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Blockchain and IoT-Enabled Earning Mechanism for Driver Safety Rewards in Cooperative Platooning Environment

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ABSTRACT

Road safety is a global priority, with aggressive driving behaviors posing serious risks to drivers and communities. This paper introduces a blockchain driven framework integrated with Internet of Things (IoT) technologies for rewarding safe driving practices through a novel earning method, focusing on cooperative platooning scenarios. The proposed model assesses driver behavior daily, assigning ranks and rewarding cryptocurrency tokens based on driving performance. Special emphasis is placed on the roles within a platoon, with leaders—who manage communication and maneuvers—earning higher rewards than followers. This incentivization mechanism is securely implemented using blockchain technology, allowing for transparent transactions and fair distribution of rewards. The framework's effectiveness is tested through simulations, highlighting the potential of a token-based reward system leveraging IoT data to promote responsible driving and improve road safety within cooperative platooning setups.

Key words: Blockchain, Internet of Things, Internet of Vehicles, Connected Cars, Driver Safety Reward, Ethereum Rinkeby, Platooning, SUMO, PERMIT, Urban Mobility Simulation

1. INTRODUCTION

Road safety is a responsibility that is shared by transportation authorities as well as every driver and in turn it is irrevocably linked to the behavior of drivers. Adherence to traffic regulations and responsible interactions among drivers is paramount in curtaining the rates of accident and injuries on the road. Positive reinforcement of good driving is more effective than penalizing negative driving. The National Highway Traffic Safety Administration (NHTSA) estimated 42,795 losses in motor vehicle traffic crashes in 2022 [1, 2]. This reflects a modest 0.3% reduction from 2021 where 42,915 perished. 2021 witnessed a 10.5% increase from the 38,824 fatalities of 2020 [2, 3]. NHTSA estimates 9,330 people died in motor vehicle traffic crashes in the first quarter of 2023 [2, 4]. This is a decrease of about 3.3% as compared to a similar period from 2022 that saw a spike during the pandemic [1, 2]. We have envisaged a regime of an incremental positive incentives for good driving behavior using crypto tokens [5, 6]. We have introduced ranking and monetization based on the driving behavior using blockchain [7].

The PLEXE [8] simulation tool is a platooning extension for SUMO [9], an open-source platform available to the community. PLEXE supports a variety of Cooperative Adaptive Cruise Control (CACC) car-following models, enabling researchers to conduct diverse experiments related to vehicle platooning. It includes wireless communication protocols for simulating platoon formation and management, along with support for mixed traffic scenarios to implement and evaluate different platooning maneuvers. The authors in [10] developed a simulator that implements maneuvers such as joining an existing platoon and merging two platoons. In [11], a state-of-the-art simulator based on VENTOS [12] was developed, utilizing SUMO for advanced simulations. PERMIT [11] further builds on PLEXE, providing capabilities to simulate complex maneuvers like joining, merging, leaving, and splitting within platoons.

Currently, only a few researchers are exploring how to effectively combine blockchain technology with platooning to maximize its potential benefits. The authors in [13] leveraged blockchain as a communication medium in transportation systems, enabling secure communication between vehicles in a platoon using blockchain public key infrastructure and hardware-based side channels. In [14], they focused on reducing blockchain transaction validation time while also verifying vehicle identity. The study in [15] emphasized secure and rapid information sharing within platoons using blockchain. Additionally, the authors in [16] proposed a blockchain-based reputation system for managing trust among anonymous vehicles. In [17], a leadership incentive mechanism was implemented using blockchain for heterogeneous and dynamic platoons, rewarding effective leadership within platoon networks.

In our previous work [7], we extracted significant features from a simulated driving dataset and assigned ranks to drivers based on their behavior on the road. Drivers with better ranks were rewarded with crypto tokens, with transaction details and driver attributes stored securely on a blockchain network. Section 2 provides a detailed explanation of our methodology for monetizing driver behaviors.

2. MONETIZATION OF DRIVING BEHAVIOR

Driving behavior plays a major role in improving the road safety. Lately, with the advancements in smart devices and Internet of Things (IoT) [18, 19], the sensors generate huge amounts of data. The data that can be extracted but not limited to speed, braking, accelerations, trip distance, accelerometer, magnetometer, gyroscope information etc. [20]. Inspired by credit scoring in financial security, driver behavior ranking is assigning credit for safe driving [21]. They extracted driving habits and observed traffic violations. A classification model was used to filter out irrelevant features and scored each driver with selected features. Abnormal driving behavior recognition algorithms detect erratic behaviors. The authors in paper [22] proposed different abnormal driving behavior recognition algorithms. They obtained the data from OBD[1] terminal that combines acceleration changes and behavior. The model combined the driving data of the driver, along with the proportion of abnormal driving behavior, it used the entropy weight and the analytic hierarchy process to obtain the index weight. Their model analyzed and evaluated the driving behavior of the driver and gave a score for driver's behavior. Our driver scoring model uses a few parameters to rank the driver. The following are the basic scoring steps.

1. Compute the total trip distance and scale using min-max normalization.
2. Speed Limit percentage (OSL) is computed using total trip distance and Over-Speed Limit count (OSL).
3. The Acceleration Percentage (AP) and Deceleration Percentage (DP) are computed.
4. We assign relative weights for the above three parameters as 60% for deceleration, 30% for acceleration, and 10% for OSL.

$$\text{Score} = \frac{0.3 \times AP + 0.6 \times DP + 0.1 \times OSL}{100} \tag{1}$$

5. The score is computed using a weighted average.

Using scaled total distance (S_{dis}) and the earning rate (ER), the total test tokens to be credited in the Ethereum Rinkeby[2] [23] driver wallet is determined by the following formulation.

$$E_{\text{tokens}} = S_{\text{dis}} \times ER \tag{2}$$

On a range of 5 to 1, the rank of 5 is excellent whereas the score 1 is considered very bad. To monetize, for earning rates for scores of 5-1 are assigned earning rates of $0.15, 0.12, 0.09, 0.03$ and 0.01 respectively. A Rinkeby test network is used as our Ethereum network. Two smart contracts are used with one for tokenization and the other for storing driver record. Tokenization contract initially approves the driver-record contract with certain limit of driver DSR test tokens and transfer few DSR test tokens to the driver-record contract. Now, the driver-record will be able to credit the DSR test tokens to the assigned drivers based on the ranking to their wallet. For illustration, the tokenization contract generated the $10{,}000{,}000 (10^7)$ DSR test tokens and approved the data-record to spend those. The contract transfers 10,000 DSR test tokens to data-record for further assigning them to the drivers. The MetaMask [3] [24] represents 9,990,000 (0.999×10^7) DSR test tokens in the admin wallet. After inserting the data-record into the Rinkeby test network, 2 DSR test tokens are credited into "Driver_1" account. Moreover, driver data can be retrieved from the network using defined method [7].

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3. DSR IN COOPERATIVE PLATOONING

Our framework includes platooning environment to improve the road usage and cooperative driving [25]. Road safety is improved by virtual connection between two or more vehicles by utilizing inter-vehicle communication. The leader vehicle is crucial as it manages the platoon, establishing communication among remaining vehicles. It performs platoon maneuvers namely Join, Merge, Leave, and Split [26, 27]. As the leader of the platoon has multiple responsibilities than followers, our model rewards more incentives to the leader than to followers [10, 17]. This digital monetization method is accomplished by secure transactions using blockchain [28]. This section presents the entire overview of the proposed framework as shown in the Figure 1. This methodology put forward in 5 steps, namely: (1) Driving Rank Designation Model (2) Simulation with PERMIT (3) Feature Extraction (4) Digital Monetization with Platoons (5) Storing in Blockchain.

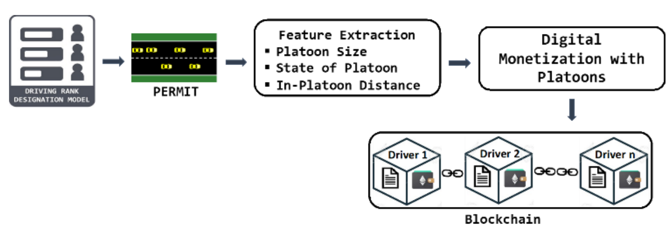

Figure 1: Cooperative Platoon Earning Methodology

Cooperative driving uses vehicle-to-vehicle and

[1] On-Board Diagnostics

[2] https://www.rinkeby.io/

[3] https://metamask.io/

infrastructure-to-vehicle wireless communication system and [29] emphasizes the technology aids in the interchange of data gathered from other cars that is impossible to obtain via on-board sensors. The Advanced Transportation Technology (PATH) project in California [30] first proposed the idea of cars traveling together on the road in 1980. Cooperative driving can improve the driving experience on the road by relieving the driver from some of the driving obligations. Traditional sensor based Adaptive Cruise Control (ACC) isn't enough for cooperative platooning, instead Cooperative Adaptive Cruise Control (CACC) should be considered [31]. CACC broadcasts information such as speed, acceleration, and distance through wireless communication. By allowing CACC, the distance between vehicles can be minimized by following closely, improving both safety and fuel efficiency [32]. A platoon state represents two features: (1) number of cars, and (2) distance travelled. For example, in Figure 2, a platoon is represented with five different states. First state S_1 has two cars. Car C_3 has joined the platoon reaching to state S_2. Similarly, S_3 is achieved. In contrast, S_4 is attained by car C_3 leaving the platoon. Similarly, S_5 is also reached.

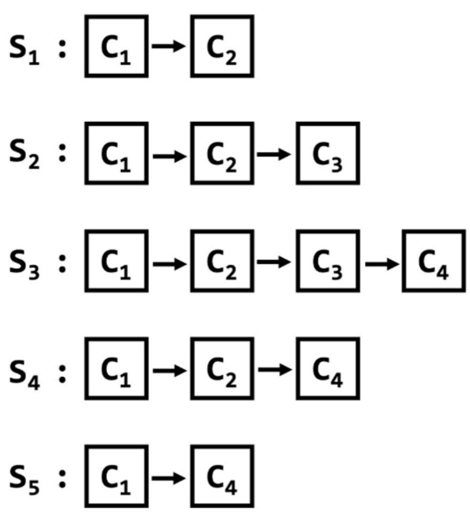

Figure 2: States in Platoon

The focus on cooperative driving or platooning has increased globally in recent years because of the potential it holds in road transportation mainly focusing on automated and mixed traffic [33, 34]. Truck platooning [25, 35] and CACC [31] were prominent examples of cooperative driving, which target minimizing inter-vehicular distance by obeying the "Three Second Rule" safety rule [36]. Having a good leader for a platoon is crucial in forming, maintaining, and improving safety. There are a lot of methods in electing a platoon leader. There has been a incentive-based strategy using blockchain proposed to elect a leader who is the best for the safety of the platoon [15, 37]. The other way is through voting to elect the platoon leader [12]. Some other methods may be through scoring and ranking the drivers based on the everyday driving and the driver with the best rank can only initiate platoon formation. Our inspiration is drawn from the ranking method [38, 39]. We added an incentive or monetization factor for selecting a platoon leader based on rank. When a driver of a vehicle drives everyday there will be a rank assigned to the driver performance and the driver with the best rank can become a platoon leader and other drivers will be followers. To encourage more drivers to be platoon leaders, a monetization system is required that is fair for all members. This digital monetization is implemented by the usage of a smart contract in blockchain technology that holds users to a higher level of behavior, which is promising in this regard [6]. This smart contract establishes what constitutes acceptable behavior and prevents users from breaking that standard [14, 16]. Congested roadways are linked to longer commute, lower fuel economy, and a higher risk of motor vehicle collisions. We could save a lot of travel time if we could reduce commuting times by a fraction of a second. One solution to the traffic problem is cooperative driving, also known as platooning. Vehicles in a platoon communicate using an ad-hoc network or other communication protocols. These communication channels allow platoons to drive close to each other while maintaining a safe distance. A platoon of vehicles will have a leader who will interact with the platoon followers while managing the platoon and overseeing maneuvers. The platoon leader oversees speed, lane changes, braking, and so on, while the follower vehicles are in charge of following the leader vehicle. To help improve the driving behavior, Demerit points system [40-42] and Driver Feedback systems [43] were used extensively. In recent times, driver credit or scoring systems were also introduced to enhance the road behavior. To further enhance the behavior of the drivers, we put forward a ranking framework along with monetization using the blockchain [28]. In the proposed system, a simulated driving dataset is generated. Significant features are extracted from the dataset and driver behavior is analyzed for assigning a rank for the driver. Based on the driving rank, the driver is monetized with Driver Safety Reward (DSR) tokens and the transactions are stored on a blockchain network along with driver attributes [7, 12, 44].

3.1 Digital Monetization with Platoons

With the features extracted from the previous step, we formalized the earnings (er_d) for the driver as summation of the earnings achieved while he drove in platoons (er^{in}) and earnings achieved while driving outside the platoon (er^{out}):

$$er_d = er^{in} + er^{out} \tag{3}$$

Because different maneuvers can exist inside the platoon, we decomposed the earning offered inside the platoon into the addition of earnings during join (P^{er}_{join}) and leave (P^{er}_{leave}) maneuvers.

$$er^{in} = P^{er}_{\text{j oin}} + P^{er}_{\text{leave}} \tag{4}$$

However, the er out is calculated as the product of the previous day's earnings rate (ER_{d-1}), which is determined by the Driving Rank Designation Model, and the distance traveled by the driver outside the platoon (d^{out}).

$$er^{\text{out}} = ER_{d-1} \times d^{\text{out}} \quad (5)$$

As mentioned earlier, a platoon leader will have a little favor by this model due to his responsibilities. Join and Leave Maneuvers are calculated using two different equations: one representing the Leader and the other representing the Follower in the platoon.

Join Maneuver For every platoon, the driver joined on a particular day, and for all the states in each platoon, we calculate the product of the average of the States of the platoon (S_i) and the sum of the previous earning rate of the driver (ER_{d-1}) and $n\delta$. The State (S_i) is defined as the product of the Length of Platoon (L_i) at state (i) and the distance traveled inside the platoon (d_i^{in}). Here, the term $j\delta$ is the additional incentive for the leader of the platoon. It represents the summation of the balancing factor over the number of cars joined in the platoon. The balancing factor δ is used to control the amount of incentive given to the drivers during the platoon. We assigned it as 0.01.

$$P_{\text{join}}^{er}(L) = \sum_{p=1}^{w} \sum_{i=1}^{n} S_i(ER_{d-1} + j\delta) \quad (6)$$

The difference between Leader and Follower is that there will be no additional incentives for the follower. Instead, only the balancing factor is added to the previous day's earning rate (ER_{d-1}). The platoon follower doesn't require the length of the platoon, so it just uses the distance traveled in each state.

$$P_{\text{join}}^{er}(F) = \sum_{p=1}^{w} \sum_{i=1}^{n} d_i(ER_{d-1} + \delta) \quad (7)$$

Leave Maneuver: During the Leave Maneuver, for the leader, instead of the number of cars joined (j), the number of cars left (j j) is considered. Additionally, there will be a penalty if a car leaves the platoon before traveling η miles. In other words, earnings for the followers will start only after traveling η miles. The overhead incurred by changing the structure of the platoon while on the move is the main reason for the penalty. Here we considered η=10.

$$P_{\text{leave}}^{er}(L) = \sum_{p=1}^{w} \sum_{i=1}^{n} S_i \times (ER_{d-1} + i\delta) + \text{penalty}_{\eta w} \quad (8)$$

Where:

$$S_i = L_i \times d_i^{in}$$
$$\text{Penalty} = \begin{cases} (d_i^{in} - \eta) \times \delta, & \text{if } d_i^{in} < \eta \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

In this study, various notations are used to represent mathematical equations. Table 1 provides a summary of these notations.

Table 1: List of Notations

Symbol	Definition
er_d	Earnings of particular day
er_{out}	Earnings outside of the platoon
er_{in}	Earnings inside of the platoon
ER_{d-1}	Earning Rate of previous day
d^{out}	Out-platoon distance
n	Number of cars in a platoon
j	Number of followers in the platoon in join maneuver
l	Number of cars left the platoon in leave maneuver
δ	Balancing Factor
η	Penalty Factor
S	State-of-platoon
L_i	Length of the platoon at state i
d^{in}	In-platoon distance at state S
w	Number of platoons a driver traveled
$P_{\text{join}}^{er}(L)$	In-platoon earnings with join maneuver of leader
$P_{\text{join}}^{er}(F)$	In-platoon earnings with join maneuver of follower
$P_{\text{leave}}^{er}(L)$	In-platoon earnings with leave maneuver of leader

3.2 Algorithms

In this section, we present multiple algorithms for calculating the daily earnings of a driver within a platoon. These algorithms incorporate different maneuvers such as joining, merging, leaving, and splitting from a platoon, each affecting the total earnings differently depending on the driver's role as a leader or follower.

The first snippet outlines the overall calculation of daily earnings for a driver, where the total earnings are derived from the combined earnings from joining (Je) and leaving (Le) maneuvers. This provides a simple yet effective way to determine a driver's total earnings over a day.

$$J^{er} \coloneqq JoinEarnings$$
$$L^{er} \coloneqq LeaveEarnings$$
$$Earnings = J^{er} + L^{er}$$

The second snippet details the calculations involved during a join maneuver. If multiple cars are joining, earnings are calculated based on merging efforts (*merge_earnings*, see Algorithm 1). If only one car joins, the earnings are calculated based on the driver type, either as a leader or follower. Leaders typically earn more due to their responsibilities, while followers receive a smaller portion.

$JoinEarnings$
if $number\_of\_cars\_joining > 1$
calculate $merge\_earnings$
else
calculate $earnings("leader")$ **or**
calculate $earnings("follower")$

Similarly, the earnings for leaving a platoon are computed in the next snippet. If more than one car is leaving, the earnings are calculated based on split efforts (split_earnings, see Algorithm 2). If a single car leaves, earnings are again computed based on whether the driver is a leader or a follower. The split mechanism is designed to ensure fair distribution among all members.

$LeaveEarnings$
if $number\_of\_cars\_joining > 1$
calculate $split\_earnings$
else
calculate $earnings("leader")$ **or**
calculate $earnings("follower")$

The merge earnings algorithm (Algorithm 1) calculates earnings based on the role of the driver in the platoon during a merge maneuver. Platoon leaders are awarded higher earnings for managing the coordination, while followers earn based on their adherence to platoon instructions.

Algorithm 1 $merge\_earnings$
if $platoon\_1\ leader$ **then**
$earnings("leader")$
end if
if $platoon\_2\ leader$ **then**
$earnings("follower")$
end if
if $platoon\ follower$ **then**
$earnings("follower")$
end if

The split earnings algorithm (Algorithm 2) calculates earnings differently during a split maneuver. In this case, both leaders are slightly penalized for splitting from their platoons. Followers are also penalized, but to a lesser extent. This incentivizes maintaining stable platoon configurations.

Algorithm 2 $split\_earnings$
if $platoon\_1\ leader$ **then**
$penalized\_earnings("leader")$
end if
if $platoon\_2\ leader$ **then**
$penalized\_earnings("leader")$
end if
if $platoon\ follower$ **then**
$penalized\_earnings("follower")$
end if

The earnings algorithm (Algorithm 3) calculates the earnings for a driver based on their type (leader or follower) and the number of states the platoon undergoes during the day. Leaders receive additional rewards proportional to the number of cars that join their platoon, emphasizing the added responsibility they bear. The state-based calculation further refines the earnings to reflect different driving conditions and leadership efforts throughout the journey.

Algorithm 3 $earnings\ (driver\_type)$
Require: $P^{er}_{join} = 0, \delta = 0.01$
for w **do** in $num\_of\_platoons$:
if $driver = Platoon\_Leader$ **then**
$P_{er} = ER_{d-1} + (joined\_cars * \delta)$
for s **do** in num_of_states:
$S_p = S_p + (L_s * d_s)$
end for
else
$P_{er} = ER_{d-1} + \delta$
for s **do** in $number\_of\_states$:
$S_p = S_p + (d_s)$
end for
end if
$P^{er}_{join} = P^{er}_{join} + S_p + P_{er}$
end for

Finally, the penalty earnings algorithm (Algorithm 4) is used to calculate the penalties when a driver or platoon member leaves abruptly or causes instability in the platoon. The leader is penalized more heavily compared to followers, given their role in maintaining the platoon's integrity. The penalties are added to the daily earnings, ensuring that any disruptive behavior is accounted for in the final reward calculation.

Algorithm 4 $penalty\_earnings\ (driver\_type)$
Require: $P^{er}_{join} = 0, \delta = 0.01$
for w **do** in $num\_of\_platoons$:
calculate $penalty$

if $driver = Platoon\_Leader$ **then**
    $P_{er} = ER_{d-1} + (left\_cars * \delta)$
    for s **do** in num_of_states:
        $S_p = S_p + (L_s * d_s)$
    end for
else
    $P_{er} = ER_{d-1} + \delta$
    for s **do** in $number\_of\_states$:
        $S_p = S_p + (d_s)$
    end for
end if
$P^{er}_{join} = P^{er}_{join} + S_p + P_{er} + penalty$
end for

These algorithms collectively aim to balance the reward system by incentivizing stable and efficient platoon behaviors while also discouraging maneuvers that may negatively impact platoon cohesion.

4. EXPERIMENTS

Next, we outlined our computational setup and observations. Vehicle Telematics is a technology that has transformed the way we monitor and assess driver behavior. It combines telecommunications and informatics to capture, transmit, and analyze data from vehicles in real-time. Telematics consists of a network of sensors and data collection devices strategically integrated into the vehicle [20]. These sensors gather a wealth of information, including vehicle speed, acceleration, braking, steering, and even more advanced metrics such as location, fuel consumption, and engine diagnostics. The collected data is then transmitted wirelessly to a central platform, where it is processed, analyzed, and converted into actionable insights [14, 16]. The primary goal of telematics concerning driver behavior is to enhance safety, reduce risks, and minimize operational costs. By monitoring how drivers interact with their vehicles, telematics can help identify unsafe driving habits such as aggressive acceleration, harsh braking, excessive speeding, and erratic steering. This information is then used to provide constructive feedback to drivers, enabling them to make necessary adjustments to their behavior on the road.

Vehicle Telematics leverages technology to provide valuable information and insights related to vehicles and driving behavior. This technology enables the collection and exchange of real-time information between vehicles and a central system, often through wireless communication networks. These systems typically involve the use of sensors and Global Positioning System (GPS) technology to gather data from vehicles and transmit it for various purposes, including tracking, monitoring, and analysis [45, 46]. Some of the key aspects of vehicle telematics for driver behavior analysis include:

1. **Safety**: Telematics systems can help identify risky behaviors that can lead to accidents. It allows for the early detection of unsafe driving practices, enabling to take corrective actions before an incident occurs.
2. **Efficiency**: Telematics also contributes to improved fuel efficiency and maintenance. By monitoring engine performance and fuel consumption, it helps in identifying issues that can be addressed to reduce operating costs.
3. **Compliance**: In many regions, there are strict regulations regarding driver behavior and safety standards. Telematics data can be used to ensure compliance with these regulations.

Telematics enhances safety and contributes to cost savings. There are several vehicle telematics platforms, and one such platform we used in our study is Damoov[4] [47]. Damoov provides the full suite of embedded mobile telematics services, including Telematics SDK, Mobility platform to process and analyze driving data, API services to consume services, analytics and data, Datahub - self-service portal to manage product and work with data via web-portal, and even Zenroad[5] - the open-source telematics mobile application [48]- a full-function telematics app that companies can use straight away to solve the issues we covered in the article. Damoov Datahub is a web portal that provides clients with a telematics dashboard and product management functionality. It's a centralized system for data storage, definition, and delivery. Damoov is a telematics infrastructure for tracking and safe driving mobile applications. With Damoov's mobile telematics, drivers can get realtime data on their vehicles' location, speed, and performance as well their driving behavior attributes such as Acceleration count, Deceleration count, Cornering, Phone usage, Over Speeding(miles), Distance travelled and soon.

Metamask is a widely recognized and highly utilized cryptocurrency wallet and browser extension that plays a pivotal role in the realm of decentralized applications and blockchain technology. Initially developed by Consensys[6] [49], a prominent blockchain software company, Metamask has evolved into a versatile tool that simplifies the interaction between users and the Ethereum blockchain. It enables secure storage of digital assets and seamless engagement with Decentralized Applications (DApps).

As the Ethereum ecosystem has grown, Metamask has played a crucial role in facilitating user-friendly access to this complex and rapidly evolving landscape. It essentially serves as a bridge between users and the Ethereum blockchain, allowing individuals to manage their digital assets, interact with smart contracts, and engage with a variety of DApps directly from their web browsers.

One of Metamask's primary functions is to act as a non-custodial cryptocurrency wallet. Users can create and manage multiple Ethereum accounts, each with its own unique address, which is essential for storing, sending, and

[4] https://www.damoov.com/

[5] https://github.com/Mobile-Telematics

[6] https://consensys.io/

receiving Ether (ETH) and various ERC-20 tokens [50]. This non-custodial approach means users retain full control over their private keys and funds, enhancing security and decentralization.
Metamask also acts as a DApp browser, seamlessly integrating with web browsers like Chrome, Firefox, and Brave. Users can access a wide array of decentralized applications, ranging from DeFi [7] platforms to NFT [8] marketplaces, without the need to install separate software or browser extensions. This integration makes it more convenient for users to explore and engage with blockchain-based services and applications.
Additionally, Metamask offers users the ability to manage their own blockchain identity, which is particularly valuable in the world of DeFi and other blockchain-based services. Users can sign transactions and interact with smart contracts using their Metamask wallet, opening up a world of possibilities for financial transactions, gaming, and more, all without relying on traditional intermediaries.

4.1 Data Collection

In order to test our hypothesis of "Providing incentives for good driver behavior may enhance and encourage the road safety", we conducted an experiment. We used Zenroad[9] [48, 51], an open-source telematics application provided by Damoov, as mentioned earlier to collect the driver behavior. We recruited twelve subjects to capture the driver behavior and installed the Zenroad mobile application on their mobile devices. They provided consent to Location services and Motion & Fitness. Location services refer to the capabilities and technologies that enable devices, such as smartphones, tablets, and computers, to determine and share their physical geographical location.
These services use a combination of different technologies, including GPS (Global Positioning System), Wi-Fi, cellular network data, and sometimes even Bluetooth, to pinpoint a device's coordinates on the Earth's surface [52]. "Motion fitness" refers to monitoring driver behavior, such as speeding, harsh acceleration, and harsh braking, allowing for the identification of unsafe driving practices [53].

Our experiment has two phases. In the first phase, we started our experiment with subjects initially without disclosing the information about providing the incentives for their driver behavior. This phase was prolonged for eighteen days. The second phase, also lasted for eighteen days, however, users were aware of incentives. In both phases, for each trip made by the user, we extracted the driving behavior characteristics such as distance traveled in miles, sharp acceleration count, hard braking count, and over-speed limit in miles.

4.2 Web Application

A web application is built using typical web technologies such as HTML5, CSS3, and vanilla JavaScript. The main purpose of the application is twofold. One to communicate with the Damoov Datahub API for the required driving behavior attributes and calculate the driving score, rank, and earnings based on them. The other is to connect to the MetaMask wallet, which can be used to redeem the obtained Driver Safety Reward (DSR) test tokens for multiple vehicular purposes like paying for parking, gas, tolls, and so on. Figure 3 depicts the screenshot of our web application [2].

4.3 Results

Upon receiving the data every day from every user, we calculated the Driving score, Rank, and Earnings for each user as mentioned in Chapter 3. The results for the first and second phases are tabulated in Table 2. Table 3 shows the trend for the Rank in both phases of the experiment. As we can observe, the trend of the rank improved for five of the users, while no change was observed in five other users. A detailed analysis of these changes is provided below.

Table 2 presents the rank calculation for driver behavior in Phase 1. It includes key metrics such as Acceleration Count, Deceleration Count, Overspeed occurrences, Average Score, and Rank for each driver. The data indicates variability in driving behavior across different users, reflecting both aggressive and cautious driving patterns. Notably, drivers with lower Acceleration and Deceleration Counts generally achieved higher ranks, suggesting that smoother driving behaviors were associated with better scores.

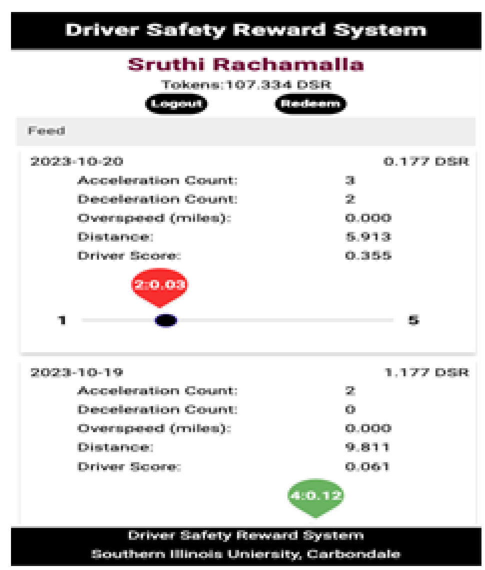

Figure 3 : Screenshot of Driver Safety Reward System

In Table 3, the rank calculation for Phase 2 is presented. A comparison with Phase 1 indicates improvements in certain drivers' behavior. For example, Driver_1 showed a significant reduction in Acceleration and Deceleration Counts, which resulted in an improved rank. Driver_9 consistently

[7] Decentralized Finance
[8] non-fungible token
[9] https://www.damoov.com/telematics-app/

maintained a high rank across both phases, demonstrating steady and safe driving practices. These results emphasize the importance of consistent driving improvements and highlight the effectiveness of providing incentives for safer driving.

Table 2: Rank Calculation for Driver Behavior of Drivers in Phase-1

Phase-1					
User	**Acceleration Count**	**Deceleration Count**	**Over speed**	**Avg. Score**	**Rank**
Driver_0	33	29	0.35	12.53	2
Driver_1	60	68	2.08	8.22	3
Driver_2	21	31	0.28	15.43	1
Driver_3	23	21	0.27	6.41	3
Driver_4	102	130	4.14	13.25	2
Driver_5	5	13	0.17	12.48	2
Driver_6	15	19	1.25	5.20	4
Driver_7	10	8	0.14	2.62	5
Driver_8	65	163	1.46	17.12	1
Driver_9	49	114	1.72	16.62	1
Driver_10	9	5	0.35	4.71	4
Driver_11	16	48	0.30	11.82	2

Table 3: Rank Calculation for Driver Behavior of Drivers in Phase-2

Phase-2					
User	**Acceleration Count**	**Deceleration Count**	**Over speed**	**Avg. Score**	**Rank**
Driver_0	30	22	1.02	16.19	2
Driver_1	32	44	1.70	15.28	2
Driver_2	19	36	0.69	9.99	3
Driver_3	19	32	0.24	8.97	3
Driver_4	44	51	4.04	5.06	4
Driver_5	17	9	1.27	5.65	4
Driver_6	62	49	7.09	5.56	4
Driver_7	2	3	0	2.91	5
Driver_8	85	129	4.32	12.60	3
Driver_9	75	147	0.57	24.19	1
Driver_10	11	22	5.03	6.11	4
Driver_11	19	66	0.91	8.84	3

Table 4 summarizes the rank trends for both phases, showing whether each driver improved, maintained, or declined in rank. For example, Driver_2 experienced an increase in rank from Phase 1 to Phase 2, indicating a decline in driving performance, while Driver_1 showed an improvement. These trends provide insight into how the awareness of incentives influenced driving behavior. Overall, five drivers showed improvement, while five others remained unchanged. This suggests that the incentive mechanism had a mixed impact, with some drivers responding positively and others showing no change.

Table 4: Rank Trend for Drivers in Phase-1 and Phase-2

User	Phase-1	Phase-2	Trend
Driver_0	2	2	no change
Driver_1	3	2	down
Driver_2	1	3	up
Driver_3	3	3	no change
Driver_4	2	4	down
Driver_5	2	4	up
Driver_6	4	4	no change
Driver_7	5	5	no change
Driver_8	1	3	up
Driver_9	1	1	no change
Driver_10	4	4	no change
Driver_11	2	3	up

Figure 4 illustrates the results graphically, showing the trends in driver rank across the two phases. The figure provides a visual representation of the changes in rank for each driver, allowing for easy comparison of performance between phases. The graph highlights the positive trend observed in some drivers and emphasizes the stability in others. Drivers who improved their rank did so by adhering to safer driving practices, such as reducing over-speeding and smoother acceleration and deceleration. This visualization underscores the impact of incentives on promoting safer driving behavior and the potential benefits of such systems in real-world applications.

Both Phase 1 and Phase 2 trends are plotted in Figure 4. The figure illustrates how drivers' ranks changed between the two phases of the experiment, highlighting improvements and consistency in driving behavior. The visualization provides a clear depiction of the overall effect of incentives on driver performance, emphasizing the positive outcomes of the reward system.

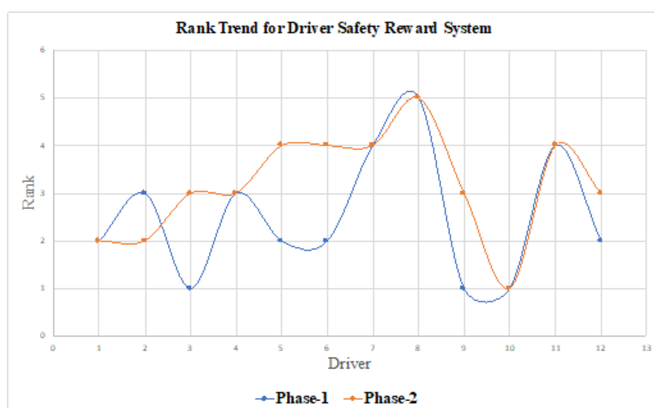

Figure 4: Screenshot of Driver Safety Reward System

Although our experiment was limited in scope, the results indicate positive trends towards encouraging good driving behavior through incentives. The data from Phase 2 show that informing users about potential rewards can motivate improvements in their driving, as observed in several drivers who improved their ranks compared to Phase 1.

5. CONCLUSION AND FUTURE WORK

To promote safer driving practices, we proposed a methodology to quantify and monetize driver behavior by analyzing driving patterns and rewarding good performance. Using SUMO simulation software, we generated a dataset consisting of 17 drivers over four days and extracted key aggressive driving features [54]. From these features, we developed a driver scoring model to assess aggressive driving tendencies. The scoring system rates drivers on a scale from 1 to 5, with 1 representing “Very Bad” and 5 representing ”Excellent” driving behavior. Additionally, we designed a reward-based mechanism where drivers are awarded crypto tokens based on their rank, providing an incentive for improving their driving habits. These Driver Safety Reward (DSR) tokens, which cannot be exchanged for currency, are logged in a decentralized Rinkeby Test network to ensure transparency and accessibility for different stakeholders.

We extended our model to include incentives for drivers in a platoon environment. Specifically, we devised a system to calculate earnings for drivers participating in a platoon, considering different maneuvers such as joining, leaving, merging, and splitting. This system was implemented using PERMIT [11], a simulation tool for platoon dynamics, to evaluate the behavior of drivers under various maneuvers. The Rinkeby test network was also used here to distribute test tokens based on the calculated earnings of drivers in the platoon.

Our experiment aimed to test the hypothesis that providing incentives for good driving behavior could enhance driver safety. The results demonstrated that small, consistent rewards are more effective in encouraging positive behavior compared to large, infrequent incentives. This finding suggests that frequent, reliable incentives can motivate drivers to adopt safer driving practices, ultimately leading to improved road safety.

Currently, our framework only considers a limited set of parameters, such as acceleration, deceleration, and over-speeding, in evaluating driver behavior. Future work will aim to enhance this framework by incorporating additional parameters, including cornering, weather conditions, time of day, and demographic factors such as age and gender, using real-time datasets. Expanding the range of variables will allow for a more comprehensive assessment of driving behavior. Furthermore, this framework can be scaled to optimize platoon dynamics, thereby improving road usage efficiency and promoting cooperative driving behavior among multiple vehicles.

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