# Realization of SCM and CRM by Using RFID-captured Consumer Behavior Information

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***Abstract*— Physical store retailers are facing a tougher situation than ever. In order to tackle this tough situation, they need not only to reduce cost by effectively executing SCM but also to introduce measures to increase profit like CRM. They are effective by themselves, but if they are combined the retailers can enjoy more benefits from these practices. However, there is no good application that realize both two business practices together. In this study, assuming that RFID system captures consumer behavior information on the sales floor, we propose an application, in which discount prices are offered to FSP member customers based on their loyalty level and the discount prices are computed to achieve a target inventory turnover rate. To realize this application, we also propose two algorithms that effectively control an inventory turnover rate at the same time reward FSP customers based on their loyalty status. For evaluation, we develop a prototype system of the application for a proof of concept and run a numerical study to show the validity of the proposed algorithms.**

***Index Terms*— RFID, SCM, CRM, FSP, Dynamic Pricing**

## I. INTRODUCTION

The situation that physical store retailers, retailers that have physical stores, are facing is getting tougher. These retailers need to deal with many product stock keeping units (SKUs) that manufacturers are shipping to meet diversifying consumer preferences and buy right amount of the products to maximize their profits [1]. Competitors of these retailers are not only other physical store retailers in the same geographical area but also a myriad of e-store retailers that usually provide cheaper prices [2]. Moreover, physical store retailers need to cope with savvy consumers armed with the Internet who have both product knowledge and price information of other stores in a real time basis [3]. Some of the effective strategies to tackle this situation are to guarantee profitability by displaying salable items on the floors to make the most use of their store space and to identify loyal customers and strengthen the relationship with them.

Because of the space constraint, these physical stores retailers need to select salable items carefully. Even when they mistakenly buy an unpopular item, they should not keep it in order to meet the profit goal of this specific item; they should remove the item and buy another more salable item to improve the total profit.

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There are several ways to get rid of unpopular items from stores, but one common way is to discount and evoke demands. Whether or not an item is sold depends not only on the fact that there are people who want to buy it but also the fact that the item price is lower than their allowable price, the price that they are willing to pay for it. With this basic mechanism, it is possible to adjust inventory level of the stores by reducing item prices, and there are many literatures to study this mechanism [4], [5].

Regarding the relationship with loyal customers, it is said that how to execute one-to-one marketing effectively is a key to success. From the fact that 80 % of retailers' revenue come from top 20 % loyal customers [6], one challenge for the physical store retailers is to learn how to enclose customers who visit the retailer once, to build a good relationship with them, and to deal with them differently from other bargain hunters. As a tool to realize this, many retailers are introducing frequent shoppers program (FSP) and rewarding their loyal customers by providing member discount price, sending coupons and bargain information, and so forth.

Both measures, to increase an item turnover rate by pricing and to reward customers based on their loyalty level, should be effective by themselves, but if they are combined, the physical store retailers could enjoy more benefits: discounting based on FSP customers loyalty status. However, it is difficult to identify customers while they are selecting items on the sales floor, which makes it difficult for the retailers to effectively execute FSP. Moreover, it is also difficult to show different prices to customers in a different loyalty status because price tags on the shelves are usually static. With these constraints, it has been impossible for the physical store retailers to execute both pricing and differentiating loyal customers together.

However, with the recent progress of the radio frequency identification (RFID) technology, both RF tag embedded loyalty cards and RFID readers with a display become available in a commercial basis [7], and RFID systems to use these devices become available as well. With this kind of RFID system, it becomes realistic to realize the application described above. What is necessary now is a mechanism to compute different prices for different loyalty level customers that also control inventory turnover rate, in other words, a mechanism of how to achieve both customer relationship management (CRM) and supply chain management (SCM) together. In this study, we propose two algorithms for this mechanism.

This proposed application also gives a solution to a challenge that physical store retailers have: how to provide appropriate information to their shopping customers in order to improve customer satisfaction and to promote sales. As explained previously, one-to-one marketing is a key to success for retailers, but for physical store retailers, it is difficult to know who they are while customers are shopping. They might identify themselves at a checkout counter if they are member of the retailers' FSP. However, the proposed application gives an incentive to member customers to identify themselves while they are shopping. As a result, the retailers have a clue to execute one-to-one marketing, such as providing information and/or services only to the customer. In the prototype implementation, we include recommender system to show a benefit of providing (for customers) and acquiring (for retailers) shopping behavior information on the sales floor.

The structure of the rest of this paper is as follows: in section II, three industry practices, FSP, Dynamic Pricing (DP), and recommender system, which are necessary for our proposal, are explained; in section III, system overview to realize the proposed mechanism is explained; in section IV, evaluation of the proposal is made; and conclusion, limitation and future possibility follows in section V.

## II. Supporting Practices

### A. Frequent Shoppers Program (FSP)

FSP is a business practice to reward customers by giving various incentives, such as discounting services/products, offering free services/products, and sending coupons or the latest service/product information. FSP was first introduced in the airline industry as *frequent flyer program*. Since it was so successful in the industry, other industies, such as retailers, hotels, and financial services, introduce the program as FSP [8]. To reward customers is important in these industies because 1) most of the revenues come from small percentage of high loyal customers and 2)"customer retention costs are generally lower than customer acquisition costs [6]". Usually the more the member uses the company's services/products, the more she gets from the company. One basic rule for the customer to be rewarded is that she needs to identify herself when she uses/buys the provider's services/products, accumulate the records of how much she spends, and apply what she wants. Since customers usually show their loyalty cards at a check out counter, it has been impossible to reward customers while they are selecting products, which actually affects customer's purchase decisions.

### B. Dynamic Pricing (DP)

A study to optimize revenue out of given resources, such as services and products, under given constraints, such as expiration date, is called revenue management. Dynamic pricing is considered to be a part of this revenue management practices, and its focus is to optimize revenue by using pricing: how to set prices, when to discount, and so forth [9].

In this study, we use DP as a means to adjust an inventory turnover rate to improve profitability. As explained in section I, since to keep a high inventory turnover rate is a condition to increase revenue, we assume that all the goods on the shelves have certain time limits to meet a profitability goal even though they do not have expiry or they are continuously replenished. This assumption is valid considering the fact that product lifecycle is getting shorter these days [10] and products in most retail stores have seasonality.

With this assumption, the problem becomes a dynamic pricing without replenishment problem and is expressed by Problem (1), where $d(t)$ is demand at time $t$, $C$ is initial inventory level, $r(t, d(t))$ is revenue at time $t$, and $T$ is the number of periods in the sale horizon [9].

$$\begin{aligned} max \sum_{t=1}^{T} r(t, d(t)) \\ s.t. \sum_{t=1}^{T} d(t) \leq C \\ d(t) \geq 0 \end{aligned} \tag{1}$$

### C. Recommender System

Recommender system is a category of systems that recommend services/products to the customers based on service/product attributes and customers' preferences. This system is popular in e-commerce sites, such as *Amazon.com* [11]. Recommender system is classified into three groups from how recommendations are made [12]: 1) Content-based recommendations, 2) Collaborative recommendations (collaborative filtering), and 3) Hybrid approaches. A common characteristic of these approaches is that they usually use algorithms to find services/products that a specific customer most likely to buy based on her own shopping history and shopping histories of other customers whose purchase behavior is similar to the customer.

The business practice enabled by the recommender system is not limited to e-store retailers, but it is more popular in e-stores than physical store retailers in two reasons. Firstly, recommender system usually use huge amount of data to find services/products that suit for the individual customers, and that huge amount of data is easily captured at the e-commerce sites through just collecting "clicks" of the customers. Secondly, it is easy to show different information to different customers once they log on to the e-commerce site. With these reasons, recommender system gets popular in e-store retailers, but there are a few trials that apply the algorithms used in these e-commerce sites to physical store retailers [13].

There are many literatures that propose and evaluate the algorithms [14], [15], [16]. Since the purpose of this study is to propose an application and algorithms to realize both inventory management and customer relationship management together, we make the evaluation of the recommendation algorithm out of the scope of this study. In prototype implementation, we utilize outputs of an existing research. Details about the research are explained in section IV.

## III. Proposed System

### A. System Overview

Figure 1 shows the overview of the proposed system.

**Loyalty Card with RF tag:**
This card is used to uniquely identify each FSP customer.
**RFID reader with display:**
This RFID reader provides useful information (e.g., discount price) only to the FSP member who scans her loyalty card.
**Dynamic pricing Engine (DPE):**
This engine computes appropriate prices by using customer's loyalty status, current and future inventory levels, and product information; and provides the results to RFID readers. In case the system provides recommendations to the FSP member, it also sends a query to Recommendation Engine, gets recommendations, and consolidates the information with the price information.
**Customer DB:**
This database manages FSP customer and decides loyalty status based on the shopping history and the configuration made by the retailer.
**Inventory Management System (IMS):**
This system manages inventory including inventory level forecasting based on sales trend and initial inventory level.
**Recommendation Engine (RE):**
This engine collects customer ID and scanned item information and computes recommendations based on these information.

Work flow of the application is as follows:

(1) An FSP member customer lets her loyalty card scanned by the RFID reader with a display at the item that she wants to buy.
(2) The reader sends a customer ID to the DPE and the DPE starts computing the sales price for the customer. The link information between the item and the reader is either sent every time or registered as an initial configuration.
(3) The DPE gets the customer loyalty status from the customer DB.
(4a) The DPE then gets inventory information from the IMS.
(5) The DPE computes a price for the customer based on the information gotten in step (3) and (4a).
(6) The DPE sends back the computed price to the RFID reader, and it shows the price to the FSP member customer.

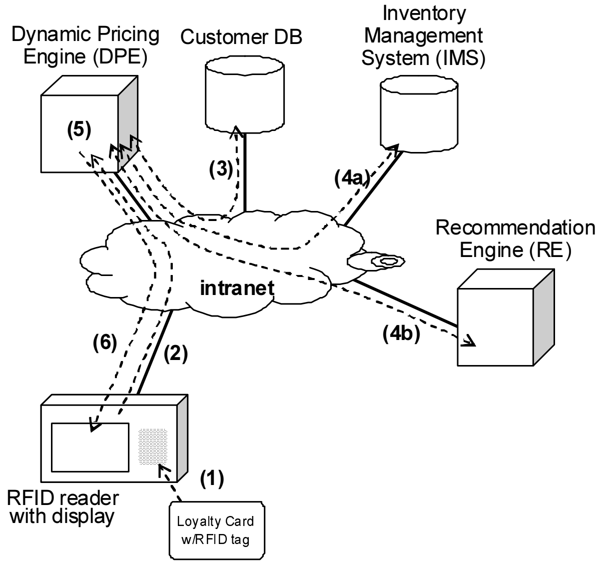


Figure 1. System Overview

In case recommender system is used, a step (4b) needs to be added and steps from (5) and (6) need to be modified.

(4b) The DPE then sends a query to RE with Customer ID and scanned item ID and gets recommendation information from RE.
(5') The DPE computes a price based on the information gotten in step (3) and (4a) and consolidates the price information with recommendation information.
(6') The DPE sends back the computed price and the recommendations to the RFID reader, and it shows these information to the FSP member customer.

### B. Proposed Algorithms for Dynamic Pricing Engine

Two algorithms are used in this proposed application:

**Base Target Discount Price calculation algorithm (BTDP Algorithm)**:
This algorithm is used to compute a price that is necessary to achieve a target inventory turnover rate. In this algorithm, the difference in the loyalty status is not taken into account. This algorithm uses Problem (1) and computes an appropriate price to make inventory level zero at the end of sale period. Actual procedure of the algorithm is described in Figure 2. The price calculated with this algorithm is denoted as $P_{BTDP}$ hereafter.

**Member type Target Discount Price calculation algorithm (MTDP Algorithm)**:
This algorithm is used to compute appropriate prices for FSP customers who have different loyalty statuses. This algorithm uses the price calculated by the BTDP algorithm ($P_{BTDP}$) and derives prices for each member

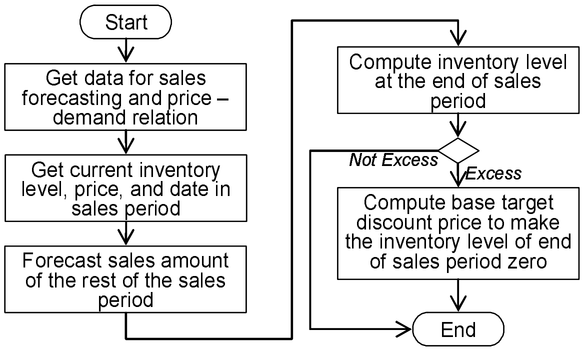


Figure 2. System overview

($P_{MTDP}$(i) $i \in n$) by using the number of statuses ($n$), the percentage of each member group (cust_ class(i) $i \in n$ $i = 0$ is non member), discount rate differences between each member statuses ($disc$), and a list price ($P_{LIST}$). The relation between $P_{BTDP}$ and $P_{MTDP}$(i) is expressed by Eq.2.

It should be noted that these algorithms are not used to maximize the profits; they are used to realize a target inventory turnover rate and reward customers differently based on their loyalty status. Therefore, if a company wants to maximize its profit by using this loyalty based dynamic pricing, it could do this by improving Eq. (2) and carefully choosing the number of loyalty customer statuses and discount rate differences. However, if the company does not use Eq. (2), it will need more time to achieve the target inventory level or it could not achieve the target in the worst case.

Regarding the algorithm for the RE, we use a collaborative filtering algorithm proposed in an existing study. Details about the study are explained in the next section.

## IV. Evaluation

### A. Numerical Study

This subsection reports on a numerical study that evaluates how the proposed algorithms achieve a target inventory turnover rate and rewarding customers differently based on their loyalty status. In order to show the validity of the algorithms, we need to confirm below four items:

(i) if the algorithms only work when there is excess inventory in the store,
(ii) if the algorithms increase the profit of the store,
(iii) if the algorithms reward customers based on their loyalty levels,
(iv) if the algorithms make the inventory level at the end of sale period zero.

In items from (i) through (iii), we need both two situations in which the algorithms work and not work because the algorithms should work only when there is excess inventory. So we make forecast demand as a variable and change the value from less than initial price demand to more than initial price demand ($100 \sim 150$ [item/week]) and see the effect of the algorithms. Regarding item (iv), we fix forecast demand at one level that is more than the initial price demand ($144$[item/week]) and see how the algorithms affect the inventory level of the store.

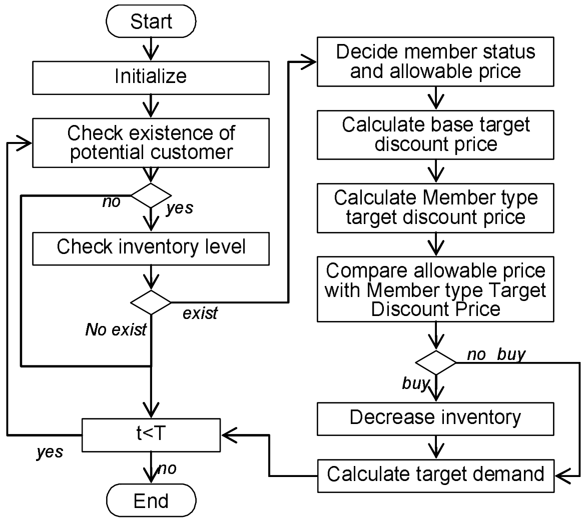


Figure 3. Simulation Flow

For simulation settings we carefully choose parameters that are equivalent to the real business situation. The item that we assume is a short lifecycle item, such as fashion item and electric appliance, of which forecasting and inventory control is more difficult than commodities. We choose $60$ days for sales period, which is equal to $3$ months in $5$ business days/week. We also assume that the store makes decisions of how many items to buy for the season before the sales season starts and can not change the amount after that. What they do is to forecast average sales demand of the item during the season, buy the number of items that correspond to the forecast, and sell them as far as they have stock on hand during the sales period. We do not consider shortage cost nor salvage value for simplicity purpose.

Price settings to run the numerical study are as follows: wholesale price is $800$ [yen], initial list price ($P_{LIST}$) is $1,200$ [yen], and difference in discount rate ($disc$) is $4$ %. We also use a monotonic decreasing function to show the relation between demand ($d$) and price ($p$), which is commonly used in the DP studies (Eq. (3)). From this equation, the demand at the initial list price is $120$ [item/week] (initial price demand). We also assume that price adjustments by DP are executed in every five days after the $30^{th}$ day and that the arrival of the potential customers follows Poisson distribution. The simulation flow is shown in Figure 3.

$$d = 600 - 0.4p \tag{3}$$

For comparison, we ran simulation in three cases:

(I) Without DP
(II) With DP. Without loyalty status differentiation (only difference in FSP member and non-

$$P_{BTDP} = cust\_class(0) \cdot P_{LIST} + \sum_{k=1}^{n} cust\_class(k) \cdot (1 - disc)^{k-1} \cdot P_{MTDP}(1) \quad (2)$$
$$P_{MTDP} = (1 - disc)^{i-1} \cdot P_{MTDP}(1) \quad i = 2, \cdots, n$$

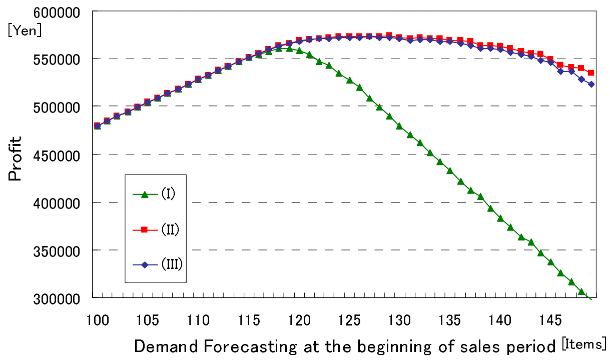


Figure 4. Profit for each case

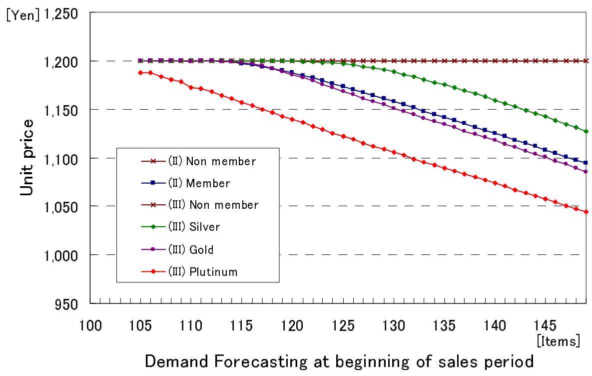


Figure 5. Purchase price for each case

member)

(Ⅲ) With DP. With loyalty status differentiation (three statuses: Platinum, Gold, and Silver; and non-member)

Figure 4 shows the profit of each case (vertical axis) with forecast demand as a variable (horizontal axis). From this figure, we see that profits from all the three cases are the same when the forecast demand is less than the initial price demand but that the profits of cases (Ⅱ) and (Ⅲ) are more than that of case (I) when the forecast demand is more than the initial price demand(120[item/week]). From this result, we see that the algorithms only work when there is excess inventory in the store and that the algorithms increase the profit of the store when there is excess inventory.

Figure 5 shows the unit price of the item (vertical axis) with forecast demand as a variable (horizontal axis). From this figure, we see that rewards to loyal customers are made based on their loyalty status. The higher the loyalty status (Platinum $>$ Gold $>$ Silver $>$ Non member), the lower the unit price when there is excess inventory in the store.

From Figure 6, we see that in cases (Ⅱ) and (Ⅲ) the inventory level at the end of the sales period becomes zero and that that of case (I) is not. This result means that the algorithms successfully reduce the inventory level at the end of sales period.

From these results, we confirm the validity of the algorithms proposed in the section Ⅲ.

### *B. Prototype Implementation without Recommender System*

This subsection explains how we develop a prototype system for a proof of concept. We assume a hypothetical situation, in which an electric appliance retailer adopts

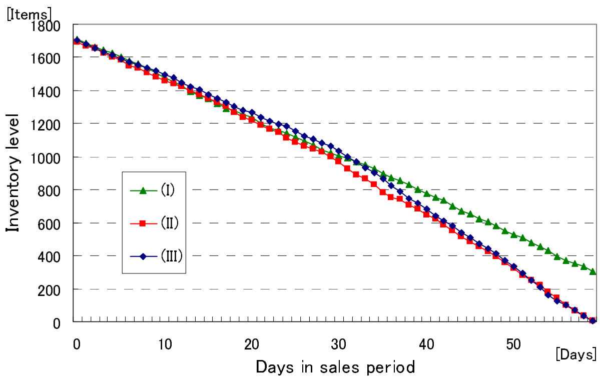


Figure 6. Inventory Level

this application. We assume that 1) this retailer uses FSP and distributes loyalty cards with an RF tag to its members, 2) the retailer places RFID readers with a display on its stores to show information and collect data, 3) each displayed item (hard disc recorder) has a reader, and 4) the store has excess inventory.

We develop two modes in the prototype implementation. One is a mode without recommendation, which is explained in this subsection, and the other is a mode with recommendation, which is explained in the next

TABLE I.
SYSTEM COMPONENTS

| Item | Description |
|---|---|
| PC | Panasonic Let's Note CF-W4 |
| RFID Reader | Omron V720S-HMF01 |
| RF Tag | ISO/IEC 15693 compatible |
| Operating System | Windows XP Professional SP2 |
| Development platform | J2SE 1.4.2-18 |
| Database | MySQL v4.1.22 |
| Recommeder system | CoFE v0.4 [17] |


Figure 7. Application screen snap shot(Without recommendation, FSP member status: Silver)


Figure 8. Application screen snap shot(Without recommendation, FSP member status: Platinum)

subsection. The reason why we implement two modes is that, in order to provide recommendations, the store needs data that is captured when its FSP customers' scan their loyalty card. But in order for the FSP members to be willing to scan, the store needs to provide some incentives to its customers. Without initial data, the store can not provide recommendations. This is what is called a cold start problem. In this study, we assume that we can collect initial data by providing discount information. In other words, we assume that the discount information gives member customers an incentive to scan their card. Once the store collects sufficient data to compute recommendations, it can change the mode from without recommendation to with recommendation. This is the reason why we implemented two modes in this study.

For the prototype system, we use a PC with an RFID reader as a substitute because RFID reader with a display was not available this time. We implement DPE, customer DB, IMS, and RE on the same PC. Table I shows the system components of the prototype system. They are commonly used in both modes.

In the prototype, we took a method to issue queries to the Customer DB and the IMS every time a loyalty card is read by the RFID reader (common in both with/without recommendation). However, considering the timeliness required on the retail store floors, it is envisaged that some kind of mechanism to speed the inquiry up would be required. Since the demand at the retail store has a week cycle, inventory forecasting could be done in weekly basis (A high demand on Sunday does not mean that the store has the equivalent demand on next Monday). Therefore, the DPE does not need to query the inventory status every time; it could cache the inventory data and update it in a certain period of time.

Figure 7 and Figure 8 show the screen snap shots of the prototype application when silver member and


Figure 9. Application screen snap shot(With recommendation, FSP member status: Silver)


Figure 10. Application screen snap shot(With recommendation, FSP member status: Platinum)

platinum member cards are scanned, respectively. These screens shows that more discount is offered to a higher status customer (Platinum) than to a lower status customer (Gold).

### *C. Prototype Implementation with Recommender System*

This subsection explains how we develop an prototype application with recommender system. Since the evaluation of the recommender system itself is out of the scope of this study, we use open source software and an existing algorithm for the recommender system. Since we use Java for the prototype development, we choose CoFE [18], [17] for RE. Considering the use case of how customers scan their loyalty card, it is foreseeable that the captured data would be binary data. Therefore, we choose a recommendation algorithm for binary data proposed in [19].

Since we just implement one RFID reader system this time, we do not get data for recommendation from the prototype implementation. Therefore, we generate data to compute recommendations used by the RE. The data is for 38 items in the same product category scanned by 20 FSP members in the different loyalty statuses. Figure 9 and Figure 10 show the screen snap shots of the prototype system when the same loyalty cards as the without recommender mode case are scanned at the RFID reader. Although Figure 9 and Figure 10 are different from Figure 7 and Figure 8 in that Figure 9 and Figure 10 have three recommended items on the screen. However, discount rates for both loyalty statuses are the same.

## V. Conclusion, Limitation and Future Possibility

### A. Conclusion

The situation that physical store retailers are in is severer than before. They have to make profit under strong competition not only with other physical store retailers in the same geographical area but also with e-store retailers. The vast many SKUs that they need to deal with also make the situation worse because they makes it difficult for those retailers to forecast right amount of items to sell during the sales season especially when the item has a short lifecycle. To cope with this severe situation, effective control over store inventory and building of a good relationship with loyal customers are said to be a key to success. Those two practices are effective by themselves, but they need cost to execute. However, if the retailers can combine these two practices and use the discount for inventory control to reward loyal customers, the retailers execute these two practices more cost effectively.

In order to realize these two practices together, in other words to realize SCM and CRM together, they need to know who is shopping in their store. It has not been possible to get this kind of consumer behavior information, but with the development of both RF tag embedded loyalty cards and RFID readers with a display, it becomes possible to utilize this kind of information. In this study, we assume that RFID system is available to physical store retailers and propose an application to achieve inventory management control and as well as to reward FSP customers based on their loyalty status. We also develop a prototype system for a proof of concept.

In order for this application to effectively realize both two practices, the retailers also need a mechanism to better control both inventory of their store and rewards to FSP customers. In this study, we also propose two algorithms for this mechanism. One algorithm is based on dynamic programming algorithm and computes an appropriate price that makes inventory level at the end of sales period zero. The other algorithm takes the price computed by the first algorithm and calculates different prices for customers in the different loyalty status. We also evaluate the validity of these algorithms by a numerical study in this study.

### B. Limitation

In order for this application to be used in a commercial basis, measures to protect consumer privacy need to be taken. Measures, such as to prevent other people from seeing the display of the RFID reader, will be effective. Moreover, consumers will have strong concerns about the information captured on the sales floors because it is a piece of privacy information that some people want to conceal. To wipe away this kind of concerns, companies should take appropriate measures, such as complying with the international guidelines [20] to protect peoples' privacy.

Another potential issue is the legality of showing different prices to different customers. The application proposed may be considered unfair in some countries and may be restricted, especially when items are necessities of lives. Companies that want to implement the proposed practice should confirm the legality of the practice in advance.

### C. Future Possibility

The benefit of having consumer behavior information on the sales floor is enormous for both consumer and business. Benefits for consumer include having information not only about discount prices but also recommendations based on consumer profiles and purchase behavior of other customers who have similar preferences as studied in this paper.

Regarding benefits for business, companies can get two types of information that they do not have otherwise. One is information like how each consumer selects a specific item, who are the competitors of the item, how long the selecting process takes, and so forth; and the other is information like how crowded and where in the store is crowded in a real-time basis. The benefit of the first information is for both retailers and manufacturers. Since POS information only shows the *result* of consumer decision, it does not give manufacturers of unsold goods and retailers any clue of why some goods are sold and others are not. The information they may get, however, gives much more granular information that would be useful when deciding list price and promotional sales timing.

The benefit of the second information, on the other hand, is used to streamline store operation. The distribution of scan data gives information to the store of how many potential customers are there in the store aisle level. The store manager may send additional sales representatives to the *hot* areas. As such, the information acquired on the store floor has the possibility of giving many benefits to both consumer side and business side.

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