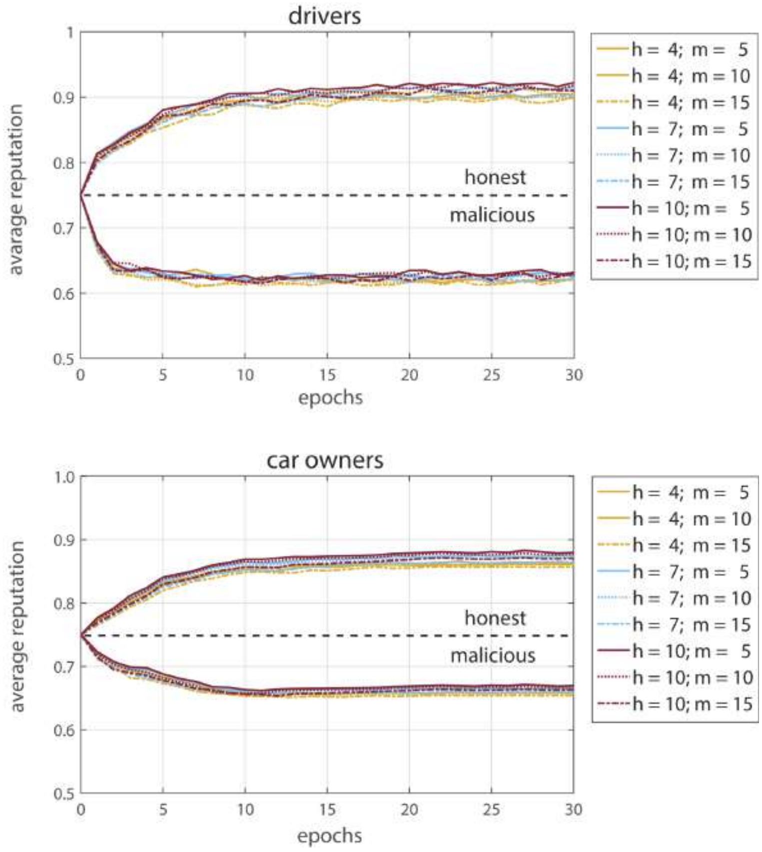


**Figure 7.** Average reputation of honest and malicious for different horizons ($h$) and percentages of malicious actors ($m$).

### *4.5. Implications*

The proposed CSRS and P2P-CS framework makes it possible to give advantages to honest drivers involved in P2P-CS services, in order to discourage malicious actors and promote this type of mobility. Particularly, honest drivers are rewarded by reducing the fare they have to pay for a given CS service accordingly to their reputation scores. To test this option, in the experiments we assumed that honest drivers receive a discount on the rental fare proportional to their earned reputation over their initial one (i.e., 0.75). On the contrary, if their reputation score is under a given threshold, they are considered unreliable and then cannot benefit from CS services; in other words, they would not find car owners willing to rent them their cars. Figure 8 depicts the cumulated percentage of money saved by an honest driver, averaged over different horizons ($h$) and percentages of malicious actors ($m$), compared to the base fare.

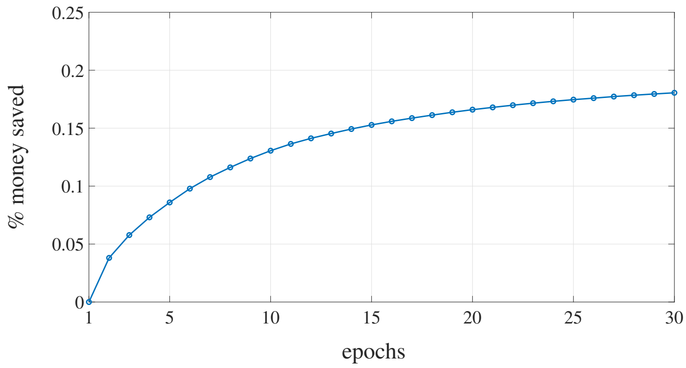


**Figure 8.** Percentage of cumulative average increase of the rental cost, for different horizons ($h$) and percentages of malicious actors, with respect to the fare an honest driver would pay.

As the experiments proved, the proposed CSRS and P2P-CS framework allows us to identify the level of driver aggressiveness with adequate accuracy by using limited computational and storage resources. In addition, CSRS is able to discriminate between malicious and honest actors, particularly drivers, which is a key factor for fostering trust between car owners and consumers.

The reward mechanism applied to the CS fare is intended to encourage honest behaviours by giving drivers economic advantages. At the same time, discounted fares apply when drivers' reputation score increases, which also means drivers have greater reliability that they may use for fostering their reputation towards car owners.

## 5. Conclusions

In the coming years, the development of car-sharing activities could support public and private mobility to mitigate the traffic and environmental problems that usually affect urban contexts. In particular, the promotion of car-sharing activities that exploit private cars is really attractive but, unfortunately, there is a lack of trustworthiness between customers and car owners. To this end, advances in several technological fields can help establish increasing confidence between the parties, together with economic convenience, to develop P2P-CS.

To address this issue, in this paper we have proposed a reputational-based approach to provide each actor with useful information to select good partners. To this aim, a distributed reputation mechanism, called *Car-Sharing Reputation System* (CSRS), suitable for P2P-CS scenarios, has been proposed. It is able to provide car owners and customers with the information referred to driver habits and rented cars, respectively. While car owner reputation is handled conventionally, consumer reputation is computed based on kinematic measures, automatically detected by a simple sensing platform, to asses drivers' aggressiveness. To make this information reliable, public, and immutable and to disseminate it to the community, we supported the CSRS with blockchain technology.

Two experiments have been performed, conducted on real and simulated data, to verify the opportunity of adequately computing automatic feedback on driver's aggressiveness and the effectiveness of the CSRS, which has also been compared with some other known RSs. The proposed CSRS has shown better performances than its competitors in the tested CS scenarios and, in particular, CSRS is more responsive and needs fewer epochs, also in the worst scenario, to detect malicious actors. In addition, the real nature of honest and malicious actors is quickly recognized by using the values of the reputation scores. Finally, a rewarding mechanism, in terms of economic advantages for the use of the CS service, has been implemented for honest consumers, which is expected to foster trust between the involved actors.

The positive results of these experiments show that the proposed framework and the implemented CSRS can boost P2P-CS activities and encourage further developments and future research in this area.

**Author Contributions:** Conceptualization, M.N.P. and G.M.L.S.; Methodology, M.N.P. and G.M.L.S.; Software, G.M.L.S.; Validation, M.N.P. and G.M.L.S.; Formal analysis, M.N.P. and G.M.L.S.; Writing—original draft, M.N.P. and G.M.L.S. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** Not applicable.

**Conflicts of Interest:** The authors declare no conflict of interest.

## References

1. Chang, Y.S.; Lee, Y.J.; Choi, S.S.B. Is there more traffic congestion in larger cities?—Scaling analysis of the 101 largest US urban centers. *Transp. Policy* **2017**, *59*, 54–63. [CrossRef]
2. Velazquez, L.; Munguia, N.E.; Will, M.; Zavala, A.G.; Verdugo, S.P.; Delakowitz, B.; Giannetti, B. Sustainable transportation strategies for decoupling road vehicle transport and carbon dioxide emissions. *Manag. Environ. Qual. Int. J.* **2015**, *26*, 373–388. [CrossRef]
3. Saladié, Ò.; Bustamante, E.; Gutiérrez, A. COVID-19 lockdown and reduction of traffic accidents in Tarragona province, Spain. *Transp. Res. Interdiscip. Perspect.* **2020**, *8*, 100218. [CrossRef] [PubMed]
4. Litman, T. *Evaluating Public Transit Benefits and Costs*; Victoria Transport Policy Institute: Victoria, BC, Canada, 2015.
5. Ferguson, E. *Travel Demand Management and Public Policy*; Routledge: New York, NY, USA, 2018.
6. Caulfield, B. An examination of the factors that impact upon multiple vehicle ownership: The case of Dublin, Ireland. *Transp. Policy* **2012**, *19*, 132–138. [CrossRef]
7. Tao, S.; He, S.Y.; Thøgersen, J. The role of car ownership in attitudes towards public transport: A comparative study of Guangzhou and Brisbane. *Transp. Res. Part F Traffic Psychol. Behav.* **2019**, *60*, 685–699. [CrossRef]
8. Enzi, M.; Parragh, S.N.; Pisinger, D.; Prandtstetter, M. Modeling and solving the multimodal car-and ride-sharing problem. *Eur. J. Oper. Res.* **2021**, *293*, 290–303. [CrossRef]
9. Stahel, W.R. The circular economy. *Nature* **2016**, *531*, 435–438. [CrossRef]
10. Velte, C.J.; Scheller, K.; Steinhilper, R. Circular economy through objectives—Development of a proceeding to understand and shape a circular economy using value-focused thinking. *Procedia CIRP* **2018**, *69*, 775–780. [CrossRef]
11. Münzel, K.; Boon, W.; Frenken, K.; Blomme, J.; van der Linden, D. Explaining carsharing supply across Western European cities. *Int. J. Sustain. Transp.* **2020**, *14*, 243–254. [CrossRef]
12. Ramos, É.M.S.; Bergstad, C.J.; Chicco, A.; Diana, M. Mobility styles and car sharing use in Europe: Attitudes, behaviours, motives and sustainability. *Eur. Transp. Res. Rev.* **2020**, *12*, 1–12. [CrossRef]
13. Seign, R.; Schüßler, M.; Bogenberger, K. Enabling sustainable transportation: The model-based determination of business/operating areas of free-floating carsharing systems. *Res. Transp. Econ.* **2015**, *51*, 104–114. [CrossRef]
14. Despeisse, M.; Kishita, Y.; Nakano, M.; Barwood, M. Towards a circular economy for end-of-life vehicles: A comparative study UK–Japan. *Procedia Cirp* **2015**, *29*, 668–673. [CrossRef]
15. Expósito-Izquierdo, C.; Expósito-Márquez, A.; Brito-Santana, J. Mobility as a Service. In *Smart Cities Foundations, Principles and Applications*; John Wiley & Sons, Inc.: Hoboken, NJ, USA, 2017.
16. Li, M.; Zeng, Z.; Wang, Y. An innovative car sharing technological paradigm towards sustainable mobility. *J. Clean. Prod.* **2021**, *288*, 125626. [CrossRef]
17. Bellos, I.; Ferguson, M.; Toktay, L. The car sharing economy: Interaction of business model choice and product line design. *Manuf. Serv. Oper. Manag.* **2017**, *19*, 185–201. [CrossRef]
18. Millard-Ball, A. *Car-Sharing: Where and How It Succeeds*; Transportation Research Board: Washington, DC, USA, 2005; Volume 60.
19. Belk, R. You are what you can access: Sharing and collaborative consumption online. *J. Bus. Res.* **2014**, *67*, 1595–1600. [CrossRef]
20. Car2Share. 2022. Available online: https://www.car2share.com (accessed on 1 September 2022).
21. Drife. 2022. Available online: http://dryfe.it (accessed on 1 September 2022).
22. Getaround. 2022. Available online: https://www.getaround.com/san-francisco (accessed on 1 September 2022).
23. Richter, C.; Kraus, S.; Brem, A.; Durst, S.; Giselbrecht, C. Digital entrepreneurship: Innovative business models for the sharing economy. *Creat. Innov. Manag.* **2017**, *26*, 300–310. [CrossRef]

24. Cohen, B.; Kietzmann, J. Ride on! Mobility business models for the sharing economy. *Organ. Environ.* **2014**, *27*, 279–296. [CrossRef]
25. Münzel, K.; Boon, W.; Frenken, K.; Vaskelainen, T. Carsharing business models in Germany: Characteristics, success and future prospects. *Inf. Syst. e-Bus. Manag.* **2018**, *16*, 271–291. [CrossRef]
26. Puschmann, T.; Alt, R. Sharing economy. *Bus. Inf. Syst. Eng.* **2016**, *58*, 93–99. [CrossRef]
27. RAC Foundation. 2022. Available online: https://www.racfoundation.org/media-centre/cars-parked-23-hours-a-day (accessed on 1 September 2022).
28. Prieto, M.; Baltas, G.; Stan, V. Car sharing adoption intention in urban areas: What are the key sociodemographic drivers? *Transp. Res. Part A Policy Pract.* **2017**, *101*, 218–227. [CrossRef]
29. Wilhelms, M.P.; Henkel, S.; Merfeld, K. You are what you share: Understanding participation motives in peer-to-peer carsharing. In *Disrupting Mobility*; Springer: Cham, Switzerland, 2017; pp. 105–119.
30. Shaheen, S.; Martin, E.; Bansal, A. *Peer-To-Peer (P2P) Carsharing: Understanding Early Markets, Social Dynamics, and Behavioural Impacts*; Institute of Transportation Studies, UC Berkeley: Berkeley, CA, USA, 2018.
31. Wilhelms, M.P.; Henkel, S.; Falk, T. To earn is not enough: A means-end analysis to uncover peer-providers' participation motives in peer-to-peer carsharing. *Technol. Forecast. Soc. Chang.* **2017**, *125*, 38–47. [CrossRef]
32. Amatuni, L.; Ottelin, J.; Steubing, B.; Mogollón, J.M. Does car sharing reduce greenhouse gas emissions? Assessing the modal shift and lifetime shift rebound effects from a life cycle perspective. *J. Clean. Prod.* **2020**, *266*, 121869. [CrossRef]
33. Gao, S.; Jing, J.; Guo, H. The role of trust with car-sharing services in the sharing economy in China: From the consumers' perspective. In Proceedings of the International Conference on Cross-Cultural Design, Vancouver, BC, Canada, 9–14 July 2017; Springer: Cham, Switzerland, 2017; pp. 634–646.
34. Santana, J.; Parigi, P. Risk aversion and engagement in the sharing economy. *Games* **2015**, *6*, 560–573. [CrossRef]
35. Bolton, G.; Greiner, B.; Ockenfels, A. Engineering trust: Reciprocity in the production of reputation information. *Manag. Sci.* **2013**, *59*, 265–285. [CrossRef]
36. Wu, J.; Balliet, D.; Van Lange, P.A. Reputation, gossip, and human cooperation. *Soc. Personal. Psychol. Compass* **2016**, *10*, 350–364. [CrossRef]
37. Erlandsson, F.; Boldt, M.; Johnson, H. Privacy threats related to user profiling in online social networks. In Proceedings of the 2012 International Conference on Privacy, Security, Risk and Trust and 2012 International Confernece on Social Computing, Amsterdam, The Netherlands, 3–5 September 2012; pp. 838–842.
38. Shaheen, S.A.; Mallery, M.A.; Kingsley, K.J. Personal vehicle sharing services in North America. *Res. Transp. Bus. Manag.* **2012**, *3*, 71–81. [CrossRef]
39. Ballús-Armet, I.; Shaheen, S.A.; Clonts, K.; Weinzimmer, D. Peer-to-peer carsharing: Exploring public perception and market characteristics in the San Francisco Bay area, California. *Transp. Res. Rec.* **2014**, *2416*, 27–36. [CrossRef]
40. Meiring, G.A.M.; Myburgh, H.C. A review of intelligent driving style analysis systems and related artificial intelligence algorithms. *Sensors* **2015**, *15*, 30653–30682. [CrossRef]
41. Hughes-Morgan, M.; Kolev, K.; Mcnamara, G. A meta-analytic review of competitive aggressiveness research. *J. Bus. Res.* **2018**, *85*, 73–82. [CrossRef]
42. Hong, J.; Margines, B.; Dey, A. A smartphone-based sensing platform to model aggressive driving behaviours. In Proceedings of the 32nd Conference on Human Factors in Computing Systems, Toronto, ON, Canada, 26 April–1 May 2014; pp. 4047–4056.
43. Sagberg, F.; Selpi; Bianchi Piccinini, G.F.; Engström, J. A review of research on driving styles and road safety. *Hum. Factors* **2015**, *57*, 1248–1275. [CrossRef]
44. Toledo, G.; Shiftan, Y. Can feedback from in-vehicle data recorders improve driver behaviour and reduce fuel consumption? *Transp. Res. Part A Policy Pract.* **2016**, *94*, 194–204. [CrossRef]
45. Tselentis, D.I.; Yannis, G.; Vlahogianni, E.I. Innovative motor insurance schemes: A review of current practices and emerging challenges. *Accid. Anal. Prev.* **2017**, *98*, 139–148. [CrossRef]
46. Progressive. 2022. Available online: https://www.progressive.com/auto/discounts (accessed on 1 September 2022).
47. UE COM(2018) 286 Final. 2022. Available online: https://road-safety.transport.ec.europa.eu/statistics-and-analysis/statistics-and-analysis-archive/fatigue/vehicle-detection-and-warning-devices_en (accessed on 1 September 2022).
48. Zheng, Z.; Xie, S.; Dai, H.N.; Wang, H. *Blockchain Challenges and Opportunities: A Survey*; Work Paper 2016; 2016. Avaliable online: Available online: https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjQ0L7hnIr9AhXmALcAHZxJAKkQFnoECAwQAQ&url=https://www.henrylab.net/wp-content/uploads/2017/10/blockchain.pdf&usg=AOvVaw0Oh9kpeFoBZDHcOuCWNng0 (accessed on 1 September 2022).
49. Svennevik, E.M.; Dijk, M.; Arnfalk, P. How do new mobility practices emerge? A comparative analysis of car-sharing in cities in Norway, Sweden and the Netherlands. *Energy Res. Soc. Sci.* **2021**, *82*, 102305. [CrossRef]
50. Auer, S.; Nagler, S.; Mazumdar, S.; Mukkamala, R.R. Towards blockchain-IoT based shared mobility: Car-sharing and leasing as a case study. *J. Netw. Comput. Appl.* **2022**, *200*, 103316. [CrossRef]
51. Kim, J.; Rasouli, S.; Timmermans, H. Satisfaction and uncertainty in car-sharing decisions: An integration of hybrid choice and random regret-based models. *Transp. Res. Part A Policy Pract.* **2017**, *95*, 13–33. [CrossRef]
52. Cook, K.S.; Yamagishi, T.; Cheshire, C.; Cooper, R.; Matsuda, M.; Mashima, R. Trust building via risk taking: A cross-societal experiment. *Soc. Psychol. Q.* **2005**, *68*, 121–142. [CrossRef]

53. Ter Huurne, M.; Ronteltap, A.; Corten, R.; Buskens, V. Antecedents of trust in the sharing economy: A systematic review. *J. Consum. Behav.* **2017**, *16*, 485–498. [CrossRef]
54. Kim, J.; Yoon, Y.; Zo, H. Why People Participate in the Sharing Economy: A Social Exchange Perspective. In Proceedings of the 9th Pacific Asia Conference on Information Systems, PACIS 2015, Singapore, 5–9 July 2015.
55. WU, L.h. Understanding Collaborative Consumption Business Model: Case of Car Sharing Systems. In Proceedings of the 2016 International Conference on Materials, Manufacturing and Mechanical Engineering (MMME 2016), Beijing, China, 30–31 December 2016; pp. 403–409.
56. Resnick, P.; Kuwabara, K.; Zeckhauser, R.; Friedman, E. Reputation Systems. *Commun. ACM* **2000**, *43*, 45–48. [CrossRef]
57. Postorino, M.N.; Sarnè, G.M.L. A Neural Network to Identify Driving Habits and Compute Car-Sharing Users' Reputation. In Proceedings of the Italian Workshop on Neural Nets, Vietri sul Mare, Italy, 14–16 June 2017; Springer: Cham, Switzerland, 2017; pp. 207–216.
58. Nakamoto, S. Bitcoin: A peer-to-peer electronic cash system. *Decentralized business review*. **2008**; p. 21260. Available online: https://assets.pubpub.org/d8wct41f/31611263538139.pdf (accessed on 1 September 2022).
59. Ethereum. 2022. Available online: https://www.ethereum.org (accessed on 1 September 2022).
60. Hyperledger. 2022. Available online: https://www.hyperledger.org (accessed on 1 September 2022).
61. Ripple. 2022. Available online: https://ripple.com/ (accessed on 1 September 2022).
62. Stellar. 2022. Available online: https://www.stellar.org (accessed on 1 September 2022).
63. Szabo, N. Smart contracts. 1994, *Unpublished manuscript*.
64. Pilkington, M. 11 Blockchain technology: Principles and applications. In *Research Handbook on Digital Transformations*; Edward Elgar Publishing: Cheltenham, UK; Northampton, MA, USA, 2016; p. 225.
65. Chalaemwongwan, N.; Kurutach, W. State of the art and challenges facing consensus protocols on blockchain. In Proceedings of the 2018 International Conference on Information Networking (ICOIN), Chiang Mai, Thailand, 10–12 January 2018; pp. 957–962.
66. Vukolić, M. Rethinking permissioned blockchains. In Proceedings of the ACM Workshop on Blockchain, Cryptocurrencies and Contracts, Abu Dhabi, United Arab Emirates, 2 April 2017; pp. 3–7.
67. Bauer, I.; Zavolokina, L.; Leisibach, F.; Schwabe, G. Exploring Blockchain Value Creation: The Case of the Car Ecosystem. In Proceedings of the 52nd Hawaii International Conference on System Sciences, Maui, HI, USA, 8–11 January 2019.
68. Hans, R.; Zuber, H.; Rizk, A.; Steinmetz, R. Blockchain and Smart Contracts: Disruptive Technologies for the Insurance Market. In Proceedings of the AMCIS 2017, Boston, MA, USA, 10–12 August 2017.
69. HireGo. HireGo—Decentralised Shared Mobility Platform. 2022. Available online: https://steemit.com/software/@laylavasted/hirego-decentralised-shared-mobility-platform (accessed on 1 September 2022).
70. Helbiz. 2022. Available online: https://www.helbiz.com (accessed on 1 September 2022).
71. FFQuest. 2022. Available online: https://ffquest.com/ (accessed on 1 September 2022).
72. Car-Next Door. 2022. Available online: https://www.carnextdoor.com.au/ (accessed on 1 September 2022).
73. Akash, M.; Symeonidis, I.; A Mustafa, M.; Preneel, B.; Zhang, R. SC2Share: Smart contract for secure car sharing. In Proceedings of the International Conference on Information Systems Security and Privacy, Prague, Czech Republic, 23–25 February 2019.
74. Symeonidis, I.; Aly, A.; Mustafa, M.A.; Mennink, B.; Dhooghe, S.; Preneel, B. Sepcar: A secure and privacy-enhancing protocol for car access provision. In Proceedings of the European Symposium on Research in Computer Security, Oslo, Norway, 11–15 September 2017; Springer: Cham, Switzerland, 2017; pp. 475–493.
75. Saurabh, N.; Rubia, C.; Palanisamy, A.; Koulouzis, S.; Sefidanoski, M.; Chakravorty, A.; Zhao, Z.; Karadimce, A.; Prodan, R. The ARTICONF Approach to Decentralized Car-Sharing. *Blockchain Res. Appl.* **2021**, *2*, 100013. [CrossRef]
76. Martinez, C.M.; Heucke, M.; Wang, F.Y.; Gao, B.; Cao, D. Driving style recognition for intelligent vehicle control and advanced driver assistance: A survey. *IEEE Trans. Intell. Transp. Syst.* **2017**, *19*, 666–676. [CrossRef]
77. McGuire, F.L. *A Study of Methodological and Psycho-Social Variables in Accident Research*; *A Study of Methodological and Psycho-Social Variables in Accident Research*; Public Health Service: Washington, DC, USA, 1971.
78. Ericsson, E. Variability in urban driving patterns. *Transp. Res. Transp. Environ.* **2000**, *5*, 337–354. [CrossRef]
79. Cheng, Z.J.; Jeng, L.W.; Li, K. Behavioural classification of drivers for driving efficiency related ADAS using artificial neural network. In Proceedings of the 2018 IEEE International Conference on Advanced Manufacturing (ICAM), Yunlin, Taiwan, 16–18 November 2018; pp. 173–176.
80. Mitrovic, D. Reliable method for driving events recognition. *IEEE Trans. Intell. Transp. Syst.* **2005**, *6*, 198–205. [CrossRef]
81. Castignani, G.; Derrmann, T.; Frank, R.; Engel, T. Driver behaviour profiling using smartphones: A low-cost platform for driver monitoring. *IEEE Intell. Transp. Syst. Mag.* **2015**, *7*, 91–102. [CrossRef]
82. Wang, W.; Xi, J.; Chong, A.; Li, L. Driving style classification using a semisupervised support vector machine. *IEEE Trans. Hum.-Mach. Syst.* **2017**, *47*, 650–660. [CrossRef]
83. Aljaafreh, A.; Alshabatat, N.; Al-Din, M.S.N. Driving style recognition using fuzzy logic. In Proceedings of the 2012 IEEE International Conference on Vehicular Electronics and Safety (ICVES 2012), Istanbul, Turkey, 24–27 July 2012; pp. 460–463.
84. Brombacher, P.; Masino, J.; Frey, M.; Gauterin, F. Driving event detection and driving style classification using artificial neural networks. In Proceedings of the 2017 IEEE International Conference on Industrial Technology (ICIT), Toronto, ON, Canada, 22–25 March 2017; pp. 997–1002.

85. Vaiana, R.; Iuele, T.; Astarita, V.; Caruso, M.V.; Tassitani, A.; Zaffino, C.; Giofrè, V.P. Driving behaviour and traffic safety: An acceleration-based safety evaluation procedure for smartphones. *Mod. Appl. Sci.* **2014**, *8*, 88. [CrossRef]
86. Johnson, D.A.; Trivedi, M.M. Driving style recognition using a smartphone as a sensor platform. In Proceedings of the 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), Washington, DC, USA, 5–7 October 2011; pp. 1609–1615.
87. Wahlström, J.; Skog, I.; Händel, P. Driving behaviour analysis for smartphone-based insurance telematics. In Proceedings of the Proceedings of the 2nd Workshop on Physical Analytics, Florence, Italy, 22 May 2015; pp. 19–24.
88. Vasconcelos, I.; Vasconcelos, R.O.; Olivieri, B.; Roriz, M.; Endler, M.; Junior, M.C. Smartphone-based outlier detection: A complex event processing approach for driving behavior detection. *J. Internet Serv. Appl.* **2017**, *1*, 1–30.
89. Chakravarty, T.; Ghose, A.; Bhaumik, C.; Chowdhury, A. MobiDriveScore—A system for mobile sensor based driving analysis: A risk assessment model for improving one's driving. In Proceedings of the 2013 Seventh International Conference on Sensing Technology (ICST), Wellington, New Zealand, 3–5 December 2013; pp. 338–344.
90. Chhabra, R.; Verma, S.; Krishna, C.R. Detecting Aggressive Driving Behaviour using Mobile Smartphone. In Proceedings of the 2nd International Conference on Communication, Computing and Networking, Chandigarh, India, 29–30 March 2018; Springer: Singapore, 2019; pp. 513–521.
91. Yuksel, A.; Atmaca, S. Driver's black box: A system for driver risk assessment using machine learning and fuzzy logic. *J. Intell. Transp. Syst.* **2020**, *25*, 482–500. [CrossRef]
92. Meseguer, J.; Toh, C.; Calafate, C.; Cano, J.; Manzoni, P. Drivingstyles: A mobile platform for driving styles and fuel consumption characterization. *J. Commun. Netw.* **2017**, *19*, 162–168. [CrossRef]
93. Osafune, T.; Takahashi, T.; Kiyama, N.; Sobue, T.; Yamaguchi, H.; Higashino, T. Analysis of accident risks from driving behaviours. *J. Intell. Transp. Syst. Res.* **2017**, *15*, 192–202.
94. Vlahogianni, E.I.; Barmpounakis, E.N. Driving analytics using smartphones: Algorithms, comparisons and challenges. *Transp. Res. Part C Emerg. Technol.* **2017**, *79*, 196–206. [CrossRef]
95. Yang, L.; Li, X.; Guan, W.; Jiang, S. Assessing the relationship between driving skill, driving behaviour and driving aggressiveness. *J. Transp. Saf. & Secur.* **2020**, *14*, 737–753.
96. Symeonidis, I.; Mustafa, M.A.; Preneel, B. Keyless car sharing system: A security and privacy analysis. In Proceedings of the 2016 IEEE International Smart Cities Conference (ISC2), Trento, Italy, 12–15 September 2016; pp. 1–7.
97. Dmitrienko, A.; Plappert, C. Secure free-floating car sharing for offline cars. In Proceedings of the Seventh ACM on Conference on Data and Application Security and Privacy, Scottsdale, AZ, USA, 22–24 March 2017; pp. 349–360.
98. Ferreira, J., Jr.; Carvalho, E.; Ferreira, B.V.; de Souza, C.; Suhara, Y.; Pentland, A.; Pessin, G. Driver behaviour profiling: An investigation with different smartphone sensors and machine learning. *PLoS ONE* **2017**, *12*, e0174959. [CrossRef] [PubMed]
99. Dannen, C. *Introducing Ethereum and Solidity*; Apress: Berkeley, CA, USA; 2017; Volume 1.
100. TruffleSuite. 2022. Available online: https://www.trufflesuite.com/ (accessed on 1 September 2022).
101. Zacharia, G.; Moukas, A.; Maes, P. Collaborative reputation mechanisms for electronic marketplaces. *Decis. Support Syst.* **2000**, *29*, 371–388. [CrossRef]
102. Li, X.; Wang, Q.; Lan, X.; Chen, X.; Zhang, N.; Chen, D. Enhancing cloud-based IoT security through trustworthy cloud service: An integration of security and reputation approach. *IEEE Access* **2019**, *7*, 9368–9383. [CrossRef]
103. eBay. 2022. Available online: https://www.ebay.com/ (accessed on 1 September 2022).
104. Bidgoly, A.J.; Ladani, B.T. Benchmarking reputation systems: A quantitative verification approach. *Comput. Hum. Behav.* **2016**, *57*, 274–291. [CrossRef]
105. Houser, D.; Wooders, J. Reputation in auctions: Theory, and evidence from eBay. *J. Econ. Manag. Strategy* **2006**, *15*, 353–369. [CrossRef]