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Design and Evaluation of an Incentive Decision Method for an Agricultural Information Sharing System

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Abstract

Agriculture in Japan is facing a crisis due to the aging of farmers and a shortage of successors. In addition, much of agriculture depends on know-how that new farmers cannot easily obtain; therefore, new farmers often give up farming after a few years. Consequently, it is necessary to share agricultural know-how with new farmers. However, the difficulty in verbalizing this know-how poses a challenge in sharing it. Therefore, it is necessary to provide incentives to the providers of know-how. In this paper, we propose an incentive decision method using auto-negotiation while considering the intentions of the know-how providers. This method consists of agents that have utility functions, which express the intentions of farmers, and a service. The performance of our method is evaluated by simulation experiments. We verify that our method collects a large amount of high-quality know-how with low incentives. The results indicate that our proposed method performs better than the existing methods considered in the experiments.

Keywords: Agriculture Information, Information Sharing, Incentive

1 Introduction

Japan is witnessing an unprecedented crisis in the maintenance and growth of agriculture due to the aging farmers and a shortage of successors [20]. In addition, much agricultural work is based on know-how that farmers obtain over a long time; hence, new farmers do not have sufficient topical know-how, and they often give up farming after a few years, which creates a problem [21]. Therefore, it is necessary to transfer agricultural know-how and techniques from experienced farmers to new farmers. However, because most of the know-how is based on tacit knowledge [6,19], which is difficult to explain, providing such know-how imposes a burden on experienced farmers, making it difficult for them to positively share this know-how with new farmers. Therefore, it is necessary to provide experienced farmers with an incentive to undertake the cumbersome task of transferring the relevant know-how.

The incentives may be monetary (e.g., money and goods) and non-monetary (e.g., honor and gratitude). Regarding monetary incentives, collecting higher quality know-how and suppressing incentives are related to the sustainability of the service. Therefore, for assuring the sustainability of the service, it is necessary to reduce the amount of monetary incentives for experienced farmers who provide low-quality know-how and prioritize the experienced farmers who provide high-quality know-how.

The objective of this study was to develop a method to prompt experienced farmers to provide their know-how positively while maintaining the sustainability of the service by determining the incentive amount based on the intention of the experienced farmers and the service quality. We built an incentive amount decision mechanism that determines the incentive amount based on auto-negotiation. This auto-negotiation is performed between agents that represent experienced farmers and those that represent the service. An experienced farmer agent has a utility function for the farmer's intention, and a service-side agent has a utility function for the intention of the service.

In addition, we constructed a reliability calculation mechanism. This mechanism calculates the reliability of the experienced farmers by weighting the know-how and a parameter that reveals how appropriately the experienced farmers evaluate their own know-how. Using a combination of the two, an incentive decision method can be developed for prompting experienced farmers to provide their know-how while considering the sustainability of the service.

This paper is structured as follows. Section 1 describes the background and purpose of this study. Section 2 deals with information sharing in a Japanese agricultural information sharing system, a method of prompting actions by giving incentives, and a method of determining the incentive amount. Section 2 also describes the research issues in this study and presents a proposal to overcome the challenges. Section 3 details the incentive amount decision mechanism and the reliability calculation mechanism. Section 4 describes an experiment and the insights gained therefrom. Finally, Section 5 concludes this paper and presents proposals for future work.

2 Related work and research issues

2.1 Agricultural knowledge sharing

Conventionally, agricultural knowledge (e.g., know-how and skills) is directly shared with new farmers [15,31]. For example, in Japan, new farmers work as trainees with experienced farmers and learn from them. The communication between local and new farmers is based on such direct communication. However, for accomplishing such learning, each region should streamline the system to accept the new farmers and the new farmers should act positively. Against this background and considering the widespread use of the Internet and information technology (IT) devices, some studies are being conducted to encourage the application of IT in agriculture [7,8,12,13,16]. These studies are aimed at enabling the experienced farmers, who are information providers, to easily grasp the farming status and share information and enabling the new farmers, who are the information receivers, to collect a wide range of information easily. Such studies have indicated the problem of the delay in the introduction and adoption of IT in rural areas [13]. However, IT-device ownership ratio of farmers considerably increased from 2005 to 2012 [22,23]; hence, studies on the application of IT in agriculture will gain importance.

It is known that agricultural knowledge is the tacit knowledge that farmers obtain over long periods of time [11,29,30,34,35]. Since such tacit knowledge is usually not verbalized, the accumulated knowledge of agriculture may be lost if an experienced farmer gives up farming [35]. Hence, to prevent the loss of tacit knowledge while creating new knowledge, attempts were made to transform tacit knowledge into explicit knowledge by employing the SECI model—the socialization, externalization, combination, and internalization model [25]—and sharing the explicit knowledge between individuals or groups [10,11,29,30,34,35]. However, to make the tacit knowledge explicit and to share it, the experienced farmers have to explain the know-how and have to be interviewed; in addition, cooperation between the experienced and new farmers is necessary [34]. These requirements impose a burden on the experienced farmers.

2.2 Prompting information sharing

To prompt information sharing, it is necessary to provide incentives—monetary or non-monetary [4, 18, 24]. In particular, monetary incentives have been used as a motivation to prompt various actions in some studies [1, 2, 14, 17, 26, 32, 33].

Providing monetary incentives for improving driving behavior [2] and for encouraging provision of life-log information [14] has been shown to be effective in improving and prompting the actions of the information providers. However, the necessary incentive amount differs according to individual users [1, 5], and the amount of the incentives may be remarkably changed by each user's intention.

Meanwhile, monetary incentives can lead to a high cost for maintaining the sustainability of the service [2, 28]. Furthermore, sometimes, monetary incentives are not efficient [14, 33]. Since inefficient incentives can cause rapid depletion of financial resources and considerably hamper the sustainability of the service, it is necessary to keep service sustainability in mind when providing monetary incentives.

Some Internet services (e.g., LINEQ [3], nanapi Works [9]) actually employ monetary incentives; however, some services have already been terminated. LINEQ [3], which is no longer available, was a Q&A website that provided redeemable points with the users without considering the quality of the questions and the answers. Therefore, the responses included low-quality answers and hoaxes, and, consequently, the service was terminated. Thus, providing incentives without considering the quality of the actions considerably affects the service sustainability.

2.3 Deciding the incentive amount

A simple method to decide the amount of the incentives is to assign a constant incentive value for a service. However, as described in Section 2.2, the necessary incentive amount should differ according to the users' intentions and should consider the action quality. Therefore, it is inappropriate to use a fixed incentive amount.

An earlier study in which the incentive amount was determined by reversed auction [17] showed that considering the users' intentions when determining the incentive amount is effective for saving the monetary resources and for prompting continuous information sharing by the information providers; however, the target of this study was participatory sensing for which the quality of the provided information remains more or less the same. On the other hand, in the case of agricultural knowledge, there are large differences in information depending on the provider, and, hence, the method employed in the previous study cannot be applied for this knowledge. Therefore, regarding agricultural knowledge, it is necessary to decide the incentive amount while focusing on the quality of the information as well as the providers' intentions.

2.4 Research issues

As mentioned earlier, sharing of agricultural knowledge imposes a burden on the experienced farmers. To solve this problem, the methods that prompt and improve the actions of the users by providing incentives (Sections 2.2–2.3) can be used. The research issues involved in prompting sharing of agricultural information while considering the differences between individual intentions and service sustainability are as follows:

(I1) It is difficult to provide experienced farmers with sufficient incentives to prompt them to provide know-how.
The amount of incentive sufficient for such prompting differs depending on the individual intentions of experienced farmers. Hence, it is difficult to determine the absolute sufficient incentive amount for all experienced farmers.

(I2) It is difficult to rationally distribute the limited incentive resources.
The resources for monetary incentives are limited. It is difficult to rationally distribute such a resource to experienced farmers while considering their intentions and the quality of the know-how.

In this study, the following measures are proposed to solve the abovementioned research issues.

(S1) Incentive decision-making via auto-negotiation between agents that have utility functions while considering the intentions of the experienced farmers and the sustainability of the service
This method helps reduce the incentive amount and to collect more high-quality know-how by considering the self-evaluations of the know-how of experienced farmers and service sustainability. It determines the sufficient incentive amount based on the intentions of the experienced farmers and sets the utility functions of the agents by considering the quality of the know-how, employing auto-negotiation between these agents when deciding the incentive amount.

Utility functions are used to express the intentions of the experienced farmers and the service. Auto-negotiation using simple utility functions cannot consider the know-how quality. The utility function of the experienced farmer expresses the intention of the experienced farmer, who requests more incentives. Meanwhile, the utility function of the service expresses the intention of the service to reduce the incentive amount appropriately based on the know-how quality. Such auto-negotiation allows consideration of the intention of the experienced farmer and service sustainability.

3 Incentive decision method

3.1 Outline

The incentive decision method proposed in this study encourages experienced farmers to provide information while maintaining stable service. For this purpose, this method employs auto-negotiation between the software agents that represent the experienced farmer and the service. The utility function of the experienced farmer agent expresses the farmer's intention, while that of the service agent expresses the intention of the service. The two agents act according to their respective intentions. Furthermore, the utility function of the service agent also considers the reliability of the farmers to judge the quality of the provided know-how.

We performed several simplifications while constructing this method. The targets of this study are rational humans. Humans are rationally bounded; they do not necessarily act to improve the utilities of themselves and the whole society. However, it is difficult to evaluate the bounded rationality because of the amount of calculation required and the assurance of reasonability. Therefore, we conducted simulation experiments using simple models. In addition, we assumed that the actions of experienced farmers and service users followed a normal distribution. Thus, the effectiveness of our method can be further verified by the demonstration experiments.

Figure 1 presents the process flow of the incentive decision method. The incentive decision method consists of a reliability calculation mechanism and an incentive decision mechanism. The incentive amount is decided by these mechanisms. The reliability calculation mechanism calculates the reliability of each experienced farmer via self-evaluation, service evaluation, and the use frequency of the know-how provided by that farmer. The incentive decision mechanism decides the incentive amount via self-evaluation, service evaluation, and the reliability calculated by the reliability calculation mechanism. The parameters used in this method are described in the following paragraphs.

Self-evaluation
Experienced farmers evaluate their own know-how. This value expresses the experienced farmer's expectation of the incentive amount.

Service evaluation
The information sharing service collects the evaluations of the know-how made by the users and uses these evaluations to calculate the service evaluation.

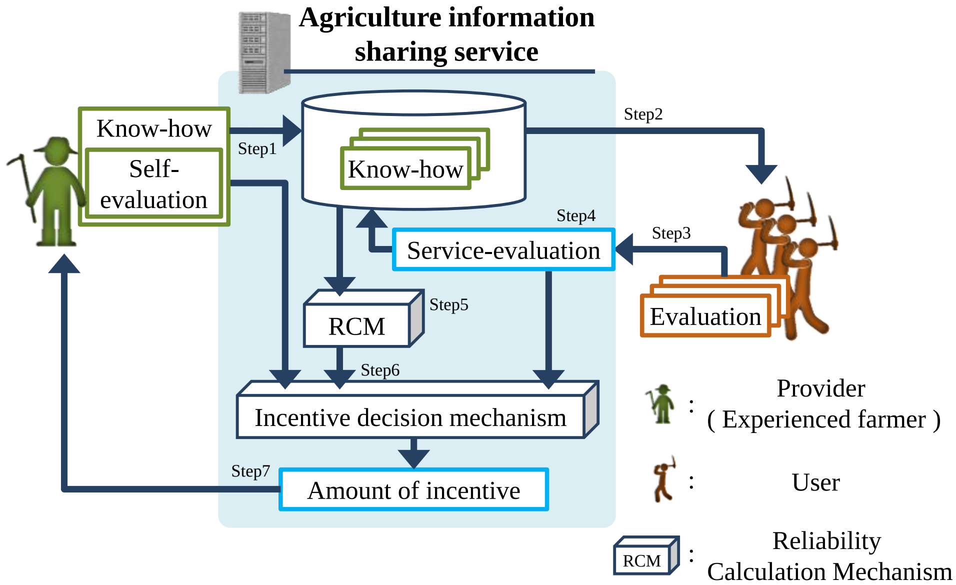

Figure 1: Process flow of the incentive decision method.

Reliability
This value lies in the interval $[0, 1]$ and expresses how reliable an experienced farmer is. This value indicates how appropriately experienced farmers evaluated their own know-how.

The process flow of this method is described below (see Figure 1).

Step 1. The experienced farmer sends know-how and its self-evaluation to the agricultural information sharing service.

Step 2. The users receive the know-how from the service and use it.

Step 3. The users send evaluations of the used know-how to the service.

Step 4. The service calculates the service evaluation of the know-how based on the received evaluations.

Step 5. The reliability calculation mechanism in the service calculates the reliability based on the provided know-how and its evaluations.

Step 6. The incentive decision mechanism in the service decides the amount of incentive based on self-evaluation, service evaluation, and reliability.

Step 7. The service provides the decided incentive for the given experienced farmer.

3.2 Reliability calculation mechanism

The reliability calculation mechanism calculates the reliability of the experienced farmer based on self-evaluation and service evaluation. In addition, to weight the know-how according to its use frequency, a parameter, namely the degree of interest is defined. The parameters are as follows:

Use frequency
This value indicates the number of times the know-how is used by the users. The value is incremented by one each time the know-how is used.

Degree of interest
This value indicates the level of interest of the users in the know-how. In this study, this value is calculated based on use frequency.

The degree of interest of the i-th know-how I_i is defined by the following formula:

$$I_i = \frac{u_i}{\sum_{j=1}^{N} u_j}$$

where N denotes the number of the know-how items received from the experienced farmer who is the target of the reliability calculation mechanism, and u_i denotes the use frequency of the i-th know-how. Moreover, reliability r is calculated as

$$r = \min\left(\frac{\sum_{i=1}^{N}(E_{si} \times I_i)}{\sum_{i=1}^{N}(E_{ei} \times I_i)}, 1\right)$$

where E_{si} denotes the service evaluation of the i-th know-how, and E_{ei} denotes the self-evaluation of the i-th know-how.

3.3 Incentive decision mechanism

The incentive decision mechanism decides the amount of the incentive based on self-evaluation, service evaluation, and reliability. The incentive amount is determined by auto-negotiation of the incentive amount between the experienced farmer agent and service agent. The utility function of the experienced farmer agent is built based on self-evaluation and service evaluation, whereas that of the service agent is built on service evaluation and reliability. Here self-evaluation indicates the incentive amount expected by the experienced farmer, and service evaluation indicates the incentive amount that the service wants to provide. Each agent performs auto-negotiation while trying to satisfy its own requirement, and the value finally accepted is decided as the incentive amount. The process flow of the incentive decision mechanism is given below.

Step 1. The experienced farmer agent receives the self-evaluation and service evaluation values, and the service agent receives the service evaluation and reliability values.

Step 2. Each agent constructs its utility function based on the received parameters.

Step 3. The two agents perform auto-negotiation based on the constructed utility functions.

Step 4. The incentive decision mechanism decides the value accepted in the negotiation as the incentive amount.

3.3.1 Auto-negotiation

The incentive decision mechanism decides the incentive amount through single-issue auto-negotiation of the incentive amount between the two agents. In this mechanism, auto-negotiation proceeds according to Alternating Offers Protocol [27]. In this protocol, each agent chooses one from three actions—*Offer*, *Accept*, and *End Negotiation*. Each agent iterates *Offer* to the partner until either of the two agents chooses *Accept* or *End Negotiation*. The three actions in Alternating Offers Protocol are shown below.

(i) *Offer*
The agent denies the offer from the partner and sends a new offer to the partner.

(ii) *Accept*
The agent accepts the offer from the partner and decides the offer as the incentive amount. The negotiation is then finished.

(iii) *End Negotiation*
The agent denies the offer from the partner and finishes the negotiation.

In this study, when an agent proposes a new offer, the offer is made according to its utility function as a probability distribution. In addition, if either agent chooses *End Negotiation*, the incentive amount is set to zero. Algorithm 1 shows the algorithm of the auto-negotiation in this study.

Algorithm 1 Determine the incentive I.

Require:

Self-evaluation $E_e \in [0,1]$
Service-evaluation $E_s \in [0,1]$
Utility function of the experienced farmer $U_e(x) \in [0,1]$
Utility function of the service $U_s(x) \in [0,1]$
Maximum times of negotiation $lim \in \mathbb{R}$
$\textsc{randomAccordingTo}(U) \in [0,1]$ ▷ Creating a random number according to U as a probability distribution
$\textsc{randomIn}(a,b) \in [0,1]$ ▷ Creating a random number in interval$[a,b]$
$\textsc{probability}(U(x), t) \in [0,1]$ ▷ Deciding an *Accept* probability by considering the elapsed time

Ensure:

Incentive amount $I \in [0,1]$

$t \leftarrow 0$
while $t < \frac{lim}{2}$ **do**
▷ *Offer* of the experienced farmer agent
  $t' \leftarrow \frac{2t}{lim}$
  if $E_s \leq E_e$ **then**
    $x \leftarrow \textsc{randomAccordingTo}(U_e)$
  else
    $x \leftarrow E_e$
  end if
  $p \leftarrow \textsc{probability}(U_s(x), t')$
  $r \leftarrow \textsc{randomIn}(0,1)$
  if $r < p$ **then return** $I \leftarrow x$ ▷ *Accept* of the service agent
  end if
▷ *Offer* of the service agent
  $t' \leftarrow \frac{2t+1}{lim}$
  if $E_s \leq E_e$ **then**
    $x \leftarrow \textsc{randomAccordingTo}(U_s)$
  else
    $x \leftarrow E_e$
  end if
  $p \leftarrow \textsc{probability}(U_e(x), t')$
  $r \leftarrow \textsc{randomIn}(0,1)$
  if $r < p$ **then return** $I \leftarrow x$ ▷ *Accept* of the experienced farmer agent
  end if

  $t \leftarrow t + 1$
end while
return 0 ▷ If *End Negotiation* is chosen, $I \leftarrow 0$

3.3.2 Utility function

The utility function indicates the degree of satisfaction, i.e., the utility, which a person feels will depend on the profit or loss. However, the utilities differ according to the intentions of the individuals who experience the profits and losses, even if the profits and losses are equal for all individuals. Therefore, it is necessary to express this difference in the utilities properly by means of the utility functions. The incentive decision mechanism applies the utility function that reflects the intention of the experienced farmer to the experienced farmer agent and the utility function that reflects the intention of the service to the service-side agent. In this study, the utility value is defined in the range $[0, 1]$. If the utility is 0, the person is extremely unsatisfied with the profit and loss. If the utility is 1, the person is completely satisfied with the profit and loss.

3.3.3 Utility function of an experienced farmer

The utility function of an experienced farmer expresses his/her intention. To realize this, this function should be defined by considering the farmer's intention regarding the incentive amount. Generally, if an experienced farmer receives more incentive, he/she will feel greater satisfaction. Therefore, this utility function is set to monotonically increase as the incentive amount increases. In addition, if auto-negotiation fails, the incentive amount becomes zero. Hence, experienced farmers will avoid this negotiation failure. Therefore, to avoid such failure, the utility function of the experienced farmer is set to be risk averse.

The utility function of an experienced farmer $U_e(x)$ is defined by the formula

$$U_e(x) = \begin{cases} \max\left(\frac{E_s}{E_e}, -\frac{(x-E_e)^2}{E_e|E_e-E_s|} + 1\right) & (x \le E_e \land E_s \le E_e) \\ 1 & (E_e < x \lor E_e < E_s) \end{cases}$$

where E_e denotes self-evaluation; E_s, service evaluation; and x, incentive amount. Figure 2 presents the general form of this function. This function increases monotonically with the incentive amount increases and is a concave function. Consequently, it is a risk-averse utility function. For the utility values over the broken line shown in Figure 2, the probability of acceptance of the negotiation partner's offer increases. In other words, this utility function shows the farmer's risk-averse intention and tends to avoid negotiation failure. Figure 3 shows the Arrow-Pratt coefficient of the utility function of the experienced farmer. This coefficient expresses how risk-averse the owner of the function is. This coefficient $f_a(x)$ is defined as follows.

$$f_a(x) = -\frac{U_e''(x)}{U_e'(x)} = \frac{1}{E_e - x}$$

As Figure 3 shows, in the utility function of the experienced farmer, the degree of averseness to risk increases with the incentive amount.

The utility function set as described above expresses the farmer's intention to successfully conclude a negotiation with a high incentive and to avoid negotiation failure.

3.3.4 Utility function of service

The utility function of the service expresses the intention of the service regarding the incentive amount. To operate the service, it is necessary to provide sufficient incentive to experienced farmers while reducing the incentive for low-quality know-how to maintain the sustainability of the service. Therefore, to avoid excessive incentives, this utility function is set to accept requests by reliable experienced farmers and to deny requests by unreliable farmers.

Therefore, the utility function of the service $U_s(x)$ is defined as follows:

$$U_s(x) = \begin{cases} -\frac{1}{2}\exp\left(\frac{\alpha(x-x_{ip})}{x_{ip}}\right) + 1 & (x \le x_{ip}) \\ \frac{1}{2}\exp\left(-\frac{\alpha(x-x_{ip})}{x_{ip}}\right) & (x_{ip} < x) \end{cases}$$

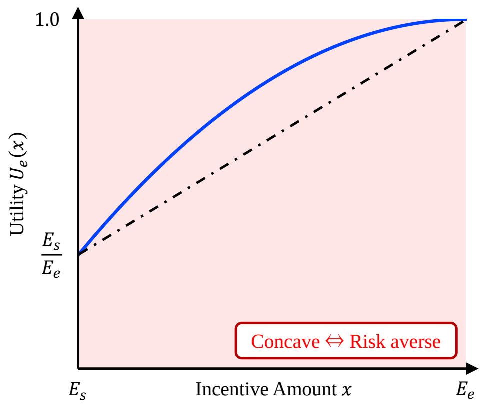

Figure 2: General form of the utility function of the experienced farmer.

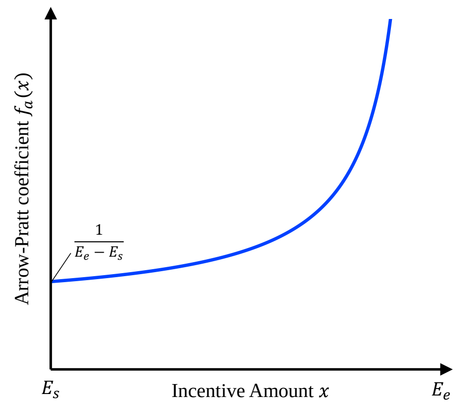

Figure 3: Arrow-Pratt coefficient of the utility function of the experienced farmer.

where x denotes the incentive amount, α is a parameter that adjusts the slope of this function, and x_{ip} the an inflection point of this function.

Figure 4 presents the general form of the utility function of the service. This function decreases monotonically as the incentive amount increases. In addition, the behavior of the function changes at the inflection point x_{ip}, allowing it to accept requests from reliable experienced farmers and reduce the incentive for the farmers who provide low-quality know-how. Thus, in the interval lower than x_{ip}, this function is a risk-averse function that accepts farmers' requests to avoid negotiation failure. However, in the interval higher than x_{ip}, it is a risk-taking function that denies requests without any fear of failure. Thus, utility values under the broken line in Figure 4 indicate the firm attitude of the service achieved by reducing acceptance probability. The inflection point x_{ip} is calculated by the following formula:

$$x_{ip} = r \cdot E_s$$

where r denotes the reliability of the experienced farmer. When an appropriate inflection point x_{ip} is set, the negotiation respects requests from experienced farmers with high reliability; in this case, the function has a large risk-averse interval, as shown in Figure 5. In contrast, for low-reliability farmers, the function has a large risk-taking interval, as shown in Figure 6.

Thus, the utility function of the service expresses the intention of the service to respect requests of experienced farmers who provide high-quality know-how and to reduce the incentive for those who provide low-quality know-how.

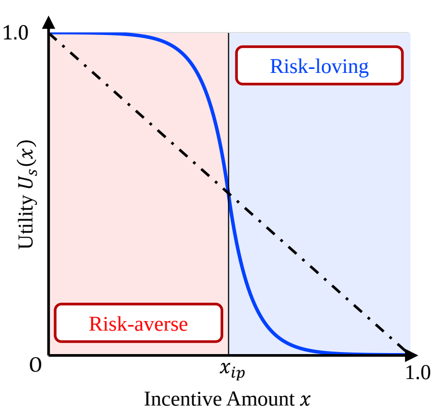

Figure 4: General form of the utility function of a service.

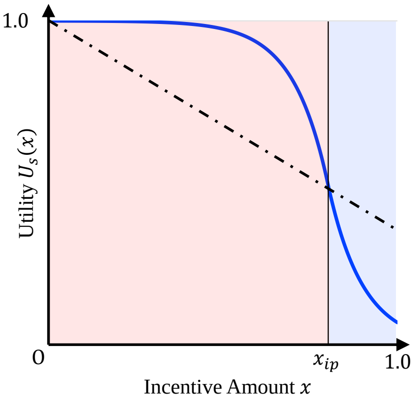

Figure 5: $U_s(x)$ for the high-reliability experienced farmer.

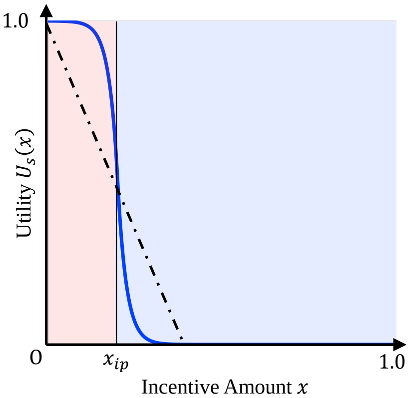

Figure 6: $U_s(x)$ for the low-reliability experienced farmer.

3.4 Design of the agricultural information sharing model

In this study, an agricultural information sharing model was constructed and the proposed incentive decision method was applied. Figure 7 and Figure 8 provide overviews of the model. This model consists of agents, an agricultural information management server, which communicates with the providers and the users via the agents, and the incentive decision method.

Experienced farmer agent (EA)
This agent represents the experienced farmer.

Incentive negotiation agent (INA)
This agent acts as the agent of the service and negotiates with the EA.

Know-how agent (KA)
This agent manages the know-how received from the experienced farmers.

Know-how sharing agent (KSA)
This agent shares the know-how with the users.

User agent (UA)
This agent represents the user and receives the know-how and sends the know-how evaluations.

Incentive decision method (IDM)
This method determines the incentive amount via auto-negotiation.

The process flow of this model is described below (see Figure 7 and Figure 8).

Step 1. The experienced farmer sends the know-how to the EA, and the EA sends it to the INA.

Step 2. The INA sends the received know-how to the KA, and the KA manages it.

Step 3. The INA evaluates the received know-how (an early evaluation) and sends the evaluation to the IDM.

Step 4. The IDM performs auto-negotiation between the EA and INA with the early evaluation and provides the result of the negotiation with the experienced farmer as an early incentive.

Step 5. The KSA shares the know-how the KA manages with the user.

Step 6. The user sends the evaluation of the know-how to the KSA via the UA.

Step 7. The KSA sends the collected user evaluations to the INA.

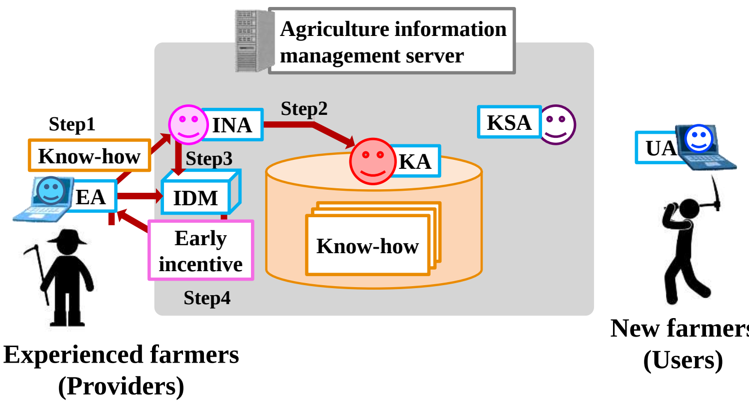

Figure 7: Overview of the agricultural information sharing model (Steps 1–4).

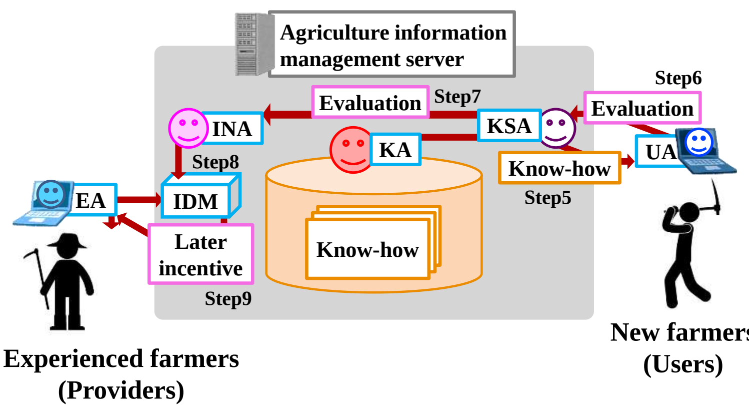

Figure 8: Overview of the agricultural information sharing model (Steps 5–9).

Step 8. The INA evaluates the know-how (a later evaluation) based on the received evaluations and sends the evaluation to the IDM.

Step 9. The IDM performs auto-negotiation between the EA and the INA with the later evaluation and provides the result of the negotiation with the experienced farmer as a later incentive.

Thus, this model prompts experienced farmers to share the know-how with users.

4 Experimental result and discussion

4.1 Evaluation of the reliability calculation mechanism and incentive decision mechanism

4.1.1 Purpose

To evaluate the effectiveness of each mechanism in the proposed incentive decision method (IDM), we performed a simulation experiment. In this experiment, we assumed nine types of experienced farmers with different know-how qualities and incentive requests to verify whether each mechanism rationally performed for each type of farmers.

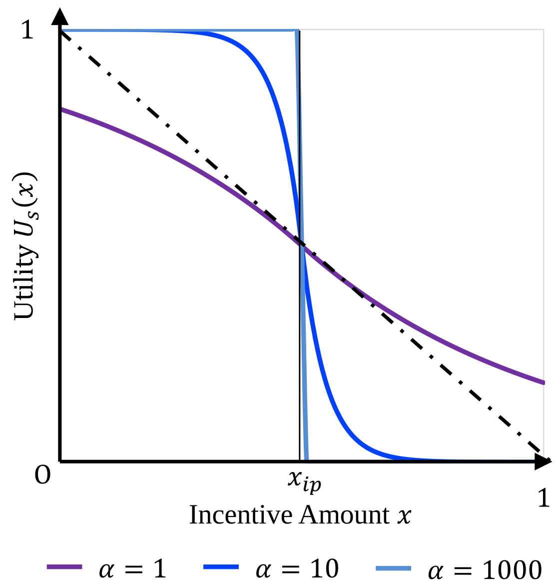

Figure 9: $U_s\left(x\right)$ with $\alpha = 1, 10$, and 1000.

Table 1: Nine assumed types of experienced farmers.

Experienced farmer type	Quality of the know-how Q	Self-evaluation E_e
Farmer-HH	High $[0.7, 1.0]$	High $[0.7, 1.0]$
Farmer-HM	High $[0.7, 1.0]$	Middle $[0.3, 0.7]$
Farmer-HL	High $[0.7, 1.0]$	Low $[0.0, 0.30]$
Farmer-MH	Middle $[0.3, 0.7]$	High $[0.7, 1.0]$
Farmer-MM	Middle $[0.3, 0.7]$	Middle $[0.3, 0.7]$
Farmer-ML	Middle $[0.3, 0.7]$	Low $[0.0, 0.30]$
Farmer-LH	Low $[0.0, 0.30]$	High $[0.7, 1.0]$
Farmer-LM	Low $[0.0, 0.30]$	Middle $[0.3, 0.7]$
Farmer-LL	Low $[0.0, 0.30]$	Low $[0.0, 0.30]$

4.1.2 Summary

In this experiment, the parameter α (see Section 3.3.4) was set as 1, 10, and 1000. Figure 9 presents the utility function of the service for each α. In addition, we assumed nine types of experienced farmers listed in Table 1 (each type had 100 farmers) and 3000 users of the service. Under the above condition, the experienced farmers and the users acted for 50 days. The experiment results were the reliability r set to each experienced farmer, the incentive amount I paid to each farmer, and the total amount of the know-how N provided by each farmer. In this experiment, the experienced farmers and the users performed the actions described in Sections 4.1.3–4.1.4 once daily.

Farmer-HH comprises experienced farmers who understand the value of their know-how and request large incentives. Farmer-HL includes farmers who provide high-quality know-how but make humble requests. Farmer-LH comprises the farmers who do not understand the value of their know-how but request a large incentive, and Farmer-LL comprises the farmers who understand the value of their lower-quality know-how. The notation “M” indicates an intermediate stage between H and L. The actions of the experienced farmers and the users are described in the next subsection (each step involves the same process as those described in Section 3.4).

4.1.3 Actions of the experienced farmers

i. The experienced farmers decide whether they should provide their know-how based on the utility that they feel is indicated by the received incentive. The minimum provision probability is 0.1 (Step 1).

ii. If the experienced farmers provide their know-how, they send the know-how to the INA via the EA. If they do not provide the know-how, they finish their actions (Steps 1 and 2).

iii. The INA evaluates the received know-how under the assumption that this evaluation follows a normal distribution. The mean value of the distribution is the know-how quality Q, and the variance is 0.1 (Step 3).

iv. The IDM performs the auto-negotiation between the EA and the INA using the evaluation. Here, lim in Algorithm 1 is set to 30 (Step 4).

v. As the early incentive, the INA provides the calculated incentive in iv to the experienced farmers via the EA (Step 4).

4.1.4 Actions of the users

i. The users select 50 know-how items managed by the KA. Under the assumption that the users will select a superior know-how, the know-how with high-quality Q is preferentially selected (see Section A) (Step 5).

ii. The users decide whether they will evaluate the chosen know-how using the know-how quality Q as the evaluation probability (Step 6).

iii. The users evaluate the selected know-how under the assumption that their evaluations follow a normal distribution. The mean value of the normal distribution is the know-how quality Q, and the variance is 0.1 (Step 6).

iv. The users send the evaluation to the KSA (Step 6).

v. The INA searches the know-how that is the target of the later incentive. In this experiment, the target of the later incentive is the know-how that was provided 10 days ago (Step 7).

vi. The INA decides the average of the user evaluations as the later evaluation (Step 8).

vii. The IDM performs auto-negotiation between the EA and the INA using the later evaluation. Here, lim in Algorithm 1 is set to 30 (Step 9).

viii. As the later incentive, the INA provides the incentive calculated in vii to the experienced farmers via the EA (Step 9).

4.1.5 Results

Tables 2–4 and Figures 10–12 present the experimental results for reliability r. Tables 5–7 and Figures 13–15 present the experimental results for the incentive amount I and the know-how amount N. In this section, the results for $\alpha = 10$ are considered to be a representative of the overall results. In terms of the average reliability r, farmer-HH, HM, HL, MM, ML, and LL scored over 0.95. In contrast, the score of farmer-MH was 0.61, which was 39% less than that of farmer-HL. In addition, farmer-LH and farmer-LM scored 78% and 61% less than farmer-HL, respectively. The minimum variance of r was 0.00 for farmer-HM, HL, and ML. Farmer-MM, HH, and LL also exhibited a small variance, whereas LM exhibited the highest variance. Farmer-HH received the largest incentive, followed by HM, MM, and MH. Farmer-LH received the least incentive of only 4.8% of the incentive amount of farmer-HH. Regarding the know-how amount N, all the farmers in the HL type provided 50 know-how items. HL was followed by HM, HH, ML, MM, and LL. Similar to the observation in case of the incentive amount, farmer-LH provided the least amount of know-how. Same results were obtained for $\alpha = 1$ and 1000. In terms of I and N, the results for $\alpha = 1$ were higher than those for $\alpha = 10$ and 1000.

Table 2: Experimental results for reliability r ($\alpha = 1$).

Experienced farmer type	Average	Variance
Farmer-HH	0.976	0.000478
Farmer-HM	1.00	0.000
Farmer-HL	1.00	0.000
Farmer-MH	0.607	0.00175
Farmer-MM	0.994	0.000340
Farmer-ML	1.00	0.000
Farmer-LH	0.223	0.00339
Farmer-LM	0.385	0.00815
Farmer-LL	0.998	0.000353

Table 3: Experimental results for reliability r ($\alpha = 10$).

Experienced farmer type	Average	Variance
Farmer-HH	0.978	0.000423
Farmer-HM	1.00	0.000
Farmer-HL	1.00	0.000
Farmer-MH	0.607	0.00157
Farmer-MM	0.988	0.000818
Farmer-ML	1.00	0.000
Farmer-LH	0.217	0.00342
Farmer-LM	0.374	0.00827
Farmer-LL	0.990	0.00290

Table 4: Experimental results for reliability r ($\alpha = 1000$).

Experienced farmer type	Average	Variance
Farmer-HH	0.978	0.000467
Farmer-HM	1.00	0.000
Farmer-HL	1.00	0.000
Farmer-MH	0.601	0.00200
Farmer-MM	0.989	0.000744
Farmer-ML	1.00	0.000
Farmer-LH	0.226	0.00290
Farmer-LM	0.386	0.00653
Farmer-LL	0.997	0.000486

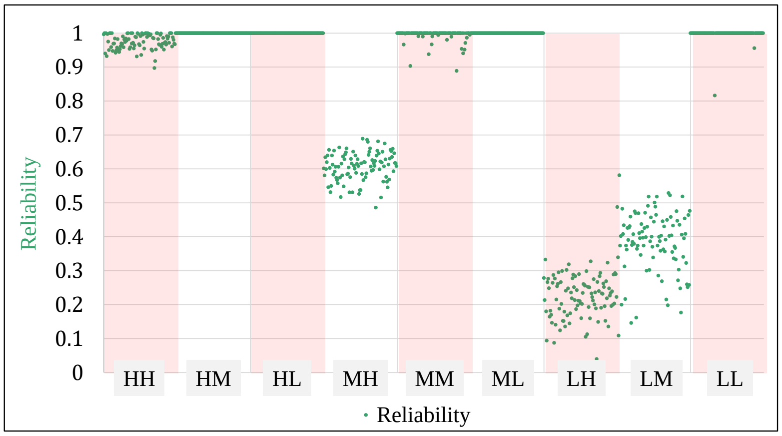

Figure 10: Experimental results for reliability r ($\alpha = 1$).

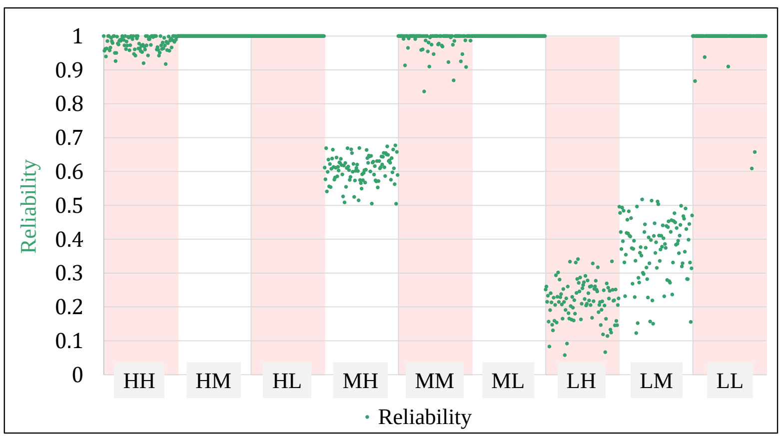

Figure 11: Experimental results for reliability r ($\alpha = 10$).

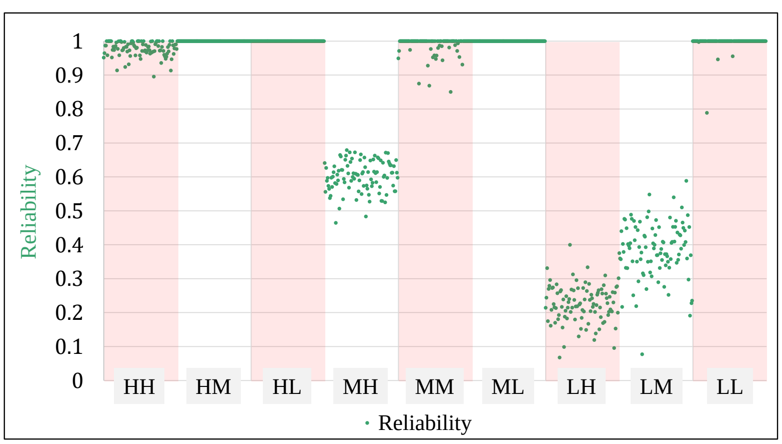

Figure 12: Experimental results for reliability r ($\alpha = 1000$).

Table 5: Experimental results of the incentive amount I and know-how amount N ($\alpha = 1$).

Experienced farmer type	Average I	Variance I	Average N	Variance N
Farmer-HH	67.8	7.06	47.3	2.70
Farmer-HM	45.1	1.98	50.0	0.0384
Farmer-HL	13.5	1.22	50.0	0.000
Farmer-MH	36.3	32.8	35.3	21.3
Farmer-MM	36.5	5.23	45.6	5.24
Farmer-ML	13.5	1.53	49.9	0.226
Farmer-LH	4.09	2.89	12.4	16.3
Farmer-LM	6.84	5.85	20.2	27.7
Farmer-LL	8.98	1.77	42.3	15.9

Table 6: Experimental results of the incentive amount I and know-how amount N ($\alpha = 10$).

Experienced farmer type	Average I	Variance I	Average N	Variance N
Farmer-HH	66.0	8.08	46.6	3.60
Farmer-HM	44.5	2.09	49.9	0.168
Farmer-HL	13.6	1.19	50.0	0.000
Farmer-MH	27.7	24.0	30.8	23.7
Farmer-MM	33.4	7.83	43.5	10.5
Farmer-ML	13.4	1.32	49.8	0.201
Farmer-LH	3.51	1.66	11.3	11.2
Farmer-LM	5.53	3.02	17.9	19.2
Farmer-LL	7.70	1.86	39.2	24.2

Table 7: Experimental results of the incentive amount I and know-how amount N ($\alpha = 1000$).

Experienced farmer type	Average I	Variance I	Average N	Variance N
Farmer-HH	65.4	7.53	46.3	3.18
Farmer-HM	45.0	2.13	49.9	0.0936
Farmer-HL	13.5	1.73	50.0	0.000
Farmer-MH	26.2	11.3	29.4	12.3
Farmer-MM	33.2	4.36	43.4	5.11
Farmer-ML	13.4	1.64	49.7	1.56
Farmer-LH	3.31	1.43	10.7	9.77
Farmer-LM	5.76	2.96	18.8	20.4
Farmer-LL	7.78	1.57	39.6	18.1

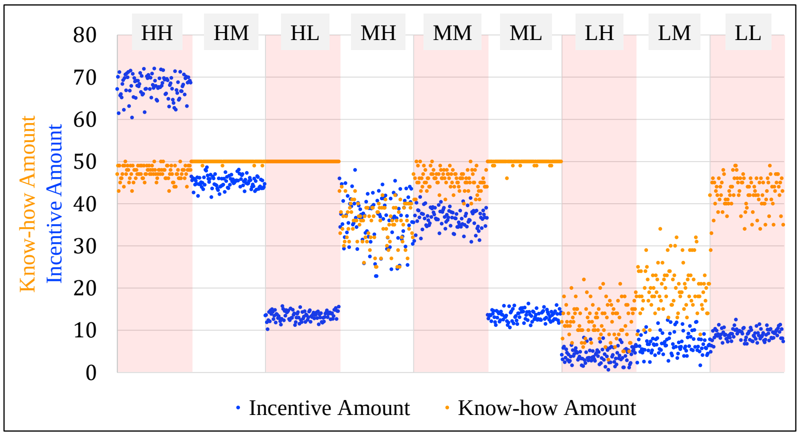

Figure 13: Experimental results of the incentive amount I and know-how amount N ($\alpha = 1$).

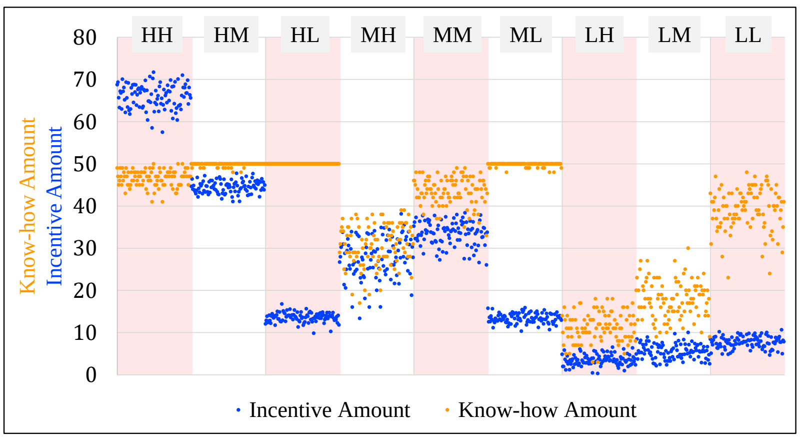

Figure 14: Experimental results of the incentive amount I and know-how amount N ($\alpha = 10$).

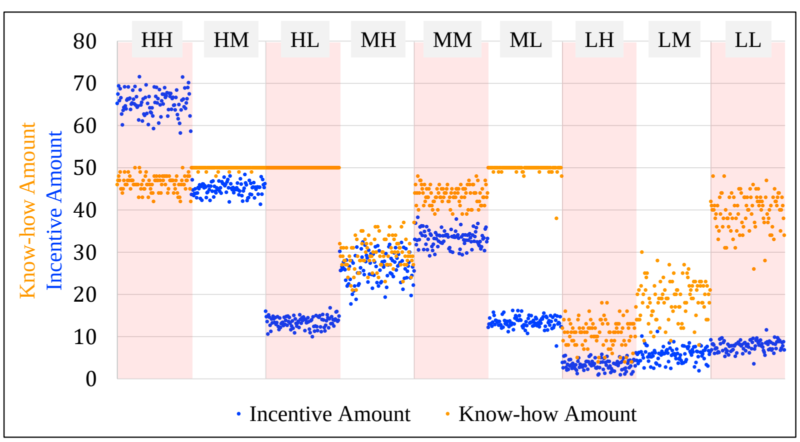

Figure 15: Experimental results of the incentive amount I and know-how amount N ($\alpha = 1000$).

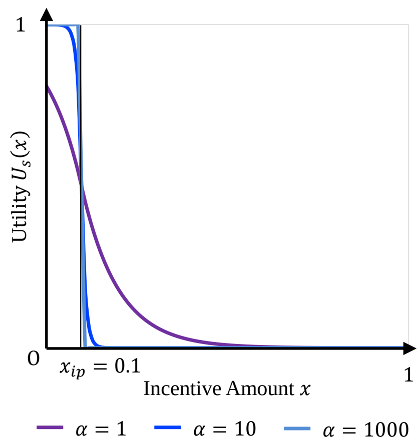

Figure 16: $U_s(x)$ with low x_{ip}.

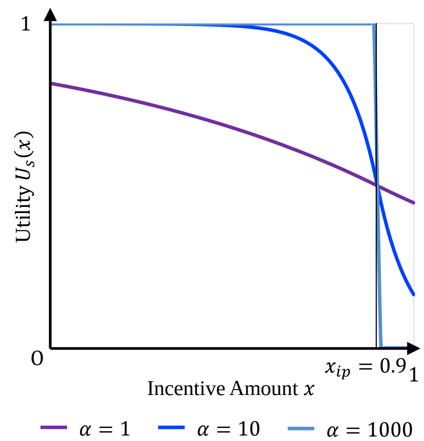

Figure 17: $U_s(x)$ with high x_{ip}.

4.1.6 Discussion

Reliability r

For farmer-HH, HM, HL, MM, ML, and LL, which requested modest incentives, high reliabilities were set. In contrast, for types MH, LH, and LM that excessively evaluated their own know-how, low reliabilities were set. In addition, the reliability calculation mechanism set the lowest reliability for farmer-LH, which was the most unreliable type of farmer. Thus, the reliability calculation mechanism set a high reliability for reliable farmers and a low reliability for unreliable farmers. Because the reliability was not related to α, there were no large differences for different values of α.

Incentive amount I

Among farmer-HH, HM, and HL that provided high-quality know-how, the HH type received a high incentive. The HH farmers provide high-quality know-how but request high incentives. Therefore, if the incentive is low, the amount of high-quality know-how will decrease. Hence, the service, which intends to collect the high-quality know-how, provided the highest incentive to prompt the HH-type farmers to share their know-how. In contrast, because the HL-type farmers were satisfied even with small incentives, the service, which intended to reduce the incentive, provided them with low incentives. Thus, the intentions of the experienced farmers regarding the expected incentive and the objectives of the service to collect high-quality know-how while reducing the incentive amount were considered. For farmer-MH, MM, and ML, which provided intermediate quality know-how, and farmer-LH, LM, and LL, which provided low-quality know-how, the lower the requested incentives, the greater were the provided incentives. This experimental condition involved collecting large know-how while reducing the incentive amount, preferably by satisfying farmers with low requirements, thereby helping to maintain the sustainability of the service. Thus, the incentive decision mechanism was able to determine the appropriate incentive amount by considering both the service sustainability and the intentions of the experienced farmers.

In addition, as depicted in Figure 9, the service utility function for $\alpha = 1$ reduced the utility more gently than the functions for $\alpha = 10$ and 1000. Therefore, the results for $\alpha = 1$ were higher than those for $\alpha = 10$ and 1000.

Know-how amount N

Tables 8–10 present the average know-how of the farmers who provided high-quality know-how (HH, HM, and HL), intermediate know-how (MH, MM, and ML), and low-quality know-how (LH, LM, and LL). It can be seen that a larger amount of high-quality know-how was provided when compared with the amount of low-quality know-how. Therefore, the incentive decision

Table 8: The average know-how amount N for each know-how quality ($\alpha = 1$).

Experienced farmer type	Average
Farmer-HH, HM, and HL	49.1
Farmer-MH, MM, and ML	43.6
Farmer-LH, LM, and LL	25.0

Table 9: The average know-how amount N for each know-how quality ($\alpha = 10$).

Experienced farmer type	Average
Farmer-HH, HM, and HL	48.8
Farmer-MH, MM, and ML	41.4
Farmer-LH, LM, and LL	22.8

Table 10: The average know-how amount N for each know-how quality ($\alpha = 1000$).

Experienced farmer type	Average
Farmer-HH, HM, and HL	48.8
Farmer-MH, MM, and ML	40.8
Farmer-LH, LM, and LL	23.0

mechanism helped the service to effectively use the incentive resources to prompt farmers to provide more high-quality know-how than low-quality know-how. Thus, we verified the rational distribution of the incentive resources achieved using the incentive decision mechanism.

In addition, majority of the results denoted that the know-how amount tended to increase when α became small. However, the results for farmer-LH, LM, and LL did not exhibit such a tendency. This was because the functions for $\alpha = 10$ and 1000 exhibited similar forms when x_{ip} was small, as illustrated in Figures 16 and 17.

4.2 Evaluation of the incentive decision method

4.2.1 Purpose

To evaluate the effectiveness of the proposed method, we performed a simulation experiment and compared the results obtained using the proposed method and existing methods. In this experiment, I assumed four types of experienced farmers, who had different know-how qualities and incentive requests, to verify whether the proposed method provide more rational incentives than the existing methods.

4.2.2 Summary

In this experiment, the parameter α (see Section 3.3.4) was set as 1, 10, and 1000. In addition, we considered that there are 500 experienced farmers and 3000 service users. Furthermore, we assumed that the quality of the know-how followed a normal distribution. The mean value of the normal distribution was 0.5, and the variance was 0.1. The self-evaluation also followed a normal distribution. The mean value of the normal distribution was equal to the quality Q, and the variance was 0.1. The experienced farmers and users performed their actions (Sections 4.1.3–4.1.4) for 50 days. The total amount of the provided know-how N_{KH}, the average quality of the provided know-how $\bar{Q}$, and the total amount of incentive paid I were determined, and these results were used to compare the performances of different methods.

4.2.3 Existing methods

The following three existing methods were considered.

Table 11: Experimental results for $N_{KH}, \bar{Q}$, and I.

	Proposed $\alpha = 1$	Proposed $\alpha = 10$	Proposed $\alpha = 1000$	Quality	Request	Constant
N_{KH}	22094	21118	21128	22087	25000	23202
$\bar{Q}$	0.50103	0.50069	0.50044	0.50165	0.49921	0.49853
I	16563	14928	14922	19973	22903	20894

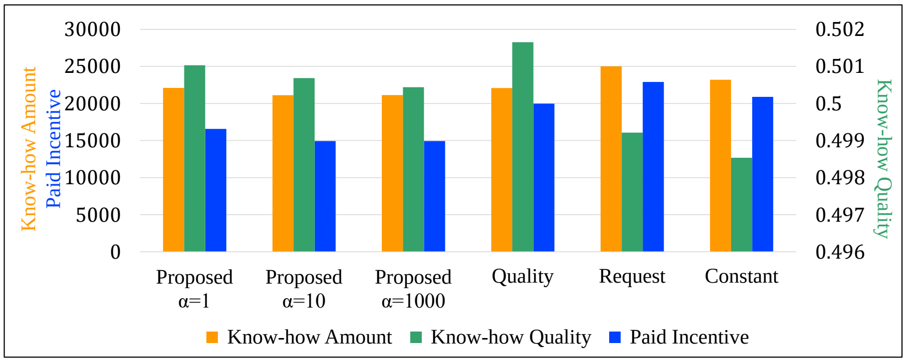

Figure 18: Experimental results for $N_{KH}, \bar{Q}$, and I.

Quality-based method
In this method, the service provides the value of the know-how quality as the incentive; thus, the value of the provided incentive becomes equal to the know-how quality Q. For example, if the quality of the know-how is 0.7, the service will provide an experienced farmer with an incentive of 0.7.

Request-based method
In this method, the service provides the value of the request received from the experienced farmer as the incentive; thus, the value of the provided incentive becomes equal to the self-evaluation by the experienced farmer. For example, if the requirement of the experienced farmer is 0.3, the service will provide that farmer with an incentive of 0.3.

Constant incentive method
In this method, the service provides a fixed amount of incentive to the experienced farmer, regardless of the quality or requirement. In this experiment, the service provided a fixed incentive of 0.5.

4.2.4 Results

Table 11 and Figure 18 present the experimental results of the total amount of the provided know-how N_{KH}, the average quality of the provided know-how $\bar{Q}$, and the total amount of the paid incentive I. The value of N_{KH} in the proposed method ($\alpha = 10$) was 4.39%, 15.5%, and 8.98% less than those in the quality-based, request-based, and constant incentive methods, respectively. In other words, the request-based method exhibited the largest know-how. The quality $\bar{Q}$ for the proposed method ($\alpha = 10$) was less than that for the quality-based method by 0.193% although it was higher than those for the request-based and constant incentive methods by 0.295% and 0.432%, respectively. Thus, the quality-based method exhibited the largest high-quality know-how. Finally, the proposed method ($\alpha = 10$) provided the least incentive; the value of I was less than those of the quality-based, request-based, and constant incentive methods by 25.3%, 34.8%, and 28.6%, respectively.

With respect to the changes in α, $\alpha = 1$ had the highest N_{KH}, $\alpha = 1$ had the highest $\bar{Q}$, and $\alpha = 1000$ had the lowest I.

4.2.5 Discussion

Regarding N_{KH}, the request-based method, which accepted the farmers' requests directly, scored the highest value because each farmer's request was always satisfied and the know-how provision probability was 1.0. However, as this method always accepted the requests regardless of the know-how quality, the quality and incentive paid were the worst among all methods. Regarding $\bar{Q}$, the quality-based method, which provided the know-how quality value as the incentive, provided the highest quality because it assigned little incentive for farmers who provided low-quality know-how, and the provision probability decreased gradually. However, for high-quality know-how, this method provides high incentives regardless of the farmers' requests. Hence, this method paid more incentive than that paid in the proposed method. Regarding I, the effect of the given incentive on N_{KH} (E_N) and $\bar{Q}$ (E_Q) can be calculated as follows.

$$E_N = \frac{N_{KH}}{I}, E_Q = \frac{\bar{Q}}{I}$$

Table 12 and Figure 19 present the calculated E_N and E_Q. The proposed method ($\alpha = 10$) had an E_N value greater than those of the quality-based, request-based, and constant incentive methods by 27.9%, 29.6%, and 27.4%, respectively. Therefore, our proposed method improved the amount of the collected know-how while providing less incentive when compared with that provided by the existing methods. Our proposed method ($\alpha = 10$) had an E_Q value greater than those of the quality-based, request-based, and constant incentive methods by 33.5%, 53.9%, and 40.6%, respectively. Thus, our method improved the quality of the collected know-how while providing less incentive when compared with that provided by the existing methods.

In addition, while changing α, the E_N and E_Q values of the proposed method were the highest among all the methods for $\alpha = 1, 10$, and 1000. The value of $E_N(\alpha = 1000)$ was 5.791% higher than $E_N(\alpha = 1)$ and that of $E_Q(\alpha = 1000)$ was 9.803% higher than $E_Q(\alpha = 1)$. However, the value of $E_N(\alpha = 1000)$ was 0.09098% higher than $E_N(\alpha = 10)$ and that of $E_Q(\alpha = 1000)$ was 0.005657% lower than $E_Q(\alpha = 10)$. Thus, the values of E_N and E_Q for $\alpha = 1$ were the lowest. This was because the functions for $\alpha = 1$ could not express the intention of the service. As illustrated in Figure 9, the utility values were not over the broken line in an interval lower than x_{ip} and were not under the broken line in an interval higher than x_{ip}. Therefore, to appropriately form the functions, α should be set to become more than approximately 4 (see Figure 20).

Therefore, this experiment verifies that the proposed method collected more high-quality know-how while providing less incentive by considering the intention of the experienced farmers and the quality of the provided know-how.

5 Conclusion

5.1 Summary

An IDM comprising of two mechanisms—the reliability calculation mechanism and incentive decision mechanism—is proposed here. This method aims to prompt stably the experienced farmers to provide their know-how in the agricultural information sharing service. To achieve this purpose, the method considers the intention of the experienced farmers and the sustainability of the service. It employs auto-negotiation between software agents representing these farmers and the service.

Table 12: Experimental results of E_N and E_Q.

	Proposed $\alpha = 1$	Proposed $\alpha = 10$	Proposed $\alpha = 1000$	Quality	Request	Constant
E_N	1.3339	1.4146	1.4159	1.1059	1.0916	1.1105
E_Q	0.000030250	0.000033540	0.000033538	0.000025117	0.000021797	0.000023861

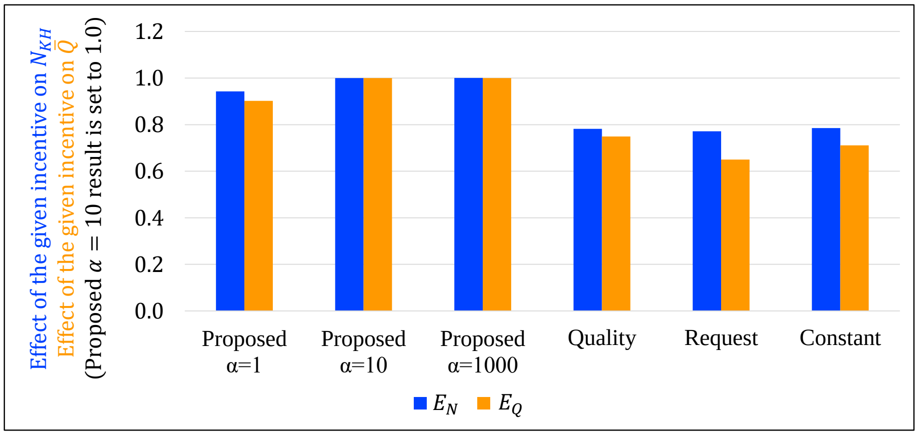

Figure 19: Experimental results of E_N and E_Q.

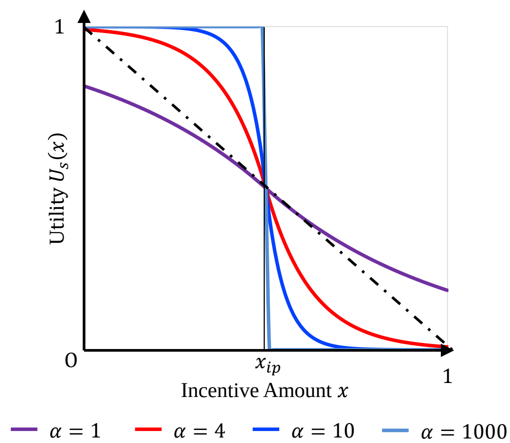

Figure 20: $U_s(x)$ with $\alpha = 1, 4, 10$, and 1000.

We evaluated the method via a simulation experiment and validated the effectiveness of both the mechanisms in the proposed method.

In the evaluation experiment of the two mechanisms, we verified the reliability calculation, the incentive decision, and the amount of the collected know-how. The results of this experiment showed that the reliability calculation mechanism set high reliability values to reliable farmers and low reliability values to unreliable farmers and that the incentive decision mechanism reduced the incentive by considering the farmers' intentions. Moreover, we verified that the incentive decision mechanism prompted the sharing of more high-quality know-how than low-quality know-how. Thus, we can conclude that each mechanism performs effectively to maintain service sustainability by considering the farmers' intentions.

In the evaluation experiment of the IDM, various types of experienced farmers, who had different know-how qualities and incentive requests, were considered. The performances of the proposed method and three existing methods were compared. In terms of the effect of the given incentive on the amount and quality of the know-how, the proposed method yielded the most amount and highest quality of know-how while providing less incentive than the existing methods.

In future, to verify the practicality of the proposed method, we will apply the IDM to other information sharing systems.

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A Algorithm

In this section, we present an algorithm of the actions of users in Section 4.1.4.

Algorithm 2 Choose the high-quality know-how preferentially.

Require:
List of know-how L
$\textsc{get}(l, n)$ ▷ Getting n-th know-how in a list l.
$\textsc{sortDescendingByEvaluation}(l)$ ▷ Sorting a list l descending according to natural sort order of the know-how evaluation.
$\textsc{sumByEvaluation}(l)$ ▷ Summing the evaluations of know-how in a list l.
$\textsc{randomIn}(a, b) \in \mathbb{R}$ ▷ Creating a random number in interval$[a, b]$
$\textsc{searchCumulatively}(l, v)$ ▷ Summing the evaluations of know-how in a list l in order. Returning the know-how when the total value exceeds the value v.

Ensure:
Chosen know-how k
1: $\textsc{sortDescendingByEvaluation}(L)$
2: $sum \leftarrow \textsc{sumByEvaluation}(L)$
3: $rand \leftarrow \textsc{randomIn}(0, sum)$
4: **return** $\textsc{searchCumulatively}(L, rand)$