PAPER

An Agent-Based Expert System Architecture for Product Return Administration

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SUMMARY Product return is a critical but controversial issue. To deal with such a vague return problem, businesses must improve their information transparency in order to administrate the product return behaviour of their end users. This study proposes an intelligent return administration expert system (iRAES) to provide product return forecasting and decision support for returned product administration. The iRAES consists of two intelligent agents that adopt a hybrid data mining algorithm. The return diagnosis agent generates different alarms for certain types of product return, based on forecasts of the return possibility. The return recommender agent is implemented on the basis of case-based reasoning, and provides the return centre clerk with a recommendation for returned product administration. We present a 3C-iShop scenario to demonstrate the feasibility and efficiency of the iRAES architecture. Our experiments identify a particularly interesting return, for which iRAES generates a recommendation for returned product administration. On average, iRAES decreases the effort required to generate a recommendation by 70% compared to previous return administration systems, and improves performance via return decision support by 37%. iRAES is designed to accelerate product return administration, and improve the performance of product return knowledge management.
key words: *product return, intelligent agent, case-based reasoning, intelligent system design*

1. Introduction

Customer return policy is a contentious issue [5], [18], costing approximately $100 billion annually in lost sales and reverse logistics [2]. Actually, product return is a necessary and unavoidable evil for business and reverse logistics [2], [7]. Various industries are thus forced to provide their customers with a guaranteed return policy [13], [14], [17]–[19], including even the pharmaceutical sector [10]. In practice, product return policies vary from strict to lenient. A comprehensive return policy, known as the most lenient, enables customers to return products with the guarantee of an unconditional refund. Customers usually associate a generous return policy with commercial goodwill, and form a favourable impression that product quality must be excellent since they can return the product if they do not like it [2], [6]. Mukhopadhyay and Setaputra even claimed that the most generous return policies can be regarded as a strategic weapon to enhance business competitiveness [16].

Therefore, product return policies have become an increasingly important strategy in enabling businesses to maintain their competitive edge [2], [16]. Customers expect that businesses with the most generous type of return policy offer an unconditional refund [10], [15]. Certainly, a generous return policy can stimulate the purchasing decisions of customers, but it is, on the other hand, accompanied by a higher number of return transactions that incur additional administration and logistics costs [3]. Moreover, uncertain return quantities complicate the accurate estimation of the revenues and stock value of a business [11]. Providing an unconditional return policy has become an unavoidable trend for businesses, though it presents contradictions. Therefore, achieving effective product return administration in the face of considerable return volumes is a priority concern.

For the past few decades, however, return-related issues, particularly return administration, have seldom been addressed [2]. Most previous return-related research has been devoted to return policy optimization, and thus formulated the returns policy problem into a mathematical model. For illustration, Padmanabhan and Png examined how a returns policy affects pricing and stocking in a competitive retail sector, indicating that manufacturers should accept returns if the production costs are sufficiently low and the demand uncertainty is not prohibitively high [18]. Mukhopadhyay and Setoputro developed a profit maximization model for manufacturers that allowed them to jointly consider the level of the return policy (i.e., the buyback price for returned products) and the level of modularity in product design for build-to-order products [15]. However, handling product return quickly is an increasingly important issue that receives little attention. For illustration, Chang et al. probed the issue of returns in the Taiwan bookstore industry. According to their findings, the return ratio for the release of new books is, on average, 30%. Additionally, for a book wholesaler, the return issue is becoming worse because book retailers are not willing to bear any stock risk and reverse logistics cost. [12] Therefore, return-relevant information, such as return forecasting, is becoming an important issue. Furthermore, there should be a mechanism to accelerate return administration, which would enable businesses to provide their customers with the most generous return policy.

Usually, product returns are initiated by the end users, thus making them extremely difficult to predict, prevent, or prepare for [3]. Businesses attempting to resolve and accelerate the unpredictability associated with product return must improve upon information transparency with respect to the return activities of the end users [11]. As mentioned

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before, Chang et al. combined case-based reasoning and genetic algorithms to formulate a hybrid prediction mechanism for book returns. Such a mechanism can provide wholesalers with return forecasting information for book return management, such as publication date adjustment [12]. Furthermore, Yang and Wang asserted that real-time return-relevant information (e.g., predictions of the possibility of a product being returned by a customer) can enhance the information visibility of the overall supply chain [8]. Indeed, information transparency is expected to positively relate to return administration. Meanwhile, knowledge management of product returns is also an important issue for business strategy. For example, by studying the return pattern analysis of product attributes, some return patterns may reveal that particular product types are returned more often by customers. Therefore, relevant product design changes can be issued in order to decrease the frequency of returns. As another example, return reason analysis may uncover marketing opportunities, such as pricing strategy adjustments (e.g., if many customers claimed that the product was too expensive). Businesses should pay more attention to product returns and their corresponding return administration.

This study proposes an agent-based intelligent return administration expert system (iRAES) architecture to improve the accessibility of information about product returns and enhance the information transparency of the overall supply chain. An agent-based mechanism is appropriate for embedding in a supply chain system architecture. Si and Lou have successfully applied a fuzzy adaptive agent to their supply chain management strategy adjustment; this proved particularly successful for material order and inventory management. As their research results show, intelligent agents can automatically achieve target inventory levels via agent interactions. Indeed, their research enabled them to win a supply chain agent competition in 2006 [20]. Employing an intelligent agent is actually an appropriate methodology for automatic event-driven processes (such as a return administration trigger) and relevant interaction processes [20]. Consequently, we intend the iRAES architecture to accelerate the product return process by providing return administration recommendations on the basis of previous cases. Therefore, though a generous return policy may cause a considerable amount of product returns, iRAES enables businesses to provide their customers with a lenient return policy that can be viewed as a timely business strategy. The rest of this paper is organized as follows: Section 2 introduces an integrated agent-based iRAES framework; Section 3 then demonstrates a 3C-iShop scenario and experiment to illustrate the feasibility and effectiveness of the proposed iRAES architecture. Finally, we draw together our conclusions in Sect. 4, along with recommendations for future research.

2. Intelligent Return Administration Expert System (iRAES) Architecture

For general transactions, there are two interacting flows of the entire supply chain between supplier, manufacturer, and retailer: the physical logistics flow and the information flow. The physical logistics flow, as Fig. 1 shows, is further divided into two types: the forward logistical flow and the reverse logistical flow. From a forward logistics perspective, merchandise (or product) is delivered from the original supplier to the customer at end of the chain. Of course, customers may receive their products via multiple selling channels (such as via a retailer) or from the manufacturer directly. To protect customer transaction equity for a particular guarantee period, most suppliers promise their customers (including the end user, retailer, and manufacturer) to issue a return transaction and send a sold product back (to their upstream suppliers). In general, customers are able to issue a return transaction even without a reason. Therefore, when return transactions are triggered and a product is sent back from the customer to the supplier, it is known as the return logistics for the product, and these are represented by the red solid lines in Fig. 1. When a return transaction is issued, a return centre clerk should deal with the return transaction as soon as possible, because the returned product value is positively related to return administration efficiency. In Fig. 1, for example, to increase the returned products' value, businesses should try to resell these products at their original price rather than at a discounted rate. However, these returned products should be inspected before reselling. Therefore, the acceleration of return administration is a priority concern for optimal business benefit. The return centre clerk should interact with customers and implement the relevant return administration as soon as possible.

The information flow of business transactions, shown as the grey dashed lines in Fig. 1, is recorded in the

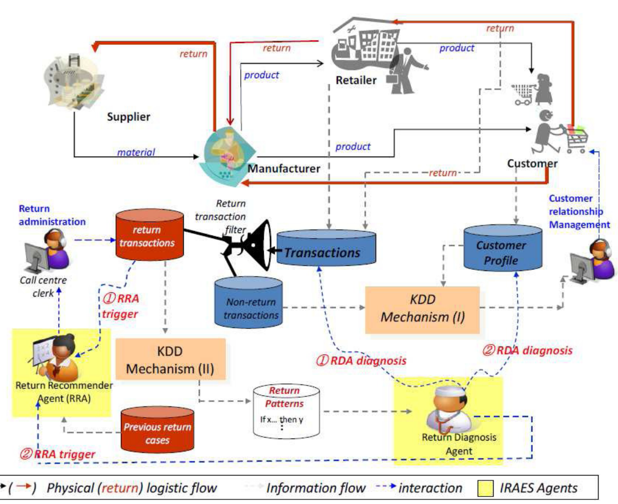


Fig. 1 Architecture of the intelligent return administration expert system (iRAES).

Table 1 RDA and RRA variable definitions.

Variable	Definition
C_i	The i^{th} case in the case base that recorded a previous product return case and relevant return administration process, $i = 1,2,\ldots,n$
fet^j	The j^{th} feature to describe a return case and target transaction, as in the following conditions: $fet^j_{C_i}$ to represent the j^{th} feature of the i^{th} case; fet^j_T to represent the j^{th} feature of the target transaction; $j = 1,2,\ldots,m$
difference($\vec{C_i}, \vec{T}$)	An evaluation function for case-based reasoning mechanisms to calculate the difference between the i^{th} case and the target transaction, and then retrieve the most similar case to refer to for return administration recommendations. A difference function is defined in equation (1) below.

transaction DB, which associates the corresponding customer profile in the customer DB and the product DB. For instance, a transaction is recorded in the transaction DB with its corresponding customer profile and information on the purchased product. In addition, iff (if-and-only-if) a return transaction is issued, the transaction is then stored in the return transaction DB, where it awaits return administration by a return centre clerk. To accelerate the return administration process, iRAES can predict the return possibility and then provide a return centre clerk with suggestions for return administration. Figure 1 displays the overall architecture of the proposed agent-based iRAES architecture.

Two intelligent agents, a return diagnosis agent (RDA) and a return recommender agent (RRA), and two knowledge discovery and data mining (KDD) mechanisms, are involved in iRAES. As a return transaction is issued, the RDA of iRAES (the yellow area in Fig. 1) is able to improve the information visibility of return behaviour by matching return patterns. In addition, the RRA functions as a sophisticated expert to provide a business clerk with recommendations for return transaction administration. The KDD mechanism algorithms and intelligent agent designs are detailed below. The variable definitions of RDA and RRA are detail in Table 1.

2.1 KDD Mechanism

The return transaction filter shown in Fig. 1 is designed to distinguish return transactions from general transactions, and then form return and non-return DBs, respectively. Both return and non-return DBs are analyzed via KDD mechanisms (KDD mechanism I and KDD mechanism II), allowing data mining patterns to be generated for specific purposes. KDD is an abbreviation for knowledge discovery and data mining, and it is the process of extracting patterns from large data sets by combining statistical and artificial intelligence methods. Data mining is a classical KDD application that has been successfully applied in various industries for business strategy development. A number of data mining algorithms, such as cluster, classification, and association computing, reveal some potential patterns from the general transaction DB. For instance, the most widely cited Wal-Mart application probes product associations among all transaction records. In this case, an interesting product package pattern of diapers and beer can comprise a sales promotion program, because these two products are found to be bought together.

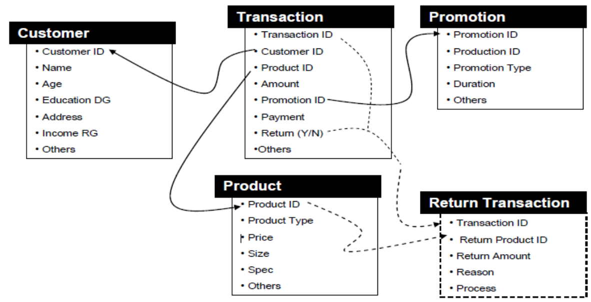


Fig. 2 DB architecture for general transactions.[†]

To enable KDD to function well, a structured DB is required. Figure 2 shows an entity-relationship diagram for the general transaction record of a non-product-returned transaction DB, including transaction, customer, product, and promotion tables. Consequently, the KDD (I) mechanism is applied to non-return transaction DB analysis using description and prediction data mining algorithms, such as classification, cluster, and association. Additionally, because of the entity relationship among tables, all those in Fig. 2 can execute SQL joint operations to generate a new table; for example, the customer and product tables can be joined with the transaction table via the customer ID and product ID relationship. This supports advanced KDD analysis and the discovery of synergistic marketing strategies [3]. Finally, analysis results from the KDD (I) mechanism can be applied to customer relationship management.

As specific return transactions are triggered by customers, the relevant return information would be further recorded into the Return Transaction table in Fig. 2. Consequently, we use the KDD (II) mechanism for return transactions. Similar to the KDD (I) mechanism, KDD (II) is also implemented by description and prediction data mining approaches. In contrast with KDD (I), the KDD (II) mechanism attempts to discover return patterns from return transactions. The KDD (II) mechanism consists of two stages to discover C-rules (using cluster analysis) and A-rules (using the Apriori algorithm). Each dimension in Fig. 2 is pair-wise associated with another dimension to elicit return patterns. The KDD (II) mechanism can successfully identify return

[†]The dashed lines represent return transaction record actions. Return transaction records are a kind of extension of general transaction records, because not all transactions will be returned.

```
While (Customer education degree = High)
  {
   Return Alarm is green light;
   If (complaint calls > 2)
        Break;
  }

While(warranty valid)
{
If ((complaint calls ≥ 3 || sale amount ≥ 4 ) & product
type = 3C & product size = small ) then
        Return alarm is red light;
else if (sale amount < 3 & product type = 3C)
        Return alarm is yellow light;
else    Return alarm is green light;
   }
```

Fig. 3 Illustration of a return pattern from the KDD (II) mechanism.

patterns, and is represented in a rule-based format. For illustration, Yu and Wang applied the KDD mechanism to identify specific customer types that intend to return a product or, conversely, specific products that are often returned by customers [3]. The return pattern can be regarded as business intelligence and further used by the return diagnosis agent to detect and diagnose customer return behaviour. By way of example, Fig. 3 displays an interesting return pattern, wherein the customer made more than two complaint calls and purchased a small 3C product; so according to experience, the customer intends to return the purchased product.

2.2 Diagnosis Agent (RDA) Design

A return diagnosis agent (RDA) functions as an intelligent forecaster to predict the possibility that a customer will return a product. According to the return patterns discovered via the KDD (II) mechanism above, the RDA monitors the transaction DB, and a return alarm is issued iff a particular return pattern is matched. The RDA can issue various levels of return alarms to the RRA, including green, yellow, and red, according to the return pattern generated by the KDD (II) mechanism. As a result of these alarms, the business clerk can prepare or even prevent uncertain returns as early as possible. Figure 4 shows the BNCL representation (XML format) and the interaction between RDA and RRA agents according to the FIPA reference.[†] The RDA issues a request interaction to the RRA for return alarm confirmation and administration.

2.3 Return Recommender Agent (RRA) Design

The RRA functions as a senior consultant to provide the business clerk with a feasible recommendation for return treatment. It can provide an inexperienced business clerk with suggestions to accelerate the administration of returns [4] and maintain the relevant knowledge and experience to cope with business returns. The RRA is implemented via a case-based reasoning (CBR). This is a classical artificial intelligence algorithm that can be applied to various problem solving domains [1], [4], [9]. A CBR is particularly useful for dealing with an ill-defined problem; thus, it is appropriate for dealing with the problem of product returns [1]. Similar to a human expert, the RRA can retrieve the most comparable previous case, and either reuse or revise the solution prior to further application.

```
(request
: Send RDA
: Receiver RRA
: Language xml
: Interaction-protocol NCL-request
: Ontology-base: NCL-ontology
: Content <? Xml version =“1.0”>
<action> alarm issue </action>
<args> green, yellow, red </args>
<protocol> request-inform </protocol>
<reply-with> yes or no, not-understood </reply-with>
<ontology> default </ontology>
)
```

Fig. 4 Return diagnosis agent design.

In order to provide recommendations for return administration, all previous return transactions and relevant treatments are stored in a case base for further reuse. A target transaction with a return alarm is then compared with a previous return case in the case base to provide return administration recommendations. Equation (1) is used to evaluate the difference between the current return transaction (Target) and all previous return transactions (cases) in the case base. The treatment of the most similar case (that with the least difference) is identified and regarded as a recommendation for returned product administration. For illustration, according to the DB schema in Fig. 2, all return transactions are described by a return transaction ID, return product ID, return amount, and return reason with relevant treatments. These return transactions have been closed appropriately and, thus, their administration process can be reused as a reference for other return transactions. These administration processes were also parts of a case described by q features, such as return policy (full return or partial return) and customer satisfaction.

$$\text{difference}\left(\vec{C}_i, \vec{T}\right) = \text{cosine}\left(\vec{fet}_m^{\,C_i}, \vec{fet}_m^{\,T}\right) = \frac{\vec{fet}_m^{\,C_i} \bullet \vec{fet}_m^{\,T}}{\left\|\vec{fet}_m^{\,C_i}\right\|_2 \times \left\|\vec{fet}_m^{\,T}\right\|_2} \tag{1}$$

According to Yu and Wang, for some fashion goods, the return value is positively related to return disposition

[†]The Foundation for Intelligent Physical Agents (FIPA), http://www.fipa.org/ available on 2010/10/1.

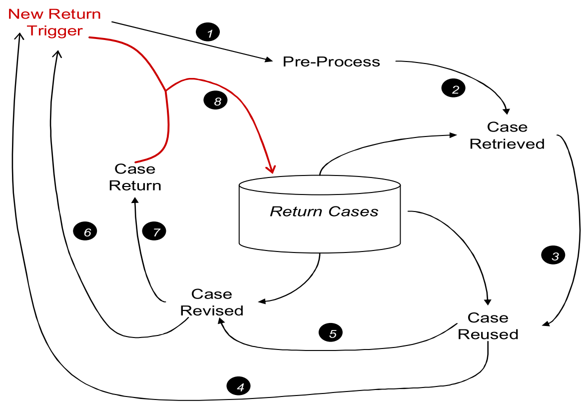


Fig. 5 Eight-step reasoning process of the RRA.

(inform
:Sender RRA
:Receiver RDA
:Language xml
:Interaction-protocol NCL-request
:Ontology-base: NCL-ontology
:Content (alarm_confirmed(green, yellow, red))
:Reply-with (agree, reject, not understood)
:Ontology default
)

Fig. 6 Return recommender agent design.

speed [3]. The RRA can definitely accelerate return administration via a previous successful experience. In addition, *iff* a return administration process is revised, an altered return treatment can be stored in the case base for further reuse, as demonstrated in step 8 of Fig. 5. The eight steps detailed in Fig. 5 show the famous 4R-cycles (the 4Rs being retrieve, revise, reuse, and return) of the traditional CBR algorithm. The RRA is awakened by a return alarm (which is issued by RDA), and then provides return administration recommendations according to previous experience stored in the case base. This can assist even an inexperienced clerk in handling product return appropriately, because RRA functions as a senior experiential entity. Therefore, as expected, return administration can be accelerated by reusing a previous return treatment, as demonstrated by steps 3 to 6 in Fig. 5. Finally, Fig. 6 exhibits the BNCL representation (XML format) of the RRA agent design. The RRA confirms the request from the RDA and further provides a suggestion to the business clerk.

3. iRAES Demonstrations and Experimental Validation

To validate the feasibility of the proposed hybrid iRAES architecture, a three-tier system is implemented. In addition, a 3C iShop scenario is designed as an experiment for the purposes of iRAES demonstration and validation. Similar to a physical online shop, the 3C iShop is an imitative electronic commerce website that facilitates online shopping and specializes in selling 3C products. All product information, customer profiles, and transaction details are recorded in their entirety in the corresponding DBs. The administrator of the 3C iShop has recently noted a more serious return trend than anticipated and would like to establish an intelligent return management system based on the iRAES architecture.

3.1 Scenario Design: 3C iShop Demonstrations

According to Fig. 2, the architecture of the 3C iShop DB records the customer profile, including customer ID and customer name, and the product profile, including product ID and product type. For instance, Jenny's customer profile (C00168 [Customer ID], Jenny [Customer Name], 32 [Age], Master's [Educational level], North division [Address], 60,000–100,000 NT$ [Income range]) would be recorded in the customer DB. Additionally, a product profile, specifically that of an ASUS EPC (P0105 [Product ID], 3C [Product type], Notebook [Sub-type], NT$ 9,999 [Price], 226 mm × 191.2 mm × 28.5–38 mm and 1.4 kg [Product size], DDRII 1024 MB, SATA 80 GB, 6-cell battery [Product specification]), would be recorded in the product DB. Recently, Jenny received a 3C iShop promotional e-mail about the EPC, which is on sale. New promotional activities can be recorded in the promotion DB via attributes (A20100305 [Promotion ID], P0105 [Product ID], payment divided into 12 months and without extra interest [Promotion type], 1 week [Duration]). Thus, Jenny decided to purchase three EPC pocket computers from the 3C iShop website. Finally, the transaction is recorded with attributes (T0201003080081 [Transaction ID], C00168 [customer ID], P0105 [Product ID], 3 [amount], A20100305 [Promotion ID], credit-card [Payment], N [Return tag]) in the transaction DB.

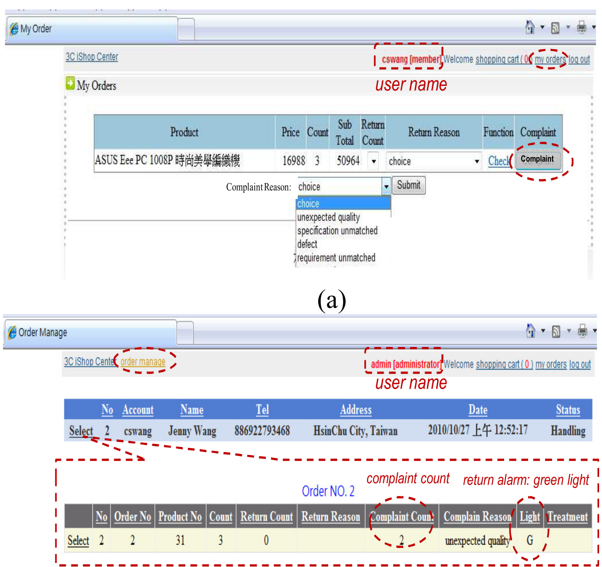
iRAES provides a business clerk with recommendations for returned product administration based on previous return transaction records. In this experiment, a total of 100 return cases are stored in the case base for reference. For these 100 return cases, there are six return reasons. The return ratio (RR) is the ratio of return transactions to total transactions.

The return frequency ratio (RFR) is the ratio of return transaction amount to total transaction amount. For example, considering different product types in Table 2 shows that the RR of LCD monitors (30%) is higher than that of computers (15%) and cellular phones (25%); however, the RFR of LCD monitors is the lowest (13.42%) among all product types. Because LCD monitors are cheaper than cellular phones and computers, although their RR is high, the RFR is low. Thus, both RR and RFR should be taken into consideration when evaluating the similarity between the return case(s) in the case base and the current case. Table 2 summarizes the RR and the RFR for distinct demographics and product dimensions. For instance, the gender variable in the demographic dimension suggests there is no difference in RR between males and females.

Table 2 Description statistics of 100 return cases in the iRAES demonstration scenario.

Dimension	Variable	Attribute	Return ratio[†] (Return frequency ratio)[††]
Demographic	Gender	Female	30 (50)
		Male	30(50)
	Age	Low	30 (40)
		Middle	30(40)
		High	30 (20)
Product	Type	Computer	15 (19.46)
		Pocket computer	40 (46.98)
		LCD monitor	30 (13.42)
		Cellular phone	25 (20.13)
	Size	Small	35 (67.11)
		Large	22.5 (32.89)
Others	Return reason	Unexpected quality	10 (19.46)
		Specification mismatch	20 (20.13)
		Defect	30 (20.13)
		Requirement mismatch	40 (20.14)
		Too expensive	50 (20.14)

Note: return ratio and return frequency ratio are represented as percentages in Table 2.



(b)

Fig. 7 iRAES demonstration of 3C iShop: administrator login and order management.

3.2 Step 1 Demonstration of iRAES: Product Return Diagnosis

In Taiwan, for general transactions, the duration of a product warranty lasts for seven days after the customer's receipt of the purchased merchandise. During the warranty period, the customer, Jenny, can return her new notebooks with a full money-back guarantee *iff* she kept the product invoice, and the warranty becomes void once the package has been opened. As Fig. 7 (a) shows, the customer can access a "Complaint" button to voice dissatisfaction with issues such as unexpected quality, high price, and so on. In addition, as Fig. 7 (b) shows, the 3C iShop administrator can use the order management page to verify the order status

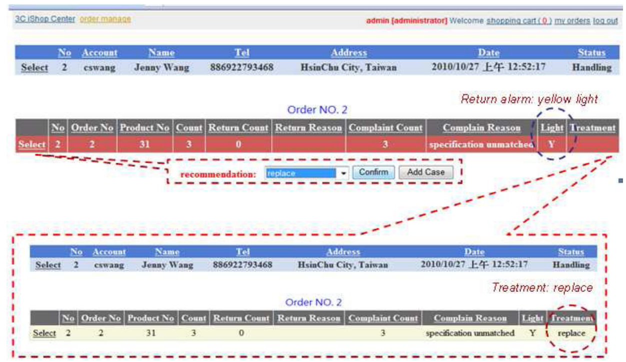


Fig. 8 iRAES demonstration of 3C iShop: yellow return alarm management.

(such as a return alarm). In Fig. 7 (b), according to the return pattern in Fig. 3, no return alarm has been issued for Jenny's order; therefore, the return alarm field retains the green light.

According to the return pattern in Fig. 3, as the customer made more than two complaint calls and purchased a small 3C product, the customer probably intends to return the product. In Fig. 8, we assume that Jenny made three complaint calls due to a product specification mismatch. Because all three purchased EPCs are still under warranty, the RDA would issue a yellow alarm to the RRA to prepare for and prevent a possible return. According to previous return case(s), the RRA can provide the business clerk with appropriate suggestions on how to deal with such a yellow return alarm quickly. Figure 8 illustrates how the most similar cases for such a yellow alarm about product specification mismatch are retrieved. Initially, the RRA attempts to prevent a return from the customer. Therefore, to meet Jenny's concerns, two new products are sent to her to replace the purchased EPCs.

3.3 Step 2 Demonstration of iRAES: Return Administration Recommendation

In our experimental scenario, we assume that Jenny still intends to return two of the EPCs she purchased. In Fig. 9 (a), Jenny has selected 'too expensive' as the return reason. According to the return pattern in Fig. 3, the RDA would issue a red alarm to inform the return centre and the RRA, as shown in Fig. 9 (b). Consequently, the RRA would provide the business clerk with a recommendation for return administration to accelerate the return process appropriately. To deal with such a red return alarm, the RRA retrieves similar cases from the database of previous returns.

As shown in Fig. 10, Jenny eventually decided to return two EPCs because she found a more reasonably priced EPC on another selling channel. In Jenny's return case, to accelerate such a red return-alarm process, the RRA found

[†]Return ratio is the ratio of return transactions to total transactions.

[††]Return frequency ratio is the ratio of return transaction amount to total transaction amount.

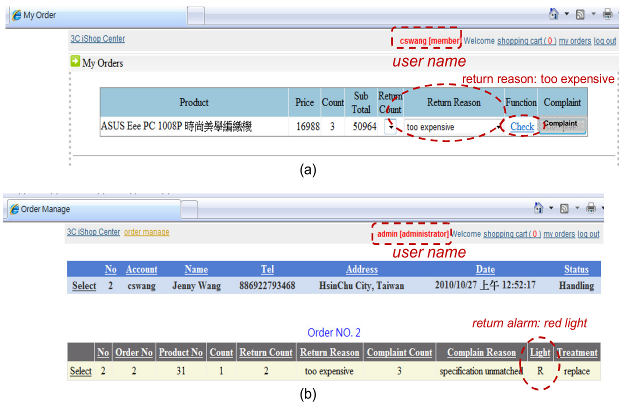


Fig. 9 3C iShop demonstration: customer order management and product return.

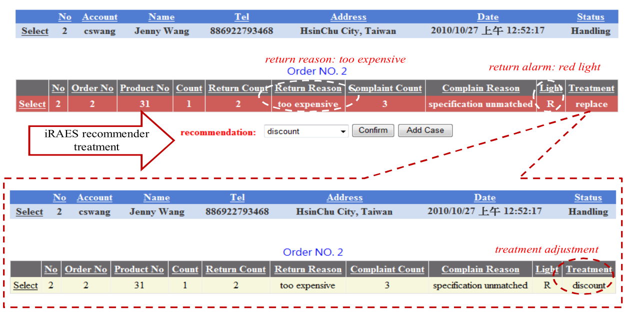


Fig. 10 iRAES demonstration of 3C iShop: red return alarm management.

Table 3 Cross analysis of return reason and product type.

	PQ	SPE	DF	RM	EXP
Computer	50%	50%	-	-	-
Pocket computer	-	25%	25%	15%	35%
LCD Monitor	50%	-	-	-	50%
Cellular Phone	-	50%	50%	-	-

a feasible manner of administering the return from a previous case that provided Jenny with a pricing discount to prevent a possible return, as shown in Fig. 10. Therefore, in Fig. 10, the previous recommendation for mismatched product specification is adjusted. As the 3C iShop experiment demonstrates, iRAES can accelerate the return administration process via the interaction of two intelligent agents, the RDA and the RRA.

For business knowledge management purposes, the cross analysis of return reasons and product types is tabulated in Table 3. Some necessary product improvements and adjustments to marketing strategy can be discovered via such cross analysis. There are five return reasons in Table 3: unexpected quality (PQ), specification mismatched (SPE), defect (DF), requirement mismatched (RM), and too expensive (EXP). This cross analysis implies that the defect rate of cellular phones is higher (50%) than that of the other products, and that the product quality management for both PCs and LCD monitors should be enhanced. Additionally,

Table 4 Cross analysis of return reason and administration recommendation.

	TMA	TMB	TMC	TMD	TME	TMF
PQ	25%	-	40%	-	5%	30%
SPE	15%	-	50%	20%	5%	10%
DF	-	-	-	-	100%	-
REQ	10%	35%	50%	5%	-	-
EXP	-	75%	-	-	25%	-

the pricing of LCD monitors (50%) and pocket computers (35%) should be adjusted because a lot of customers, including Jenny, have claimed that prices are too high. Product return management can be regarded as a kind of customer interaction activity, and an efficient return administration process can actually enable a business to maintain its competitive edge.

Finally, the efficiency of iRAES can be validated via the cross analysis of return reason (as listed in Table 3) and return administration, as shown in Table 4. There are six treatments for returned product administration. Treatment A (TMA) arranges personal contact for returned product administration, TMB provides a customer discount for the returned product, TMC replaces the returned product with a new one, TMD assists the customer in solving the problem, such as an operational issue, TME arranges the return process to get the product back, and TMF instigates a QC process for the returned product. From this cross analysis, a feasible treatment can easily be found for the particular return reason. For example, a yellow return alarm because product specifications were not matched, iRAES can decrease the evaluation effort in about 50% of the cases and improve performance during return administration by 50%. In addition, for a red return alarm because of high pricing, iRAES reduces the evaluation effort in 25% of the cases and improves case handling. On average, by retrieving a similar previous return administration experience, iRAES can decrease evaluation efforts in about 70% of cases and improve performance by providing appropriate suggestions in about 37% of cases.

For the case adoption of iRAES, including: revise, reuse and retain, call centre clerk can confirm the return alarm according to the iRAES diagnosis result and therefore accelerate to product return administration. Clerks either revise the recommendation result before reuse or apply the diagnosis result directly. According to experimental result, iRAES indeed assists call centre clerk in initial return alarm identification. In particular, iRAES can be recognized as a repository for accumulating valuable working experiences that can be used for on-site training. For the case retain, to solve overflow, redundancy and convergence issues, a new case must be double-checked no duplication in terms of both the symptoms and the treatment for product return issue before filed to case base.

4. Conclusion and Further Work

Product return is an increasingly important issue. Some businesses view an effective return policy as a corporate strategy. In Taiwan, more and more electronic commerce websites provide their customers with the most generous return policies, which guarantee an unconditional refund. Therefore, achieving effective administration in the face of considerable return volumes is a priority concern. Return administration is expected to become an emerging issue for important business strategy.

This research proposed an intelligent return administration expert system (iRAES) architecture to accelerate the return administration process and improve the information transparency of the entire supply chain. The interaction between two intelligent agents in iRAES enables the business to diagnose return likelihood and provides the return centre clerk with recommendations for return administration. As shown by the results of our experiment, the proposed iRAES architecture can be useful for predicting and even preventing a customer product return. In addition, as the demonstration scenario showed, for distinct return alarms, iRAES determines different treatments accordingly and initially attempts to prevent the product return. Additionally, in order to base the procedure on similar previous return cases, iRAES can decrease the effort of case evaluation by 70% and improve performance via return administration suggestions by 37%. Furthermore, the iRAES architecture successfully implements business knowledge management about product returns via return patterns analysis and product return management. Therefore, return administration can be accelerated via iRAES and can enhance performance. Finally, a validation process for iRAES across multiple industries should be conducted to further validate the concepts.

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