Fall 2023

BIMEE: Blockchain Based Incentive Mechanism Considering Endowment Effect

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BIMEE: BLOCKCHAIN BASED INCENTIVE MECHANISM CONSIDERING ENDOWMENT EFFECT

A Master's Thesis

Presented to

The Graduate College of

Missouri State University

In Partial Fulfillment

Of the Requirements for the Degree

Master of Science, Computer Science

By

Jayanth Madupalli

December 2023

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Computer Science

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ABSTRACT

Crowdsensing, a paradigm in modern data collection, harnesses the collective power of mobile users equipped with sensory devices to contribute valuable data based on task-specific criteria. The efficacy of crowdsensing relies on sustained engagement from proficient users over extended periods. Incentivizing long-term participation is crucial, and blockchain technology emerges as a promising framework, providing a decentralized and immutable ledger. However, existing blockchain-based incentive mechanisms for crowdsensing encounter challenges. Firstly, they often overlook users' inherent bias towards loss aversion, a psychological phenomenon where individuals prioritize avoiding losses over acquiring equivalent rewards. Secondly, fairness issues arise, especially concerning newly participating users in auction scenarios. In response to these challenges, an innovative solution is presented — Blockchain-based Incentive Mechanism considering Endowment Effect (BIMEE). BIMEE not only leverages the security and transparency of blockchain but also integrates behavioral economic principles to enhance the efficiency of the incentive mechanism. Specifically, we introduce the Endowment Effect, emphasizing the psychological tendency of individuals to overvalue items they possess. Additionally, we incorporate Fairness Preference, addressing the equitable treatment of newly engaged users during the auction process. Our implementation of BIMEE utilizes Smart Contracts on the Ethereum blockchain. Through extensive experimentation, we demonstrate that BIMEE significantly enhances the participation rate of mobile users in sensing tasks, improves platform utility, and elevates the average utility experienced by users. This multifaceted approach not only aligns with the technical advancements in blockchain but also incorporates crucial behavioral insights to foster a more effective and user-friendly crowdsensing ecosystem.

KEYWORDS: blockchain, crowdsensing, incentive mechanism, endowment effect, smart contract, Ethereum, behavioral economics, BIMEE

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ACKNOWLEDGEMENTS

I extend my heartfelt gratitude to my advisor, Dr. Hui Liu, for their invaluable guidance and mentorship throughout this research journey. My sincere appreciation also goes to the members of my thesis committee and the Department of Computer Science for their support through valuable insights and constructive feedback.

A profound and heartfelt thank you to my mother, the cornerstone of my journey. Her unwavering support and boundless encouragement have been more than pillars of strength—they have been the very foundation of my pursuit. The sacrifices she made, her deep understanding, and the resilience with which she managed everything back in India while I chased my master's degree abroad are gifts that resonate deeply. Her love and sacrifices are the heartbeat of my accomplishments, and I am forever grateful for her immeasurable contribution to my academic and personal odyssey.

On a lighter note, a warm thank you to coffee, my steadfast companion through late nights and early mornings. Your caffeinated presence has been both a source of comfort and motivation.

To everyone who has been part of this academic adventure, thank you for contributing to the realization of this milestone.

Dedicated to those who rise resilient from life's hardships, dedicating their lives to knowledge and dreams.

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1. INTRODUCTION

Crowdsensing, often referred to as Mobile Crowdsensing (MCS) [1], is a dynamic process where data is collected from sensory devices by a multitude of users, known as "workers," to accomplish large-scale sensory tasks initiated by data requesters or task publishers. However, sustaining long-term worker engagement necessitates an effective incentive mechanism to offset their costs and acknowledge their time investment. In a traditional crowdsensing framework, the three key components are workers, platform, and task publishers as shown in Figure 1. Task Publishers define sensory tasks, and workers fulfill these tasks, with the platform serving as the intermediary facilitating all activities and transactions. While efficient, a centralized platform raises concerns, including vulnerability to attacks, a single point of failure, lack of computational transparency, and privacy issues for workers.

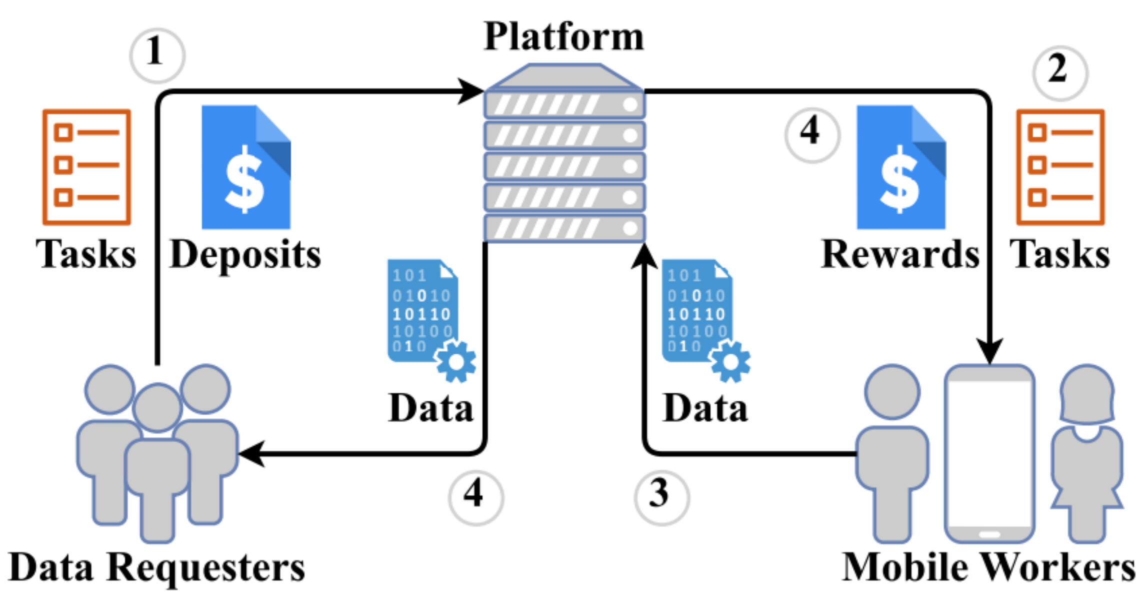

Figure 1. Crowdsensing Overview

To address these concerns, a decentralized crowdsensing framework powered by Blockchain technology emerges as a transformative solution. Blockchain [2], a distributed ledger underpinned by a consensus mechanism, ensures the validity of transactions before adding them to the ledger. Smart contracts [3] enable the deployment of intricate code as immutable transactions, each with a specific verifiable address within the blockchain. In a decentralized implementation, such as the one facilitated by Ethereum [4] smart contracts, the platform relinquishes control over monetary transactions, fostering direct transfers from task publishers to workers' wallets, thereby preserving worker privacy.

However, existing blockchain-based incentive mechanisms in crowdsensing frameworks that are discussed in the related works face two significant challenges. Firstly, they often overlook users' inherent inclination towards loss aversion, a psychological phenomenon prioritizing the avoidance of losses over acquiring equivalent rewards. Secondly, fairness issues emerge, particularly concerning newly participating users during auctions.

In response, I introduce a pioneering solution: the Blockchain-based Incentive Mechanism considering Endowment Effect (BIMEE). The Endowment Effect [5], rooted in behavioral economics, reveals that individuals assign higher value to objects they already possess than those they don't. The proposed mechanism addresses this by allocating initial endowment tokens to workers, imbuing these tokens with value and influencing preference during bid-winning processes, thereby encouraging sustained participation. Moreover, inspired by fairness preference theory [6], which asserts that users' utility depends not just on their actual income but also on the fairness of income distribution, fairness preference is integrated into the reward allocation process by calculating each worker's profitability and implementing a profitability cutoff. The mechanism ensures fairness for all Workers and particularly incentivizes new platform participants to provide competitive bidding prices.

In the subsequent sections of this thesis, I undertake an in-depth exploration of critical facets, including background information, related work, the system model, and the proposed incentive mechanism deployed on the blockchain framework. The implemented incentive mechanism, realized through a Solidity smart contract, incorporates Endowment Effect and Fairness Preference, employing Preferential Bias and Profitability cutoffs. The smart contract is deployed and tested comprehensively on a local Ethereum environment utilizing "Hardhat," with meticulous evaluation based on key metrics such as worker participation rate, bid win rate, platform utility, worker utility, and task success rate.

These experimental simulations and the insights drawn from the conducted experiments demonstrate how BIMEE exhibits superior performance in these metrics when compared to the Internet of Vehicles - Blockchain Crowdsensing Implementation (IoVBCI) [7], an alternative crowdsensing framework integrating blockchain technology and a reverse auction mechanism. BIMEE's incentive mechanism is implementation on the Ethereum blockchain, combined with Preferential Bias and Profitability cutoffs, and demonstrates a substantial improvement in worker participation, bid win rates, and overall utility metrics.

In conclusion, BIMEE leverages principles from behavioral economics, specifically the Endowment Effect and Fairness Preference, to enhance the efficiency of the incentive mechanism. The integration of blockchain technology addresses privacy concerns, while decentralization mitigates the risk of a single point of failure, collectively contributing to a robust and effective crowdsensing framework.

2. BACKGROUND

2.1 Mobile Crowdsensing (MCS)

Crowdsensing, also known as participatory sensing [8], is a data collection approach that leverages the power of crowds or communities of individuals to gather information using their mobile devices, sensors, or other means. This approach involves people actively participating in data collection, sharing, and analysis, typically through smartphone apps or other connected devices. Crowdsensing refers to a broader concept of collecting data from a crowd or a large group of individuals using various types of sensors and devices. The term "Mobile Crowdsensing" was introduced by Ganti et al. [9] to describe a broader concept than just "mobile phone sensing", a precursor to MCS, which was popular when mobile phones had limited storage, communication, and computational capabilities. It focused on individual sensing applications like elderly fall detection and personal well-being. Guo et al. [8] further clarified the distinction, defining MCS as a new sensing paradigm that enables regular citizens to contribute data collected from their mobile devices. This data is then aggregated and processed in the cloud to extract crowd intelligence and deliver people-centric services.

MCS relies on sensors and communication capabilities found in everyday mobile devices like smartphones and wearables, which contain an impressive array of sensing components: camera, microphone, GPS, accelerometer, gyroscope, magnetometer, Bluetooth as proximity sensor, and some wearables are equipped with health and pollution monitoring sensors. These devices have become integral to our daily lives, serving various purposes, including business, communication, and entertainment. MCS specifically focuses on data collection using mobile devices carried by individuals, such as smartphones, wearables, or tablets.

The statistics provided in [10] underscore the widespread adoption of mobile technology. In 2018, global smartphone sales reached 1.55 billion units, and wearable device shipments amounted to 178.91 million, with an increase to 453.19 million in 2022. Wearable devices, such as smartwatches, glasses, rings, gloves, and helmets, are experiencing significant growth, contributing to an estimated revenue of USD 95.3 billion in 2021. Compared with the tiny energy constrained sensors of static wireless sensor networks, mobile devices carried by people, such as smartphones or wearables can support more complex computations, have larger storage memory and access internet directly. Therefore, MCS is a scalable and cost-efficient alternative to deploy static wireless sensor networks for dense sensing coverage across large areas.

Additionally, there is a substantial growth in the crowd analytics market, which is predicted to reach USD 5.7 billion by 2030, compared to USD 912.68 million in 2020, indicating a compound annual growth rate of 20.4% from 2021 to 2030. This growth reflects the increasing importance and applications of crowdsourced data and analytics in various industries [11].

2.1.1 MCS Architecture

MCS is introduced as a layered architecture in [10], consisting of four layers: Application, Data, Communication, and Sensing. These layers are described as a framework for understanding MCS systems. For a clear understanding, they are illustrated in Figure 2 and briefly explained below:

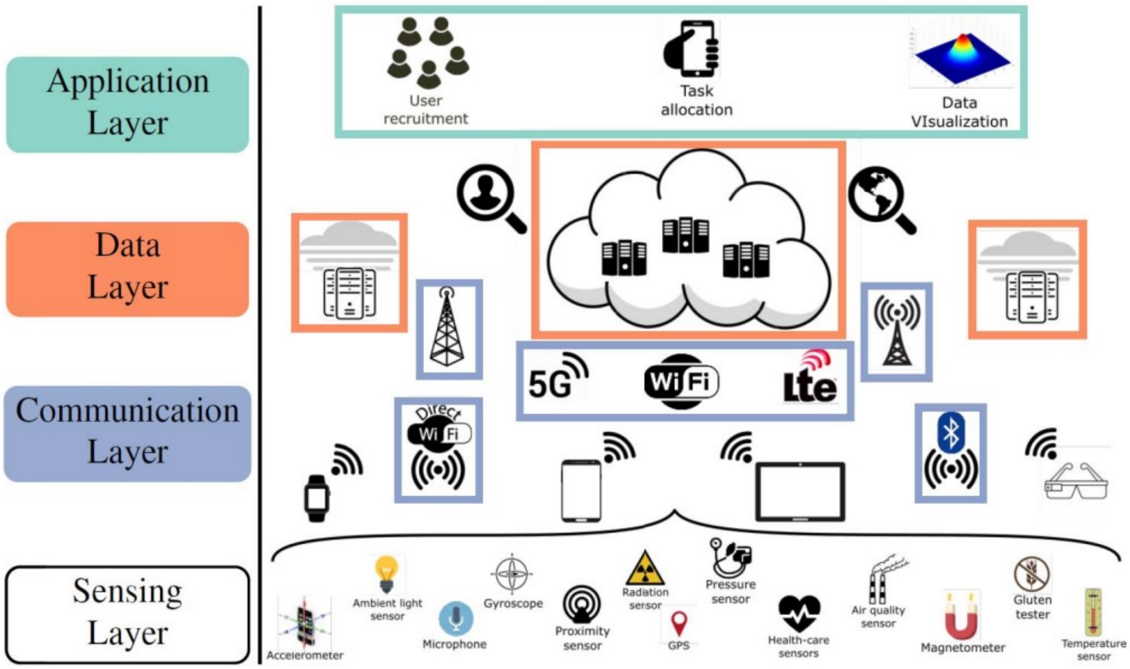

Figure 2. MCS as a Layered Architecture

Application Layer: The top layer, the Application layer, deals with user and task-related aspects of MCS campaigns. This includes campaign design, user recruitment strategies, task scheduling, and approaches to maximize data quality while minimizing user contributions.

Data Layer: The Data layer focuses on the storage, analysis, and processing of data collected from contributors. This layer operates in the cloud or closer to end-users through fog servers. It involves inferring information from raw data and assessing data utility and quality.

Communication Layer: The Communication layer encompasses technologies and methodologies for transmitting data collected from mobile devices to a central collector in the cloud. It considers various radio interfaces (e.g., cellular, Wi-Fi, Bluetooth) and optimizations to enhance data transmission efficiency.

Sensing Layer: The Sensing layer involves the acquisition of data from mobile devices, primarily through built-in sensors such as gyroscopes, GPS, cameras, microphones, temperature sensors, and more. It also considers the use of specialized sensors connected to mobile devices for specific sensing campaigns. Data acquired through sensors is transmitted to the MCS platform via mobile device communication capabilities.

2.1.2 MCS Applications

Mobile Crowdsensing can be applied to various domains and has numerous applications, including environmental monitoring, urban planning, healthcare, transportation, and more. The widespread adoption of smartphones and wearables, equipped with a variety of built-in sensors, has been instrumental in the success of the Mobile Crowdsensing (MCS) paradigm. Several applications have already been developed and are actively used. For instance:

- HealthAware, MPCS, and DietSense promote healthy eating habits by collecting images of food consumed and tracking daily user activities, including the time and location of meals, using sensors like the accelerometer, GPS, and microphone.
- Nericell monitors traffic conditions.
- GasMobile, HazeWatch, and Third-Eye engage citizens in monitoring air pollution.
- Creekwatch, created by the IBM Almaden research center, allows for monitoring watershed conditions by crowdsourcing data about water levels, trash accumulation along riverbanks, flow rates, and images of waterways.
- Garbage Watch and WasteApp facilitate the monitoring of recycling bin contents, aiming to enhance recycling programs.
- Google Maps utilizes crowdsensing as part of its mapping and navigation features. Crowdsensing, in this context, involves collecting data from the smartphones of users who have the Google Maps app installed and actively use the service.

These examples illustrate how MCS leverages the sensors in smartphones and wearables to address diverse challenges and create applications that benefit society in several ways, from health and environmental monitoring to traffic management and waste reduction.

Mobile Crowdsensing holds the potential to significantly enhance the daily lives of citizens and contribute to the development of smarter cities as also illustrated in applications section above. In the context of building smart cities, which aim to use information and communication technology (ICT) to improve the quality of life for residents, MCS is a crucial solution.

The Internet of Things (IoT) is a key enabler for deploying sensing infrastructure in smart cities. Also, citizen participation can extend coverage of existing sensing systems without needing significant additional investments. MCS leverages human intelligence, which offers a deeper understanding of contextual information compared to traditional sensor networks.

Cities often face infrastructure deficits, and human involvement can play a vital role in monitoring and maintaining these services. Specific use cases illustrate the potential of MCS, such as using data from smartphone accelerometers to detect bridge vibrations. MCS also contributes to smart traffic management and offers services like free parking spot detection. Examples include ParkSense, which identifies available parking spots using Wi-Fi scans, and ParkGauge, which reports real-time information about indoor parking occupancy and uses low-power sensors like accelerometers to detect driving states. Overall, MCS can transform urban environments and improve the efficiency of various city services.

2.1.3 MCS challenges

The success of a crowdsensing campaign heavily depends on achieving a large and active participation from citizens. Incentives play a fundamental role [12] in this regard, encouraging users to engage in sensing activities, report information effectively, and be rewarded for their contributions. Research efforts [10] in user recruitment for MCS have highlighted the crucial role of Incentive mechanisms, which are broadly categorized into entertainment-based, service-based, and monetary-based incentives. Incentives play a multifaceted role in crowdsensing, addressing various crucial aspects of user participation.

Incentives motivate individuals to participate in crowdsensing activities. Without incentives, users may be less willing to contribute their time, effort, and data to a crowdsensing campaign. They foster sustained user engagement throughout the campaign, ensuring users remain active and consistently contribute data - a vital component of campaign success. The presence of incentives can significantly enhance the quality of the data collected. Users tend to be more conscientious in providing accurate and reliable data when they stand to gain personal benefits, such as rewards or privileges.

Incentives play a pivotal role in attracting and recruiting users to the campaign, particularly for tasks that may be time-consuming or require substantial effort. In some cases, individuals may be concerned about sharing their data due to privacy considerations. Incentives can help individuals feel more comfortable sharing their data by offering something of value in return. Incentives can introduce an element of competition among participants, which can lead to increased engagement and better data collection.

The traditional Mobile Crowdsensing triangle architecture comprises three key components: mobile workers, the platform, and task publishers. Within MCS systems, the intersection between mobile workers and the platform, as well as the interactions between the platform and task publishers, engender significant privacy vulnerabilities. The sensing devices used by mobile workers have the potential to collect sensitive data about individuals, thereby raising profound privacy concerns. For instance, GPS sensor readings can unveil confidential information, such as the daily commuting routes and locations of individuals. Notably, when mobile workers upload their sensing data to the platform, they relinquish control over their data and associated attributes. In the unfortunate event of a platform breach or its loss of trustworthiness, the risk emerges of their personal information being potentially used for commercial recommendations and political election analyses, thereby exposing users' privacy.

Numerous studies have been undertaken to scrutinize these privacy threats, and the treatment of concerns related to personal data acquisition and disclosure in existing application scenarios can be found in references [10] and [13]. Moreover, privacy considerations transcend mere data collection and extend into various aspects of task management within the context of crowdsensing. Privacy concerns may surface during user recruitment, task distribution, and even reward allocation, particularly in cases involving monetary incentives, which could potentially expose users' financial information.

Hence, it becomes imperative to devise an incentive mechanism that not only addresses privacy concerns within MCS systems but also ensures sustained user participation and contribution.

In summary, crowdsensing leverages the collective capabilities of individuals and their interconnected devices to amass valuable data that informs decision-making, enhances services, and addresses multifaceted societal challenges. This research centers on the perpetuation of user engagement in data collection through the implementation of incentive mechanisms and the effective use of blockchain technology to address privacy concerns.

2.2 Blockchain, Consensus mechanisms, & Smart contracts

Blockchain, consensus mechanisms, and smart contracts are fundamental concepts in the realm of blockchain technology, which is commonly associated with cryptocurrencies like

Bitcoin but has far-reaching applications beyond digital currencies. Let's explore each of these concepts:

2.2.1 Blockchain

A blockchain is a distributed and immutable ledger that records transactions across a network of computers in a secure and transparent manner. The general structure of a blockchain is displayed in Figure 3. It consists of a chain of blocks, where each block contains a set of transactions.

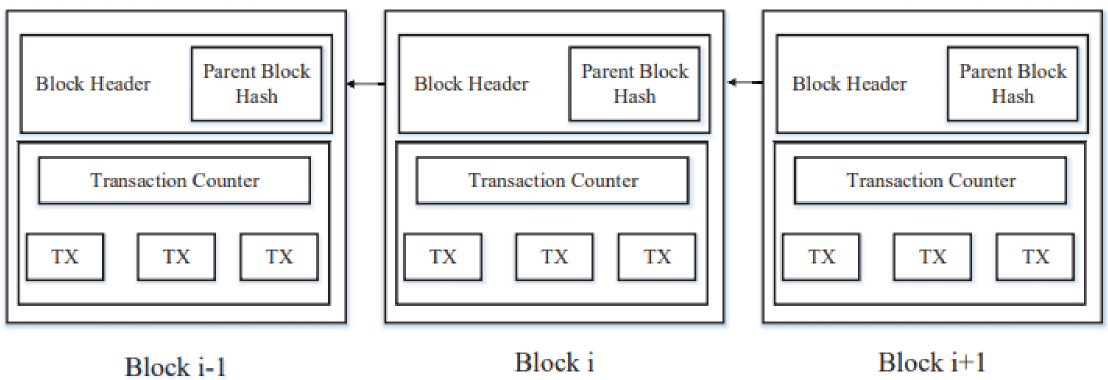

Figure 3. Blockchain Structure

Transactions are grouped into blocks, and each block is linked to the previous one through a cryptographic hash. This chaining of blocks creates a chronological and unchangeable history of all transactions on the network. Blockchain operates on a decentralized network, meaning there is no central authority or intermediary controlling the ledger. Instead, multiple nodes (computers) in the network validate and maintain the blockchain collectively.

2.2.2 Consensus Mechanisms

Consensus mechanisms are protocols used in blockchain networks to ensure that all participants agree on the validity of transactions and the order in which they are added to the blockchain. Consensus is crucial for maintaining the integrity and security of the ledger.

Some common consensus mechanisms include:

Proof of Work (PoW): This mechanism, used by Bitcoin, requires participants (miners) to solve complex mathematical puzzles to add new blocks to the blockchain. The first one to solve the puzzle gets the right to add a block and is rewarded with cryptocurrency.

Proof of Stake (PoS): In PoS, validators are chosen to create new blocks based on the amount of cryptocurrency they "stake" as collateral. Validators are rewarded with transaction fees and sometimes newly created coins.

Delegated Proof of Stake (DPoS): Similar to PoS, DPoS relies on coin holders to vote for a limited number of delegates who validate transactions and create new blocks.

Proof of Authority (PoA): PoA requires validators to have a certain level of authority or reputation within the network. It is often used in private or consortium blockchains.

Proof of Space-Time (PoST), Proof of History (PoH), etc.: Various other consensus mechanisms have been developed to address specific needs and challenges in different blockchain projects.

New consensus mechanisms continue to be developed in the world of blockchain and distributed ledger technology. This ongoing development is driven by the need to address various limitations and challenges associated with existing consensus mechanisms and to accommodate the diverse requirements of different blockchain projects and applications.

2.2.3 Smart Contracts

Smart contracts are self-executing contracts with the terms of the agreement directly written into code. They automatically execute and enforce the terms of the contract when predefined conditions are met. These contracts run on blockchain platforms, and their code is stored and executed on the blockchain. They can be used to automate various processes and transactions without the need for intermediaries.

Ethereum, one of the most well-known blockchain platforms, introduced the concept of smart contracts, allowing developers to build decentralized applications (DApps) that rely on these contracts for their functionality. The general overview of Ethereum network and smart contracts is displayed in Figure 4. The different aspects involved in the smart contracts are discussed below:

Smart Contract Creation: Smart contracts are created by developers using Ethereum's programming language, Solidity, or other compatible languages. These contracts are then compiled into bytecode that can run on the Ethereum Virtual Machine (EVM), which exists in the participating nodes of the Blockchain.

Contract Deployment: To deploy a smart contract, a user initiates a transaction that includes the bytecode and any required parameters. This transaction is broadcasted to the Ethereum network.

Mining and Consensus: Miners on the Ethereum network validate and verify transactions, including smart contract deployments, through a consensus mechanism called

Proof of Stake (PoS) or, previously, Proof of Work (PoW). Once verified, the contract is added to the blockchain.

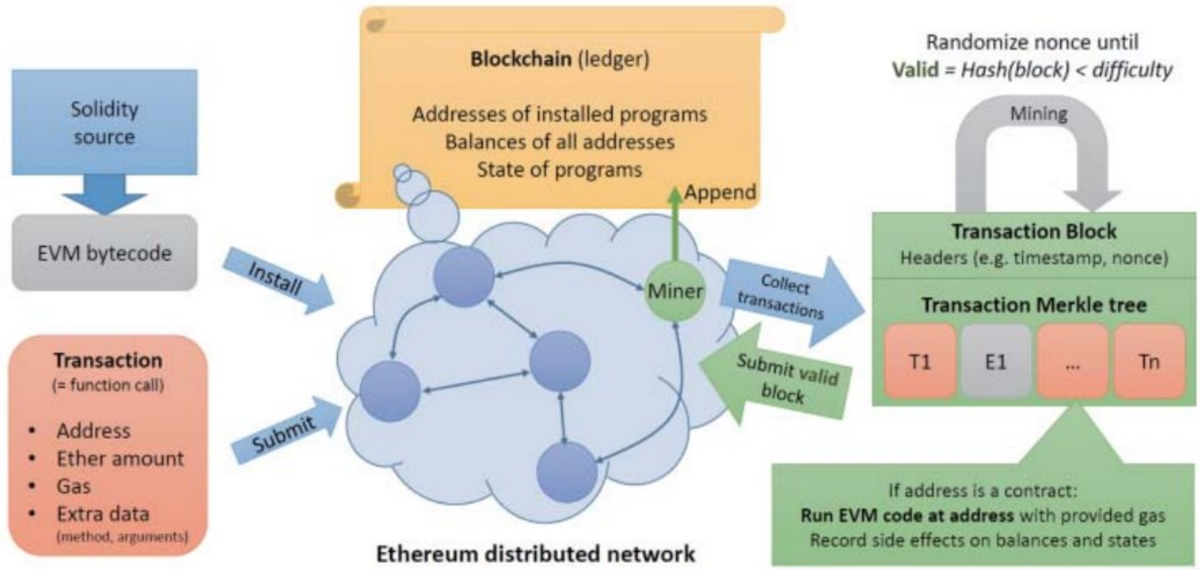

Figure 4. Ethereum Network Overview

Contract Address: Each smart contract is assigned a unique address on the Ethereum blockchain. This address is used to interact with the contract and acts as an identifier for the smart contract on the blockchain.

Contract Execution: Smart contracts are executed by the Ethereum Virtual Machine (EVM) when specific conditions or trigger events occur. These conditions are typically defined in the contract's code, I.e., explicit method invocation or an event trigger. The smart contract will contain the instructions to be executed according to the specific conditions met.

Transaction Trigger: Users initiate transactions with the contract's address, specifying a function or method within the contract that they want to execute. These transactions include any required inputs or parameters.

Gas: Ethereum requires a form of payment for contract execution called "gas." Gas is a unit of the cryptocurrency 'Ether,' used to cover the computational cost of executing the contract. Users specify the gas limit and gas price when sending a transaction.

Contract Logic: The EVM processes the transaction and executes the contract's logic according to the code's instructions. This may involve calculations, storage operations, or interactions with other contracts on the blockchain.

State Changes: Smart contracts can modify their internal state or interact with other contracts. These changes are recorded on the Ethereum blockchain, creating a permanent, immutable record of the contract's actions.

Transaction Receipt: After execution, a transaction receipt is generated and stored on the Ethereum blockchain. This receipt includes details about the transaction's success, gas used, and any events triggered by the contract.

Events: Smart contracts can emit events during execution. These events can be observed by external applications, enabling real-time updates and notifications based on contract activity.

Smart contracts inherit the characteristics of blockchain technology and append them to the functioning computer code embedded in them. This makes smart contracts a powerful tool for automating, securing, and streamlining a wide range of processes. Smart contracts can be used in a wide range of applications, including financial services (e.g., lending, insurance), supply chain management, voting systems, and more. Some of their characteristics are described below:

Immutable and Transparent: Once deployed, smart contracts are immutable, meaning their code cannot be changed. They operate transparently, and their execution and state changes are visible to anyone on the Ethereum network. Anyone can look up their code on the blockchain using any of the available blockchain scanning tools.

Security: Blockchain technology provides a high level of security through cryptographic techniques. Smart contracts are resistant to hacking, fraud, and unauthorized alterations due to their immutable nature. On the other hand, vulnerabilities in the code can lead to exploitation or loss of funds. Auditing, testing, and best practices are essential to ensure the contract's security.

Interoperability: Smart contracts on Ethereum can interact with each other, even smart contracts on other blockchains using some form of cross-chain communication or interoperability protocol, enabling the creation of complex decentralized applications (DApps) that use multiple contracts to achieve their goals.

Decentralization: Smart contracts operate on a decentralized network of nodes, making them censorship-resistant and eliminating the need for intermediaries or trusted third parties. Smart contracts operate in a trustless environment. Users do not need to trust a centralized authority to execute the contract fairly. Instead, they trust the decentralized network and the predefined code of the contract.

In summary, blockchain is the foundational technology that provides a secure and transparent ledger, consensus mechanisms ensure agreement and security in decentralized networks, and smart contracts enable automated and trustless execution of agreements and processes on the blockchain. Together, these elements have the potential to revolutionize various industries by providing a tamper-proof, decentralized, and programmable infrastructure for a wide range of applications. This amalgamation of components presents a transformative potential, particularly in the context of privacy-preserving, trustable, and transparent crowdsensing incentive mechanisms.

By leveraging blockchain technology, the crowdsensing framework gains inherent security and transparency. The decentralized nature of the blockchain ensures that no single entity has control, reducing the risk of manipulation or unauthorized access. Through consensus mechanisms, the network attains a robust and agreed-upon state, enhancing trust among participants. Smart contracts, as self-executing agreements, foster a trustless environment, eliminating the need for intermediaries and ensuring the reliable execution of incentive mechanisms.

The integration of these blockchain components into crowdsensing incentives establishes a tamper-proof infrastructure. It not only addresses privacy concerns but also instills trust in the system's operation. Transparency is inherent in the blockchain's design, allowing participants to verify transactions and incentive distributions. This holistic approach holds the promise of revolutionizing crowdsensing, providing a foundation that is both technologically advanced and inherently trustworthy.

2.3 Behavioral Economics

Behavioral economics [1] is a field of economics that combines insights from psychology and economics as illustrated in Figure 5, to understand how people make decisions in real-world situations. It recognizes that individuals often deviate from the rational, self-interested behavior assumed by traditional economic theory. Instead, behavioral economics studies the cognitive biases and psychological factors that influence decision-making.

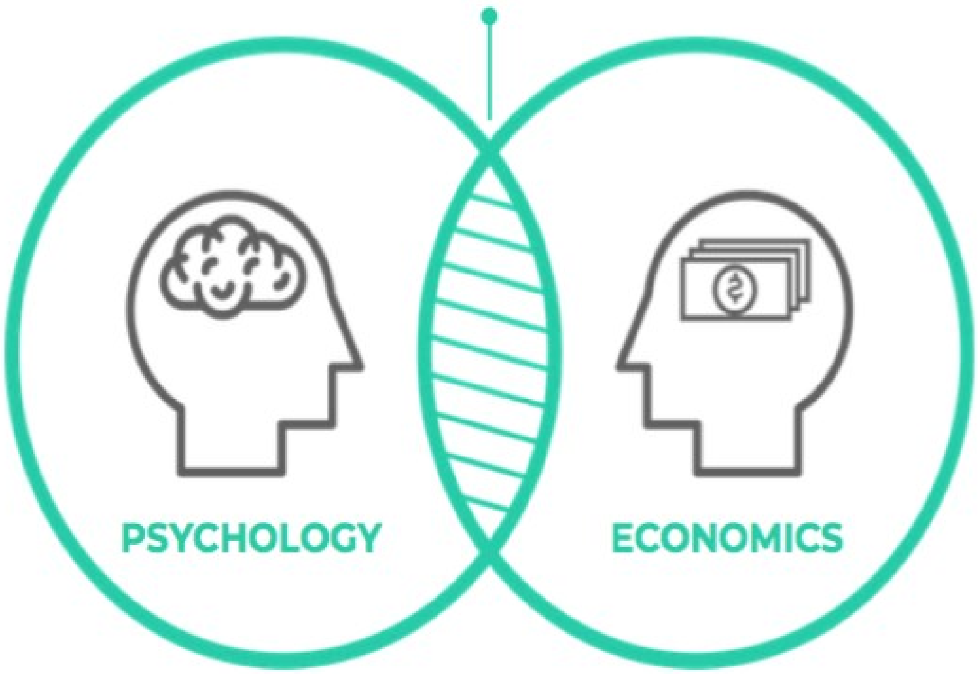

Figure 5. Behavioral Economics Illustration

The two pivotal concepts from behavioral economics embraced into BIMEE are: the Endowment Effect and Fairness Preferences. The Endowment Effect posits that individuals tend to assign higher value to items they possess, introducing a psychological bias that can significantly impact economic transactions. Fairness Preferences, on the other hand, underscore the importance of equitable outcomes in decision-making, acknowledging that individuals derive utility not only from absolute gains but also from the perceived fairness of those gains.

These two concepts Endowment Effect and Fairness Preference highlight the importance of understanding the cognitive and emotional factors that influence economic decisions. Behavioral economics has practical applications in various fields, including marketing, public policy, and finance, as it provides insights into how individuals make choices in the real world, often deviating from the predictions of classical economics.

As we transition into the methodology section, these behavioral economic principles become integral components influencing the design and efficacy of the proposed incentive mechanism for crowdsensing. The application of the Endowment Effect plays a pivotal role in shaping user perceptions and motivations within the system, fostering a sense of ownership and attachment to incentivized tokens. Simultaneously, the incorporation of Fairness Preferences ensures that the reward allocation process considers the equitable distribution of incentives, thereby enhancing user satisfaction and system engagement.

By integrating insights from behavioral economics into the incentive mechanism, this research aligns the economic model with real-world decision-making patterns. This not only contributes to a more comprehensive understanding of user behavior within crowdsensing but also bolsters the adaptability and effectiveness of the proposed incentive framework. The subsequent sections will delve deeper into the practical implementation of these behavioral economic principles within the methodology, shedding light on their implications and benefits in the context of crowdsensing.

3. RELATED WORK

3.1 Incentive Mechanisms

In the context of crowdsensing, incentive mechanisms [12] are strategies or systems put in place to motivate individuals or a crowd of participants to actively contribute their data, resources, or efforts to a crowdsensing project or platform. Ordinary individuals often hesitate to join and contribute their sensing abilities to crowdsensing systems because they lack adequate incentives.

Participation in these systems can come with costs and potential risks. For instance, when a smartphone user engages in a task to collect sensor data, it inevitably consumes various smartphone resources like processing power, communication capabilities, and battery energy. Moreover, the gathered data often includes location information, which can make privacy-conscious users feel uneasy. Consequently, it is reasonable to expect that regular individuals will not actively engage in sensing tasks unless they are provided with strong motivation or incentives.

Hence, incentive mechanisms play a crucial role in encouraging users to participate in crowdsensing activities.

3.1.1 Types of Incentives

Although there are several types of incentives, [14] describes three primary categories of incentives: entertainment, service, and money. Each category of incentives prioritizes specific user needs, encompassing aspects like enjoyment, convenience, satisfaction, and financial gain. Here are concise descriptions of the three incentive categories:

Entertainment Incentives: These involve turning crowdsensing tasks into enjoyable sensing games, especially, inspired by location-based mobile games [15]-[17] where users contribute their mobile device's computational or sensing capabilities while playing. The challenge lies in ensuring that these games are engaging enough to motivate users.

Service Incentives: Service incentives are based on the mutual-benefit principle, where users both consume and provide services within the system. To benefit from the services offered by the system, users must also contribute to it in some way. There are many research implementations like the one proposed by Hoh et al. [18], TruCentive, for crowdsourced parking information systems. A popular real-world example for this type of incentive is Google Maps, and how its traffic congestion detection algorithms work for the collective improvement of their service.

Monetary Incentives: In this category, the system provides financial rewards to incentivize potential participants. Users receive compensation for utilizing their resources, typically smartphone sensors, to complete various distributed tasks. Monetary incentives offer a versatile approach applicable to a wide range of sensing tasks.

3.1.2 Effectiveness of Monetary Incentives

As discussed in [14], The use of monetary incentives in various online scenarios has been explored extensively. It started with efforts to measure web content usage, where users were paid based on their page visits to websites. This concept expanded to fields like online music and applications, where payment schemes were introduced. In the realm of participatory sensing, monetary incentives have been investigated to motivate users to participate in data collection in numerous studies.

Musthag et al. [19] assessed the effectiveness of different payment models for gathering data via wearable sensors. They compared three schemes: UNIFORM, which offered a fixed 4-cent payment per question, VARIABLE, which provided variable payments between 2 to 12 cents per question, and HIDDEN, which concealed payment amounts until questionnaire completion. VARIABLE reduced costs by 50% compared to UNIFORM, with HIDDEN being the least effective.

Reddy et al. [20] investigated payment impact on user participation in a recycling assessment task, utilizing five incentive groups. Additionally, Danezis et al. [21] determined the price at which users would disclose their location privacy, finding a median bid of 10 pounds, which increased with commercial interests.

In summary, research on monetary incentives has shown that users have varying payment expectations for the same sensing task, and they often prefer to have a say in determining the payment structure. Effective schemes involve transparent payment structures that allow users to make informed decisions about their participation.

3.1.3 Monetary Incentives and Auctions

Monetary incentive mechanisms primarily focus on effective negotiations between the system and users, often utilizing auction-based designs. Several potential research directions for auction-based incentive mechanisms are envisioned in [14]:

Online Mechanism Design: Current monetary systems assume static settings where enough users are available for the interaction between the platform and users. An online setting, however, is considered more practical, allowing asynchronous and sequential interactions. Researchers [22], [23] have explored this online setting based on offline budget-feasible mechanisms, and more research in this direction is anticipated.

Task Assignment: While most mobile crowd sensing systems collect data passively for specific applications, spatial crowdsourcing introduces a new paradigm where users actively respond to spatial queries by visiting specific locations. Designing incentive mechanisms for spatial crowdsourcing [24] presents new challenges as mechanisms must select users and assign suitable tasks, suggesting potential areas for research as spatial crowdsourcing develops.

Quality Control: Existing mechanisms considering user quality in mobile crowd sensing have limitations, as they require the platform to maintain extensive user information, which may be inefficient. Research opportunities lie in exploring methods akin to Internet crowdsourcing tasks [25], [26] that utilize statistical tools for high-quality data summarization without the need for comprehensive user information logs.

Privacy Tradeoff: Monetary compensation to participants may compensate for privacy leaks, but protecting participants' privacy remains a significant concern. Mobile crowd sensing tasks are location-dependent, yet many incentive mechanisms disregard privacy protection. Research should aim to develop efficient incentive mechanisms with privacy safeguards. For instance, Singla and Kause [27] propose a mechanism where users only reveal obscured locations during bidding, enhancing privacy while sacrificing some platform utility in the user selection phase. More work is needed in this area to balance privacy and compensation.

This research contributes to addressing some the significant privacy concerns in crowdsensing with regards to monetary incentives in auctions by utilizing the blockchain technology, which is guaranteed to be transparent, immutable, and provides security and anonymity to users.

In summary, effective incentive mechanisms in crowdsensing depend on understanding the motivations and preferences of the target participants and aligning those incentives with the project's goals. A well-designed incentive system can lead to more active and sustained participation, resulting in a richer dataset and more successful crowdsensing initiatives.

3.2 Incentive Mechanisms using Blockchain

Related works on utilizing Blockchain technology in the implementation of a decentralized incentive mechanism for crowdsensing were reviewed to have further insight.

[7] is a proposed solution to the privacy limitations of traditional crowdsensing systems using blockchain technology and an incentive mechanism. The system runs on the Ethereum platform, which supports decentralized applications through smart contracts - immutable pieces of code stored on the blockchain and executed by the Ethereum Virtual Machine. An auction algorithm determines the payment a user receives for completing a crowdsensing task.

The system architecture involves Crowdsensing Service Providers (CSPs) publishing tasks and sending a request to Internet Service Providers (ISPs) through smart contract transactions. The ISP triggers another smart contract transaction and publishes the task to a specific set of vehicles (users), who bid on the request. Winning bids are selected, and data transfer is initiated, with a data hash stored in a smart contract and the actual data in encrypted storage of the ISP. Once the CSP releases payment to the ISP, the ISP shares the encryption key and data with the CSP and transfers payment to the vehicle. Two smart contracts are used for registration and bid selection, with data hashes verifying the integrity of the data transferred. Temporary IDs preserve the identity of the vehicle/user.

The system's performance was evaluated through a simulation on the Ethereum testnet using Remix, an in-browser Ethereum environment. The auction algorithm was run with 10 users and randomly generated CSP task requests and bid prices, with results obtained and observed from smart contract logs.

[28] proposes using blockchain and smart contracts on the Ethereum platform to create a decentralized mobile crowdsensing framework. In a centralized system, all transactions go through a single platform, which is susceptible to manipulation and failure. However, in a decentralized system, all transactions go through blockchain smart contracts, which are resistant to centralized drawbacks.

The proposed architecture includes a smart contract, computing oracles, data requesters, and mobile workers. Initially, everyone registers through the smart contract. A data requester publishes tasks through the smart contract, and mobile workers retrieve the tasks, create sensing plans, and submit them to the smart contract. Computing oracles select the best sensing plan, and mobile workers complete their tasks, submitting data hash values to the blockchain for later verification. The rewards are then transferred from the data requester to the mobile workers through the smart contract. The author also proposes solutions for path selection and planning for mobile workers based on location and distance to the destination.

A simulation was conducted with a limited sensing region of 100m, 10 tasks, and 15 mobile workers. Bidding paths were selected based on minimum transaction costs and the number of tasks a mobile worker had in their travel path. The author's computer served as a computing oracle to determine resultant paths and rewards, and winning mobile workers completed the sensing tasks. Data was submitted using a hashing function, and the smart contract verified the data before distributing rewards.

[29] proposes an auction-based reward system for IoT collaboration that uses smart contracts to maintain privacy, as sensitive information is often involved. To keep participants involved and incentivize those who drop out due to certain failures, a dropper recruitment scheme is proposed. Since IoT managers own the sensors and therefore the data, one of the main issues addressed is the "incentive cost explosion" where a few data sellers control the bidding process and set high prices if the number of sellers falls below a certain level. To prevent this, a virtual credit system is used to encourage data sellers to stay and participate in the auction process. These credits are awarded when their bid is not selected in an auction, and they can use them in future auctions to obtain a discount on their bid price. The dropper recruitment scheme also helps to maintain a healthy bidding competition. The author suggests revealing the maximum bidding price of the winners to the dropped managers to increase their chances of winning the bid in the next auction.

The blockchain-based implementation involves customers publishing their service requests to the service provider, who then sends these requests, along with task details, to IoT managers via a blockchain smart contract. The IoT managers assess the task details and provide bids based on their estimates, which are then published on the blockchain. The winning bid is determined through the auction mechanism within the blockchain smart contract, and the winners are expected to transfer the data, which is verified using a data hash and submitted data. To prevent bid prices from being leaked prior to the auction's completion, there are two phases of data transfer. In the first phase, the hash of the data and the bid prices are stored, and after the bidding is closed, the IoT managers submit the actual price and data hash, revealing the winning bid.

However, most of the current blockchain based incentive mechanisms only consider privacy preservation, decentralization, and simply use a reverse auction mechanism and work with traditional economic principles.

3.3 Incentive Mechanisms using Behavioral Economics

[30] describes that addiction can be a powerful motivator for participation in crowdsensing tasks, and they propose a new addictive incentive mechanism to increase participation and engagement. The mechanism is based on the principles of behavioral economics, which considers the ways in which people make decisions and respond to incentives.

The addictive incentive mechanism works by offering participants a reward for completing a certain number of tasks, and then increasing the reward as they continue to complete tasks. This creates a sense of momentum and progress that can be addictive, leading participants to continue participating even after they have met their original goals.

To evaluate the effectiveness of the addictive incentive mechanism, the authors conducted a series of experiments using a crowdsensing platform that collects data on air quality. The results showed that the mechanism was effective in increasing participation and engagement, and that it outperformed other incentive mechanisms such as monetary rewards and social recognition.

[31] argues that the traditional incentive mechanisms such as monetary rewards and social reputation are not effective in motivating vehicle owners to participate in offloading tasks due to various factors such as privacy concerns.

To address this issue, the authors propose a gift-based incentive mechanism that leverages the endowment effect, a psychological phenomenon where people tend to overvalue objects they own. The mechanism works as follows: when a vehicle owner offloads a task, they receive a gift in return, which can be either a physical item or a digital token. The gift serves as an endowment, increasing the perceived value of the offloaded task and thus increasing the likelihood that the owner will participate.

The authors conducted a simulation-based experiment to evaluate the effectiveness of the mechanism using a real-world dataset of taxi trajectories in Beijing. The results showed that the gift-based incentive mechanism outperformed the traditional monetary reward and social reputation-based mechanisms in terms of both participation rate and task completion rate.

[32] proposes a new incentive mechanism that leverages the decoy effect and fairness preferences to encourage participation in crowdsensing tasks. The decoy effect refers to the phenomenon where adding a third, less attractive option can influence the choices people make. Fairness preference refers to people's desire for a fair outcome in social interactions.

The proposed incentive mechanism involves presenting participants with three options: a low effort task with a small reward, a high effort task with a large reward, and a decoy task with a moderate reward. The decoy task is designed to be less attractive than the high effort task but more attractive than the low effort task. The authors hypothesize that the presence of the decoy task will increase the attractiveness of the high effort task by creating a contrast effect, and that fairness preferences will lead participants to choose the high effort task over the decoy task.

The results from the experiments showed that this incentive mechanism was effective in increasing participation and engagement, and that it outperformed other incentive mechanisms such as a fixed payment and a variable payment based on task completion.

However, these related works using the concepts of behavioral economics implement their framework in centralized MCS. They have not considered that blockchain with smart contracts can improve the security of the system and preserve the privacy of users when the transactions keep growing.

Thus, this motivates us to propose a novel blockchain-based MCS framework that preserves privacy and secures both the sensing process and the incentive mechanism considering endowment effect and fairness preference to guarantee the long-term users' participation rate. First, we describe the framework of the blockchain-based MCS with smart contracts and its workflow. This framework provides the solution of participants' privacy and sensing procedure security. Second, we design the reverse auction process considering fairness preference and endowment effect. BIMEE gives initial endowment tokens to users based on their reputation, the platform selects winners of bidding with endowment tokens promotion and uses profitability values to control fairness of participating bids. Third, we have implemented the proposed framework and incentive mechanisms on the Ethereum testbed to prove the efficiency.

4. METHODOLOGY

4.1 Overview

This part of the document covers the technical details, structure, and functioning of our decentralized blockchain framework. It also describes the incentive mechanism with fairness preference and endowment effect. The implementation is done in a single smart contract written in Solidity, which contains various structures for holding data, such as User, Task, Bid, and Task Result. The smart contract has checks to ensure that methods are invoked in the correct order and by users with the correct roles. The system emits events to notify workers and publishers about the status of tasks and bids. This smart contract implementation of BIMEE serves as the cornerstone of this research. It facilitates the interaction between various users, including task publishers and workers, ensuring fair and efficient crowdsensing operations.

The contract introduces several vital data structures and functions to use and work with required data within the blockchain and smart contract environment:

4.1.1 Data Structures

User Structure (User):

- Tracks user type (Task Publisher or Worker).
- Captures usernames and wallet addresses.
- Manages registration status, endowment tokens, and user locations.

Task Structure (Task):

- Handles task-related information, such as task ID, publisher ID, worker IDs, budget, deadline, location, and status.
- Utilizes arrays to store worker IDs, enabling multi-worker tasks.
- Allows publishers to publish tasks, initiate task phases, and receive results.

Bid Structure (Bid):

- Manages bid information, including bid ID, task ID, worker ID, bid amount, and status.
- Supports the bid selection process by marking selected bids.

Task Result Structure (TaskResult):

- Facilitates result submission, including result ID, task ID, worker ID, data hash, data, and completion status.
- Facilitates data verification and ensures integrity by supporting result retrieval for task publishers.

4.1.2 Modifiers & Functions

Modifiers: The contract employs modifiers to restrict access to specific functionalities, ensuring that only authorized users can perform certain actions.

- \`onlyOrganizer\`: Limited to the contract organizer.
- \`onlyPublisher\`: Reserved for registered task publishers.
- \`onlyWorker\`: Restricted to registered workers.
- \`onlyNewUser\`: Ensures that new users can register.

Functions: The contract includes a range of functions for user registration, task publishing, bidding, task initiation, and result submission. Notable functions include:

- \`addUser\`: Allows new users to register with user type, name, and location.
- \`publishTask\`: Empowers publishers to create tasks with budgets, deadlines, and location criteria.
- \`submitBid\`: Permits workers to submit bids for open tasks.
- \`closeBidding\`: Enables publishers to close bidding and select winning bids.
- \`initiateTask\`: Allows workers to initiate tasks they've been assigned.
- \`submitTask\`: Facilitates result submission by workers.
- \`completeTask\`: Enables publishers to complete tasks, rewarding successful workers and penalizing failures.

In summary, this smart contract implementation offers a robust infrastructure for this research thesis. It introduces an innovative incentive mechanism that drives user participation and task success in a privacy-preserving environment.

The workflow of the system is displayed in Figure 6 and involves different phases for tasks, including Published, Bid Closed, Initiated, Submitted, and Completed. Workers can access all open tasks and submit bids using the "submitBid()" method. Publishers can create and publish tasks, close bidding, and execute task completion. The profitability of workers is calculated during the reverse auction process to ensure platform fairness, and endowment tokens are allocated based on their reputations to encourage long-term participation.

4.2 Task Cycle and Workflow

Each published task transitions from one phase to another according to its status in its cycle as illustrated in Figure 6. The distinct phases of the task are described below:

Published: This is the initial phase of a task when a task publisher publishes a task with a specified budget, number of workers and other task parameters. All tasks in this phase are returned when workers fetch all open tasks to submit bids for.

Bid Closed: Whenever the task publisher determines that they have received enough bids, they can invoke the "closeBidding()" method to change the task from "Published" phase to "Bid Closed".

Initiated: Once bidding has been closed by the publisher, Workers can start working on the tasks by invoking the "initiateTask()" method. Once all workers whose bids were selected invoke the specified method, the Task transitions to this phase.

Submitted: Once a worker determines they meet the task criteria, they can submit their collected data, and the data hash to the "submitTask()" method. Once all the designated workers for the Task have invoked the above method, The task transitions to the "Submitted" phase.

Completed: Once a task is in the "Submitted" phase, the publisher of the corresponding task invokes the "completeTask()" method to verify the submissions and transfer the bid/reward amount from their wallet to the workers’ wallet respectively, thus, finalizing the task.

Once a task is published, workers can access it and submit their bids. The publisher can then close the bidding and initiate the task by invoking the "initiateTask()" method. Once all designated workers submit their collected data using the "submitTask()" method, the task transitions to the "Submitted" phase. Finally, the publisher verifies the submissions and transfers the reward to the workers' wallets using the "completeTask()" method to finalize the task.

After the workers finish the task, they use keccak256, a one-way hashing algorithm to generate a hash of the data, which they then submit to the "submitTask()" method along with the actual data. This hash is used to confirm that the data hasn't been tampered with and is still intact.

In this implementation, both data input and verification happen within the smart contract. When the Task publisher invokes the "completeTask()" method, the verification takes place, and the bid submitted by the worker is retrieved and transferred from the publisher to the worker. To optimize this process, it would be useful to have a platform that acts as an intermediary between the smart contract and the users, fine-tuning the parameters, performing computations and passing data and invocations to the smart contract.

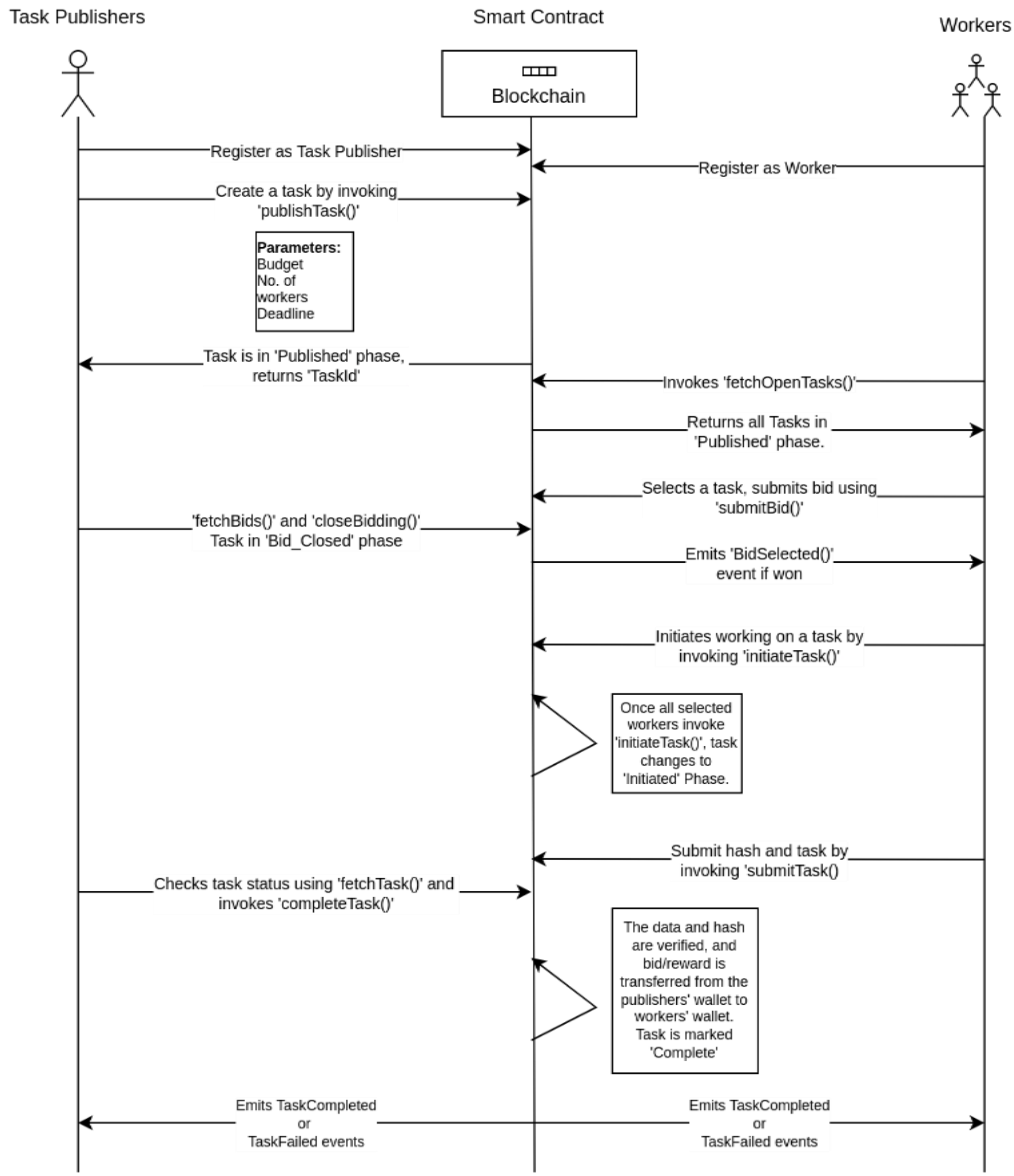

Figure 6. BIMEE Workflow

To ensure that only the task owner can mark it as complete and fetch its bids, and that workers can only perform their duties, several checks and constraints have been implemented. The blockchain's characteristics guarantee that these constraints work as intended.

4.3 Endowment Effect

The Endowment Effect is a psychological phenomenon that describes how people tend to overvalue objects they possess or own, even if the objects have no inherent or market value. In other words, individuals place a higher value on things merely because they own them. This can lead to irrational decision-making, such as refusing to part with an item unless offered a price significantly higher than its perceived value.

The Endowment Effect challenges the traditional economic assumption that individuals make decisions solely based on the objective utility or value of an item. It suggests that emotions, attachment, and the mere act of possession can significantly influence how people value and trade items.

4.3.1 Illustration of Endowment Effect

The experiment conducted by Richard Thaler at Cornell University as described in [33], highlights the phenomenon where people tend to overvalue items they own. In this experiment, participants were randomly assigned to one of two groups. Group A received a coffee mug as a token of ownership, while Group B did not receive a mug. Subsequently, both groups were given the opportunity to engage in a trading activity.

What made Thaler's experiment intriguing was that the coffee mugs were not personalized or of unique significance. They were regular, run-of-the-mill mugs with no inherent sentimental or functional value. Despite this, the participants who were given a mug (Group A) displayed a strong reluctance to part with their mugs when asked if they wanted to trade with members of Group B, who did not own mugs.

Thaler's findings indicated that individuals who had been endowed with the mugs (Group A) placed a higher subjective value on their mugs merely because they possessed them, as illustrated in Figure 7. They were often unwilling to make an even exchange, suggesting that they perceived their mugs as more valuable than the identical mugs offered by Group B. This tendency to ascribe higher value to owned items compared to equivalent items they don't own became a foundational concept in behavioral economics and was termed the "endowment effect."

Figure 7. Mug Experiment Illustration

Thaler's experiment effectively demonstrated that the endowment effect is a robust psychological phenomenon, leading to the formulation of insights and theories related to human decision-making, preferences, and the evaluation of possessions. This cognitive bias has far-reaching implications for various fields, including economics, marketing, and psychology, as it shapes the way individuals make choices and interact with the world around them.

4.3.2 Effect on Incentive Mechanisms

The Endowment Effect can impact incentive mechanisms by affecting how individuals respond to changes in ownership or endowments. For example, if people overvalue what they already own, they may be less motivated to trade or exchange their possessions, even if such exchanges could potentially lead to more efficient outcomes or vice versa, if we can make people value the incentive more, this will benefit an incentive mechanism. This can affect the willingness of individuals to participate in incentive programs or initiatives that involve trading or giving up their existing assets. Here's the breakdown of how the Endowment Effect can influence incentive mechanisms and improve efficiency:

Perceived Value: The Endowment Effect causes individuals to overvalue items or benefits they already possess. In the context of incentive mechanisms, this means that individuals may overvalue the rewards or incentives they receive as part of the mechanism. They perceive the incentives as more valuable than they objectively are, which can motivate them to participate more actively in tasks or behaviors associated with the incentives.

Participation and Engagement: When individuals feel a sense of ownership or attachment to incentives, they are more likely to participate in activities or tasks to maintain or increase those incentives. Incentive mechanisms that capitalize on the Endowment Effect can enhance participation rates and engagement levels. For example, in crowdsensing systems, individuals may be more motivated to contribute data or complete tasks if they have an endowment of tokens or rewards.

Retention: Incentive mechanisms that trigger the Endowment Effect can improve user retention. Participants who feel attached to their accumulated rewards are less likely to abandon the system. Retained users contribute to the long-term success of the mechanism.

In summary, the Endowment Effect can enhance the effectiveness of incentive mechanisms by increasing perceived value, participation, engagement, and retention. It can be a valuable tool in motivating individuals to take desired actions or make decisions that benefit both users and the system implementing the incentives.

4.3.3 Applications of Endowment Effect

The Endowment Effect, a cognitive bias in which individuals tend to overvalue items or possessions merely because they own them, has been studied in various real-world contexts. Here are some examples of its applications in different domains:

Real Estate: The study [34] examined the impact of the Endowment Effect on consumer preferences for real estate. Results showed that people often perceive more value in a house or property they own compared to an equivalent one they do not, leading to potentially inflated valuations.

Market Pricing: The research [35] investigates how the Endowment Effect can influence market pricing. Sellers tend to value their goods higher than potential buyers, leading to disparities in price expectations and potential difficulties in negotiations.

Psychological Ownership: The study [36] explores the concept of psychological ownership and how it contributes to the Endowment Effect. It was found that sellers tend to experience greater emotional attachment to items they own, which influences their valuation of those items.

Gift Cards and Coupons: The study [37] delves into the implications of the Endowment Effect for gift cards and coupons. It demonstrates how gift card recipients often overvalue the cards, leading to less effective usage and increased profitability for retailers.

Free Trial Subscriptions: Many streaming services, software platforms, and online publications offer free trial subscriptions to attract potential customers. During the trial period, consumers gain access to the service's features without financial commitment. Consumers who enjoy a free trial of a service may start to feel a sense of ownership and attachment to the features they've used. This sense of ownership, a key component of the Endowment Effect, can lead them to overvalue the service and potentially become paying customers.

These examples illustrate how the Endowment Effect can manifest in various aspects of decision-making, economics, and consumer behavior. The bias's influence on people's perceptions of ownership and valuation is a well-documented phenomenon in behavioral economics and psychology.

4.3.4 Endowment Effect Implementation

In this implementation, each publisher is represented as P_i, each worker is represented as W_i and initially receives a constant number of endowment tokens, denoted as T_i. Upon successful completion of a task, workers are rewarded with additional endowment tokens proportional to their bid amount, indicated as $T_{awarded\_i}$. Conversely, if a worker fails to complete the task, a certain number of endowment tokens are deducted, denoted as $T_{deducted\_i}$. These endowment tokens do not possess any monetary value but are used to provide a preferential bias in the bidding process.

Workers are categorized into different reputation levels based on the cumulative number of tokens they possess. Let R_i denote the reputation level of worker W_i. The reputation levels are represented as L_i (e.g., L_0, L_1, L_2, L_3). Workers with a higher quantity of endowment tokens receive a discount on their bid price during the bidding process, denoted as D_i (preferential bias). The discount rate (D_i) is determined by the worker's reputation level.

Initially, all workers are provided with 500 endowment tokens and commence at L_2. Workers who accumulate more than 1000 tokens are promoted to L_3, while workers with token amounts between 500 and 1000 tokens remain at L_2. Workers holding between 100 and 500 tokens are categorized as L_1, and those with fewer than 100 tokens are placed in L_0. The specific reputation level for worker W_i is determined as follows:

L_0 = 0 -> (D_i)
L_1 = 5
L_2 = 10
L_3 = 20

If $T_i > 1000$, then
    $R_i = L_3$
If $500 <= T_i < 1000$, then
    $R_i = L_2$
If $100 <= T_i < 500$, then
    $R_i = L_1$

The workers with higher reputation levels benefit from a higher preferential bias, as they receive a more substantial discount when compared to other bids for a specific task. The number of endowment tokens awarded upon the successful completion of a particular task, is calculated using the following equation:

$$T_{awarded(i)} = 2 \cdot 10^{-9} \cdot b$$

Where, $T_{awarded\_i}$ is the number of tokens to be awarded and b is the bid amount of the respective task.

The described methodology introduces the endowment effect into BIMEE’s incentive mechanism and has the potential to improve the efficiency in the following ways:

Endowment Effect Introduction: By providing workers with endowment tokens initially, a psychological attachment to these tokens is created. This is a fundamental aspect of the endowment effect - people tend to overvalue items or assets they already possess. In this case, the endowment tokens serve as the "possession," leading workers to value them more than if they hadn't initially received them.

Reputation Levels: The grouping of workers into reputation levels based on the number of endowment tokens they hold is a way to leverage the endowment effect. Workers naturally become more motivated to accumulate these tokens because they grant them access to higher reputation levels and discounts. This progression aligns with the endowment effect as workers perceive these tokens as valuable and something they've "earned."

Discount Mechanism: The application of discount percentages based on reputation levels during the bidding process plays a crucial role. Workers with more endowment tokens (higher reputation levels) have an advantage over others, creating a preferential bias. This bias strongly appeals to the endowment effect, as workers are less likely to risk losing the perceived value of their tokens. This motivates them to bid more actively.

Token Reward and Deduction: The reward system for completing tasks successfully by earning more endowment tokens and the deduction for failure align with the principles of the endowment effect. Workers who have earned tokens will become more attached to them and strive to keep them, while the fear of losing tokens through failure creates a protective mechanism. This plays on the aversion to losses often seen in behavioral economics.

The notations used and their descriptions are listed in Table 1 below for ease of reading and understanding.

Table 1. Notations used in EE Introduction

Notation	Description
W_i	Worker (i)
P_i	Publisher (i)
B_i	Bid by worker W_i on a task
T_i	Endowment tokens initially given to worker W_i
$T_{awarded\_i}$	Endowment tokens awarded to W_i for task completion
$T_{deducted\_i}$	Endowment tokens deducted from W_i for task failure
R_i	Reputation level of a worker W_i
L_i	Reputation level (i)
D_i	Discount rate (preferential bias) for W_i

Overall, the introduced methodology effectively leverages the endowment effect by psychologically attaching workers to their endowment tokens. Workers, motivated to accumulate and retain tokens, are categorized into reputation levels, providing them with access to varying discounts based on their token holdings. This progression aligns with the endowment effect, fostering worker participation and continued involvement. The application of discount percentages during the bidding process further reinforces the preferential bias, motivating workers to bid more actively. The reward and deduction system for completing or failing tasks aligns with the principles of the endowment effect, promoting attachment to earned tokens and aversion to losses, ultimately enhancing participation and efficiency in the incentive mechanism.

4.4 Fairness Preference

Fairness preference refers to the idea that people often make decisions not only based on their self-interest but also on principles of fairness, equity, and reciprocity. Behavioral economics studies how individuals are willing to make trade-offs and decisions that may seem economically suboptimal but are driven by a sense of fairness. For example, people may be willing to accept lower monetary rewards in a negotiation if they perceive the distribution of resources as unfair. This concept challenges the traditional economic assumption of strict rational self-interest and suggests that notions of fairness and equity play a significant role in decision-making.

4.4.1 Illustration of Fairness Preference

The Ultimatum Game is a widely studied experiment in behavioral economics used to examine fairness preferences. In this game, two players, the proposer and the responder, are presented with a sum of money. The proposer decides how to divide this sum and offers a portion to the responder. The responder can then choose to accept or reject the offer. If the responder accepts, both players receive the proposed split. However, if the responder rejects, both players receive nothing. This experiment explores how people make decisions regarding fairness and self-interest. It has been observed that proposers often offer a fairly equal split, while responders tend to reject offers they perceive as unfair, even when it means they receive nothing. This demonstrates the importance of fairness in economic decision-making.

Hoffman, McCabe, and Smith (1996) conducted a significant study [38] involving the Ultimatum Game, where participants engage in both high-stakes and low-stakes versions of the game. In the high-stakes game, the proposer offers a significant sum of money (typically half of the total amount), while in the low-stakes game, the amount offered is considerably smaller. The data as shown in Figure 8 from this study revealed some intriguing behavioral patterns.

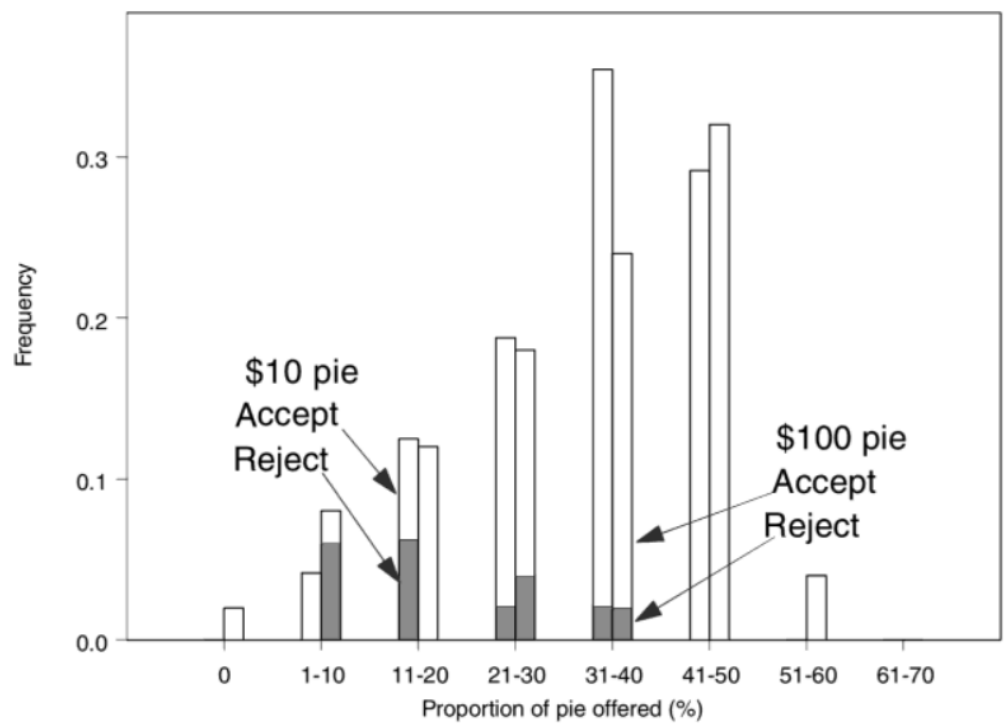

Figure 8. Offers and Rejections in High- and Low-stakes Ultimatum Games

In the high-stakes Ultimatum Game, the proposers typically made fair offers, dividing the amount almost evenly with the responders. This is in line with the notion of fairness, suggesting that proposers were motivated to make equitable offers when substantial sums were at stake.

However, the low-stakes Ultimatum Game painted a different picture. In this version, proposers often made substantially lower offers, which could be seen as unfair from the perspective of responders. Responders, despite facing smaller absolute losses in this version, exhibited a higher inclination to reject these unequal offers compared to their counterparts in the high-stakes game.

This discrepancy in behavior between high- and low-stakes games underscores the importance of context and the role of relative considerations in economic decision-making. Even when the amounts involved are relatively small, people are still influenced by perceived fairness and are willing to reject unfair offers, showing that social norms and notions of fairness play a significant role in shaping economic behavior. This research sheds light on the complexities of human decision-making and the impact of stakes on our willingness to enforce fairness norms.

4.4.2 Effect on Incentive Mechanisms

Fairness preferences play a crucial role in incentive mechanisms, particularly in situations where individuals must cooperate, share resources, or engage in reciprocal interactions. People are often willing to forgo potential gains if they perceive a distribution of rewards or resources as unfair. Incentive mechanisms need to consider these fairness concerns to motivate individuals effectively. Designing incentive mechanisms that are perceived as fair and equitable is essential to ensure they motivate desired behaviors. Here are some of the effects of Fairness Preference on incentive mechanisms based on various studies like [38]:

Participation and Cooperation: Fairness Preference encourages individuals to participate and cooperate in incentive mechanisms. People tend to favor equitable outcomes, and if they perceive that a mechanism is fair, they are more likely to engage actively in tasks or activities.

Equitable Rewards: Fairness Preference implies that individuals prefer equitable or proportional rewards. Incentive mechanisms that offer fair compensation, considering the effort and contribution of participants, are more likely to motivate individuals to perform well.

Reduced Inequality Aversion: Incentive mechanisms that promote fairness can mitigate inequality aversion. When participants perceive that the distribution of rewards is fair, they are less likely to resist income inequalities.

Sustained Engagement: Fairness Preference can lead to sustained engagement in incentive mechanisms. Participants are more likely to stay involved over the long term if they believe that the system treats them fairly and that their contributions are appropriately rewarded.

Compliance and Trust: Fairness contributes to higher levels of compliance and trust within incentive systems. Participants are more likely to adhere to the rules and trust the fairness of the system, which is essential for smooth operation.

Motivated Behavior: Fairness Preference motivates individuals to perform tasks efficiently and effectively. When they feel that their contributions are fairly recognized, they are more motivated to excel in their roles.

The design of incentive systems should consider participants' preferences for fairness and aim to balance efficiency, equity, and cooperation. Additionally, behavioral economics studies often explore how individuals' sense of fairness influences their decisions and behaviors, providing insights into the design of effective incentive mechanisms.

4.4.3 Applications of Fairness Preference

The observations of the study [38], the findings from the ultimatum game about fairness preference can be applied to broader real-world concepts like the following:

Salary Negotiations: Individuals often base their salary demands on the perceived fairness of their compensation compared to industry standards or the salaries of their colleagues. Fairness plays a crucial role in employment relationships and job satisfaction.

Taxation and Wealth Redistribution: Government policies related to taxation and wealth redistribution are often influenced by the principle of fairness. Citizens expect the tax burden to be distributed fairly, and policymakers aim to create tax systems that align with these fairness preferences.

Pricing Strategies: Companies use pricing strategies that customers perceive as fair. For example, dynamic pricing that adjusts based on demand can lead to perceptions of unfairness if not properly managed.

4.4.4 Fairness Preference Implementation

In this reverse auction system where workers can bid on open tasks after fetching them and the smart contract keeping records of all the bids, fairness is ensured in the bidding process by preventing workers from bidding on any tasks if their profitability exceeds a pre-defined constant.

Worker profitability is calculated based on this formula:

$$profitability\ (P_i) = \left(\frac{cp_i}{cc_i} \cdot 100\right)$$

In the above equation, cp_i represents the total profits earned by worker W_i across multiple tasks, while cc_i signifies the cumulative costs incurred to perform those tasks. The profitability metric, as calculated, serves as a fairness criterion by considering not only individual interests but also the equitable distribution of payments.

In line with the fairness preference theory, which suggests that individuals assess their overall utility based on the fairness of payment distribution, workers with a profitability exceeding P_{cutoff} are prevented from bidding on tasks. Such workers receive a minor penalty, defined as $P_{high\_penalty}$ to normalize their profitability for the subsequent cycle. Additionally, each worker's cost per task, denoted as $W_{cost\_\mathrm{in\_wei}}$ is used to calculate the cost penalty.

The profitability cutoff pseudocode, which enforces this fairness preference principle, is given below:

```
SET P_cutoff = 70
SET P_high_penalty = 1
SET W_cost_in_wei = 2

IF P_i < P_cutoff, then
        CONTINUE BIDDING
ELSE
        cc_i = cc_i + ( P_high_penalty * W_cost_in_wei )
```

To initiate the task completion process, the publisher calls the "fetchBids()" function which retrieves all the bids and selects the lowest "n" bidders for the task. These selected bids are then passed to the smart contract by invoking the "closeBidding()" function for the respective task, which triggers the "BidSelected" event. Upon receiving this event, the corresponding workers can start the task. The profitability cutoff is implemented during this phase of closing the bidding on a particular task.

The notations used in this methodology are listed below in Table 2 for ease of reading and understanding:

Table 2. Notations used in FP Introduction

Notation	Description
P_i	Profitability of worker W_i
cp_i	Cumulative profits earned by worker W_i
cc_i	Cumulative costs incurred by worker W_i
P_{cutoff}	Profitability cutoff threshold
$P_{high\_penalty}$	Penalty for exceeding profitability cutoff
$W_{cost\_in\_wei}$	Worker's cost per task (in wei)

The described methodology of Profitability Cutoff introduces Fairness Preference into BIMEE's incentive mechanism and improves the effectiveness in the following ways:

Equity and Fairness: By setting a profitability cutoff, fairness preference is implicitly introduced into the incentive mechanism. Workers are restricted from participating in the bidding process if their profit rate exceeds a certain specified amount. This rule is designed to ensure that workers do not disproportionately benefit from the system, thereby promoting fairness and equity in the distribution of rewards.

Fair Opportunity: The cutoff ensures that all workers have a fair and equal opportunity to participate in the bidding process. This aligns with the concept of fairness, as it prevents a subset of workers from dominating the system due to exceptionally high profit rates.

Preventing Exploitation: The profitability cutoff helps prevent any potential exploitation of the system. Without such a mechanism, highly efficient workers might continually reap the rewards, potentially discouraging others from participating. The cutoff encourages workers to maintain a reasonable profit rate, which is essential for the overall integrity of the system.

Long-Term Sustainability: The gradual reduction of a worker's profit rate when they sit out bidding cycles encourages sustained participation. This gradual approach allows workers who may have previously earned high profits to still have a chance to participate after their profit rate decreases. It fosters an environment where workers can maintain their participation over the long term.

Balanced Motivation: The cutoff ensures a balanced motivation for all workers. It discourages excessive competition that could lead to unfair outcomes. Workers are motivated to participate at a level that allows others to join the bidding process, resulting in a more balanced and cooperative environment.

Encouraging Varied Contributions: By preventing workers with excessively high profit rates from dominating the system, the methodology encourages a diverse range of contributions. Workers may explore different tasks and challenges, which can lead to a more comprehensive and varied set of data or services provided within the crowdsensing system.

In summary, the profitability cutoff methodology introduces fairness preferences into the incentive mechanism by promoting equity, preventing exploitation, and ensuring a balanced and sustainable environment. It helps maintain the integrity of the system and encourages a diverse range of contributions from workers. These aspects collectively contribute to a more effective and equitable incentive mechanism within the crowdsensing system.

5. RESULTS AND DISCUSSION

5.1 Simulation Environment

Executing the smart contract implementation involves leveraging robust development tools that facilitate testing, deployment, and simulation. One such tool is "Remix," an in-browser Integrated Development Environment (IDE) designed for programming in the Solidity language. As the official IDE for Ethereum, Remix provides a seamless interface for developers to deploy and interact with smart contracts across Ethereum main network, test networks, or a local network. Its user-friendly design enables easy access to variables, data, and the invocation of methods within the deployed smart contract, simplifying the development and testing processes.

Complementing Remix is the utilization of "Hardhat" [39], a versatile Ethereum development environment engineered to empower developers in creating, deploying, and simulating smart contract implementations. Hardhat stands out by running a local Ethereum network, affording developers precise control over crucial parameters such as the number of wallet accounts and their balances within the Ethereum blockchain. This local environment grants developers the flexibility needed to thoroughly test and optimize the implementation. Moreover, Hardhat supports TypeScript, a powerful superset of JavaScript, and seamlessly integrates with "ethers" [40], a JavaScript library used for interacting with smart contracts.

By utilizing Hardhat for simulations, the research benefits from a nuanced understanding of the implementation's behavior under varying conditions, contributing to the robustness and reliability of the proposed incentive mechanism. This combination of Remix and Hardhat as development and simulation tools, respectively, forms a well-rounded approach, facilitating a meticulous exploration of the BIMEE implementation in different scenarios and network conditions.

The BIMEE smart contract is deployed to the local Ethereum network using Hardhat, which is set up to have 100 initial accounts funded with "ether." TypeScript simulation scripts are created using the "ethers" library to connect to a specific wallet account, execute smart contract methods, and fetch emitted events.

To simulate the experiment, 100 wallet accounts are randomly assigned as either workers or publishers by calling the "addUser()" method with appropriate parameters. Each publisher creates a random number of tasks, specifying the number of workers required, budget, and deadline. Workers bid on a random selection of open tasks, and the publisher selects and closes the bidding for each task, after which the simulation script listens for the "BidSelected" event to determine the bid winners. Workers then initiate and complete the specified task, submitting both the hash and data, which is a simple integer. The simulation script then listens for the "TaskCompleted" and "TaskFailed" events when the publisher invokes the "completeTask()" method for each task.

The experiment tracks several metrics, which include the worker participation rate, bid win rate, platform utility, worker utility, max and min worker win rates, task success rate, and number of iterations. The worker participation rate is the proportion of bids submitted by workers on published tasks. The bid win rate is the percentage of bids won by workers over the total bids submitted. The platform utility is the percentage of tasks completed within the publisher's budget. Worker utility is the percentage of completed tasks that resulted in a profit for the worker or the general profitability rate for workers participating in the system. The max and min worker win rates are the average bid win rates for workers holding the maximum and minimum number of tokens, respectively, in each iteration of the simulation. The task success rate is the rate of successful task completion, randomized for benchmark and with a variable advantage induced for BIMEE. The number of iterations is the number of times each simulation is run. Table 3 lists each metric, and how they are calculated in each simulation cycle.

Table 3. Metric Equations

Metric	Equation	Notations Used
Worker Participation Rate (*WP*)	$WP = (\sum\left(\frac{N_{wb}}{N_t}\right))/N_w$	N_{wb}: Number of worker bids N_t: Number of tasks published N_w: Number of workers
Bid Win Rate (B_{WR})	$B_{WR} = \frac{B_w}{B_t}$	B_w: Number of bids won by all workers B_t: Total number of bids by all workers
Platform Utility (*PU*)	$PU = \frac{N_{tb}}{N_t}$	N_{tb}: Number of tasks completed within budget N_t: Number of total tasks
Worker Utility (*WU*)	$WU = \frac{\sum\left(\frac{cp_i}{cc_i} \cdot 100\right)}{N_w}$	cp_i: Cumulative profits of Worker W_i cc_i: Cumulative costs of Worker W_i N_w: Number of workers
Task Success Rate (*TSR*)	$TSR = \frac{N_{tc}}{N_t}$	N_{tc}: Number of tasks completed N_t: Number of total tasks

The IoVBCI (Internet of Vehicles – Blockchain Crowdsensing Implementation) version is also developed on the Ethereum platform through a smart contract that is deployed on our local testchain using Hardhat, this is loosely based on the implementation details of [7] which proposes an innovative incentive mechanism in the context of crowdsensing leveraging blockchain technology to ensure privacy and security. However, unlike the BIMEE version, the benchmark version does not incorporate any behavioral economic principles such as Fairness Preference and Endowment Effect. Instead of the profitability criterion, the benchmark version has workers randomly bidding on a certain number of tasks available in each iteration. Similarly, the maximum and minimum workers are also selected randomly in the benchmark version.

5.2 Simulation Parameters

In this research, I aimed to introduce the endowment effect through the concept of endowment tokens and incorporate fairness preference by implementing a profitability cutoff in the incentive mechanism and simulation experiments as described in 4.5 have been conducted and various metrics have been observed. Several key parameters played a significant role in running these simulations. Here is an overview of the process:

Reputation Levels: Workers are categorized into different reputation levels based on the number of endowment tokens they possess. We established three reputation levels, each with specific token thresholds. Workers at different levels receive bid discounts in the bidding process, as mentioned in previous discussions. The initial token thresholds and associated bid discounts are as follows:

- Level 1: 100 tokens, Bid discount: 5%
- Level 2: 500 tokens, Bid discount: 10%
- Level 3: 1000 tokens, Bid discount: 20%

Initial Endowment Tokens: Workers were initially provided with 300 endowment tokens. This initial provision of endowment tokens reinforces the endowment effect.

Utility Cost: This parameter is considered to calculate the worker profitability, which is used to implement the profitability cutoff. This is initialized with a value of 2 wei.

Profitability Cutoff: the profitability cutoff value is set to be 70% for the simulation, workers whose profitability exceeds this are not allowed to participate in the bidding process. To normalize their profitability for subsequent cycles, we reduce their profitability by adding a constant value defined as NO_PPENALTY * UTILITY_COST of a task to their total utility cost.

In these initial simulations, selecting constant values for key parameters, such as thresholds for Reputation levels and the profitability cutoff, was a strategic choice aimed at establishing a baseline for evaluating the proposed incentive mechanism. By fixing these values, we aimed to observe the system's behavior under controlled conditions and discern the impact of the introduced behavioral economic principles. The choice of Reputation level thresholds and the discount rates for each level reflects a gradual progression, allowing for a nuanced exploration of how users' perceived reputation influences their decision-making. The profitability cutoff at 70% was selected based on a balance between encouraging users to bid competitively while ensuring a reasonable level of profitability. This initial set of constants provided a starting point to observe the functioning of the incentive mechanism under simplified scenarios, enabling a focused analysis of the behavioral economic principles' influence. As we progress to future parameter adjustments, the insights gained from these initial simulations will inform more dynamic and varied configurations, contributing to a comprehensive understanding of the system's behavior across a spectrum of conditions.

5.3 Simulation Results

The simulation experiment runs 100 simulations each for the benchmark and BIMEE versions, with each simulation having a random number of iterations in the range of 5 and 15. The metric data is stored for both the versions, and the plots are displayed using a JavaScript library “nodeplotlib” [41], comparing both versions, respectively.

BIMEE incorporates behavioral economic principles such as the endowment effect and fairness preference. The key findings and outcomes from the study are described below based on the results observed from the simulation experiments:

Higher Worker Participation: BIMEE's integration of the profitability criterion and preferential bias into the task bidding process has led to a higher worker participation rate, as shown in Figure 9 compared to the IoVBCI version. This indicates that workers are more motivated to participate in tasks that are profitable for them.

Fairness and Equal Distribution: The profitability criterion ensures that workers with an unfair advantage due to their high profitability are not given priority. This reflects a commitment to fairness and equity in the distribution of rewards.

Higher Platform Utility: Figure 10 shows that BIMEE exhibits significantly higher platform utility, mainly due to the increased participation rate. This higher utility is a result of more bids on each task and increased competition among workers.

Increased Worker Utility: Figure 11 demonstrates that worker utility is higher in BIMEE than in the benchmark version. This increase is attributed to the more even distribution of profitability among all workers in BIMEE.

Enhanced Task Success Rate: BIMEE shows a higher task success rate compared to the IoVBCI as shown in Figure 12. This advantage is attributed to the endowment effect, which provides workers with an added incentive in the task submission process.

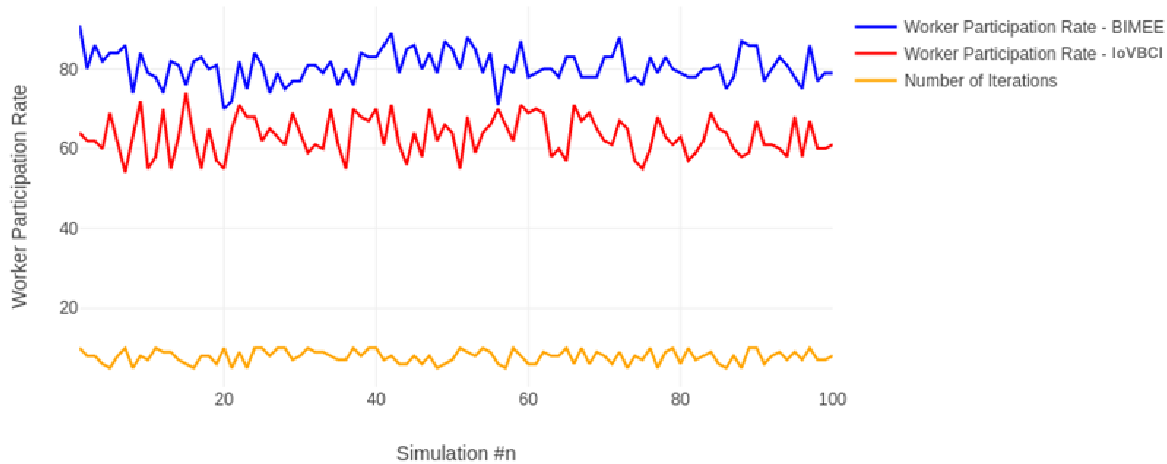

Figure 9. Worker Participation Rate

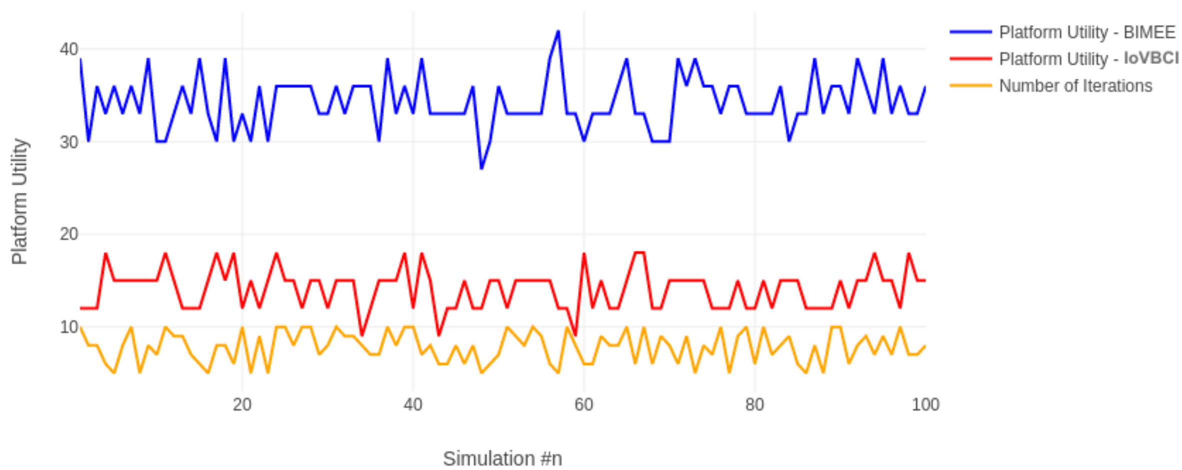

Figure 10. Platform Utility

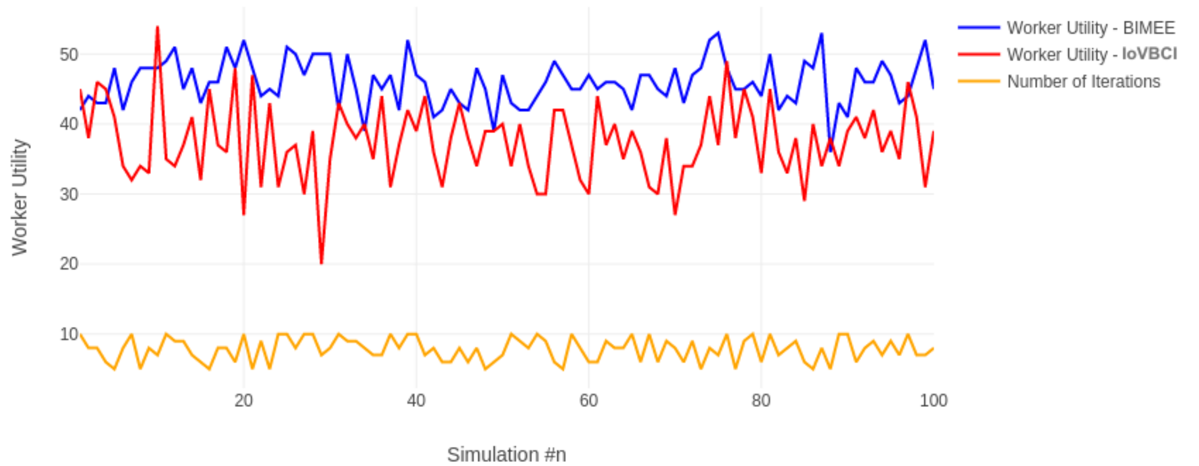

Figure 11. Worker Utility

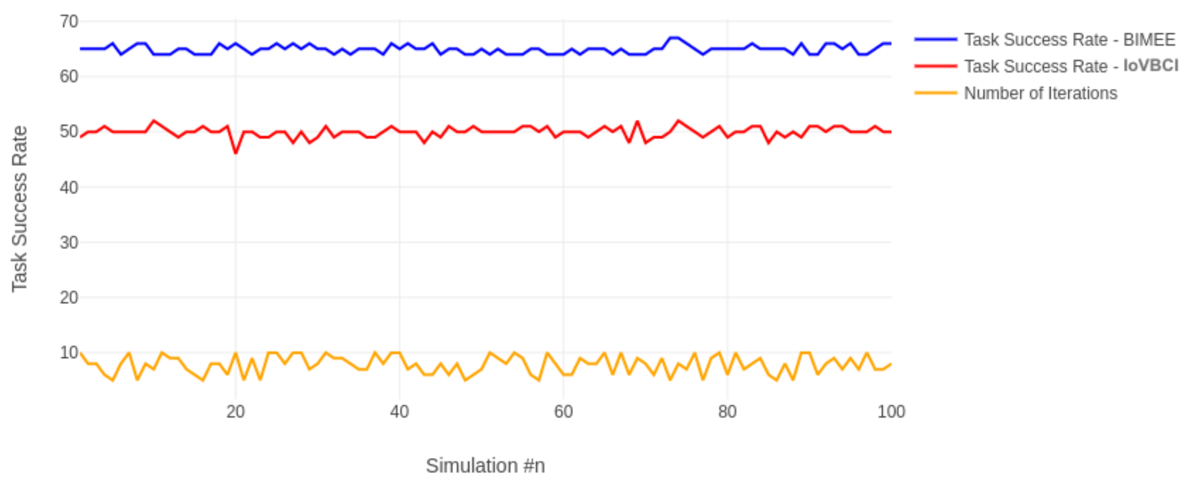

Figure 12. Task Success Rate

Preferential Bias and Endowment Tokens: Figure 13 indicates a varied spread in bid win rates in BIMEE, reflecting the implemented preferential bias based on the number of endowment tokens held by each worker. This bias motivates workers to participate more and successfully complete tasks. In contrast, the IoVBCI version does not show such variations in bid win rates as shown in Figure 14.

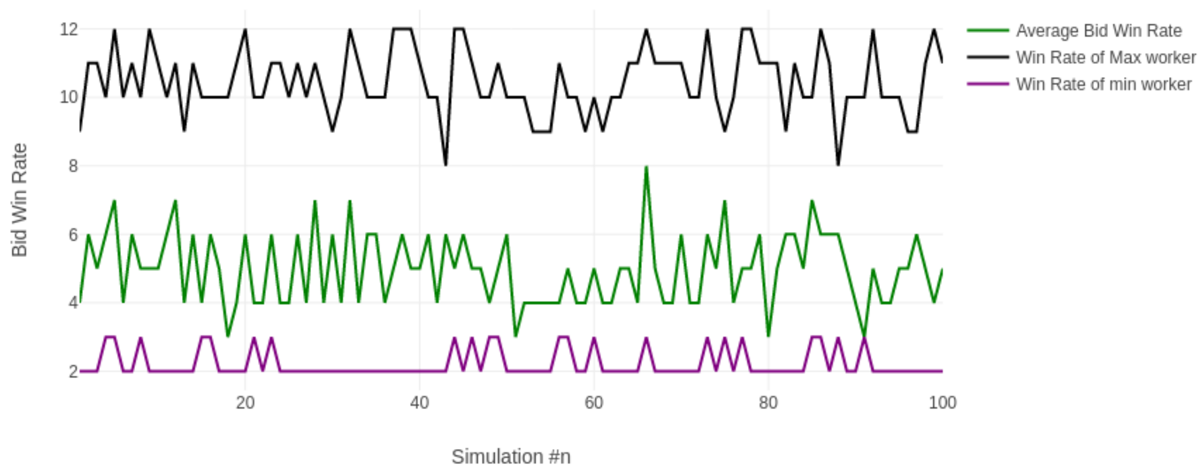

Figure 13. Bid Win Rates - BIMEE

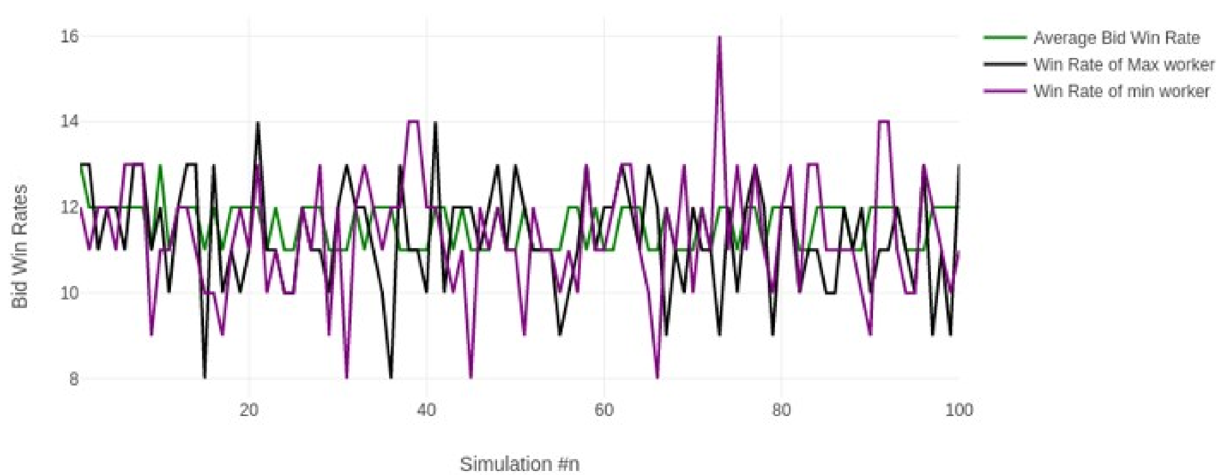

Figure 14. Bid Win Rates - IoVBCI

Overall, the results suggest that BIMEE, with its focus on the endowment effect and fairness preference, has been successful in increasing worker participation, promoting fairness, enhancing worker and platform utility, and improving task success rates in crowdsensing applications. The use of endowment tokens and preferential bias appears to be effective in motivating workers, while the profitability criterion ensures a balanced distribution of profits among participants. The study also indicates that this incentive mechanism is implemented through a privacy-preserving and smart contract-based approach.

5.4 Future Work in Parameter Adjustments

To ensure the robustness of our simulation results and to finetune the performance of our proposed incentive mechanism, we could conduct a series of iterations to find the optimal parameters. Here's an approach that was considered, in each simulation run, we execute a relatively large number of cycles, where specific parameters are systematically adjusted to gauge their impact. The parameter adjustments can be carried out as follows:

- Utility Cost (UTILITY_COST): Incremented by 1 wei in each iteration.
- No-Penalty Adjustment (NO_PPENALTY): Incremented by 0.5 during each iteration.
- Initial Endowment Tokens: Incremented by 50 in every new simulation.
- Reputation Levels: Thresholds for each reputation level were incremented in the following manner:
    - Level 1: Incremented by 5.
    - Level 2: Incremented by 25.
    - Level 3: Incremented by 50.
- Discount Percentage (Preferential Bias): Incremented by 2% for all reputation levels in each iteration.

This process can be reiterated several times, e.g., 10 times, and each simulation could encompass a relatively large number of bid cycles, e.g., 50 bid cycles. The iterative nature of this approach allows for ongoing refinement and optimization of the incentive mechanism to better understand and harness the implications of introducing the endowment effect and fairness preference in crowdsensing systems. It is important to note that while these adjustments provide valuable insights, they do not represent an exhaustive exploration of all potential parameter configurations. Therefore, there is room for further research and experimentation in this domain.

6. CONCLUSION

In this research, a blockchain-based incentive mechanism for crowdsensing systems is introduced, referred to as BIMEE (Blockchain-based Incentive Mechanism considering Endowment Effect). BIMEE leverages behavioral economic principles to enhance worker participation and fairness in crowdsensing tasks. It incorporates two fundamental concepts: the Endowment Effect and Fairness Preference.

The Endowment Effect was introduced through the issuance of endowment tokens to workers upon successfully completing tasks. These tokens do not have monetary value but provide preferential advantages in the bidding process. Workers accumulate these tokens based on task completion and are categorized into reputation levels that determine the extent of bid discounts they receive. The more tokens a worker possesses, the higher their reputation level and the greater their bid discount. This preferential bias incentivizes worker participation, and our simulations demonstrated that it has a positive impact on participation rates.

Fairness Preference was implemented through a profitability cutoff, ensuring that workers with disproportionately high profitability are excluded from bidding. Workers with profitability exceeding a specified threshold are temporarily prevented from participating, normalizing their profitability through subsequent deductions. The profitability criterion promotes fairness among workers, and our simulations indicated that it contributes to a more even distribution of profitability while maintaining a high worker participation rate.

The experiments and simulations on BIMEE, in comparison to a benchmark version that lacks these behavioral economic components, highlighted several key outcomes. BIMEE consistently achieved higher worker participation rates, utility for both workers and the platform, task success rates, and bid win rates. The introduction of endowment tokens in BIMEE provided an additional incentive for workers to engage actively in the bidding process. The profitability cutoff within the mechanism ensured that no worker could exploit the system unfairly. These results collectively demonstrate the effectiveness of our incentive mechanism in improving crowdsensing outcomes.

The findings of this research emphasize the significance of integrating behavioral economic principles into blockchain-based crowdsensing incentive mechanisms. BIMEE sets a precedent for the implementation of the Endowment Effect and Fairness Preference in incentive design, enhancing fairness and participation. The research also underscores the potential of blockchain technology in ensuring privacy, security, and efficiency in crowdsensing systems.

As with any study, certain parameters were defined to facilitate our simulations, and these parameters may require further fine-tuning to address real-world complexities and practical application. Future research can delve into refining the reputation levels and discounts, optimizing profitability thresholds, and expanding the scope of BIMEE to other crowdsensing contexts. Moreover, the privacy-preserving nature of BIMEE ensures that user data is secured within the blockchain, paving the way for the development of privacy-conscious crowdsensing systems.

In conclusion, the introduction of BIMEE as a novel blockchain-based incentive mechanism illustrates the potential of leveraging behavioral economic principles to create fair, efficient, and privacy-aware crowdsensing environments.

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