Smoothing Away the Stagnation Problem of Community Currencies with "Customized Communities" based on Satisfaction Prediction by Neural Network

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Abstract

Every community, no matter how money poor, has a wealth of abilities and capability to stimulate the local economy. From this point, idea of the community currency (CC) was emerged and was proposed as a tool to achieve a sustainable development in the local economy. However, creating a community currency was not enough to energize the local economy without addressing the stagnation problem. Thus, in the current research, we proposed a new framework (sequence of steps) to build the "customized community" where the needs of members were met with the offered market to solve the stagnation problem. The theoretical concept of customized community was discussed in our previous research by utilizing random network model while in the current study we used a real data recorded by CC-based platform called C.C.Wallet to estimate an satisfaction degree of the members of the community. Considering this, the backbone of the proposed framework is estimating the satisfaction degree of the members of the community by utilizing a Neural Network (NN) and this satisfaction degree was used as an index to determine the members who will be given thereafter a "preference" in terms of bonus premium amount to be added to their initial purchase of the CC with money. The proposed index was created based on the number of purchases of same goods and service as well as by analysing C.C.Wallet users' messages (text-based comments and impressions) regarding the offered goods and services after completing the transactions in Japanese language. Thus, to analyse the comment text recorded in C.C.Wallet, it is necessary to use the technology of Natural Language Processing (NLP) where those comments were tokenized into tokens by using python language-based module. In the current study, the engagement of the members with the provided market was monitored by computing a visual map of Shannon Entropy (SE). Our main findings suggest that proposed framework can be considered as a tool to construct the concept of "customized community" where the circulation of CCs can be accelerated and hence the local economy will be energized as a result.

Keywords

Customized Community, Community Currency Stagnation, Neural Network, Natural Language Processing.

1. Introduction

A money can be defined as a stand-alone information medium of exchange or a measure of value and the important condition of it is to be accepted by a group regardless of its size whether big or small groups (Kichiji, 2012). Considering this, shopping point, electronic money, mileage, exchange coupon and community currency should be all called "money".

In economics, community currency (CC) can be defined as a currency that organized and managed by a local community, which involves exchange of goods and services. CCs can be spent within a particular local geographical area for accomplishing the aim of revitalizing local economies. CCs have some features like 1) relatively small or finite sphere of circulation, 2) issues by administrative committees, 3) non-convertible or hard to convert into legal tender, 4) holding zero or minus interest rate. Since CCs have limited circulation as mentioned earlier, and don't be assumed to replace the national currency (the officially recognized "money"), CCs are also known as complementary currencies (Tong, 2008).

Historically, communities have issued, managed, and circulated their own currencies for the past 6000 years (DeMeulenaere, 2000). The domination of national currencies and the global financial systems makes the community currencies diminished in influence over time. However, financial crisis since 1980s have promoted communities in Asia (e.g., Japan, Thailand), and the Americas (e.g., Mexico, Argentina) to experiment with issuing local currencies to protect livelihood against the vicissitudes of the mainstream economy (Tong, 2008). Since then, many types of CCs have been set up and proposed, but it seems that those CCs have also some drawbacks in terms of stagnation. For instance, "Eco-money" which was proposed by Toshiharu Kato (Kato, 2001) as a special type of CC was used in volunteer activities among citizens to activate mutual aids and stimulate social welfare services.

Eco-money was designed to be used in volunteer activities and social welfare services. Eco-money was accumulated in the hands of participants (especially younger generations) who significantly contributed to the volunteer activities. However, they could not find desired services and products in the market to spend their "Eco-money" and hence stagnation occurred. The double triangle system (DTS) was proposed by Makoto Nishibe (Nishibe, 2004) to cope with the stagnation issue. As shown in figure 1, DTS tried to make a bridge between non-commercial (volunteer related activities) and commercial transactions to stimulate the participants to buy goods and services in the local markets. To prove the effectiveness of the DTS as a CC system, the currency circulation of DTS was examined theoretically and empirically by applying it on a community whose members were selected from Tomamae-cho city located in the prefecture of Hokkaido in Japan (Kichiji, 2006, Kichiji, 2008). The effectiveness of DTS was determined based on the fact that the volume of commercial and non-commercial transactions increased. However, some Tomamae-cho CC was accumulated at specific business partners and could not circulate smoothly due to the limited market (Kichiji, 2008).

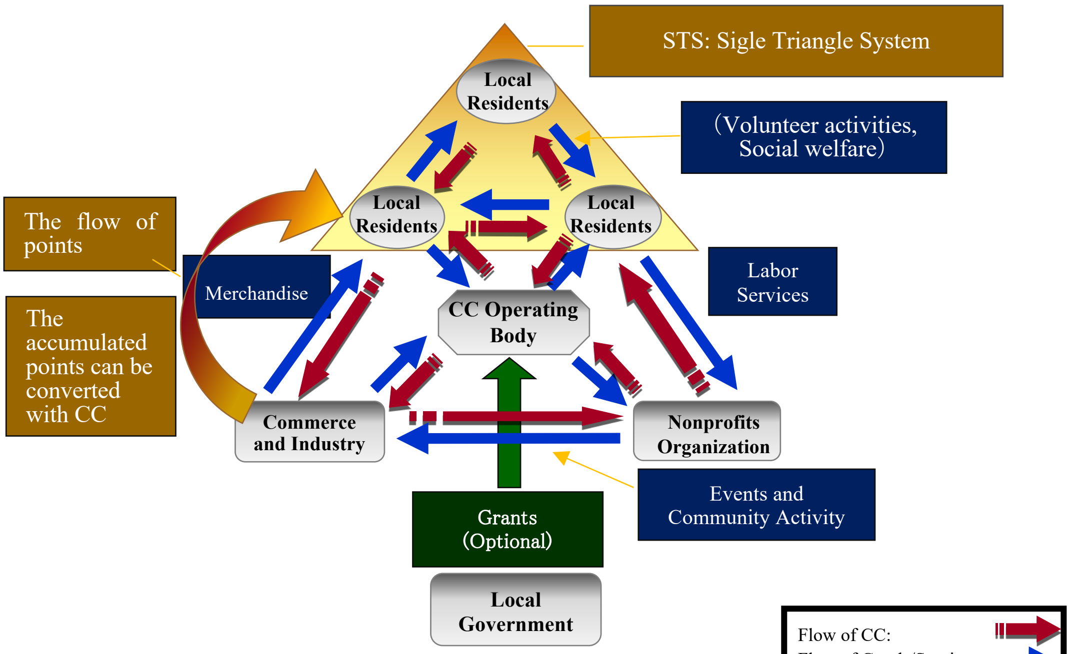


Figure 1 Double Triangle System (DTS) (Kichiji, N., 2006)

On the other hand, numerous reports have been compiled that shows the ability of CC to foster the social sustainability and have been assessed by Arnaud (Arnaud, 2015). Arnaud showed that economic benefits of CCs are limited due to their small scale. To understand this limitation, we need to give an overview about LETS which stands for "Local Exchange Trading System". LETS is one of the account type Community Currencies for whoever wants to use it and was initiated in 1983 by Michael Linton in Comox Valley, Vancouver Island, Canada (Kichiji, 2012).

Transactions using LETS are recorded in each participant's account. Participants can buy and sell products and services from each other with specific terms of price and quantities on a peer-to-peer basis. LETS can only circulate within finite physical or virtual domains. If you have a positive deposit in your account, you will not gain any interest from your savings.

In contrast, if you have no money and you want to buy something, you still can buy it by going below zero in your account by creating money units. The money in LETS can be created by individuals to buy goods or services without any limit or with a certain upper limit according to the rules of each LETS and this is the advantage of LETS. However, this is completely different from conventional money issued based on the value of commodity as money or the authoritative power of governments as issuers.

By conventional money, the seller will accept credit from the buyer and hence, the buyer incurs a debt to the seller. Considering this, the debt is generated on the side of the payer. When the central bank issues central banknotes, it gives a certificate of indebtedness stating that I (the central bank) owe you (a recipient), and this is called an “IOU”.

However, a buyer is not directly in debt to a seller in LETS. Rather, the buyer is thought to be in debt to the community, composed of all the participants in the LETS. The buyer should have an ethical responsibility to repay the debt to the LETS community. In such systems as LETS, debts and credits do not bilaterally but multilaterally balance out. In other word, LETS do not adopt bilateral netting but multilateral netting. Then we call this kind of money as in LETS, not an “IOU” but an “IOC”, which signifies “I owe Community”. Considering this, the larger the community of LETS becomes in terms of the number of participants, the more the degree of anonymity will become, and under such circumstances, it’s hard to maintain trust among the participants of the community and the stagnation related issue may arise again.

Apparently, to accelerate the circulation of CCs among the participants of the community, stagnation related problem needs to be addressed. Thus, in our previous study (Alaraj, 2020), we showed through random network simulation that the concept of “customized community” can be used as a tool to solve the stagnation problem, but in the current study we will introduce a computational platform to build such communities by estimating the degree of satisfaction of the participants using Neural Networks. Thus, the main purpose of this paper is to propose a computational framework (or sequence of steps) based on real data to build the “customized community” where the needs of members are met with the offered market. The framework was created by applying a neural network to estimate the satisfaction degree of the members who will be given thereafter a “preference” in terms of bonus premium amount to add to their initial purchase of the CC with money.

Entropy maps were then computed to monitor the engagement of the members with the provided market to achieve our goal that related increase the circulation of CCs among the members of the community and hence, the stagnation related problems will be reduced as a result.

For the practical purpose of improving the sustainability of CC, we will introduce the theoretical framework of the customized community, and we will talk also about random network model and Shannon entropy in section 2.

Next, in section 3, we will not talk only about the proposed approach to build such customized communities by estimating the degree of satisfaction of the participants through applying neural network, but also, the methods of building neural models will be explained as well.

Section 4 analyzes the results and tries to discuss the proposed approach and clarifies the link between estimating the satisfaction of the participant and customized community.

Finally, the conclusions and the possible extensions of the current work will be exposed in section 5.

2. Customized Community

2.1 The Proposed Approach to Build a Customized Community?

Currency stagnation occurs when the circulation of currency in specific areas become less than other areas due to many factors such as small number of participants or dissatisfaction with the local market.

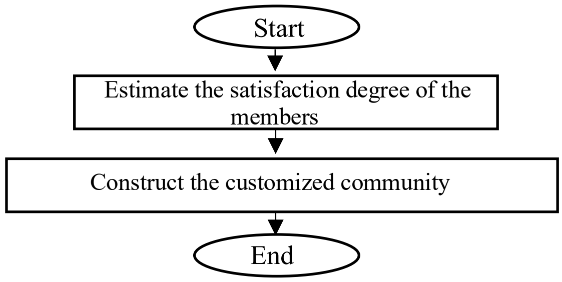


Figure 2 The proposed framework

Thus, to revitalize the local economy by using CCs, we don't need only to increase the number of persons who would like to join the community, but also, we need to increase the number of transactions using CCs. Such increasing in terms of number of participants and number of transactions will assist us to revitalize the local economy as the circulation of CCs among the members of the community will be increased.

Such increasing is important because it will reinforce the cooperation among those members of the community as the earned CCs from performing non-commercial transactions will be "absorbed" by its subsequent commercial transactions and prevent CCs from stagnating halfway through the circulation as shown in Figure 1. Thus, we need to construct a market where the demands matched the offered services and products of the other members. For example, if the number of members who are raising children in the community is few, child-related merchandises will not be likely purchased by CCs through the community, as there is a mismatch between the demands and the needs inside the community. In such cases, the problem of CC stagnation will be arisen and hence, we need a more appropriate market where the demands of the members can be satisfied. To this end, in our previous research (Alaraj, 2020), we clarified through simulation that building a customized market where the demands of members matched the offered services and products of the other members inside the community would accelerate the circulation of CCs. In this regard, we need to give an overview about customized community.

A customized community is a type of community of interest (COI) based on the commonality of members' preferences for various categories of goods and services. If we can identify these preferences of the members by estimating members' satisfaction regarding a particular category of goods or services, we can build a customized community.

For better understanding the approach of the current research, we will first explain the concept of "customized community" and then we will discuss how to build such communities. However, in practical cases, we need to reverse of the order of execution as shown in Figure 2.

2.2 What is the Customized Community

As stated above, to strengthen cooperation among members of a local community by using CC, it is better to increase "commercial transactions" after "non-commercial transactions" such as exchanges and mutual aid among members. The DTS suggests that if the members of the community use the CC acquired from non-commercial transactions in commercial transactions, this will increase the number of "commercial transactions", and the process of "absorption" into the market will be accelerated, rather than remaining in the hands of the members.

Here, if any business partners inside a particular community receive CCs and expect that such CCs will be accepted by the other the other shops, even if the business they are doing is not for non-profit purposes, the conditions to consider CCs as a money will be satisfied.

As a result of this situation, the newly created CCs through the execution of "non-commercial transactions", can be called a "currency of trust" issued by the community rather than a "currency of credit " which is issued by banks and such "currencies of trust" will affect on the "commercial transactions" and will revitalize the local economy as a result.

However, on the contrary, if the number of "commercial transactions" is increased, it will be difficult to distinguish them from ordinary market transactions because of the prominence of commercial activities for the purpose of legal tender, and as a result, there is a strong risk that cooperative relationships based on trust among members will not be formed or will be lost.

Therefore, by reshaping the CC-based market to meet the demands of the members as much as possible and avoiding the problem of currency stagnation in the middle, the "commercial transactions" will be increased.

Customized community can be constructed by giving specific members who has a frequent transaction a kind of "preference" in the form of a bonus premium amount added to the purchased CCs with legal money (e.g., Yen, USD, Euro etc.) to be used with business partners inside the community. Such a kind of "preference" can be considered as a strong incentive not only for the people who are inside a community, but also to induce other people from outside the community to join the community and contribute significantly in it. Thus, in this regard, we would like to demonstrate that we used the term "customized community" rather than "customized market" to highlight the importance of participants who have high participation rate in performing transactions within the community.

Customized community needs some parameters and rules to "filter out" who can join the community, and such rules can be determined based on information about members who frequently participated in the transactions of the community. For example, if we can select members who frequently trade in baby products, we can form a community customized with the "commonality" of "child-rearing". This would include not only fathers and mothers who are raising babies, but also grandparents, relatives, and other blood relatives who are interested in their grandchildren and cousins. Also, "commonality" can be identified in terms of the estimation of the satisfaction degree of the members based on two factors as shown below:

1. The impressions of the member who wrote his/her impression in text form, after finishing the transaction using a CCs based computational platform called C.C.Wallet.
2. The number of purchases for a particular service or products by a member in the community and hence, some concerns will be arisen due to privacy-related issues and such issues can be addressed by setting up a privacy policy and term of services in advance for the community. However, setting up such privacy policies cannot easily clear up the privacy problem without also providing valuable benefits to potential members of the community to induce them to share some personal related information (e.g., service, product category etc.).

Since that the build of customized community is performed after estimating the satisfaction degree of the member, we will talk briefly about the simulation of the customized community in advance and more details can be found in (Alaraj, 2020), while the approach to build this customized community will be explained in the current research.

2.3 The Simulation of the Customized Community

The simulation of customized community was examined throughout a random network applied using Python and the details of the development environment is shown in Table 1.

Table 1 The Development Environment of The Simulation

Application Name	Version
Jupyter Notepad	6.0.3
Python	2.7.17
Anaconda	4.5.4
Gephi	0.9.2

The efficiency of the principle of "customized community" was examined throughout a simulation using a random network. This simulation was performed by assuming that the community size consisted of 100 members (nodes) and the transactions were done among them randomly by selecting a buyer node and a seller node through generating a asymmetric adjacency matrix (*Adj*), where each value in this matrix represented the volume of transactions between each buyer and seller in the community.

$$Adj = \begin{bmatrix} a_{11} & \cdots & a_{1j} \\ \vdots & \ddots & \vdots \\ a_{i1} & \cdots & a_{ij} \end{bmatrix}, \; i = 1, \dots, 100 \;\; and \;\; j = 1, \dots, 100 \qquad a_{ij} = 0 \;\; when\, i = j \tag{1}$$

The principle of "customized community" was founded by calculating the entropy map of the transaction participation rate of all members of the community. Thus, it is needed to track the transaction history of community members over a period of time, and this period was assumed 50 days as shown in Figure 3.

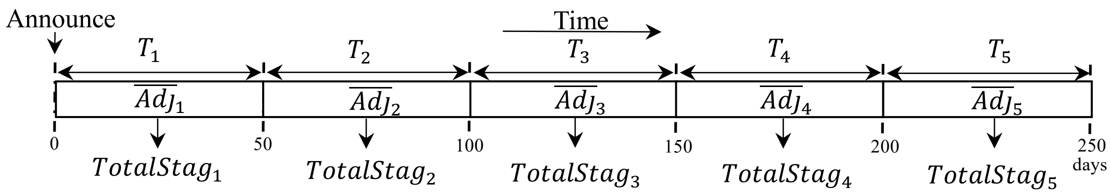


Figure 3 Schematic representation of the duration of CC simulation

Figure 4 represents the asymmetric adjacency matrix (*Adj*) where the rows represent the buyers (consumers), while the columns of *Adj* represent the sellers (providers). The flows of CCs from the buyer to the seller was represented by using arrows in the directed graph, as shown in Figure 4.

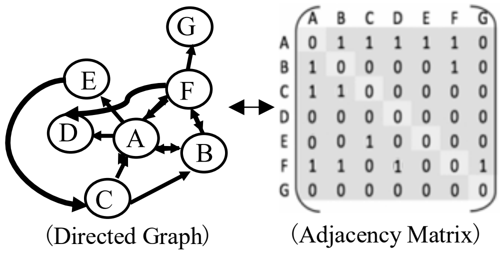


Figure 4 Example of Asymmetric Adjacency Matrix

This matrix is "asymmetric" because member X is a buyer, and another member Y is a seller, and it does not necessarily mean that the reverse is true: one member X is a seller and another member Y is a buyer.

For example, Figure 4 does not only show the case where A is the buyer and B is the seller (the corresponding element in row A, column B is 1), but also when A is the seller and B is the buyer (the corresponding elements in row B, column A is 1).

Also, Figure 4 does not only show the case where A is the buyer and E is the seller (the corresponding elements in row A, column E is 1), but also when A is the seller and E is not the buyer (the corresponding elements in row E, column A is 0).

Considering this, the adjacency matrix (*Adj*) indicates that each member wants to purchase “willingness to purchase” the product or service offered by another member and this does not necessary mean that the transaction was realized as it depends on the balance of CC that the buyer (consumers) had.

Next, the entropy map, as we will see later, represents a prototype for building a customized community based on the “commonality” of the offered products and services from the perspective of sellers and buyers.

2.3.1 The Assumptions of the Simulation

The execution of this simulation was based on the following nine assumptions. In the start of the simulation, we assumed that there were100 members in a virtual community and the initial amount of CC is 10000 CC per person. This means that the total money stock is 1 million CCs, as shown in figure 5. The period of simulation was assumed to be lasted for 250 days divided into 5 periods （T_n、$n = 1,\cdots,5$）.

1. It is assumed that the product initial price (*PCom*) is randomly generated within the range of $50 < PCom \leq Ini_n, \forall n = 1,\ldots,5$, where *Ini* is the initial amount of CC. Products and services provided by each sellers (providers) were not bartered and should be exchanged with CCs. As Figure 3 shows, the amount of CC, which were not used in community transactions for 50 days ($T_n = 50, \forall n = 1,\cdots,5$), was considered as a stagnation.
2. It was assumed that the provided products and services can be categorized, and the members of the community who make bilateral transactions can buy and sell products and services using CCs. Any transaction can be realized if the member has an amount of CCs more than the price of the product or services (*PCom*) that they want to buy. If this condition is satisfied, the price of product or service will be deduced from the CC which is hold by the member.
3. It was assumed that the transaction is executed randomly. That is, a pair of buyer and seller was randomly selected using asymmetric adjacency matrix. The Shannon entropy (SEn) was computed after a certain period (50 days).
4. The buyer executes the transaction using the CC given at the initial stage. However, there will be some members in the market do not use CC and hold some or all of it. If the remaining amount of CCs was not used until the end of the period (50-day), this amount of CC was considered as a “stagnation”. Considering this, when the participation rate (PR) decreases, the flow of CCs among the members of the community will be decreases as a result and hence, stagnation state will be occurred. In the current study, the “participation rate” was defined as a “willingness to purchase” which was represented by the “buyer-to-seller” arrow in the network, where the buyer who was represented in the rows of the adjacency matrix, wants the seller's product or service which was represented in the column.

The realization of such "willingness" was based on CC balance that the buyer has, and if this balance exceeds the price of product/service, the transaction will be realized. Thus, from this perspective, the term "participation rate" rather than "transaction rate" was used in the current research.

5. As shown in Figure 3, it was assumed that CC-based market was opened for 250 days. The amount of CC stagnation in each group and the total amount of CC retention in all groups were calculated every 50 days T_n). Therefore, the stagnation amount every 50 days (($Tn =$ $50, \forall n = 1,\cdots,5$) was defined by ($Stag_m, \forall m = 1,\ldots,6$), and the total amount of stagnation was defined by ($TotalStag_n, \forall n = 1,\cdots, 5$), as shown in Figure 3.
6. As shown in Table 2, the participation rate in each group (Group A, B, C, C, E and NS) was described in Table 2 and was assumed to be constant throughout the whole simulation.

Table 2 The Groups of the Simulation

	Stagnation Group					Non-Stagnation Group
Index of Group (*m*)	1	2	3	4	5	6
Symbol of Group Name	A	B	C	D	E	NS
Participation Rate (PR) (%)	90	80	70	60	50	100
Number of persons (Nr)	10	10	10	10	10	50

7. Also, the number of people in each group and the participation rate (PR) of the entire group were assumed to be constant throughout the whole simulation, as shown in Table 2.
8. As shown in Figure 4, the transaction was performed throughout the following steps.
   a. Set the adjacency matrix.
   b. The commodity price was randomly generated in the range of *PCom*, 50 <PCom ≤ $Ini_n, \forall n = 1,\ldots,5$.
   c. Randomly select a pair of members to be sellers and buyers. For example, select A and B, and randomly decide "A is the seller and B is the buyer".
   d. The transaction was realized when the generated commodity price (*PCom*) was below the CC balance. If the buyer runs out most of his/her, the balance of CC was stagnant because the transaction could not be performed if the commodity price was higher than the balance of CC.
9. The adjacency matrix was assumed to be calculated twice a day within 50 days and hence, the average of those two times was calculated and represented as $\overline{Adj}$, as shown in Figure 3.

2.3.2 The Formation of Customized Community Concept

The concept of "customized community" was implemented in the simulation by creating a market in the community by gradually redistributing the resulted stagnation amount during a 50-day period to the members who were frequently engaged in the transactions in the subsequent 50-day period. This was achieved by giving a bonus premium amount when those members purchased CC.

In other word, the premium amount to be awarded is calculated by the initial amount of money (*Ini*) of the previous period of time (*T*) plus stagnation amount from the previous period of time divided by the total number of members who were engaged frequently in that period. Thus, the initial money at the beginning of each period of 50-day period will be defined by Eq. (2), as shown below:

$$Ini_{k+1} = \frac{TotalStag_k}{Nr.of\ members\ in\ NS_k} + Ini_k \text{ where } Ini_1 = 10000\ , \forall k{=}1,\ldots,4, \qquad (2)$$

As can be notices in the denominator of Eq. (1), we used the number of members who were involved in the non-stagnation group (i.e., NS Group) because those members have the highest participation rates for transactions within the community.

2.3.3 Random Network Simulation

The simulation was developed by using Python. As mentioned in the previous section, the price of the goods and services (*PCom*) was randomly generated in the range of 50 <PCom ≤ $Ini_n, \forall n = 1, \ldots, 5$, as shown in Figure 3. This simulation was performed by assuming that the community size consisted of 100 members (nodes) and the transactions were done among them using adjacency matrix (Adj), where each value in Adj represents the volume of transactions between each buyer and each seller in the community (see Eq. (1)), as shown in Figure 4.

Since that Adj was generated two times per a day within the 50-day period, the average of Adj was calculated as shown in Eq. 3.

$$\overline{Adj}_n = 0.5 * (Adj_1 + Adj_2)\ , \forall n = 1, \ldots, 5 \qquad (3)$$

The stagnation amount was defined as an amount of CC which was not used in the transactions of the community during a period of 50 days. To determine the amount of stagnation, we assumed the buyer who is the member of the community is interested in the offered market, and he/she will buy the commodity whose price is *PCom* (*PCom* is generated randomly).

Amount of stagnation ($Stag_m$) that corresponds to each group was computed using Eq.4

$$Stag_m = Nr_m \times PR_{\boldsymbol{m}} \times Ini_n\ \forall m = 1,\ldots,6 \text{ and } \forall n = 1,\ldots,5 \qquad (4)$$

Table 3: Stagnation amount in terms of CC for each group in T_1

Group Name	**Group Index** (m)	**The initial amount** (*Ini*)	**Participation Rate** *(PR)*	**Amount of Stagnation** $(Stag_m)$
Group A	1	10000	90%	10000
Group B	2	10000	80%	20000
Group C	3	10000	70%	30000
Group D	4	10000	60%	40000
Group E	5	10000	50%	50000
Group NS ※	6	10000	100%	50
Total of Stagnation $(TotalStag_1)$				150050

※The transaction will be realized when the price of the commodity is less than the remaining initial amount of CC (*Ini*) and hence the price of commodity will be deducted from the initial amount of CC (*Ini*). If the buyer used up most of the initial amount of CC (*Ini*), by making many transactions where each one was within the limit of the initial amount of CC, the remaining amount of CC will be considered as stagnation, as shown in Group NS in Table 3 where the stagnation amount was 50 CC .

If the remaining amount of CC is less than the generated *PCom*, this means that the participant cannot buy the commodity and the transactions will not be realized. By contrast, if some members in the community are not interested in the offered market as much as others, they will keep some of or all of CC and this amount of CC will also be considered as stagnation. Thus, the participation rates (*PR*) of the members will be reduced and hence different ratios of stagnations will result and the flow of currency among the members of the community will slow down accordingly.

The total amount of stagnation which resulted from the amount of stagnation from each group was computed using Eq.5, and then to be used thereafter to compute the ratio of stagnation relative to overall money stock as shown in Eq. 6.

$$TotalStag_n = \sum_{m=1}^{6} Stag_m, \qquad \forall n = 1,\ldots,5 \qquad (5)$$

$$StagRatio_n = \frac{TotalStag_n}{Aggregation\ Money\ Stock}, \qquad \forall\ n = 1,\ldots,5 \qquad (6)$$

2.3.4 Shannon Entropy(*SEn*)

Shannon entropy (*SEn*) is a measure of predictability and is closely related to the probability of a random variable. The higher the participation rate, the lower the entropy, and the lower the participation rate, the higher the entropy. This is because if the probability of a specific variable is small, the predictability will be small, and the entropy value will be high.

Conversely, if the probability of a specific variable is high, the predictability will be high, and the entropy value will be low. Calculating a network map of participation rates for transactions among all participants in the community will give us an idea of how often buyer and seller transactions are taking place. This was because the stagnation problem was considered as a result of a decrease in the participation rate in transactions within the community, so the retention location can be visualized as shown in Fig. 5. The *SEn* of the random variable X can be defined as in Equation 7.

Here, P_i was defined by Equation 8, x_i indicates the *i-th* possible value of x among the r symbols, and P_i indicates the possibility of $X=x_i$.

$$H(X) = H(P_1, \ldots, P_r) = -\sum_{i=1}^{r} P_i log_2 P_i \quad (7)$$

$$P_i = Pr(X = x_i) \quad (8)$$

Figure 5 Color map of Shannon entropy for all the transactions during the simulation (Alaraj, M. and Nishibe, M., 2020)

Figure 6 represents the schematic representation of the "customized community", while Figure 7 represents the flowchart of the overall method of creating the "customized community".

All the results were reported in (Alaraj, 2020), which indicated that the ratio of stagnation was decreased from 15% to 3% after implementing the customization community-related concept (Alaraj, 2020).

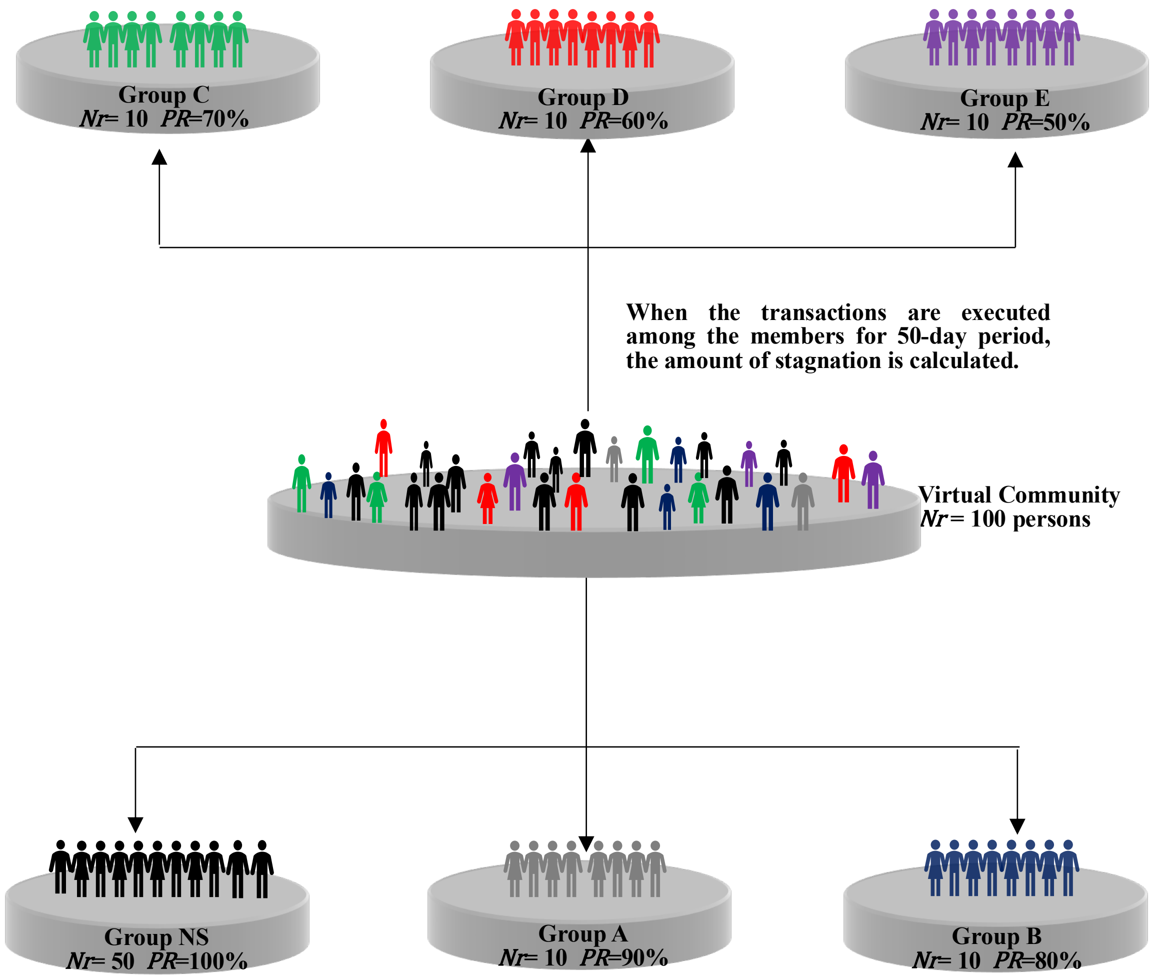


Figure 6 The schematic representation of the "customized community" during the simulation

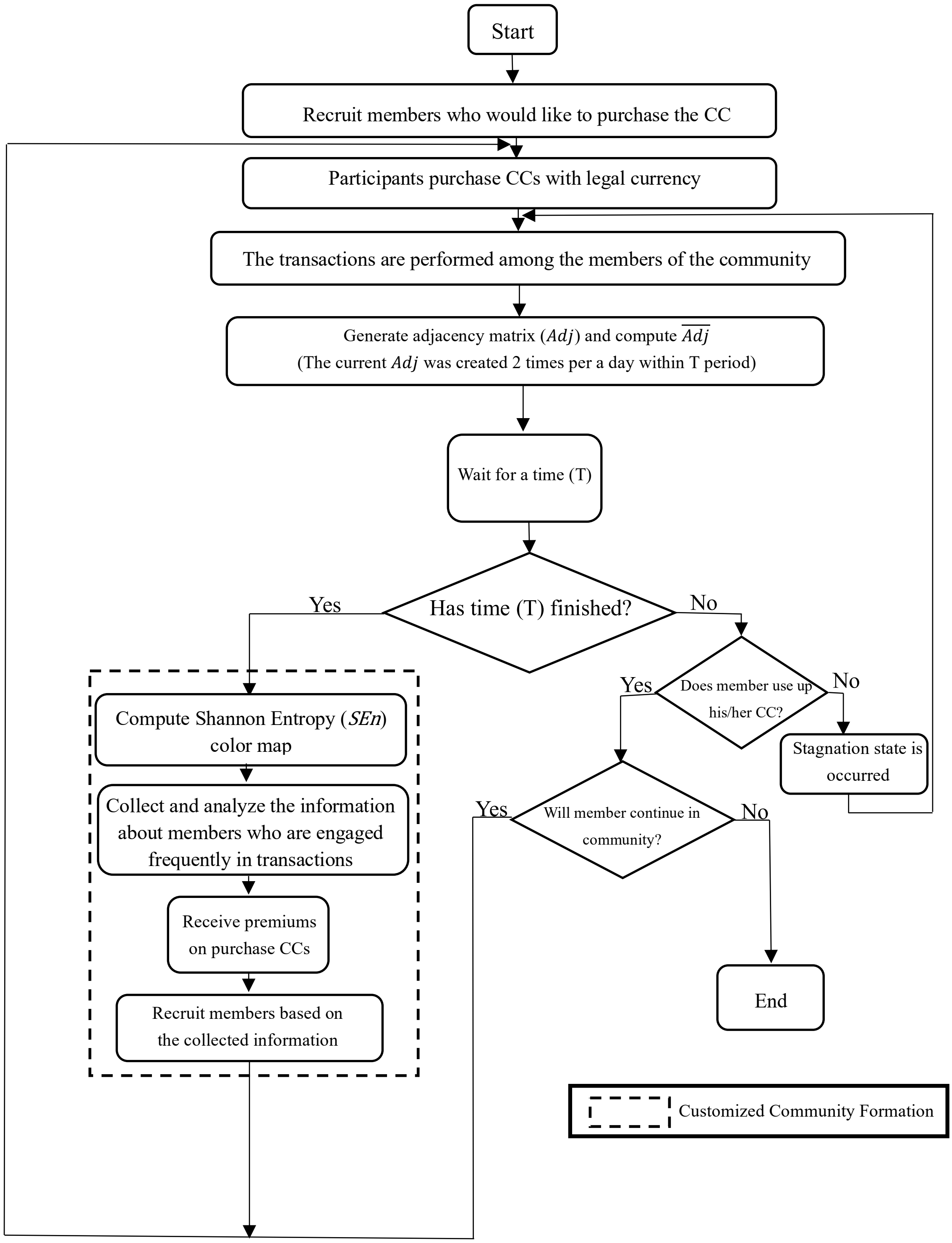


Figure 7 Flow chart of the overall method of creating customized community

3. The Method of Constructing "Customized Community"

3.1 C.C.Wallet Platform

In the current research, all the data was obtained from C.C.Wallet platform. C.C.Wallet is a CaaS (Currency as a Service) platform where users can issue and manage various community currencies. This platform enables regional development organizations and communities to design and manage depreciating currency and LETS-based metric currency based on the related communities and organization's characteristics and needs by using a mobile application to create a new sustainable society. Additionally, this platform costs low or free of charge and equipped with the following functions:

(1) Transmission Function for QR codes.

(2) Messaging Function.

(3) History Function.

This platform has been examined by using it in various regions and organizations in Japan(Maeda, 2018), and we will report the main operation of these local currencies.

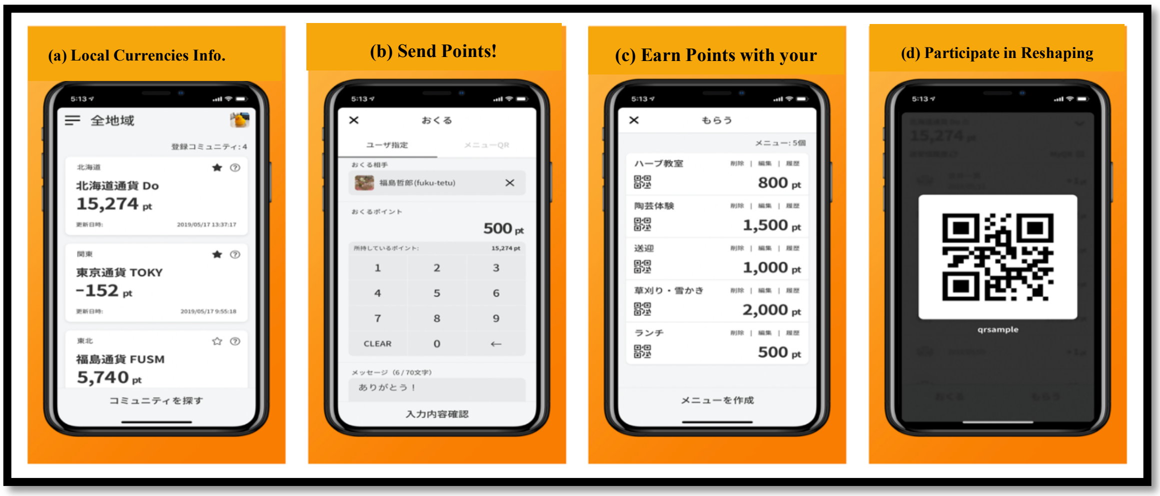


Figure 8 Community Currency Smartphone Application (C.C. Wallet) Screenshots (Maeda, 2018)

The main screen of the C.C. Wallet application is shown in Figure 8 (a), where any region, shopping district, company, or any organization can request to set their own currency, issue, and operate it. Also, we can also see in Figure 8 (b), currency amount (i.e., number of points), message and textbox for the addressee of the destination. In Figure 8 (c), we can see different skills/activities that the user has registered on the application like Herbology Class, 800pt, Chest Art Experience, 1500pt, Haircut, 2000pt, and pick-up from some place, 1000pt. Finally, the QR code which is used for transmission. can been seen in in Figure 5 (d). C.C.Wallet is available and can be download from Apple's App store or Google's Play store. The full details about C.C.Wallet as well as the implementations of this platform are reported in (Maeda, 2018).

3.2 The Transaction Data

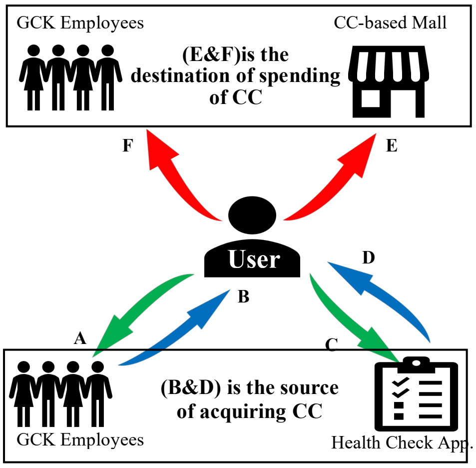
All the data was obtained from Global Communications Planning Co.Ltd. (hereafter abbreviated as GCK). The data was exported by C.C.Wallet as a CSV file form and the template of the file is shown in Figure 9.

1	2	3	4	5	6	7	8	9	10	11
A	B	C	D	E	F	G	H	I	J	K
Currency Code※1	Time Stamp	C2C	GPS Data	Trans. Point	Seller Name	Seller Balance	Seller Message※2	Buyer Name	Buyer Balance	Buyer Message

※1 ：00112: Currency of Chiba Prefecture ※2：almost null

Figure 9 The CSV template of C.C.Wallet

The data file exported by C.C.Wallet platform was not only related to bilateral transactions of products and services which were purchased by users of C.C.Wallet (member of community), but also to the transactions at CC malls (CC-based malls) as shown in Figure 10.



A. Offering products or services
B. Receive CC regarding products or services
C. Performing health check daily
D. Receive CC regard performing health check
E. Purchasing the offered products through CC-based Malls
F. Purchasing the offered products or services through bilateral transactions

Figure 10 CC Flow Paths

Table 4 The Transaction Data

Total Nr. Transactions	Total Nr. Nodes	Period of Transactions
27968	738	2019.5.9 ～ 2021.3.16

The flow of CC is shown in Figure 10, while the details of transaction data is shown in table 4. Specifically, the direction of blue arrows was used to represent the sources of CC where the CC can be earned throughout the bilateral transactions or regarding user's cooperation in recording his/her health status before starting the work on daily-basis as one of the countermeasures against Covid19, In this regard, the employees of GCK earned 5 points of CC every day when they record their health conditions such as body temperature or compliance with rule of washing the hands for 30 seconds or more etc. in the terminal where health check application is installed in, as shown in Figure 11.

On the other hand, the direction of red arrows was used to represent the destinations where CC can be spent. The green direction points to the products and services which are provided by the user.

Figure 11 **The graphical user interface of health check application in GCK**

Since C.C.Wallet does not have numerical data that directly indicates the satisfaction of the user, such as five stars for indicating the fully satisfaction regarding the offered product or services, it is necessary to predict user satisfaction in numeric form to determine the most popular product and services within the community to be used thereafter as a tool to construct the “customized community”.

Thus, it was first necessary to grasp the name of the purchased product and services not only from what it was written directly in the comments of the member (i.e., Direct Transaction Trust “DTrust”), when he/she finished the transaction, but also, we need to calculate how many times that a particular product or service was purchased (i.e., Indirect Transaction Trust “InDTrust”). In the current research, the DTrust and InDTrust could be obtained when the user finished the transaction with another user through C.C.Wallet. As a result, DTrust and InDTrust could be used as indicators for the estimating the degree of satisfaction of the user regarding the offered product and services, while InDTrust could be obtained only when the user purchases a particular product from CC-based mall.

The network of transactions can be represented by a directed graph as shown in Figure 12 where each node represents a user and each edge represent a transaction. All the details of this network are shown in Table 4.

In Figure 12, the source of the arrow represents the “buyer” and the target of the arrow represents the “seller” (i.e., “buyer” → “seller”). In graph theory, the number of edges pointing out from a particular node is called the “out degree” and hence, the user who has more “out degree”, he/she has purchased many products/services more than other users.

Considering this, since that GCK gives CCs for each employee who records his/her health status, the outdegree of GCK will be more than any another ordinary user as shown in Figure12.

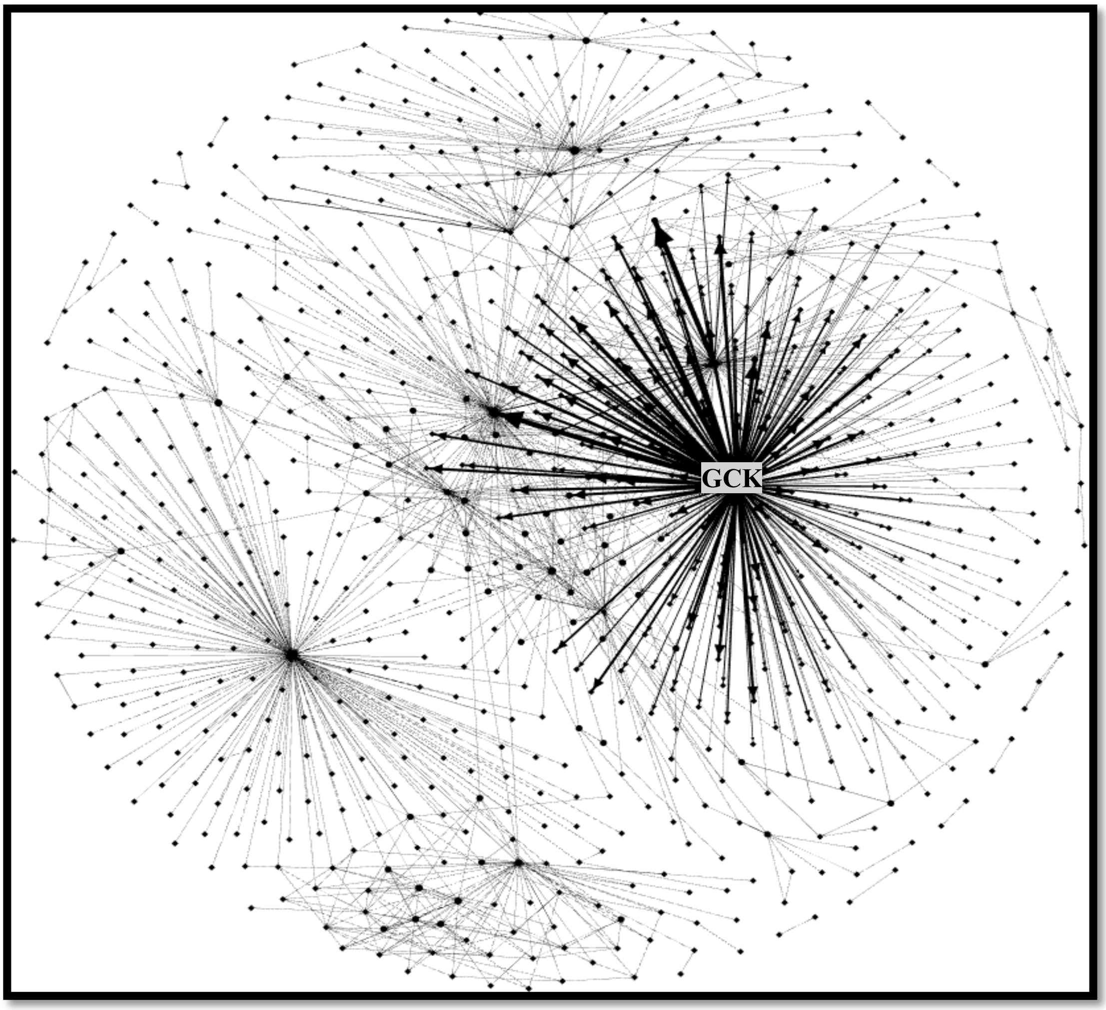


Figure 12 **The network of the transactions of C.C.Wallet**

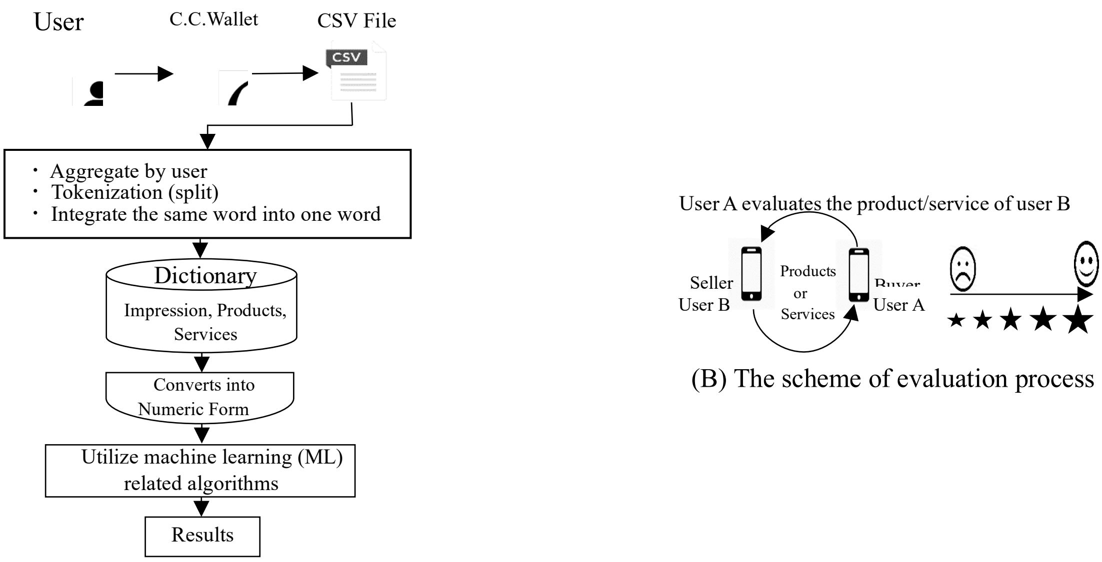
3.3 The Analysis Method

To analyze the comment text entered in C.C.Wallet, it is necessary to use the technology of Natural Language Processing (NLP). NLP is a scientific discipline that aids computers to understand human languages seamlessly. The ultimate objective of the NLP techniques is to extract meaningful information from human languages. Thus, to extract the meaningful information from the comments which were entered using Japanese language by the users (members of the community), those comments are needed to be tokenized (i.e., divide) into tokens by using python language-based module called "nagisa", as shown in Figure 13 (A).

Next, based on the entered impression and the number of purchased of the same products or services, we can estimate the satisfaction degree of the user using 5-stars scale from "5" stars to "1" star, as shown in Figure 13 (B). However, when the user did not evaluate the purchased products, "0" was used as an index indicating "no evaluation" instead of satisfaction degree.

The analysis process was focused on the 11th field of CSV-related template as shown the Figure 9 where the user (member of the community) records his/her message regarding the purchased product or services when the transaction was done between user and another user.

On the other hand, since CC-based malls are registered as users in C.C.Wallet, the sentence in 11th field of the generated CSV-related template was consisted of the following format:
"User X purchased goods Y at the mall.", where X represents the name of the user while Y represents the name of the product.
Thus, the name of the buyer and the name of the purchased products were extracted from the 11th field.



(B) The scheme of evaluation process

(A) NLP-based process

Figure 13 The process of NLP analysis as well as the representation of user's evaluation

Contrary to what happens between in the transaction between one member and another within the community, the member cannot record his/her impression when he/she bought a product from CC-based mall.

In the current study, we did not consider the price of the product/services as purchasing something expensive does not necessary mean that the user satisfy with that product/services while repeating the purchases process of the same product or service means so and hence, to predict the satisfaction degree of the purchased product, the number of times that the user repeatedly purchased the same product (InDTrust) was considered an indicator to the satisfaction degree which was evaluated on a five-point scale from a star "5" to a star "1". For example, if the same product is purchased once, the satisfaction degree is set to "1", if the same product is purchased twice, the satisfaction level is set to "2", and if it reaches 5 times or more, the satisfaction degree will be set to "5" and so on.

Table 5 The list of impression-related words in Japanese with its translations

Highly Satisfied	Satisfied	Relatively Satisfied	Not Satisfied	Not all Satisfied	No impression
	4	3	2	1	0
広め:Wide	ありがとう: Thank you	ごめん: Sorry	恐喝: Extortion	くそ: not appropriate	
わざわざご足労: Take the trouble to work	よろしく: Thank you	すみません: Sorry	できない: I can not	やだ: I don't like	
わざわざ: Take the trouble	宜しく: Thank you	すいません: Sorry	何となく: Some how		
本当にありがとう: Really Thank you	有難う: Thank you	あげる: give			
礼: Thank you	サンキュ: Thank you				
世話: Looking After	楽しん: have fun				
嬉しい: Happy	楽しみ: have fun				
甘く: Sweet	美味しい: Delicious				
さすが: As expected	美味し: Delicious				
心遣い: Thanks for consideration	美味しかっ: was Delicious				
大好き: really like	美味しく: Delicious				
ちそう: Hospitality	めでとう: Congratulations				
馳走: Hospitality	疲れ:Effort				
Go	久し: After a long time				
貴重な経験: Valuable Experience	頑張っ: Do your Best				
親切: Kindness	お試しに協力してくれてありがとう: Thank you for your cooperation				
良い: good	確認が取れました。ご協力ありがとうございます！: Thank you for your confirmation				
面白い: Interesting	おいしかっ: It was delicious				
感謝: Appreciated	立派: fine				
もう一つ: Another one					
ウインナー: Wiener					
最高: Best					
やりたいなぁ: I want to do it					
早速: Immediately					

3.3.1 Regression Analysis

Regression is a method used in statistics to predict continuous variable and it is also used in the field of machine learning. Regression analysis measures "how an increase in one variable x affects another variable y". In regression analysis, for a given two variables x and y, it is necessary to make a clear distinction between x "explanatory variable", and variable y which is called an "objective variable".

Since that "explanatory variable" is used in the learning process to generate the objective variable, we need first to determine what are the "explanatory variable" and "objective variable"?

The "explanatory variable" is determined from asking the following question, "What should we use to predict something?", while "objective variable" as its name implies, is determined by specifying the purpose of regression or operational needs.

Table 6 The learning data of AI-based model

Name of Variable	Meaning of Variable	Type of the Data	Type of Variable
Satisfaction	The satisfaction of the user	Numeric	Objective Variable
Repetition	The number of purchased item		Explanatory Variable

To use "objective variables" in the model, "impression-related words" (i.e., words expressing satisfaction) which was recorded as comments in Japanese language (DTrust) after finishing the transactions in CCWallet, was extracted as shown in Table 5. Those impression related words were linked to the satisfaction degree which was set to 5 levels ("5": highly satisfied, "4": satisfied, "3": relatively satisfied, "2": not satisfied, "1". not all satisfied, "0": No satisfaction-related words).

The full list of Japanese impressions-related words was classified in terms of satisfaction degree which was five-point scale as shown above in Table 5.

In the current study, we considered the category of the product rather than the offered product itself as well as the category of the service rather than the offered service itself as described above.

If a multiple "impression-related words" was recorded regarding multiple products/services where each of which was purchased throughout different transactions as well as classified in the same category, and those "impression-related words" had different degree of satisfaction, the average of those satisfaction degrees was calculated. For example, if the impression of a particular user (member of the community) regarding a particular product was "I really like it" which has a satisfaction degree "5", and then in another transaction, the impression of the same user regarding a particular product whose category was the same of the previous purchased one, was "thank you", which has a satisfaction degree "4", the average of the both satisfaction degrees was calculated and hence, "4.5" was considered a satisfaction degree regarding the purchased product's category.

However, since the impression-related words cannot be grasped through the transactions in CC-based mall, we calculated how many each user bought the same products (InDTrust) from CCs-based mall, and we considered such repetitions of purchases for the same category of the product as an indicator to user's satisfaction level regarding the purchased product.

Thus, the fixed format sentence ("User X purchased the goods Y in the mall", where X represents the name of the user(member of the community), while Y represent the name of the product's/service's category) which is recorded when the user of C.C.Wallet purchases a product from CCs-based mall in the 11th field of the CSV file, was extracted and evaluated on a five-point scale from the star "5" to the star "1" according to the number of purchases of the same product (InDTrust), and the satisfaction degree of the user who purchased from CC-base mall only can be computed by the following formula.

$$The\ satisfaction\ degree\ of\ user = the\ number\ of\ purchases\ of\ same\ product$$

$$\forall InDTrust \ (1 \leq InDTrust \leq 5) \qquad (8)$$

In the current study, the number of purchases of products and services were extracted per users as shown in Table 7 and Table8.

Table 7 The method of extracting the number of purchases for the products and impression-related words per user

Product Name	$User_1$	$User_2$	· · ·	$User_n$
Pro_1	For $User_1$ Pro_1 and 「$impression - related\ word$」 is extracted	For $User_2$ Pro_1 and 「$impression - related\ word$」 is extracted	⋮	For $User_n$ Pro_1 and 「$impression -$ $related\ word$」 is extracted
Pro_2	For $User_1$ Pro_2 and 「$impression - related\ word$」 is extracted	For $User_2$ Pro_2 and 「$impression - related\ word$」 is extracted	⋮	For $User_n$ Pro_2 and 「$impression -$ $related\ word$」 is extracted
⋮	⋮	⋮	⋮	⋮
Pro_m	For $User_1$ Pro_m and 「$impression - related\ word$」 is extracted	For $User_2$ Pro_m and 「$impression - related\ word$」 is extracted	· · ·	For $User_n$ Pro_m and 「$impression -$ $related\ word$」 is extracted

Where m represents the total number of products and n represent the total number of users who purchased the products.

Table 8 The method of extracting the number of purchases for the services and impression-related words per user

Product Name	$User_1$	$User_2$	$\cdots$	$User_q$
Ser_1	For $User_1$ Ser_1 *and* 「*impression − related word*」 is extracted	For $User_2$ Ser_1 *and* 「*impression − related word*」 is extracted	$\vdots$	For $User_q$ Ser_1 *and* 「*impression − related word*」 is extracted
Ser_2	For $User_1$ Ser_2 *and* 「*impression − related word*」 is extracted	For $User_2$ Ser_2 *and* 「*impression − related word*」 is extracted	$\vdots$	For $User_q$ Ser_2 *and* 「*impression − related word*」 is extracted
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Ser_p	For $User_1$ Ser_p *and* 「*impression − related word*」 is extracted	For $User_2$ Ser_p *and* 「*impression − related word*」 is extracted	$\cdots$	For $User_q$ Ser_p *and* 「*impression − related word*」 is extracted

Where p represents the total number of products and q represent the total number of users who purchased the products.

3.3.2 Neural Network Model

Typically, there are various types of neural networks (hereinafter abbreviated as NN), but the simplest form is a three-layer feedforward neural network as shown in Figure 14.

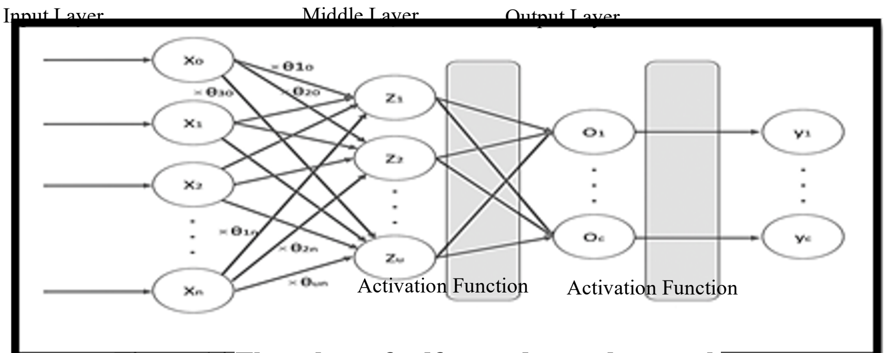


Figure 14 Three-layer feedforward neural network

3.3.3 The Theme of NN

In the current study, learning process of NN model was performed on the hypothesis that the degree of satisfaction regarding the offered product/service can be predicted based on user's number of purchases and hence, the goal of learning is to derive a model that can make such predictions.

3.3.4 The Necessary Steps for Building NN Model

When building the NN model, a series of processes are executed as shown in Figure 15. In the current study, we will explain those processes as shown in the next section.

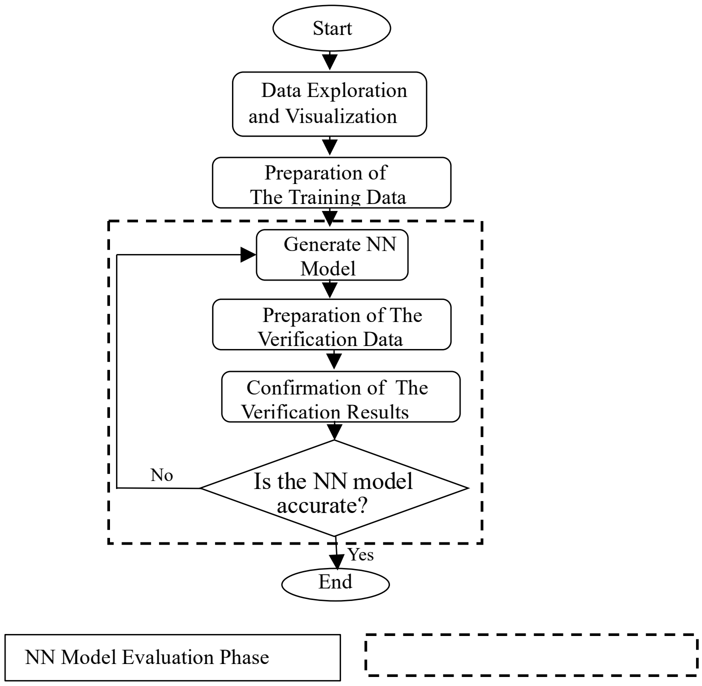


Figure 15 The process of Building a NN Model

3.4 Results

3.4.1 Data Exploration

The obtained data includes some of billing-related information and such data was excluded from the analysis as it is not related to the scope of the current research.

Each participant (node) trades as a “seller” or “buyer” and the number of sales and purchase transactions does not always match. In addition, some participants purchase and sell a large amount of products and services of various types, while others purchase and sell only a small amount of products and services and the number of transactions performed by each participant was not equal.

Since that there were many products and services, we tried to categorize the products with almost the same contents and meanings into the same category. For example, all items written in various expressions such as “pan”, “bread price”, and “pan help” as the names of products are put in the “bread” category. Similarly, services names like “drinking party”, “dining party”, “banquet”, “evening party”, “dinner” and “second party”, etc. , were categorized as “Social Gathering” and so on.

Japanese language had 3 writing systems: Kanji, Hiragana and Katakana, and all of them can be used to write the same word. Since that some of the names of the products and services were written in Kanji, while the others whose had similar names were written in Hiragana, we need to unify them into one writing systems and in the current study we chose Katakana system. It is worthy mentioned that to reduce the computational time of the processing, it is important to unify and categorize the products and services into one category and one writing system.

3.4.2 Data Visualization

To better understand the data, we used the Python language to generate statistical graphs related to products and services. The data identified 107 types of products (including products provided by the mall) and 68 types of services.

The average of purchases for the product and services were shown in Figures 16 and 17 respectively. In other words, such graphs can indicate to how much such products and services were popular among all members whose real names were replaced with animal names for anonymization and keeping privacy.

Also, a function to display the number of purchases for a particular products or services for the members after writing user's name (i.e., animal name) was developed as well. As an example, Figure 18 is a graph showing the number of products purchased by a specific user ("fin whale") at a mall, while Figure 19 is a graph showing the number of products purchased by a specific user ("fin whale") at a CC-based mall and throughout the bilateral transaction.

3.4.3 Generating NN Model

To set the learning process of NN by using Python language, we used 2 patterns of NN as shown below:

1. "1st pattern": the values of the parameters were set as below:

```
nn = (hidden_layer_sizes=(2),
        activation='relu',
        max_iter = 10000,
        verbose=True,
        learning_rate='constant')
```

2. "2nd pattern": the values of the parameters were set as below:

```
nn = (hidden_layer_sizes= [(2), (3), (4), (5)],
        'activation':['relu', 'logistic'],
        max_iter = 10000,
        verbose=False,
```

The explanation of the parameters is shown in Table 9.

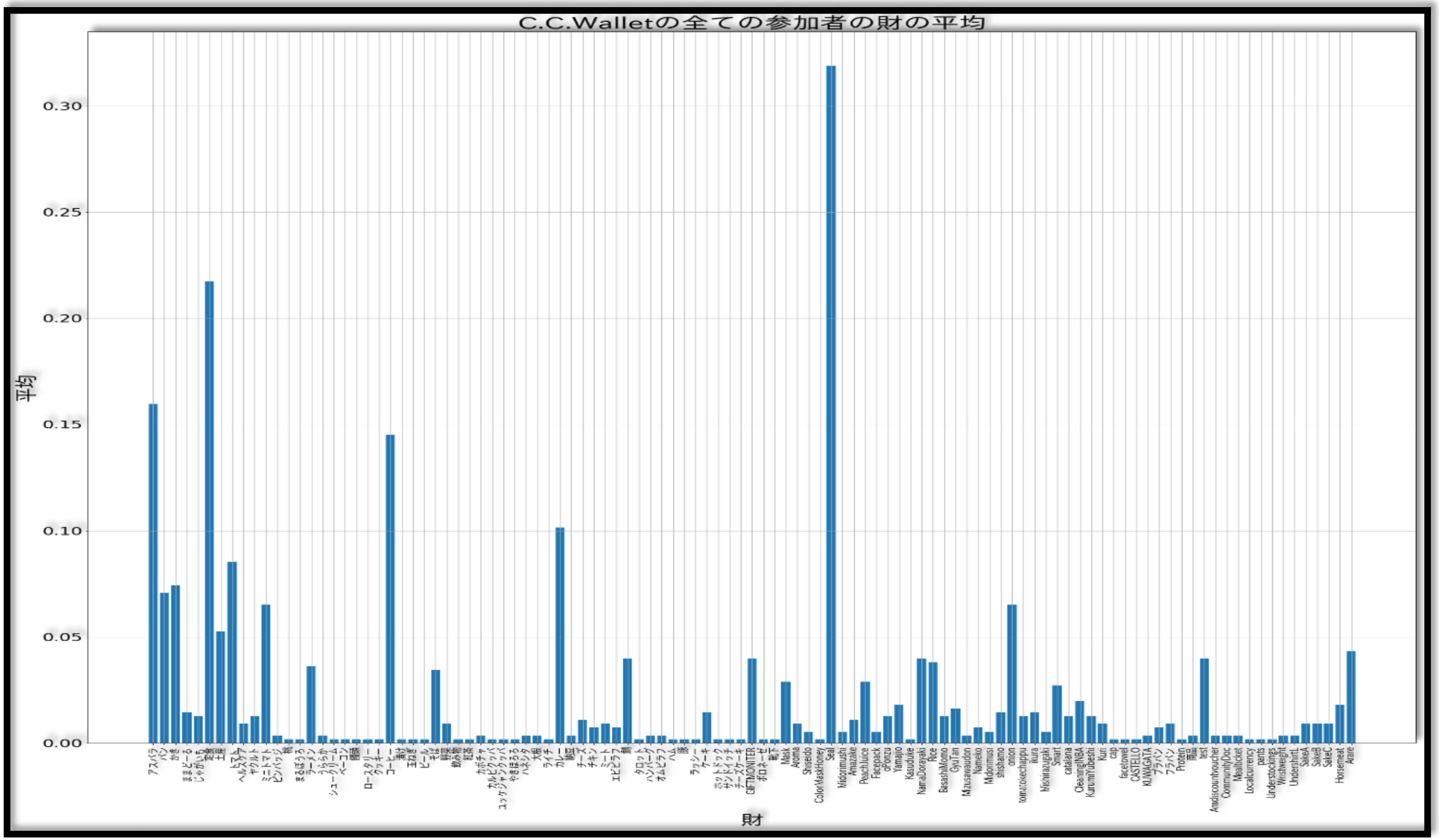


Figure 16: The Average of Purchases of the Products across the Users

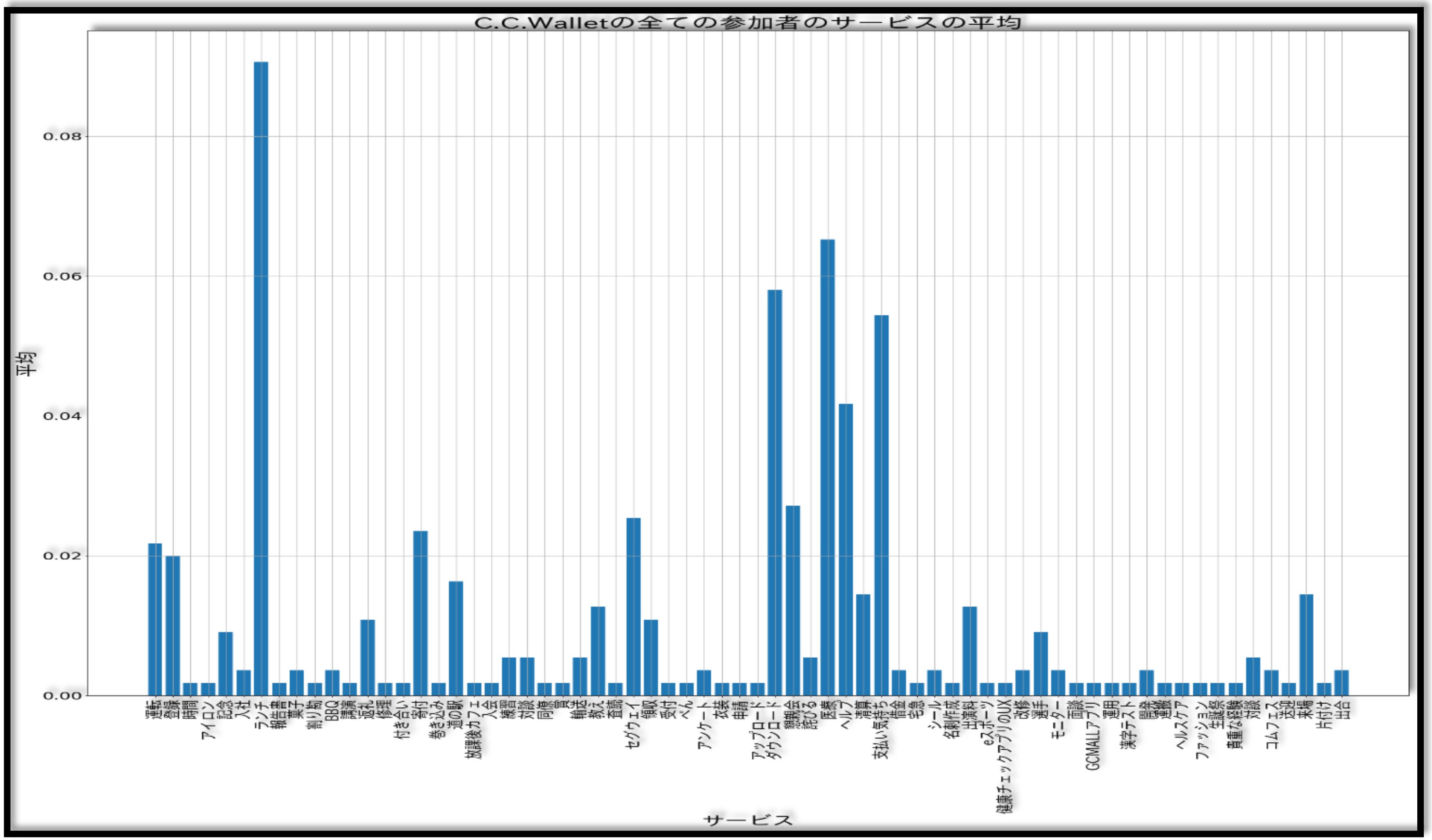


Figure 17: The Average of Purchases of Services across all Users

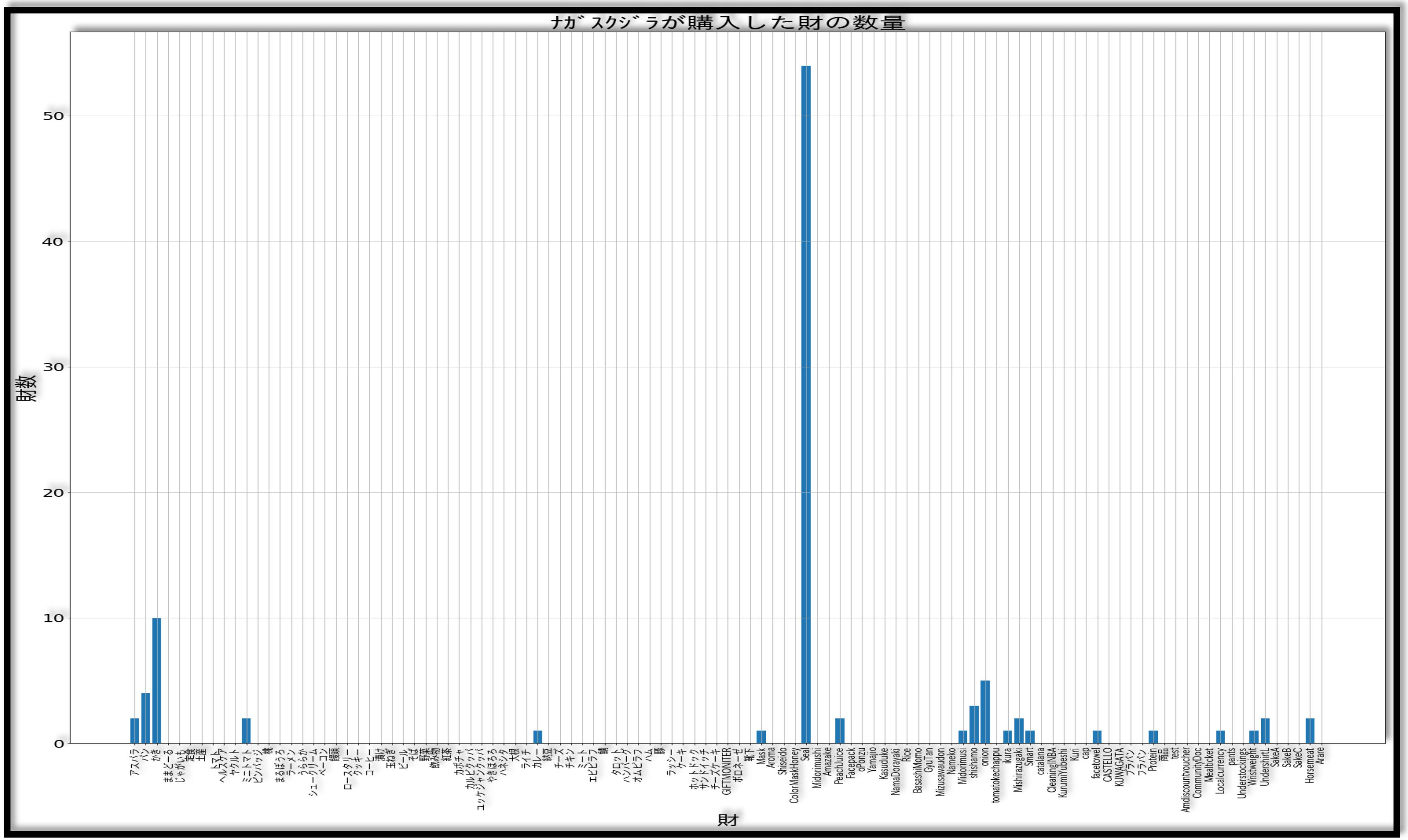


Figure 18: Quantity of Products purchased by user "Fin Whale" at Mall using C.C.Wallet

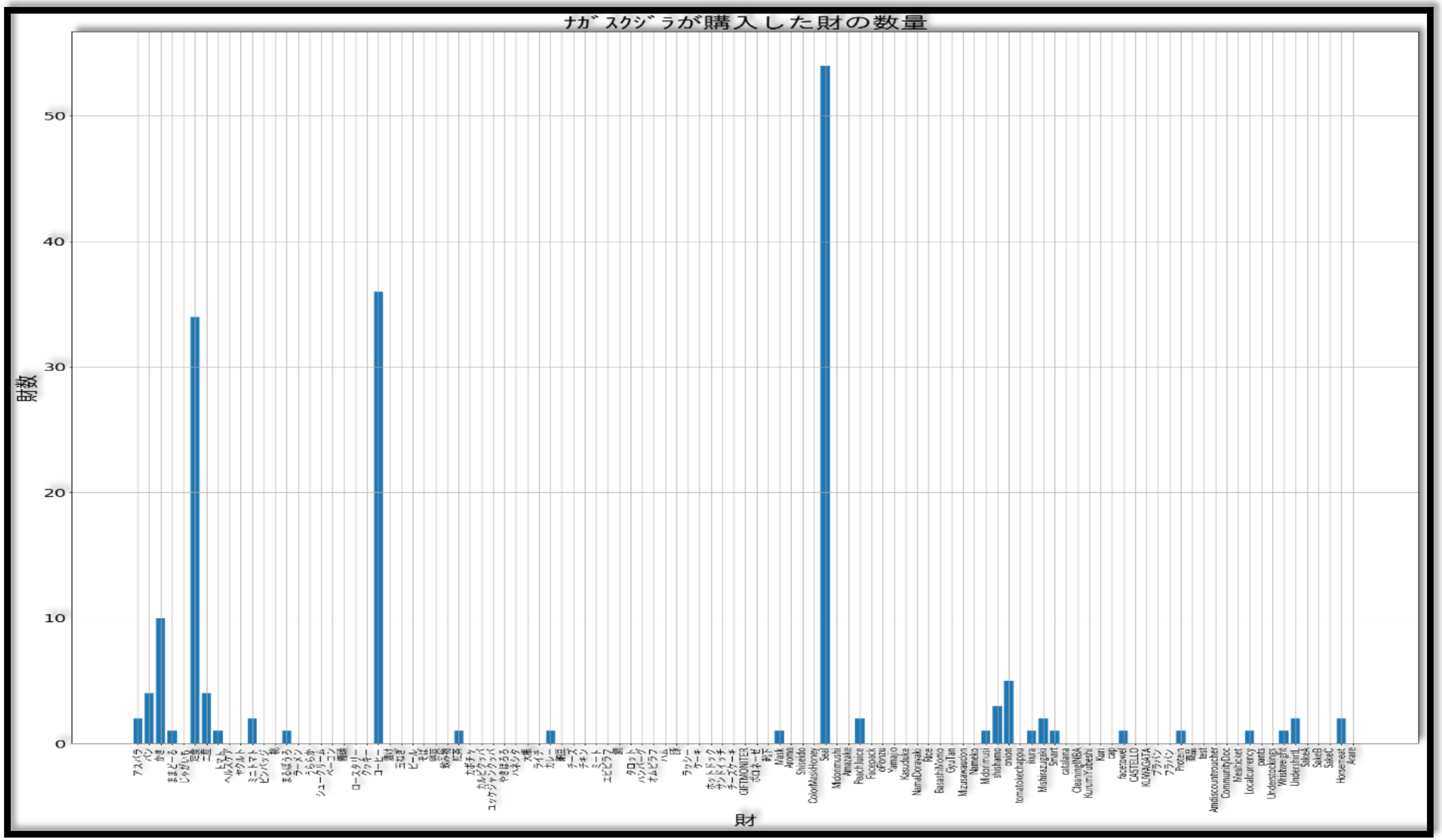


Figure 19: Quantity of goods purchased by the user “Fin Whale” in both regular bilateral transactions

Table 9 The Explanation of NN Parameters

The Name of Parameter	Meaning	The Meaning of Values
hidden_layer_sizes	**Number of Elements:** Number of calculations in the middle layer **Value of each Element:** number of neurons in each middle layer	・Two in the first layer ・ 2 in the 1st layer, 3 in the 2nd layer, 4 in the 3rd layer, 4 in the 5th layer. Since the number of calculations in the middle layer is two or more, this learning is called [deep learning].
activation	Specifying the activation function	・relu：ReLu Function (If the input value is 0 or less, it becomes 0, and if it is larger than 0, the input is output as it is). ・logstic: Logistic Function (calculates the probability value and classifies it according to whether it is above the threshold value.
max_iter	Maximum number of searches when searching for the optimal solution If -1 is specified, it repeats until it converges.	The optimum model search process is repeated up to 10000 times.
verbose	Specify whether to output a message in the process of model generation	・"True": Message will be displayed. ・"False": Message will not be displayed.
learning_rate	Update the Weight Learning Rate	・The learning rate specified in "constant" is fixedly used, and the default is here.

3.4.4 Regenerating NN Model

The second NN pattern was then used to rebuild the NN model using similar training data to improve the accuracy of predictions. However, adjusting the accuracy of the model needs to "tune" the values of parameters of NN-model. Thus, such "tuning" process was performed using "Grid Search" which is a method to find the most accurate model by setting a range of values that can be handled (e.g., 0, 1, 2, 3, etc.) for a parameter called α (alpha) used for model generation. Specifically, it is a method of executing the process of generating a model by sequentially substituting numerical values in a specific range into α and using the most accurate model among those models as the final model.

When performing grid search in Python language, we used a module called *GridSearchCV*. In the following processing, the parameters (setting values used for model generation) for generating the optimum model were obtained. For example, in the case of "fin whale", the parameters value necessary to generate the optimum model were obtained, but such values were different for each participant.

```
from sklearn.model_selection import GridSearchCV
parameters={
    'activation':['relu', 'logistic'],
    'max_iter':[10000],
    'verbose':[False],
    'random_state':[4],
    'hidden_layer_sizes': [(2), (3), (4), (5)]
}
cv = GridSearchCV(estimator=MLPRegressor(),param_grid=parameters)
```

```
'activation': 'logistic',
'hidden_layer_sizes': 2,
'max_iter': 10000,
'random_state': 4,
'verbose': False
```

Verification with verification data was also performed using the newly generated model. Root Mean Square Error (RMSE) was used as an index to of measuring the efficiency of grid search algorithm and the value of RMSE is shown in the belowTable 10.

Table 10: The value of RMSE when the satisfaction degree of "Fin Whale" is estimated using "2nd pattern"

Type of Transaction	RMSE
Products	0.722
Services	1.380

4. Discussion

So far, a community currency based monetary system has been proposed to strengthen cooperation between members by repeating non-commercial and commercial transactions among community members, but sometimes the members cannot find the desired products or services. Consequently, the CC acquired as compensation for non-profit activities stays in the hands of the members and does not circulate in the system. If such a situation occurs frequently, a stagnation problem will arise, and a new mechanism is needed to circulate CCs more smoothly and quickly to circulate CC among the members of the community.

Therefore, we proposed a method so that the feasibility and sustainability of the CC as a monetary system can be enhanced by introducing the concept of a "customized community" where commercial and non-commercial transactions can be integrated.

A manual dictionary was created by using C.C.Wallet users' messages (evaluation comments) where satisfaction-related words (i.e., impressions) regarding the offered products and services are recorded after completing the transactions in Japanese language. Thus, when a new data that did not exist before, it was necessary to update the dictionary. Moreover, if there are mistype-related mistakes in the evaluation messages recorded by members, it is necessary to manually correct those words before using them in the dictionary (e.g., “pin batch” should be “pin badge”).

Thus, as can be noticed, creating this dictionary takes time, but from the viewpoint of privacy protection, we did not use cloud-based services.

To use the NN model as a tool for predicting participant satisfaction, it is necessary to validate the results obtained by deep learning using validation data that is different from training data (training data). By this way, the obtained data needs to be divided into two sets, a training set and a verification set. With reference to the obtained data, the users of C.C.Wallets were divided into three groups, Group A, Group B, and Group C, according to the number of transactions.

Users in Group A had enough transactions, and we were able to divide the data into training sets and validation sets to build an NN model. Users in Group B did not make many transactions as participants in Group A and hence, only validation data was synthesized (i.e., not actual data).

On the other hand, Group C is a group of participants whose number of transactions is insufficient to divide into a training set and a verification set (see Figure 12 for members with a very small number of transactions), and an NN model could not be constructed.

Therefore, to be able to configure a “customized community”, it is necessary to increase the number of CC users and increase the frequency of transactions and this task was left as a future research topic.

Typically, NN model does not have a general format or optimal values for the parameter of NN in the intermediate layers (hidden layers). Since the purchasing behavior was related to the number of purchases for the same product/services which differs from one user to another, it is necessary to specify the appropriate NN parameters for each user.

In the current research, the satisfaction of the member was defined in terms of number of purchases of the same products or services as the member will repeat the purchase process as long as he/she satisfied with the offered product/services. Also, such satisfaction was expressed explicitly in the evaluation message in terms of linguistic expression.

Also, the price of the product/services was not considered as an indicator for the satisfaction of the user because buying something cheep does not necessarily mean that he/she satisfied with the offered product/service and hence, the price of product/services was not used as an explanatory variable of the satisfaction in this study.

Since, the name of products/services as well as member’s expression were not frequently expressed in the evaluation messages of C.C.Wallet platform, the test data was mainly synthesized. In this study, Since the number of users was relatively large, the computational time was shortened by reducing the number of intermediate layers of NN model as much as possible.

4. Conclusions

This study proposed a new method to accelerate the circulation of CC among the members of the community by constructing a “customized community” through estimating the satisfaction degree of the members based on NN model.

First, the satisfaction level was predicted by the comment text recorded by the member of the community throughout the C.C.Wallet. Specifically, it was executed by creating a word dictionary from the comment sentences entered by the participants after closing the transaction, thereby converting the meaning-based text into numerical values corresponding to the meaning of each word.

The NN model was constructed to estimate the satisfaction degree where the objective variable was derived based on impression-related words after converting those words from linguistic text to numeric values where five levels of numerical values (the number of stars from 5 stars to 1 star) based on their meaning in Japanese language was considered.

On the other side, determining the explanatory variables was rather complicated. It was necessary to determine the explanatory variables after considering various hypotheses because explanatory variables were considered as s variables that assist us to explain the objective variable (i.e., satisfaction degree). Therefore, for each member, the number of purchases of the same category of products/ services were calculated. Since the high and low prices of products/services do not necessarily reflect the satisfaction of the participants, the prices of products/services were not used as explanatory variables in this study.

In the current study, the estimation of satisfaction of the members was considered as a bridge to build a principle of “customized community” where the circulation of the CC was accelerated based on our simulation. Since that the purchase behavior was different from one member to another, we need to tune the values of parameters of NN and hence, the algorithm of “grid search” was used. However, some members did not have many transactions as others, and such situations disable us from building NN models. Also, some members who did not have many transactions to divide them into a training set and a validation set, the validation set was synthesized for such participants only.

Therefore, if the use of CC is expanded by using various other applications that can acquire CC to purchase products at CC malls, actual data can be increased, and more appropriate results can be obtained.

For example, a new health care application called NUCADOCO as shown in Figure 20, will be released soon for participants who are implementing health management.

Also, to increase the number of participants who use CC in their transactions, we don’t only need to use other applications like NUCADOCO, but also we need to offer a wider variety of products in the mall.

In this study, the concept of “customized community” was introduced as a tool to attenuate the stagnation problem in local economics. However, since the obtained data was not sufficient, we decided to utilize simulation experiments to indicate the efficiency of this concept in reducing the stagnation problem.

Thus, building a “customized community” using real data and proofing its efficiency is needed to be investigated using actual data obtained from empirical experiments and this task was left for future research.

Figure 20 NUCADOCO Application

Compliance with Ethical Standards

1. Disclosure of potential conflicts of interests

   This research was performed based on a mutual research collaboration between Global Communication Planning Co. Ltd. and Good Money Lab in Senshu University.

2. Author Contributions

   All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Dr. .Maen Alaraj. The first draft of the manuscript was written by Dr. Maen Alaraj and Prof. Makoto Nishibe commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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