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SIMULATING PROSUMER DATA TRADING: TESTING A BLOCKCHAIN SMART CONTRACT BASED CONTROL

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ABSTRACT

Online data trading has grown alongside the ever-increasing use of digital services. Industries are accruing the benefits of this data access to perform mission-critical tasks by analyzing available data for greater insight. Unsurprisingly, data trading has not focused on improved data seller protection with preferences and controls. The objective of this paper is to explore the enforcement of seller preferences within smart contracts using blockchain technology. Data trading is only possible when a buyer satisfies the conditions predefined by the seller. Geographic location, type or size of buyer's company are some examples of seller preferences. A preferences algorithm provides an automated contract between seller and buyer without the involvement of any broker or third party. Hybrid simulation (HS) methods are used to test and evaluate the viability of our novel data control approach.

1 INTRODUCTION

Data is a collection of behavior that is related to observation, facts, and measurements. The global economy is operating through many trading platforms where businesses continually search for ways to gather data from diverse sources to enhance their business intelligence. Data trading is not a new concept, and it is widely used to improve business intelligence.

Although data trading has been carried out for some time, here we explore how additional seller controls can improve data trading – utilizing a specific type of smart contract and tested using Ethereum blockchain technology (Buterin 2022). Prosumers both produce and consume data using new digital services. A controlled prosumer market in data (Bell 2017) is formed when data can only be sold according to preferences defined by the seller and smart contracts control this data trading activity. Controls between buyers and seller are based on the predefined seller preferences such as business localization, business type and size of business. For example, sellers can restrict their data to be sold from any buyers from a specific country.

The objective of this paper is to examine the mechanisms for controlling data sharing, using hybrid simulation that tests seller preferences in different market conditions. Hybrid simulation is able to combine market models with more granular trading models. Smart contracts are employed to validate the seller preferences and control data sharing. Buyers will be able to buy data depending on the seller preferences which are stored on the blockchain. At the time of data purchase, those preferences will be validated by a smart contract making a digital agreement without human or third-party involvement. This control (offered to the seller) is the novel element of this data trading approach.

The remainder of the paper is organized as follows. Section 2 presents related work with the gaps identified. Section 3 describes the methodology adopted to achieve the design and implementation of the seller' rights within smart contract over blockchain framework. Section 4 covers smart contract design and Section 5 focus on implementation. Experimental evaluation of the platform using hybrid simulation is also reported in Section 5 and finally, the conclusion covered in Section 6.

2 BACKGROUND

2.1 Overview

Organizations have been buying and selling consumer data for decades. The World Wide Web, launched in 1989, instigating this digital content sharing (Bing 2009). In 2022, more than 5 billion people across the world were connected (Statista 2022). This vast generation of data could be categorized into five categories (Enjolras 2014): Web & social media data, machine to machine data, transaction data, biometric data, human-generated data. Combining into "big data", which can be defined as "the capacity to search, aggregate and cross-reference large data sets" (Lyon 2014).

The value of knowing as much as possible about what a consumer is interested in, their lifestyle, living situation, income, buying habits and even their emotions and feelings allows firms to increase the efficiency of marketing and advertising (Enjolras 2014). Companies who do not directly process and analyze big data could offer their collected data for sale and their online platforms to advertisers. Web popularity in 1990s drove consumer data collection by digital advertisement companies. Advertising companies gained advantage through email marketing and loyalty marketing through customer data collection.

The mechanism employed in a blockchain network for data trading is done through a block of code which is known as Smart Contract (Chiu and Koeppl 2019). The use of a smart contract allows the transacting parties to set their terms of settlement rights before the execution of trade and as soon as the trading parties come to a consensus and input their digital signatures, the smart contract is executed automatically (Governatori et al. 2018). A major advantage of employing the use of Smart Contract for data trading between the buyer and seller is that it removes the need for the interference of a third party and can speed up the process of settlement, by removing the after-trade infrastructure that usually fragments and allows for the implementation of a flexible cycle of settlement. Furthermore, blockchain technology offers an opportunity for the trading parties to speed up the process of trading, necessary for time-limited transactions (Jin et al. 2019).

2.2 Related Work

Data privacy preservation for data auctions in cyber-physical systems has been proposed (Gao et al. 2020) using homomorphic cryptography and secured network protocol design. Specifically, a generic Privacy-Preserving Auction Scheme (PPAS), in which the two independent entities of Auctioneer and Intermediate Platform comprise an untrusted third-party trading platform. Concepts are validated through detailed theoretical analyses and extensive performance evaluations, including assessment of the resilience to attacks. Oh et al. (2020) have proposed an optimized trading model in Internet of Things (IoT) marketplaces for data brokers who buy personal data with incentives based on the willingness-to-sell (WTS), and they sell valuable information from the refined dataset by considering the willingness-to-buy (WTB) and the dataset quality. Due to a lack of transparency between providers and brokers/consumers, participants consider that the current ecosystem is not trustworthy, and new regulations with strengthening the rights of individuals were introduced.

Tian et al. (2019) maximize data seller received utility by balancing the trade-off between data trading benefit and data privacy cost. To achieve this, contract theory is utilized to design optimal contract trading mechanisms for both complete and incomplete information markets (Tian et al. 2019). Feng et al. (2018) focused on permissionless blockchains to construct a purely decentralized platform for data storage and trading in a wireless-powered IoT crowdsensing system. IoT sensors use the power wirelessly transferred from RF-energy beacons for data sensing and transmission to an access point. The data is then forwarded to the blockchain for distributed ledger services, i.e., data/transaction verification, recording, and maintenance. Weber and Prinz (2019) introduced an approach that allows users to store their data on their own smartphone and have full control over their data, allowing them to specify which companies or organizations obtain their personal data. At the same time, the blockchain technology is used for reliable negotiations involving user data without a central entity. Our approach makes it impossible for either the data provider or data collector to perform manipulations or deceive once a data exchange contract has been signed. Smart contracts are used for user authentication based on their blockchain account. Table 1 summarizes the related work and the gap identified.

Table 1: Summary of the related research area and gap identified.

S#	**Research Area**	**Conducted by**
1	Privacy preservation for data auctions.	(Gao et al. 2020)
2	Willingness-to-buy (WTB) data of consumers.	(Oh et al. 2020)
3	Maximize data seller's received utility via balancing the trade-off between data trading benefit and data privacy cost.	(Tian et al. 2019)
4	Construct decentralized platform for data storage and trading in a wireless-powered IoT crowdsensing system.	(Feng et al. 2018)
5	An approach that allows users to store their data on their own smartphone and have full control over their data, allowing them to specify which companies or organizations obtain their personal data using blockchain.	(Weber and Prinz 2019)

Seller rights (controls over buying access to data after trade execution) are missing in current work. Current research focuses on data trading management and more generic security/privacy and authentication issues. Apart from the work carried out to facilitate the data trading, this proposed research is able to extend existing work by implementing the seller rights digitally in term of seller preferences using smart contract over the blockchain framework. Hybrid simulation provides a greater insight of the system as it allows modelers to explore concerns from different dimensions (Zulkepli and Eldabi 2015). Linking simulation models in order to expand the domain of study is another benefit of HS (Powell and Mustafee 2014). Here we combine models of the wider marketplace with granular models of trading.

3 METHODOLOGY

Design Science Research (DSR) uses design, analysis, reflection, and abstraction to develop new knowledge (Vaishnavi and Kuechler 2007). DSR provides significant frameworks for IS (Information Systems) studies (March and Smith 1995). Techniques and tools are selected such as UML and BPMN (business process modeling notation) to create models of the system and flows between components. These are used for documenting software system artefacts. Constructs (in this research) consist of requirements used to support the proposed model which are discussed in the previous section. The model consists of graphical representation of key concepts, blueprint of architecture and system diagram. Table 2 describe the DSR approach applied in the next sections. It is this design process that uncovers the elements required for later simulation. Hybrid simulation is used to test these designed artefacts in a synthetic marketplace.

Table 2: DSR approach.

DSR outputs		**Section**	**Description**
	Artefact(s)	3	Designing data trading model of data and control flow
	Demonstration	4	Implementation of data trading experimental platform
	Measure	5	Evaluation of the data sellers' rights platform with simulation
	Conclusion	6	Results analysis

3.1 Trading Platform Design

DSR typically involves designing of constructs, models, methods and/or instantiations. To elaborate on the business model of the proposed platform, the main actors and their associated processes are defined in the sequence diagram. Figure 1 represents the seller activities and interaction with the core system, NoSQL/MongoDB, smart contract and blockchain ledger.

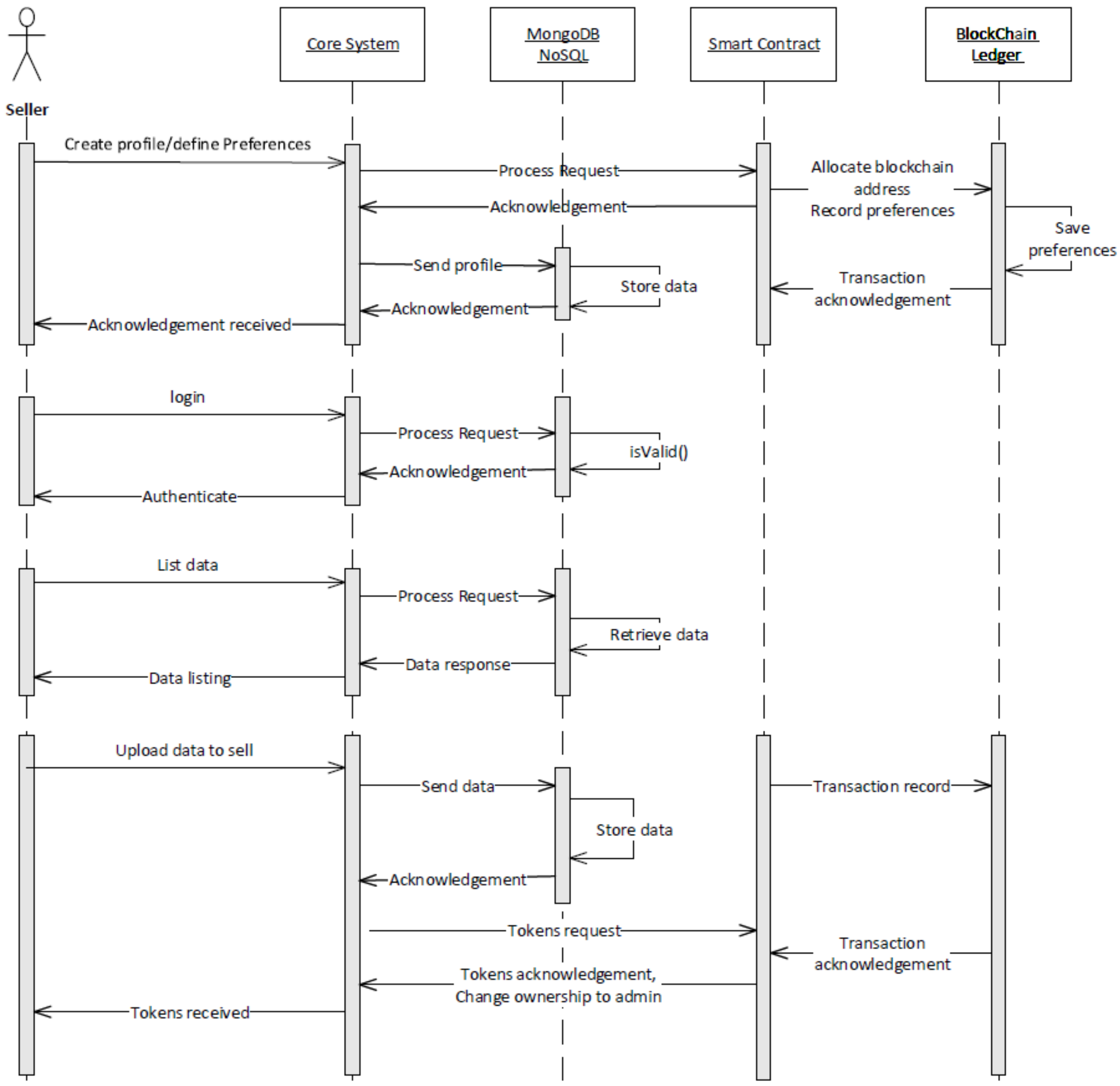

Figure 1: Seller activity.

Sellers are able to share the data on the proposed platform so that the buyer can buy available data. The system provides an interface for a seller to login and shares the data which will then be stored in the NoSQL MongoDB database. The seller can create a profile and define the preferences which are saved by the core system on the blockchain network. These preferences help the smart contract algorithm to govern over the data trading. Moreover, the core system allocates and assign an available blockchain address to each seller account for recording the transaction and validation of seller rights.

Figure 2 depicts the buyer activity specifics. Buyers are free to list the data rows for purchase. The core system will display the data block price in a standard currency along with the data listing. Buyers then attempts to pay; smart contract processes then request and validate the trade by executing the smart contract algorithm and match seller and buyer preferences. The smart contract invokes the validation of preferences method automatically and makes a decision that allows or rejects the buyer to purchase the data. Consequently, a data trade will verify preferences and thus protect the seller rights in the data trading process. At this stage, data ownership will also be changed from the core system to buyer. The specificity of preferences is important as without matchable preferences the market will be dysfunctional.

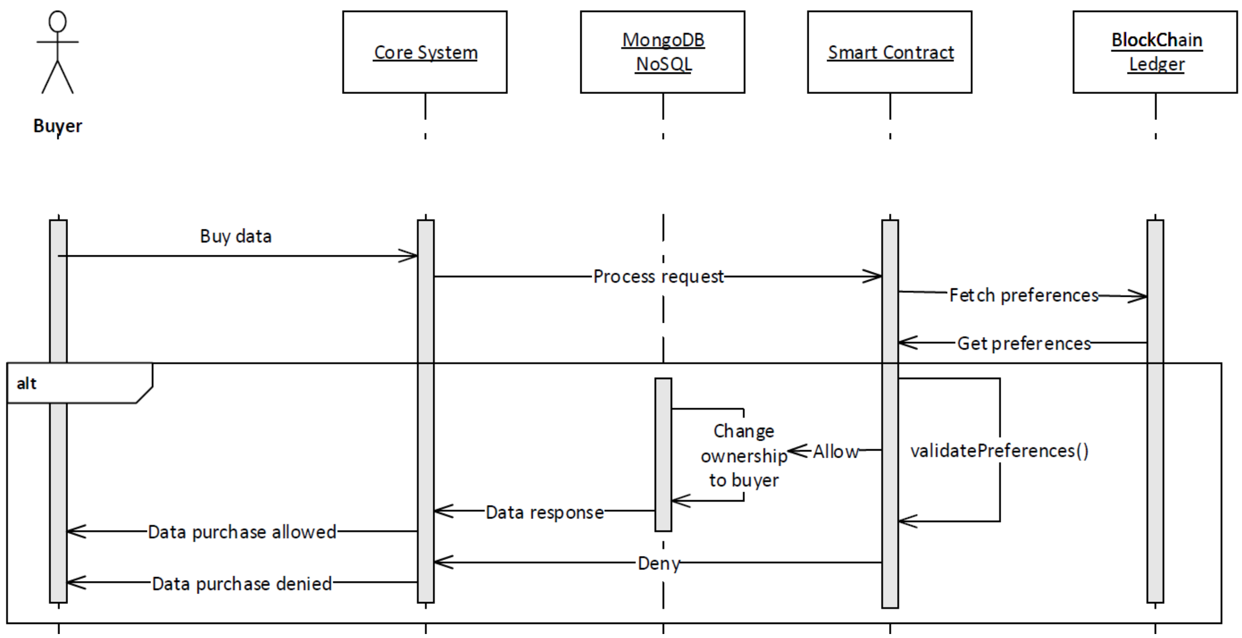

Figure 2: Buyer activity.

4 IMPLEMENTATION

To implement the smart contract in the blockchain system, Ethereum is used and is capable of executing a smart contract and perform functions automatically to complete the data trading transactions. Smart contract consists of machine language usually written in a Solidity which has functions to implement the contract stipulations. The proposed system covers those stipulations in the form of “Seller Rights” as well as the payment processes between seller and buyer. The proposed system is based on blockchain framework controlled by the smart contract - architecture and the technology are depicted in Figure 3 below.

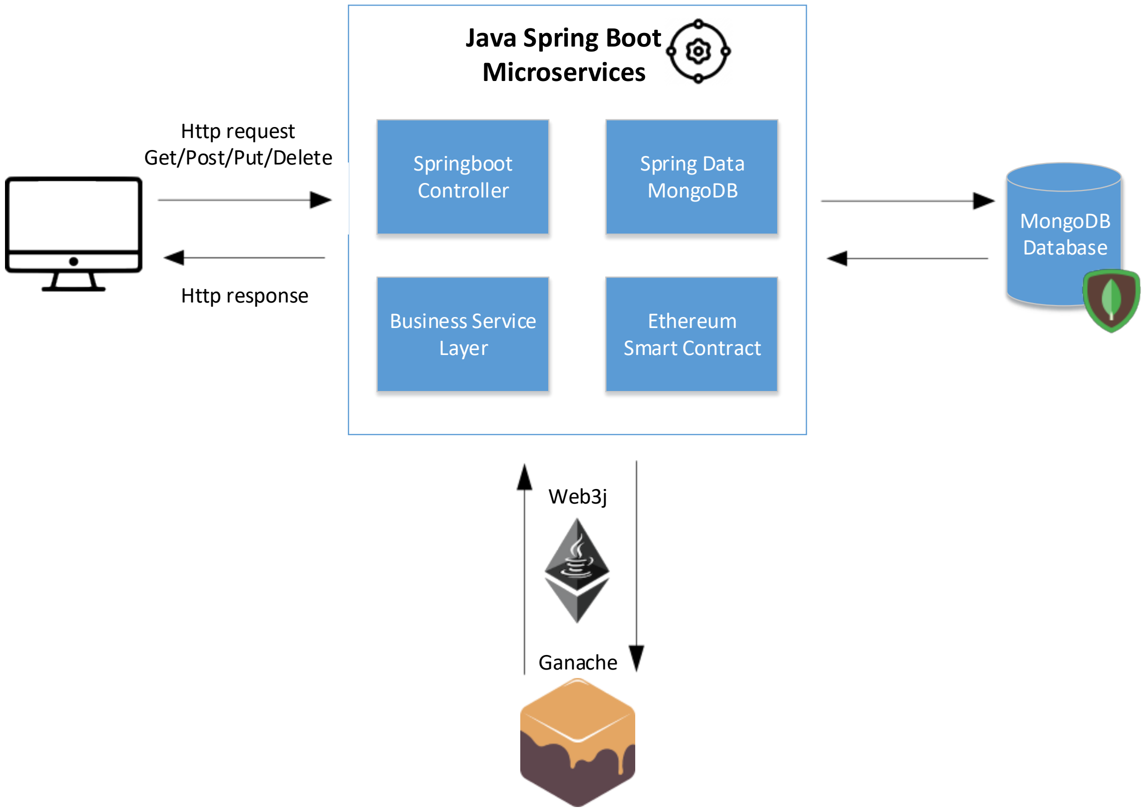

Figure 3: Data trading system architecture.

The Smart contract contains the code that controls and protects the seller in such a way that buyers must fulfil the preferences defined by the seller for conducting data trading. In other words, the system will not allow the buyer to buy the data out of smart contract rules and regulations. This platform provides the infrastructure for writing smart contracts and builds decentralize applications (dApps) where anyone can implement their functions, rules, terms, and conditions to carry out any operation (Bhattacharjee and Ray 2014). Smart contracts execute when a trade occurs between buyer and seller depending on the terms and conditions. The Solidity language is used to code a smart contract within Ethereum using Solidity online platform known as Remix and compiled on the same platform for further deployment. Ganache is a personal blockchain for rapid Ethereum and distributed application development. Ganache is used across the entire development cycle, enabling development, deployment, and testing of dApps in a safe and deterministic environment. It is a local in-memory blockchain designed for development and testing purposes. It simulates the features of a real Ethereum network, including the availability of several accounts funded with test Ether.

As the system deals with a large amount of data provided by the seller, MongoDB is used to store the data in a non-relational manner which make it much faster than traditional databases. MongoDB is a distributed database at its core, with high availability, horizontal scaling, and geographic distribution are built-in and easy to use.

The process of data trading focused on seller rights and smart contract guarantees to perform the validation on its own and settlement agreement between the buyer and seller.

5 HYBRID SIMULATION

This section describes the simulation and modeling of smart contract based on sellers' rights and exploration of the results. Designing and implementation of smart contracts have been achieved in the previous two sections and simulation will be carried out to test and validate design and implementation choices. What-if analysis are created from the higher-level market simulation and resulting in a set of scenarios.

Simulation provides a means to examine how data trading will take place between parties and depending on different seller rights scenarios. The focus is on agent-based simulation and results obtained from the simulation provide an instantiation of data trading using smart contract with protected seller rights. Data trading based on the seller rights is a new concept that enables the seller to protect his data not to be sold to any buyer but only those who meet the terms and conditions defined in the smart contract.

Anylogic software is used for the simulation purpose (Karame and Capkun 2018). The process model library is chosen to define the data trading transaction with inputs applied to test the model for testing the model functionality. Hybrid simulation is a modelling approach that combines models. However, a large proportion of the academic literature on hybrid simulation is found in computer science and engineering journals (Brailsford et al. 2019). Anyogic enables the testing and validation of our algorithm within synthetic trading environments – drawing scenario from the SD Market simulation.

We combine both real world data and illustrative data. A likely reason for using mixed data is related with the use of Hybrid Simulation to model systems at multiple levels (Brailsford et al. 2019). Sometime the real word data is only useful for standard use cases, but the data required to model more strategic aspects such as long-term feedback of data seller preferences are more difficult to obtain. Therefore, illustrative data taken from a market simulation is used. Seller rights and buyer preferences are initialized at the starting point and then random sellers and buyers are generated who are involved in the data trading process. The transaction contains the random seller and buyer having random data related to seller rights matched with the buyer preferences. Smart contract validation of the terms and conditions is based on the parameters and simulate the output as validated trade or deny the current transaction.

In principle, seller preferences are matched with the buyer profile preferences and based on that match, smart contract validates the transaction whether the transaction is successful or denied in other cases. We need to identify relevant empirical data, define a range of parameter values, and set criteria for evaluating how good is the match.

Table 3: Simulation parameters of seller and buyer.

S#	Description	Fields	Type
1	The parameters of seller preferences (Seller rights)	Country, Company Type and Company Size	Collection as Array
2	Buyer profile preferences as parameters	Company Country, Company Type and Company Size	Single set

Table 3 presents seller and buyer parameters as an input to the model and types associated with it such as a single set of parameters or collection. Each entity contains these parameters and passes on the smart contract for validation. A simple set of parameters are chosen in this experiment. Greater numbers of parameters will also require some standardization if matching is to be effective. This could also include semantic matching.

By adopting the above approach, the model will execute the smart contract functionality based on random values of parameters and produce the output as a successful data trading transaction or deny the transaction depending on the match found.

5.1 Model Formulation

The aim of the simulation is to analyze the model with a varying set of information as an input and perform the validation process of the algorithms and produce the output. If we look at the data set, then it is a set of preferences containing the information listed in the equations given below.

P = {'COMPANY SIZE', 'COMPANY COUNTRY', 'TYPE OF THE COMPANY'}
B = {'LARGE', 'RUSSIA', 'TOYS'} – Russia Company
S = {'SMALL', 'ISRAEL', 'BETTING'} – Tony

Where P contains a set of company size, company country, and type of company. As model drive the data trading transaction between buyer and seller therefore, B holds the parameter values such as Large, Russia and company type as Toys. Similarly, S is comprised of seller preferences as Small, Russia and Betting referring to the set P

$P \neq \emptyset$ (non-Empty) set of Preferences.

Before simulating the model, it is worth mentioning here, that P must not be empty, and we have to initialize with non-empty values. P can have a range of values in the form of a1, a2, a3 …. an, which denotes a set of information related to each entity. Buyer and seller preferences are chosen randomly by the simulation model which contains non-empty values and must belong to P set as mentioned in the following equations

$B \neq \emptyset$ (non-Empty).

Buyer Preferences system automatically chosen from his profile

$B = \{X: X \in P\}$.

Seller Preferences can be $S = \emptyset$ (Empty) subset of P

$S = \{Y: Y \in P\}$.

The algorithm takes these parameters in the simulation model and performs the validation process by matching the preferences of the buyer and seller that were selected automatically previously. The intersection between two sets occurs among the set of B and S which means that trade is valid if there is no match found between these two sets. Otherwise, the trade becomes invalid and denies the buyer from purchasing the data

$B \cap S = \emptyset$ (True of this condition will let the algorithm issue valid purchase).

5.2 Model Calibration and Evaluation

The calibration focuses on a qualitative match or a close, quantitative match. Qualitative matches align the parameters with literature. Close match calibration is often chosen when particular parameters could affect the model results, the parameters are thought to have reasonably independent effects on the model, and good alignment data exist (Bell 2017). For this purpose, the seller and buyer entity are created, and the parameter list is updated for each entity as mentioned in Table 3 of the previous section. This initial calibration can be pre-defined or when using a hybrid approach as output from the System Dynamic (SD) model. The SD model uses past work (Bell 2017) where the propensity to trade is defined as the likelihood of seller-buyer marching. Figure 5 presents the flow from the market participant model (SD) to the trading models. It should be noted that the trading outcome data flows back in order to impact propensity to trade decisions within the SD model. Data about trading behaviour and market environment is needed to calibrate to an actual market, but in this paper, we have used a simple scenario-based approach.

Within the trading model, a further agent is defined that contains the collection of buyer and seller entities in the form of Arrays and this agent is named as exchange. Each entity element holds the list of parameter values that are treated as inputs for the model calibration. It means that the exchange carries the collection of sellers and buyers that are participants of data trading. The next step is to randomly choose and route a buyer and a seller from the collection and then route those participants to the algorithm for validation of seller rights. When the algorithm receives the parameters from the previous stage, it matches the parameters i.e., seller preferences with buyer preferences. If a match found, then condition will return true or false and reroute the transaction to approval or denied direction. To perform the aforementioned steps, we need to design the model, define the agents, and initialize the parameter values and define the logical conditions for validation. The next step is to simulate marketplace and trading activities with the inputs parameter and analyse the behaviour by recording the results. Market simulation uses previous SD work based on the propensity to buy and sell data (Bell 2017). Figure 5 presents the interaction between the market simulation and the trading simulation. In this relatively simple experiment, the marker dictates the number of randomly generated buy and sell requests. The framework also includes buyer types to support different types of buyer and seller. Propensity to trade is generated from either a connected simulation or machine-learning generated synthetic data.

The exchange contains buyers and sellers and their respective preferences which are then routed to matching algorithm with the help of a transaction agent. The algorithm then determines the matching characteristics, and the transaction is subsequently routed on an approved or denied direction as shown in the model. Trade confirmation is based on the algorithm's decision depending on the terms and conditions. If the conditions return false, while matching the preferences.

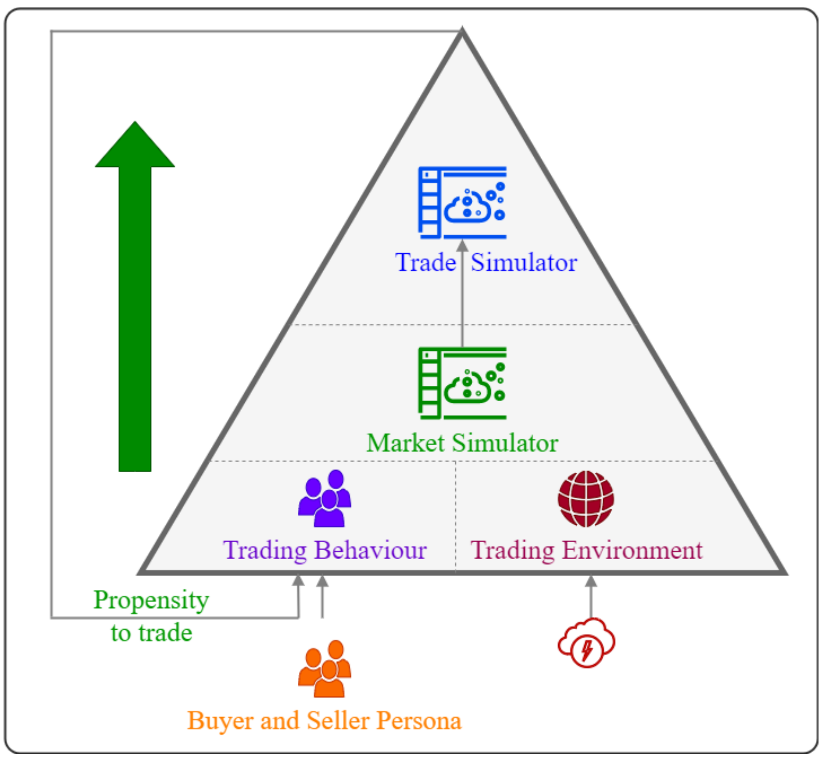

Figure 5: Conceptual hybrid data trading model.

The next step is to run the simulation and test the algorithm behaviour by initially evaluating the output visually. Figure 6 shows the simulation of the model that how transactions are initiated between buyer and seller and the behaviour of the algorithm on the current transactions according to the seller and buyer preferences. Each transaction has been simulated and tested individually and the behaviour of every transaction is recorded. Preferences of each entity involved in the transaction are compared and test for the similarity between seller and buyer preferences. All transaction metrics are compared to the real system and ideal scenarios to test the algorithm functionality. The output associated with these transactions gives a clear picture of what the real system might achieve during the data trading process and how the algorithm will respond with buyers and sellers having a range of preferences.

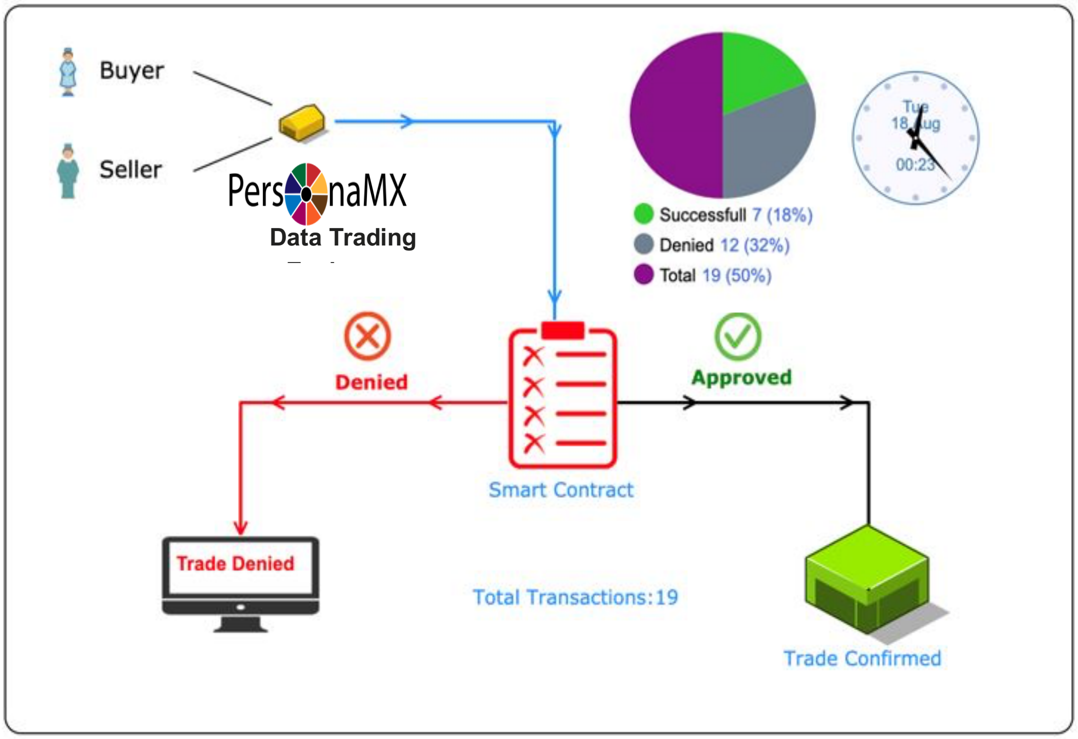

Figure 6: Trading simulation.

The simulation showed the data trading transactions based on seller rights using a range of visualization - some shown in Figure 6. The visualizations evaluate the results of the simulation and show the number of successful, denied and the total number of trades. The following transactions are recorded with the random buyers and sellers where successful, denied, and total no of the transaction can be seen in Table 4 which are processed by the algorithm depending on preferences match between them.

Table 4: Simulation parameters of seller and buyer.

Iterations	No. of buyers	No. of sellers	Successful Trades	Denied Trades	Total Trades
1	10	50	10	30	40
2	4	40	35	10	45
3	16	10	15	20	35
4	7	11	9	14	23

Buyer and seller preferences are stored as lists. Each buyer and seller have different preference values as described in Section 5.1. Each iterations takes random buyers and sellers from the array list and match the preferences, i.e., company size, country, and company type. Successful data trading relies on the preferences and matching results are produced on the basis preferences matching which are randomly collected from the arrays. For example, in iteration 1, simulation is performed on 10 buyers and 50 sellers. Random buyers and sellers have been tested and results are collected where 10 trades were successful based on un-matched seller's and buyer's preferences. Moreover, there were 30 denied trades having same preferences within arrays.

P = {'COMPANY SIZE', 'COMPANY COUNTRY', 'TYPE OF THE COMPANY'}
B = {'LARGE', 'RUSSIA', 'TOYS'}
S = {'SMALL', 'ISRAEL', 'BETTING'}

P indicates the set of preferences fields in order to control the data trading. Where B and S represents the buyer's and Seller's preferences respectively which are stored in the arrays with the random preference values. In every transaction buyer and seller corresponding preferences are matched with each other. Consequently, successful trades are based on the non-matching of any corresponding preferences. Any seller can define the preferences as large, Russia and toys, if trade is not allowed for a buyer who has large company size or based in Russia or dealing in toys. Currently these preferences are used to control the data trading between buyer and seller, however more preferences can be added as well as new matching criteria can be introduced associated with each preference in order to perform more controlled data trading.

6 CONCLUSION

A novel data trading approach is presented in this paper – one where trading is controlled by seller preferences. The approach follows the principles of seller's rights protection and control on the data sharing available in a community of users. Controls on the exchange of data on trade execution are paramount and missing from much of the current work in this area. Data trading research has typically focused on security issues, data theft, data tampering and their usage in banking, insurance, healthcare, and real estate.

Blockchain technology and smart contract mechanisms allow all parties involved in data trading transactions to be validated based on the seller preferences in a fast, secure, and trusted manner. Elimination of third-party involvement makes it cost- effective and ready to execute without any delays. Thus, all the stakeholders and systems take advantage of security, accuracy, privacy, and trust provided by the blockchain ecosystem.

A data trading platform is developed in order to understand core elements of the trading process and subsequently calibrate the trading model. Hybrid simulation is then used to explore and test trading behaviour in different market environments with four simple scenarios presented. The trading simulation was able to derive the number of successful trades (matched trades) and it is this data that can flow back to a market simulation. A hybrid approach is shown to combine market and technology simulations and enable system developers to test robust future scenario.

REFERENCES

Bell, D. 2017. "Exploring Personal Data Futures Trading with Design Fiction Based Hybrid Simulation". In *Proceedings of the 2017 Winter Simulation Conference*, edited by V.W.K. Chan, A. D'Ambrogio, G. Zacharewicz, N. Mustafee, G. Wainer, and E.H. Page, 184–191. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Bhattacharjee, P., and P.K. Ray. 2014. "Patient Flow Modelling and Performance Analysis of Healthcare Delivery Processes in Hospitals: A Review and Reflections". *Computers & Industrial Engineering* 78: 299–312.

Bing, J. 2009. "Building Cyberspace: A Brief History of Internet". In *Lee A. Bygrave, and Jon Bing (eds), Internet Governance: Infrastructure and Institutions,* 8-47. New York: Oxford University Press, Inc.

Brailsford, S.C., T. Eldabi, M. Kunc, N. Mustafee, and A.F. Osorio. 2019. "Hybrid Simulation Modelling in Operational Research: A State-of-the-Art Review". *European Journal of Operational Research.* 278(3): 721–737.

Buterin, V. 2014. Ethereum White Paper: A Next Generation Smart Contract & Decentralized Application. https://github.com/ethereum/wiki/wiki/White-Paper

Chiu, J., and T. v. Koeppl. 2019. "Blockchain-Based Settlement for Asset Trading". *The Review of Financial Studies* 32(5): 1716–1753.

Enjolras, B. 2014. "Big Data Og Samfunnsforskning: Nye Muligheter Og Etiske Utfordringer". Tidsskrift for Samfunnsforskning 55(1): 80–89.

Feng, S., W. Wang, D. Niyato, D.I. Kim, and P. Wang. 2018. "Competitive Data Trading in Wireless-Powered Internet of Things (IoT) Crowdsensing Systems with Blockchain". In *Proceedings of 2018 IEEE International Conference on Communication Systems, December* 19th-21st, Chengdu, China, 389–394.

Gao, W., W. Yu, F. Liang, W.G. Hatcher, and C. Lu. 2020. "Privacy-Preserving Auction for Big Data Trading Using Homomorphic Encryption". *IEEE Transactions on Network Science and Engineering* 7(2): 776–791.

Governatori, G., F. Idelberger, Z. Milosevic, R. Riveret, G. Sartor, and X. Xu. 2018. "On Legal Contracts, Imperative and Declarative Smart Contracts, and Blockchain Systems". *Artificial Intelligence and Law* 26(4): 377–409.

Jin, R., X. Zhang, Z. Wang, W. Sun, X. Yang, and Z. Shi. 2019. "Blockchain-Enabled Charging Right Trading Among EV Charging Stations". *Energies. 12(20): 3922*.

Karame, G., and S. Capkun. 2018. "Blockchain Security and Privacy". *IEEE Security & Privacy* 16(4):11–12.

Lyon, D. 2014. "Surveillance, Snowden, and Big Data: Capacities, Consequences". *Big Data & Society*, 1(2):1-13.

March, S.T., and G.F. Smith. 1995. "Design and Natural Science Research on Information Technology". *Decision Support Systems* 15:251–266.

Oh, H., S. Park, G.M. Lee, J.K. Choi, and S. Noh. 2020. "Competitive Data Trading Model with Privacy Valuation for Multiple Stakeholders in IoT Data Markets". *IEEE Internet of Things Journal* 7(4):3623–3639.

Powell, J., and N. Mustafee. 2014. "Soft OR Approaches in Problem Formulation Stage of a Hybrid Study". In *Proceedings of the 2014 Winter Simulation Conference*, edited by A. Tolk, S.Y. Diallo, I.O. Ryzhov, L.Yilmaz, S.J. Buckley, and J.A. Miller, 184–191. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

Statista. 2022. Our Research and Content Philosophy. https://www.statista.com/aboutus/our-research-commitment accessed 11th July.

Tian, L., J. Li, W. Li, B. Ramesh, and Z. Cai. 2019. "Optimal Contract-Based Mechanisms for Online Data Trading Markets". *IEEE Internet of Things Journal* 6(5): 7800–7810.

Vaishnavi, V.K., and W. Kuechler. 2007. *Design Science Research Methods and Patterns: Innovating Information and Communication Technology*. 1st ed. Boka Raton: Auerbach Publications.

Weber, T., and W. Prinz. 2019. "Trading User Data: A Blockchain Based Approach". In *Proceedings of the 6th International Conference on Internet of Things: Systems, Management and Security,* October 22nd-25th, Granada, Spain, 547–554.

Zulkepli, J., and T. Eldabi. 2015. "Towards a Framework for Conceptual Model Hybridization in Healthcare". In *Proceedings of the 2015 Winter Simulation Conference*, edited by L. Yilmaz, V.W.K. Chan, I. Moon, T.M.K. Roeder, C. Macal, and M.D. Rossetti, 184–191. Piscataway, New Jersey: Institute of Electrical and Electronics Engineers, Inc.

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