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Exploring the preference of customers between financial companies and agents based on TCA

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ABSTRACT

Based on transaction cost analysis (TCA), this research explores the customers' loyalty to either the financial companies or the company financial agents with whom they have established relationship. In the past, consumers were divided into those who rely on agents and those who do not. In this study, we use two processes (pre-process and post-process) to select suitable rules, and to explore into the relationship among attributes. In the pre-process, we utilized factor analysis (FA) to choose the variable and rough set theory (RST) that found decision table to construct the decision rules, and approach to data mining and knowledge discovery based on information flow distribution in a flow graph. The post-process applies the formal concept analysis (FCA) from these suitable rules to explore the attribute relationship and the most important factors affecting the preference of customers for deciding whether to choose companies or agents. The degree of the customers' dependence on agents was affected by the TCA, customer satisfaction and loyalty. The principal findings were that the different degrees of dependence of customers have various characteristics. The RST and FCA were two complementary mathematical tools for data analysis. Following an empirical analysis, we use two hit testes that incorporate 30 and 36 validated sample object into the decision rule. The hitting rate of two testes, were reached 90%. The results of the empirical study indicate that the generated decision rules can cover most new objects. Consequently, we believe that the result can be fully applied in financial research.

1. Introduction

Identifying the trends in customer consumption behavior and understanding the relationship between customers and agents are very important issues for financial companies because loyal customers are the key drivers for increasing a company sales and profitability. If a key decision-maker can accurately predict the degree of consumers' dependence on the agents, he will be able to effectively take preventive measures to stop customers who may otherwise follow the agents leaving the financial firms [12]. Hence, in this paper, we use the data mining techniques to generate decision rules that can provide the decision makers with information about the attribute of customers' preference.

Many research papers have attempted to address the issue of customers' preference in financial market; moreover, they adopted the outcome of the transaction cost analysis (TCA). The TCA was part of the "New Institutional Economics" criterion, which has replaced orthodox neoclassical economics. However, the concept of the firm has been ignored by neoclassical economics for viewing it severely as a production function. Coase's [10] initial propositions were that the firms and markets were alternative governance structures, that several methods can effectively reduce transaction costs. Specifically, Coase [10] considers that price operation would produce the costs which were generally called transaction costs under economic system of economic of specialization and exchange. In this context, transaction costs were the "costs of running the system" and include such ex ante costs as drafting and negotiating contracts and such ex post costs as monitoring and enforcing agreements.

The works of Williamson [41–43] has augmented Coase's initial framework by proposing that transaction costs include both the direct costs of managing relationships and the possible opportunity costs of making inferior governance decisions. Williamson

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emphasized that transaction costs happened due to the market failure brought by human behavioral uncertainty and environmental uncertainty. Further, he considered TCA can be discriminated between ex ante (i.e. contracting cost, negotiating cost and protecting cost) and ex post (i.e. adaptive cost, bargaining cost, constructing, and operating cost and committed cost).

In the early TCA has been applied to the manufacturing firm's decision to the supply of materials or components or distribution were mostly focused on vertical integration [3,16,18,40].

Nevertheless the TCA was widely used in the commercial field to study various staffing model such as hiring a salesperson as an independent agent or an employee of the firm [2], customer–supplier relationships [34,5], option pricing [22], entrepreneurship.

In 1975, Williamson indicated six reasons of transaction costs described bellow: (1) *Bounded rationality*: decision makers have constraints on their cognitive capabilities and limits on their rationality; (2) *Opportunism*: decision makers may unscrupulously seek to serve their self-interests; (3) *Uncertainty and complexity* environment factors; (4) *Small numbers*: some processes of trade were too proprietary or idiosyncratic; the information and resource cannot be circulated so the small numbers which control the market, causing market failure; (5) *Asymmetric information* between buyers and sellers; because of the forerunner can own more information that benefits him in the market; (6) *Atmosphere*: distrust between buyers and sellers. Making the transactional process will be a form, and increase the unnecessary transaction cost. Dahlman [11] proposed a new classification for the transaction costs. They proposed that TCA can be classified optimally within three main contextual domains: (1) search and information costs, (2) moral crisis costs, (3) asset specificity costs.

The search and information costs were indicated when the consumers want to find the product (agent) of they need, and they give the relative cost (product feature, product positioning, place, etc.). The moral crisis costs were meant that the customers must be accepted the risk of the corporate, product and brand. If the cost was higher, the customers were more distrustful of the product (agent) or brand. The asset specificity costs were the most important item; however, it was most easily to be neglected. In other words, the asset specificity costs were meant the degree of consumers' dependence on this product (agent). In conclusion, this was useless to consumers when the transaction cost was higher and higher.

Customer relationship management (CRM) was a broadly recognized, widely- implemented strategy for managing and nurturing a company's interactions with customers, clients and sales prospects. It involves using technology to organize, automate, and synchronize business processes – principally sales activities, but also those for marketing, customer service, and technical support (Wikipedia). CRM was an important and popular methodology to analyze customer behavior because it can establish a complete system of customer information.

The purpose of this study was using the points of TCA and CRM to discuss the customers' preference; then rough set theory (RST) was applied to identify attributes/characteristics of customers' preference. CRM regard both customer loyalty and customer satisfaction. This paper utilizes the customer loyalty and customer satisfaction to help us to understand the relation between the agents and customers.

The customer loyalty was affected by their satisfaction, though the structure of the relationship was not totally symmetric and linear [1,23,24]. The measure of behavioral loyalty was on the basis of attitudinal loyalty statement that was to say, actual repurchase was recommended behavior rather than intention [7]. According to Bandyopadhyay and Martell [4], the presence of such situational factors as stock being not accessible, such personal or intrinsic factors as opposition to vary or such communal and cultural factors as communal restraint intensifies the demand to discriminate customer loyalty from repurchase behavior.

A number of study focuses on the quantification of the problem by streamlining all parameters and applying statistical tools to analyze the data. Pawlak [32] proposed RST as a rule-based decision-making instrument. It can handle both crisp and fuzzy datasets. In this study, RST was used to analyze data contents and data features.

For this paper, we use two steps to perform the data analysis. The first step was pre-process, which use factor analysis (FA) to choose the variable and then utilize RST to find decision rules [17]. The second step was post-process, which creates additional values on those rules by the formal concept analysis (FCA) in order to gather the decision rules to construct the concept and to explore the relationship among attributes. This information provides prior knowledge for decision makers [37,25]. The FCA provides the mathematical theory, which belongs to algebra and was a branch of lattice theory.

This study adopts RST combined flow graphs and Formal Concept Analysis to analyze customers' preference/characteristic, and the results demonstrate that the combined approaches were well suited to find the characteristic relationship of customers between financial companies and agents. Furthermore, we applied a hit test to check the feasibility of the decision rules. It would be clear that new data matches the decision classes reaching 90%. The results of this research showed that the decision rules can effectively predict the degree of customers' dependence to agents. The analytical process was shown in Fig. A.1 of Appendix A.

The rest of this paper was organized as follows: in Section 2, concepts to be used in this study were outlined and described. Section 3 shows an empirical study to explore the customers' preference of company or agent in the financial market. Finally, in Section 4, was presented the conclusions.

2. Overview of this research

In this section, we briefly review RST, flow graphs and FCA, which were used in analyzing the customers' preference/characteristic. The theory of RST was described in Section 2.1. In Section 2.2 was narrated the flow graphs. The FCA theory was presented in Section 2.3.

2.1. Rough set theory (RST)

Rough set theory was developed by Pawlak [31,32] as a tool for processing uncertain and incomplete information. Both fuzzy set theory [48] and rough set theory were used with the indiscernibility relation and perceptible knowledge. The major difference between them was RST not need a membership function. A detailed discussion of RST can be found in Walczak and Massart [39].

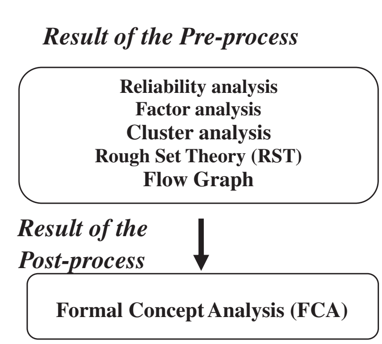


Fig. A.1. Analytic process.

Table 1
The results of factor analysis.

Dimensions	Kaiser–Meyer–Olkin (KMO)	Components
Transaction costs	0.746	Search and information costs moral crisis costs asset specificity costs
Customer satisfaction	0.800	Customer satisfaction
Customer loyalty	0.674	Behavioral loyalty attitudinal loyalty

Table 2
Approximation of decision class.

Decision class #	Number of objects #	Lower approximation	Upper approximation	Accuracy (%)
1	18	17	19	89.47
2	49	47	51	92.16
3	40	37	43	86.05
Total	107			89.23

Table 3
Decision table for decision rule of decision class 1 as example.

Rule #	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	Support	Strength (%)	Coverage (%)
1				1	1	1		2			3	16.67	6.12
2		1	2					4			1	5.56	2.04
3		1		1	1		2	1			1	5.56	2.04
4	1		1		3		1				2	11.11	4.08
5		1			2	2	2			1	2	11.11	4.08
6		2			1				1	1	3	16.67	6.12
7			1			1	3			2	3	16.67	6.12
8				2	2		2	2	1		3	16.67	6.12
9		2	2		2				2	1	1	5.56	2.04
Total											19	–	–

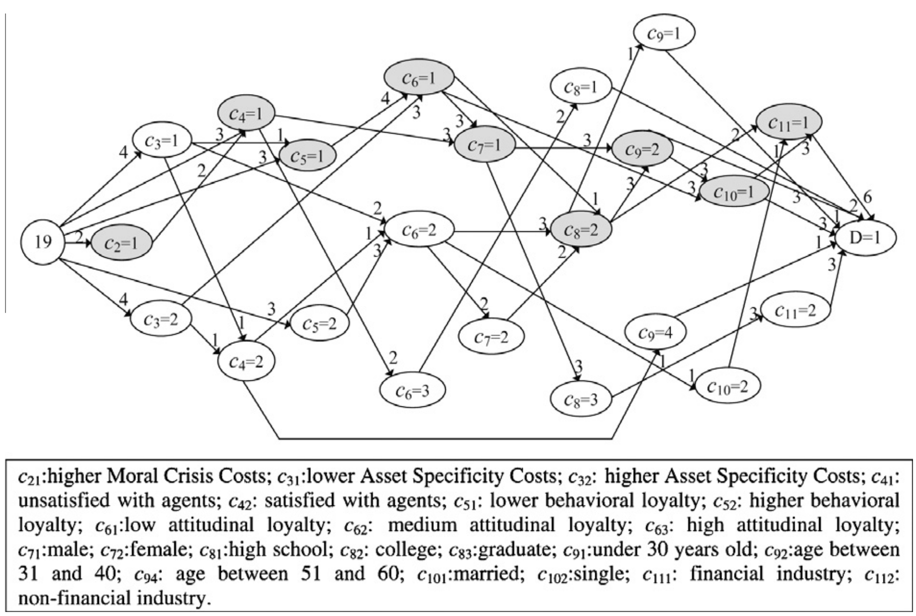


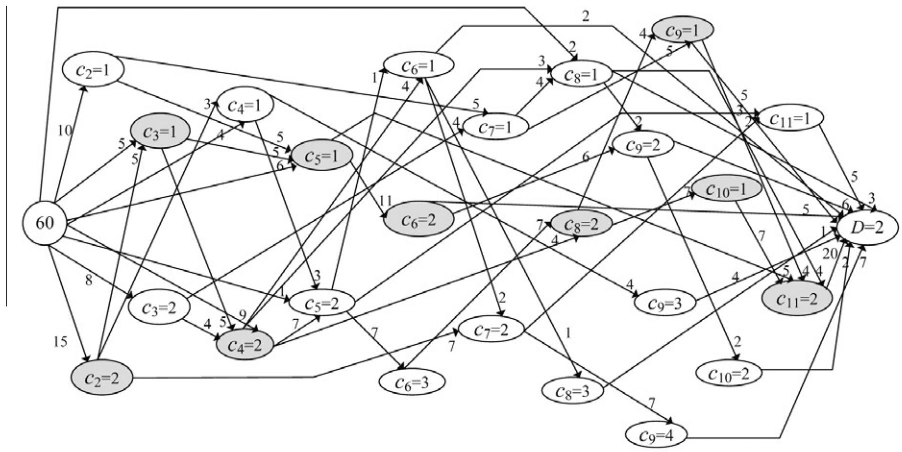
Fig. 1. Decision flow graph for rule-set of decision class 1.

RST has been applied to the management of many issues, including: medical diagnosis, engineering reliability, expert systems, empirical study of insurance data [36], machine diagnosis [49], business failure prediction [6], activity-based travel modeling [45], and data mining [9].

2.1.1. Information system and Approximation of sets

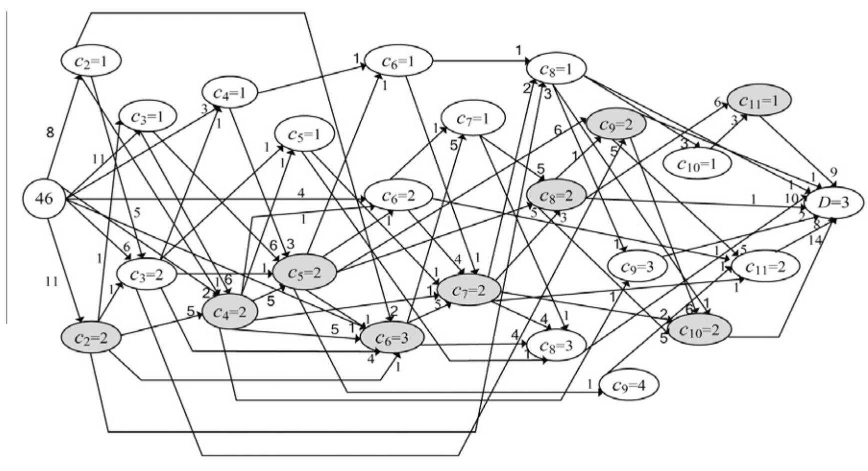
If an information system was defined by $IS = (U,A,V,f)$, where U consists of finite objects and A was a finite set of attributes/ features. If attribute a belongs to set A. Then $V = \cup_{a \in A} Va$ was a set of values of the attribute; and f_a: $U \times A \rightarrow V_a$ was a total function such as $f(x,a) \in Va$ for each $a \in A$ and $x \in U$ [28]. It defines an information function, where V_a was the set of values of a, called the domain of attribute a.

If $B = \{X_1, X_2, \ldots, X_m\}$ was a family of non-empty sets (classification) and let $B \subseteq A$ that $X_i \subseteq U$, $X_i \neq \emptyset$, $X_i \cap X_j = \emptyset$ for $i \neq j$, i, $j = 1,2,\ldots,m$ and $\cup_{i=1}^{m} X_i = U$. X_i was also called the classes of B. Then an indiscernibility relation I_B was defined when x_i and x_j were



c_{21}:higher Moral Crisis Costs; c_{22}:lower Moral Crisis Costs; c_{31}:lower Asset Specificity Costs; c_{32}: higher Asset Specificity Costs; c_{41}: unsatisfied with agents; c_{42}: satisfied with agents; c_{51}: lower behavioral loyalty; c_{52}: higher behavioral loyalty; c_{61}: low attitudinal loyalty; c_{62}: medium attitudinal loyalty; c_{63}: high attitudinal loyalty; c_{71}:male; c_{72}:female; c_{81}:high school; c_{82}: college; c_{83}:graduate; c_{91}:under 30; c_{92}:age between 31 and 40; c_{93}: age between 41 and 50; c_{94}: age between 51 and 60; c_{101}:marry; c_{102}:single; c_{111}: financial industry; c_{112}: non-financial industry.

Fig. B.1. Decision flow graph for rule-set of decision class 2.



c_{21}:higher Moral Crisis Costs; c_{22}:lower Moral Crisis Costs; c_{31}:lower Asset Specificity Costs; c_{32}: higher Asset Specificity Costs; c_{41}: unsatisfied with agents; c_{42}: satisfied with agents; c_{51}: lower behavioral loyalty; c_{52}: higher behavioral loyalty; c_{61}: low attitudinal loyalty; c_{62}: medium attitudinal loyalty; c_{63}: high attitudinal loyalty; c_{71}:male; c_{72}:female; c_{81}:high school; c_{82}: college; c_{83}:graduate; c_{92}:age between 31 and 40; c_{93}: age between 41 and 50; c_{94}: age between 51 and 60; c_{101}:marry; c_{102}:single; c_{111}: financial industry; c_{112}: non-financial industry.

Fig. B.2. Decision flow graph for rule-set of decision class 3.

indiscernible by the set of attributes B in A, if $b(x_i) = b(x_j)$ for every $b \in B$.

Two basic concepts named the *lower* and the *upper approximations* of a set referring to the elements that surely belong to the set or not. The lower approximation of X in B, denoted as $B^*X = \{x_i \in U: x_i \cap X \neq \emptyset\}$, and the upper approximation of the set X in B, denoted as $B_*X = \{x_i \in U: x_i \subseteq X\}$, where x_i expresses object $x_1, x_2, \ldots, x_n$ and i was 1 to n.

The subsets X_i (which $i = 1,\ldots,m$) are disjunctive classes of B. The sets $B^*X = \{B^*X_1, B^*X_2, \ldots, B^*X_m\}$ and $B_*X = \{B_*X_1, B_*X_2, \ldots, B_*X_m\}$ could be named as the upper and lower approximations of B in IS, respectively. Then the accuracy of approximation of classification X by the set B of attributes can be calculated as $u_B(X) = \sum_{i=1}^{m} \text{card} B_*X_i / \sum_{i=1}^{m} \text{card} B^*X_i$, where card means cardinality of a set. The quality of the classification was defined as $\gamma_B(X) = \sum_{i=1}^{m} \text{card} B_*X_i / \text{card}(U)$.

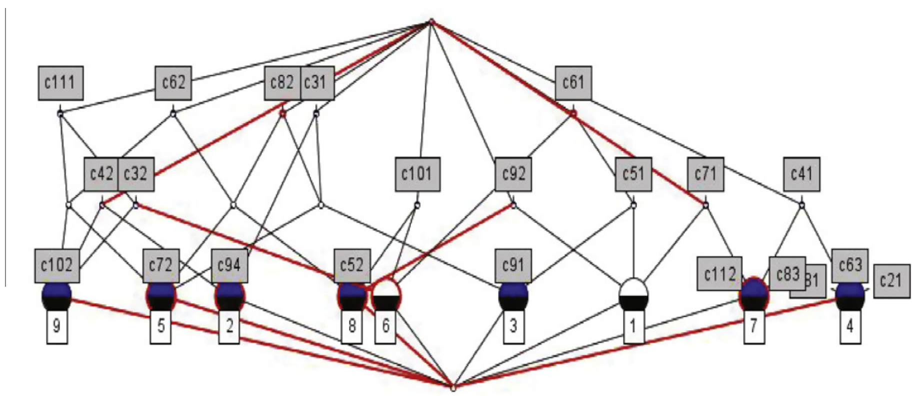
2.1.2. Decision rules

Given an attribute space $A = (CA, DA)$, let $RED(B) \subseteq A$; $RED(B)$ be the reduct set composed of a set of attributes B, reduct attributes give the decision maker a simple and uncomplicated information can eliminate the superfluous attributes Pawlak [29,30]. The core was the common portion of all reduct defined as $COR(B) = \cap RED(B)$ which was the core of B or the core attribute set.

An information system $IS = (U,A,V,f)$ can be seen as a decision table assuming that $A = CA \cup DA$ and $CA \cap DA = \emptyset$; where CA was the condition attribute set and DA was the decision attribute set,

Table 4
Context table for decision rules of decision class 1 as example.

Rule #	(c_2)	(c_3)		(c_4)		(c_5)		(c_6)			(c_7)		(c_8)			(c_9)			(c_{10})		(c_{11})	
	c_{21}	c_{31}	c_{32}	c_{41}	c_{42}	c_{51}	c_{52}	c_{61}	c_{62}	c_{63}	c_{71}	c_{72}	c_{81}	c_{82}	c_{83}	c_{91}	c_{92}	c_{94}	c_{101}	c_{102}	c_{111}	c_{112}
1						×		×			×						×					
2		×			×													×				
3		×				×		×						×		×						
4	×			×						×			×									
5		×							×			×		×							×	
6			×					×											×		×	
7				×							×				×							×
8							×		×					×			×		×			
9			×		×				×											×	×	
Frequency	1	3	2	2	2	2	1	3	3	1	2	1	1	3	1	1	2	1	2	1	3	1



c_{21}:higher Moral Crisis Costs; c_{31}:lower Asset Specificity Costs; c_{32}: higher Asset Specificity Costs; c_{41}: unsatisfied with agents; c_{42}: satisfied with agents; c_{51}: lower behavioral loyalty; c_{52}: higher behavioral loyalty; c_{61}:low attitudinal loyalty; c_{62}: medium attitudinal loyalty; c_{63}: high attitudinal loyalty; c_{71}:male; c_{72}:female; c_{81}:high school; c_{82}: college; c_{83}:graduate; c_{91}:under 30 years old; c_{92}:age between 31 and 40; c_{94}: age between 51 and 60; c_{101}:married; c_{102}:single; c_{111}: financial industry; c_{112}: non-financial industry.

Fig. 2. Lattice diagram for decision rules of decision class 1.

which were the elements of the decision table. This assumes an indiscernibility relation I_{DA}. The set of objects that have the same I_{DA} were grouped together as decision elementary sets (decision classes). In other words, the reducts of the condition attribute set will conserve the relevant relationship between condition attributes and decision classes. And then this relationship can be expressed by the decision rule.

According to Pawlak [28], the rules were logical statements "if Φ then Ψ", where Φ was called the premises (reason) and Ψ was called the consequence of the rule. The *strength* of the decision rule $\Phi \rightarrow \Psi$ in *IS* was expressed as: $\sigma_{IS}(\Phi, \Psi) = \text{supp}_{IS}(\Phi, \Psi)/\text{card}(U)$ where $\text{supp}_{IS}(\Phi, \Psi) = \text{card}(||\Phi \wedge \Psi||_{IS})$ was called the *support* of the rule $\Phi \rightarrow \Psi$ in *IS* and card(U) was the cardinality of U. With every decision rule $\Phi \rightarrow \Psi$ was associated a coverage factor/covering ratio (CR) defined as $CR_{IS}(\Phi, \Psi) = \text{supp}_{IS}(\Phi, \Psi)/\text{card}(||\Psi||_{IS})$.

CR was explained to the frequency of objects having the property Φ in the set of objects having the property Ψ. The strength of the decision rule can easily be expressed as the ratio – the number of facts that can be classified by the decision rule divided by the number of facts in the data table. Both *CR* and the *strength* of the decision rule were used to evaluate the quality of the decision rules.

2.2. Flow graphs

In this section was a briefly introduced flow graph. This methodology innovated by Pawlak [26–30]. The fundamental concept used in this study [19,25,38], each branch of a flow graph seemed as a decision rule and the entire flow graph described as decision algorithm. A flow graph was a directed acyclic finite graph $G = (N, B, \varphi)$, where N was a set of *nodes*; $B \subseteq N \times N$ is a set of directed branches; $\varphi : B \rightarrow R^{+}$ was a *flow function* and R^{+} was the set of non-negative real numbers. Input and output of a node x can defined as $I(x) = \{y \in N : (y, x) \in B, x \in N\}$ and $O(x) = \{y \in N : (x, y) \in B, x \in N\}$, respectively. Therefore, input and output of a graph G can defined as $I(G) = \{x \in N : I(x) = \varnothing\}$ and $O(G) = \{x \in N : O(x) = \varnothing\}$, respectively.

According to Ford and Fulkerson [13], if $(x,y) \in B$, then $\varphi(x,y)$ was a *throughflow* from x to y. We can define an inflow and an outflow for the whole flow graph, which were defined by $\varphi^{+}(G) = \sum_{x \in I(G)} \varphi^{-}(x)$ and $\varphi^{-}(G) = \sum_{x \in O(G)} \varphi^{+}(x)$. Then, obviously, $\varphi^{+}(G) = \varphi^{-}(G) = \varphi(G)$, where $\varphi(G)$ is a *throughflow* of graph G. Every branch (x,y) of a flow graph G associated with the *certainty* and the *coverage factors* defined as $cer(x,y) = \sigma(x,y)/\sigma(x)$ and $cov(x,y) = \sigma(x,y)/\sigma(y)$, where $\sigma(x) \neq 0$ and $\sigma(y) \neq 0$. Where $\sigma : B \rightarrow \langle 0, 1 \rangle$ is a *normalized flow* of (x,y) and $\sigma(x,y) = \varphi(x,y)/\varphi(G)$ was *strength* of (x,y). Obviously, $0 \leq \sigma(x,y) \leq 1$. The strength of the branch expresses simply the percentage of a total flow through the branch.

2.3. Formal concept analysis (FCA) and background

The purpose of FCA was to support the user in analyzing and structuring a domain of interest. It was an important mathematical tool for conceptual data analysis and knowledge processing.

Table 5
Implication relation between attributes for class 1 as example.

Imply super concept	c_{111}	c_{61}	c_{41}	c_{63}	c_{81}	c_{94}	c_{62}	c_{82}	c_{92}	c_{101}	c_{51}	c_{91}	c_{72}	c_{32}	c_{102}	c_{21}	c_{31}	c_{71}	c_{52}	c_{42}	c_{83}	c_{112}
Sub concept	c_{32}	c_{51}	c_{21}	c_{21}	c_{21}	$c_{31}c_{42}$	c_{52}	c_{52}	c_{52}	c_{52}	$c_{31}c_{61}$	$c_{31}c_{61}$	$c_{31}c_{62}$	$c_{42}c_{62}$	$c_{42}c_{62}$	c_{63}	c_{72}	$c_{61}c_{92}$	$c_{62}c_{92}$	c_{94}	c_{112}	$c_{41}c_{71}$
	$c_{31}c_{62}$	c_{91}	c_{63}	c_{81}	c_{63}		c_{72}	$c_{31}c_{61}$	$c_{61}c_{71}$	$c_{62}c_{92}$	$c_{61}c_{71}$	$c_{61}c_{82}$	$c_{31}c_{111}$	$c_{61}c_{101}$	$c_{32}c_{62}$	c_{81}	$c_{61}c_{82}$	c_{112}	$c_{82}c_{92}$	c_{102}	$c_{41}c_{71}$	c_{83}
															c_{111}							
	$c_{42}c_{62}$	$c_{71}c_{92}$	c_{81}				$c_{82}c_{92}$	$c_{31}c_{62}$	$c_{62}c_{101}$	$c_{82}c_{92}$	$c_{61}c_{82}$		$c_{82}c_{111}$	$c_{42}c_{111}$	$c_{42}c_{111}$		c_{91}	c_{83}	$c_{62}c_{101}$	$c_{32}c_{62}$		
																				c_{111}		
	c_{72}	$c_{101}c_{111}$	c_{112}				$c_{82}c_{101}$	c_{72}	$c_{82}c_{101}$	$c_{61}c_{111}$	c_{91}			$c_{61}c_{111}$			c_{94}		$c_{82}c_{101}$			
	$c_{61}c_{101}$		c_{83}				$c_{92}c_{101}$	c_{91}			$c_{61}c_{92}$			$c_{101}c_{111}$			$c_{82}c_{111}$		$c_{92}c_{101}$			
	c_{102}						c_{102}	$c_{62}c_{92}$			$c_{71}c_{92}$											
							$c_{42}c_{111}$	$c_{62}c_{101}$														
							$c_{82}c_{111}$	$c_{92}c_{101}$														
							$c_{31}c_{111}$	$c_{31}c_{111}$														
Frequency	9	6	5	2	2	2	15	15	7	7	11	4	6	10	7	2	7	4	10	5	3	3

FCA has been applied to the management of a number of issues, such as linguistics, software engineering, AI, environmental databases [8] and information retrieval. The work by Priss [33] contains an overview of FCA as applied in the field of information science. Because various concepts were semantically close, there was a method of measuring the similarity of FCA concepts presented in Formica [15]. Some related studies of RST, such as Liu et al. [20,21] proposed a reduction of the concept lattices based on RST, Yao [47] explored a kind of attribute and object reduction method for the concept lattices and concept lattices in RST.

An abundant experience with lattices of concepts has revealed a great variety of applications, mostly supported by graphical representations. Concept lattices can be used for hierarchical classification of objects, representation of the implicational logic of given attributes, construction of concept sequences, identification of objects, recognition of conceptual patterns, aggregation of data and information, and the representation and acquisition of knowledge.

2.3.1. The concept of FCA

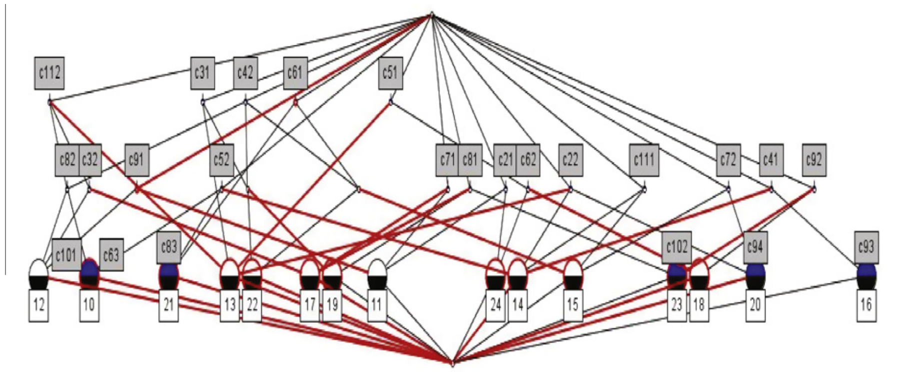
The data for analysis were described by formal context (U, A, R) in FCA which consists of universe U, attributes set A and relation $R \in U \times A$. The formal context can be represented by a cross table called a *context table*. In RST, the data for analysis were described by information system (U, A, R), which corresponds to the formal context in FCA and consists of universe U, attributes set A, and the relationships R between U and A.

In FCA, the *formal concept* and the *concept lattice* were two central issues. A formal concept consists of the set of objects and the set of attributes. The set of objects of a formal concept was called its "*extension*", and the set of attributes was called its "*intension*". For a given formal context, the extensions and intensions were uniquely defined and fixed for the formal concepts. FCA was based on a set-theoretic model for formal contexts, from which concepts and conceptual hierarchies can be formally derived. A basic result was that the formal concepts of a formal context always construct the mathematical structure of a lattice with respect to the "*subconcept–superconcept*" *relation* [44]. The relations can be expressed by a lattice diagram. From the diagram, we can derive concepts, *implication sets*, and association rules based on the context table.

Statistics and concept analysis complement each other in the field of information science, such as the mathematical lattices that were used in FCA and can be interpreted as classification systems. Formalized classification systems can be analyzed according to the consistency of their relations.

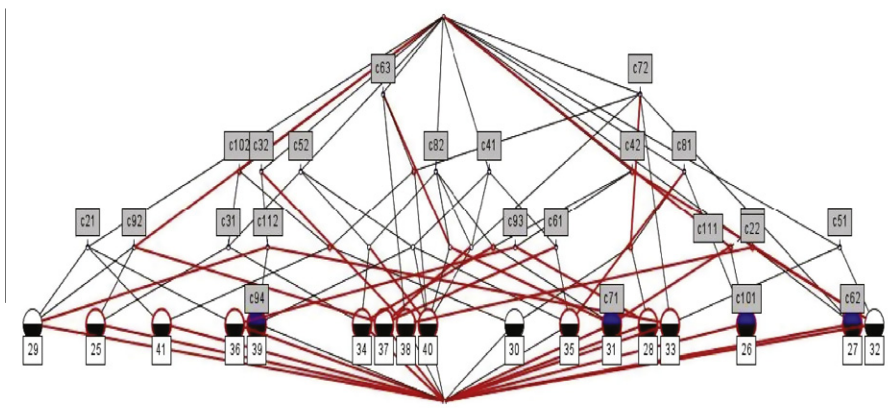
The "*subconcept–superconcept*" *relation* defines an orderly concept relation of all formal concepts in a formal context. All edges in the line diagram of a concept lattice represent "*subconcept–superconcept*" *relation*. The extension of the subconcept was contained in the extension of the superconcept, which was equivalent to the relationship that the intension of the subconcept contains the intension of the superconcept. Hence, lines going up can find more general concepts, and lines going down can find more specific concepts [46]. The "*subconcept–superconcept*" *relation* was transitive, meaning that a concept was the subconcept of any concept that can be reached by traveling upwards from it.

The concept lattices of FCA based on RST, including the attribute oriented concept lattice and the object oriented concept lattice [20,21]. Therefore, RST and FCA were two complementary mathematical tools for data analysis. Hence, FCA and RST were two important tools in knowledge representation and knowledge discovery in relational information systems.



c_{21}:higher Moral Crisis Costs; c_{22}:lower Moral Crisis Costs; c_{31}:lower Asset Specificity Costs; c_{32}: higher Asset Specificity Costs; c_{41}: unsatisfied with agents; c_{42}: satisfied with agents; c_{51}: lower behavioral loyalty; c_{52}: higher behavioral loyalty; c_{61}: low attitudinal loyalty; c_{62}: medium attitudinal loyalty; c_{63}: high attitudinal loyalty; c_{71}:male; c_{72}:female; c_{81}:high school; c_{82}: college; c_{83}:graduate; c_{91}:under 30; c_{92}:age between 31 and 40; c_{93}: age between 41 and 50; c_{94}: age between 51 and 60; c_{101}:marry; c_{102}:single; c_{111}: financial industry; c_{112}: non-financial industry.

Fig. C.1. Lattice diagram for decision rules of decision class 2.



c_{21}:higher Moral Crisis Costs; c_{22}:lower Moral Crisis Costs; c_{31}:lower Asset Specificity Costs; c_{32}: higher Asset Specificity Costs; c_{41}: unsatisfied with agents; c_{42}: satisfied with agents; c_{51}: lower behavioral loyalty; c_{52}: higher behavioral loyalty; c_{61}: low attitudinal loyalty; c_{62}: medium attitudinal loyalty; c_{63}: high attitudinal loyalty; c_{71}:male; c_{72}:female; c_{81}:high school; c_{82}: college; c_{83}:graduate; c_{92}:age between 31 and 40; c_{93}: age between 41 and 50; c_{94}: age between 51 and 60; c_{101}:marry; c_{102}:single; c_{111}: financial industry; c_{112}: non-financial industry.

Fig. C.2. Lattice diagram for decision rules of decision class 3.

Table 6
The most important factor for the degree of dependence on agents.

Degree of dependence	Most important factor	Following by
Low	Medium attitudinal loyalty (c_{62}), college (c_{82}), lower behavioral loyalty (c_{51})	Financial industry (c_{111}), and married status (c_{101})
Medium	Non-financial industry (c_{112}), satisfied with agents (c_{42}), lower moral crisis costs (c_{22})	Lower asset specificity costs (c_{31}), age under 30 years old (c_{91}), and a lower behavioral loyalty (c_{51})
High	Higher behavioral loyalty (c_{52}), higher asset specificity costs (c_{32}), college (c_{82}), and female (c_{72})	Lower moral crisis costs (c_{22}), satisfied with agents (c_{42}), and single status (c_{102})

3. Empirical study: a preference of customers between financial companies and agents

The questionnaires were distributed to customers in the North and Northeast districts of Taiwan. The respondents were of two categories: one set contains people who are active investors or have financial interests; and the other contains people with little or no financial interests. Data were collected based on nominal and ordinal scales. There were 107 valid questionnaires from a total of 118 received. The percentage of valid questionnaires was 90%. Among the valid respondents, there were 55 females and 52 males, and show in Table A.1 of Appendix A.

Table A.1
Information of respondents.

Qualified data				
1. Gender	Male 55 (51%)	Female 52 (49%)		
2. Education	High school 25 (23%)	College 60 (56%)	Graduate 22 (21%)	
3. Age	<30 40 (37%)	31–40 42 (39%)	41–50 8 (8%)	51–17 (16%)
4. Marriage	Married 49 (46%)	Single 58 (54%)		
5. Occupation	Financial industry 47 (44%)	Non-financial industry 60 (56%)		

Table A.2
Cluster distribution.

The agent of resignation	No relied on agents	Neutrality	Relied on agents
	18 16.8%	49 45.8%	40 37.4%
Total: 107			

Table A.3
Attribute specification for the personal analysis.

Attribute name	Attribute values	Attribute value sets
Condition attributes		
Search and information costs (c_1)	Lower; Higher	{1,2}
Moral crisis costs (c_2)	Higher; Lower	{1,2}
Asset specificity costs (c_3)	Lower; Higher	{1,2}
Customer satisfaction (c_4)	Lower; Higher	{1,2}
Behavioral loyalty (c_5)	Lower; Higher	{1,2}
Attitudinal loyalty (c_6)	Low; Medium; High	{1,2,3}
Gender (c_7)	Male; Female	{1,2}
Education (c_8)	High School; College; Graduate	{1,2,3}
Age (c_9)	<30; 31–40; 41–50; 51∼	{1,2,3,4}
Marriage (c_{10})	Married; Single	{1,2}
Occupation (c_{11})	Financial industry; Non-financial industry	{1,2}
Decision attributes		
Preference of customers for agents (d)	Low; Medium; High	{1,2,3}

3.1. Process of this study

In this study, the empirical process was divided into two parts. The first part involved a pre-process, which was used to select variables and to construct the decision table generated by the Rough Set Data Explorer (ROSE2) [35] tool. The second part, or a post-process, used FCA to aggregate these rules that were selected from pre-process. The post-process resulted in the attribute relationship, which helped the decision maker to perform *a priori* prediction.

3.1.1. Result of the pre-process

In this study, Cronbach's α of the questionnaires were higher than 0.8, the items to total correlations were higher than 0.5, and achieved a significant level.

There were several important components that had originated with Factor analysis (FA), and we chose the principal component analysis of extraction method. All eigenvalue extracted were over 1 and these were ranked from high to low. Therefore, the three main dimensions – transaction costs, customer satisfaction, and customer loyalty – were composed of 6 components. The extracted factors were displayed in Table 1. The original groups for each main dimension were shown in Table A.4.

After that, the cluster analysis applied to discriminate several different groups from all samples into different value domain. The results were shown in Table A.3 of Appendix A. And the

Table A.4
Results of the transaction costs factor analysis.

Dimensions	Components			
	Search and information costs	Moral crisis costs	Asset specificity costs	Communalities
You might spend time to compare the difference among financial companies	0.790	0.137	−0.207	0.686
You might spend time to compare the different financial products	0.803	0.141	−0.257	0.730
You might spend time to compare the expenses of commission	0.734	−0.065	0.158	0.568
You might spend time to compare whether there is a concessional activity or not	0.745	−0.120	0.243	0.628
You might spend time to compare different agents	0.643	0.050	0.184	0.450
You might spend time to search relevant information	0.743	−0.005	0.126	0.568
You might spend time to inquire the opinions of relatives and friends	0.411	0.078	0.196	0.214
You might believe the assurance of agent	0.062	0.666	0.181	0.480
You might believe the agent's advanced notice	0.024	0.780	0.050	0.612
You might believe that the agent will observe the contract	−0.027	0.592	0.109	0.363
You might believe that the agent will consider the customer's benefits first	−0.010	0.762	0.170	0.609
If something happened, you might believe that the agent will side with the customer	0.019	0.743	0.168	0.581
You might believe the service and explanation of the agent	0.042	0.757	0.148	0.596
You believe that the agent's attitude could influence your will of purchase	0.290	−0.264	0.415	0.326
The reason of not changing the agent is that you do not want to lose the concession of the agents	0.217	0.147	0.579	0.403
The reason of not changing the agent is that the agent offers exclusive service for you	0.170	0.197	0.771	0.662
The reason of not changing the agent is that the agent has irreplaceable value	0.009	0.198	0.757	0.612
The reason of not changing the agent is that the relatives and friends seek for the services provided by agent	0.045	0.290	0.600	0.446
Eigenvalue	4.436	3.442	1.655	
Variance explained (%)	24.64	19.12	9.19	
Cumulative variance explained (%)	24.64	43.77	52.96	

Table A.5
Results of the customer loyalty factor analysis.

Dimensions	Components		
	Behavioral loyalty	Attitudinal loyalty	Communalities
Continuous cooperate with agent and repurchase products	0.641	0.362	0.542
Continuous purchase the products which agent recommends	0.856	0.024	0.740
A will of recommending the agents to friends	0.859	0.095	0.734
A will of repurchase which only considers the original agent	0.153	0.846	0.747
Consider the agent only even if other agents can give more concessional prices to you	0.084	0.858	0.744
Eigenvalue	2.312	1.194	
Variance explained (%)	46.25	23.89	
Cumulative variance explained (%)	46.25	70.14	

Table B.1
Original rules generated from ROSE2.

Rule 1. $(c_5 = 1)$ & $(c_6 = 1)$ & $(c_7 = 1)$ & $(c_9 = 2)$ => $(d = 1)$; [3,3,16.67%,100.00%][3,0,0][{74,91,106},{},{}]
Rule 2. $(c_3 = 1)$ & $(c_4 = 2)$ & $(c_9 = 4)$ => $(d = 1)$; [1,1,5.56%,100.00%][1,0,0][{98},{},{}]
Rule 3. $(c_3 = 1)$ & $(c_5 = 1)$ & $(c_6 = 1)$ & $(c_8 = 2)$ & $(c_9 = 1)$ => $(d = 1)$; [1,1,5.56%,100.00%][1,0,0][{62},{},{}]
Rule 4. $(c_2 = 1)$ & $(c_4 = 1)$ & $(c_6 = 3)$ & $(c_8 = 1)$ => $(d = 1)$; [2,2,11.11%,100.00%][2,0,0][{8,83},{},{}]
Rule 5. $(c_3 = 1)$ & $(c_6 = 2)$ & $(c_7 = 2)$ & $(c_8 = 2)$ & $(c_{11} = 1)$ => $(d = 1)$; [2,2,11.11%,100.00%][2,0,0][{3,101},{},{}]
Rule 6. $(c_3 = 2)$ & $(c_6 = 1)$ & $(c_{10} = 1)$ & $(c_{11} = 1)$ => $(d = 1)$; [3,3,16.67%,100.00%][3,0,0][{84,93,105},{},{}]
Rule 7. $(c_4 = 1)$ & $(c_7 = 1)$ & $(c_8 = 3)$ & $(c_{11} = 2)$ => $(d = 1)$; [3,3,16.67%,100.00%][3,0,0][{58,66,74},{},{}]
Rule 8. $(c_5 = 2)$ & $(c_6 = 2)$ & $(c_8 = 2)$ & $(c_9 = 2)$ & $(c_{10} = 1)$ => $(d = 1)$; [3,3,16.67%,100.00%][3,0,0][{12,45,101},{},{}]
Rule 9. $(c_3 = 2)$ & $(c_4 = 2)$ & $(c_6 = 2)$ & $(c_{10} = 2)$ & $(c_{11} = 1)$ => $(d = 1)$; [1,1,5.56%,100.00%][1,0,0][{99},{},{}]
Rule 10. $(c_4 = 2)$ & $(c_5 = 2)$ & $(c_6 = 3)$ & $(c_8 = 2)$ & $(c_{10} = 1)$ & $(c_{11} = 2)$ => $(d = 2)$; [7,7,14.29%,100.00%][0,7,0][{},{17,19,31,34,39,46,73},{}]
Rule 11. $(c_2 = 1)$ & $(c_7 = 1)$ & $(c_9 = 1)$ => $(d = 2)$; [5,5,10.20%,100.00%][0,5,0][{},{5,16,22,77,81},{}]
Rule 12. $(c_3 = 2)$ & $(c_4 = 2)$ & $(c_8 = 2)$ & $(c_9 = 1)$ & $(c_{11} = 2)$ => $(d = 2)$; [4,4,8.16%,100.00%][0,4,0][{},{22,32,70,76},{}]
Rule 13. $(c_2 = 2)$ & $(c_3 = 1)$ & $(c_5 = 1)$ & $(c_{11} = 2)$ => $(d = 2)$; [5,5,10.20%,100.00%][0,5,0][{},{6,28,33,65,85},{}]
Rule 14. $(c_2 = 2)$ & $(c_4 = 1)$ & $(c_5 = 2)$ & $(c_{11} = 1)$ => $(d = 2)$; [3,3,6.12%,100.00%][0,3,0][{},{14,90,95},{}]
Rule 15. $(c_4 = 2)$ & $(c_6 = 1)$ & $(c_7 = 2)$ & $(c_{11} = 1)$ => $(d = 2)$; [2,2,4.08%,100.00%][0,2,0][{},{89,104},{}]
Rule 16. $(c_4 = 1)$ & $(c_9 = 3)$ => $(d = 2)$; [4,4,8.16%,100.00%][0,4,0][{},{37,40,80,90},{}]
Rule 17. $(c_3 = 2)$ & $(c_7 = 1)$ & $(c_8 = 1)$ & $(c_{11} = 2)$ => $(d = 2)$; [4,4,8.16%,100.00%][0,4,0][{},{44,59,67,78},{}]
Rule 18. $(c_5 = 1)$ & $(c_6 = 2)$ & $(c_9 = 2)$ => $(d = 2)$; [6,6,12.24%,100.00%][0,6,0][{},{9,11,24,59,65,96},{}]
Rule 19. $(c_3 = 1)$ & $(c_4 = 2)$ & $(c_8 = 1)$ => $(d = 2)$; [3,3,6.12%,100.00%][0,3,0][{},{28,97,102},{}]
Rule 20. $(c_2 = 2)$ & $(c_7 = 2)$ & $(c_9 = 4)$ => $(d = 2)$; [7,7,14.29%,100.00%][0,7,0][{},{19,29,33,38,43,68,100},{}]
Rule 21. $(c_5 = 2)$ & $(c_6 = 1)$ & $(c_8 = 3)$ => $(d = 2)$; [1,1,2.04%,100.00%][0,1,0][{},{53},{}]
Rule 22. $(c_3 = 1)$ & $(c_4 = 2)$ & $(c_6 = 1)$ => $(d = 2)$; [2,2,4.08%,100.00%][0,2,0][{},{21,28},{}]
Rule 23. $(c_8 = 1)$ & $(c_9 = 2)$ & $(c_{10} = 2)$ => $(d = 2)$; [2,2,4.08%,100.00%][0,2,0][{},{1,11},{}]
Rule 24. $(c_2 = 1)$ & $(c_5 = 1)$ & $(c_6 = 2)$ => $(d = 2)$; [5,5,10.20%,100.00%][0,5,0][{},{5,7,9,11,24},{}]
Rule 25. $(c_3 = 1)$ & $(c_5 = 2)$ & $(c_9 = 2)$ & $(c_{10} = 2)$ => $(d = 3)$; [6,6,15.00%,100.00%][0,0,6][{},{},{47,48,60,92,103,107}]
Rule 26. $(c_2 = 2)$ & $(c_8 = 1)$ & $(c_{10} = 1)$ & $(c_{11} = 1)$ => $(d = 3)$; [3,3,7.50%,100.00%][0,0,3][{},{},{13,25,82}]
Rule 27. $(c_6 = 2)$ & $(c_7 = 2)$ & $(c_8 = 3)$ => $(d = 3)$; [4,4,10.00%,100.00%][0,0,4][{},{},{23,30,52,75}]
Rule 28. $(c_4 = 2)$ & $(c_7 = 2)$ & $(c_8 = 1)$ & $(c_9 = 3)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{18}]
Rule 29. $(c_2 = 1)$ & $(c_3 = 2)$ & $(c_9 = 2)$ & $(c_{11} = 2)$ => $(d = 3)$; [5,5,12.50%,100.00%][0,0,5][{},{},{26,27,35,42,71}]
Rule 30. $(c_6 = 3)$ & $(c_7 = 2)$ & $(c_8 = 1)$ & $(c_{10} = 2)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{2}]
Rule 31. $(c_2 = 2)$ & $(c_4 = 2)$ & $(c_6 = 3)$ & $(c_7 = 1)$ & $(c_8 = 2)$ & $(c_{11} = 1)$ => $(d = 3)$; [5,5,12.50%,100.00%][0,0,5][{},{},{15,20,49,88,103}]
Rule 32. $(c_4 = 2)$ & $(c_5 = 1)$ & $(c_8 = 3)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{54}]
Rule 33. $(c_3 = 2)$ & $(c_5 = 1)$ & $(c_7 = 2)$ & $(c_{11} = 2)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{86}]
Rule 34. $(c_3 = 1)$ & $(c_4 = 2)$ & $(c_5 = 2)$ & $(c_8 = 2)$ & $(c_{10} = 2)$ => $(d = 3)$; [5,5,12.50%,100.00%][0,0,5][{},{},{47,48,63,92,103}]
Rule 35. $(c_4 = 1)$ & $(c_5 = 2)$ & $(c_6 = 1)$ & $(c_8 = 1)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{79}]
Rule 36. $(c_2 = 1)$ & $(c_4 = 2)$ & $(c_9 = 3)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{72}]
Rule 37. $(c_4 = 1)$ & $(c_6 = 1)$ & $(c_7 = 2)$ & $(c_8 = 2)$ & $(c_9 = 2)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{94}]
Rule 38. $(c_3 = 2)$ & $(c_6 = 3)$ & $(c_8 = 3)$ => $(d = 3)$; [4,4,10.00%,100.00%][0,0,4][{},{},{55,56,61,69}]
Rule 39. $(c_3 = 2)$ & $(c_4 = 1)$ & $(c_5 = 2)$ & $(c_9 = 4)$ & $(c_{11} = 2)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{41}]
Rule 40. $(c_4 = 1)$ & $(c_5 = 2)$ & $(c_6 = 3)$ & $(c_7 = 2)$ & $(c_8 = 2)$ => $(d = 3)$; [1,1,2.50%,100.00%][0,0,1][{},{},{36}]
Rule 41. $(c_2 = 1)$ & $(c_6 = 3)$ & $(c_7 = 2)$ & $(c_{10} = 2)$ => $(d = 3)$; [2,2,5.00%,100.00%][0,0,2][{},{},{42,87}]

Approximate rules
Rule 42. $(c_2 = 2)$ & $(c_3 = 2)$ & $(c_5 = 2)$ & $(c_6 = 2)$ & $(c_7 = 1)$ & $(c_8 = 3)$ => $(d = 2)$ OR $(d = 3)$; [2,2,50.00%,100.00%][0,1,1][{},{51},{57}]
Rule 43. $(c_2 = 2)$ & $(c_6 = 3)$ & $(c_7 = 2)$ & $(c_8 = 2)$ & $(c_{11} = 1)$ => $(d = 2)$ OR $(d = 3)$; [2,2,50.00%,100.00%][0,1,1][{},{4},{10}]
Rule 44. $(c_2 = 2)$ & $(c_3 = 1)$ & $(c_4 = 2)$ & $(c_6 = 2)$ & $(c_{11} = 2)$ => $(d = 1)$ OR $(d = 3)$; [2,2,100.00%,100.00%][1,0,1][{50},{},{64}]
**END

Table A.2 of Appendix A was shown the variance of the resigning agents.

The empirical study information system composed the attributes from previous analysis and some personal attributes/items into twelve attributes: eleven condition attributes, namely search and information costs (c_1), moral crisis costs (c_2), asset specificity costs (c_3), customer satisfaction (c_4), behavioral loyalty (c_5), attitudinal loyalty (c_6), gender (c_7), education (c_8), age (c_9), marriage (c_{10}), occupation (c_{11}); and one decision attribute. The decision attribute namely the preference of customers representing the various degree of tendency to agents when the agent left for the company. According to the degree of the decision attribute value domain could divided into 3 parts which named decision class 1, decision class 2 and decision class 3 represented as low dependence on agents, medium dependence on agents and high dependence on agents, respectively.

After a reduct process was applied to the condition attributes, we labeled the reduct attribute set as c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}. The attribute c_1 was superfluous and was eliminated. The core attribute set was the same as the reduct attribute set. The

Table B.2
The hit test of new sample object.

Sample	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	D	Hit
1	1	1	1	2	3	2	2	1	2	2	2	X
2	1	1	1	2	1	2	3	1	2	2	2	O
3	2	2	1	2	3	1	3	1	2	2	3	O
4	1	1	1	2	2	1	2	1	2	2	2	O
5	2	1	2	2	3	1	2	2	1	1	3	O
6	2	1	2	2	2	1	1	1	2	2	2	O
7	2	2	2	2	2	1	2	1	2	2	2	O
8	2	1	1	2	3	2	2	2	1	2	3	O
9	2	1	1	1	2	2	2	2	1	2	2	O
10	1	1	2	2	2	2	1	1	2	2	2	O
11	2	2	2	2	3	2	2	2	1	1	3	O
12	2	2	2	2	3	2	1	4	1	2	2	O
13	1	1	1	1	1	1	2	1	2	2	2	O
14	2	1	2	2	1	2	2	4	1	1	2	O
15	2	2	1	2	2	1	3	3	2	2	2	O
16	2	2	2	2	2	1	2	1	2	2	2	O
17	2	1	1	1	2	2	2	1	2	2	2	O
18	1	1	1	2	3	1	1	1	2	2	1	X
19	2	2	2	1	2	1	1	2	1	2	3	X
20	2	1	1	1	2	1	1	1	2	2	2	O
21	1	1	1	2	2	2	3	1	1	2	3	O
22	2	1	1	1	2	1	2	1	1	2	2	O
23	2	2	1	1	2	1	2	1	2	2	2	
24	1	2	2	2	3	1	2	2	1	2	2	O
25	2	2	1	2	3	1	2	2	1	1	2	O
26	2	2	1	1	3	2	2	3	2	2	2	O
27	2	2	1	2	2	2	2	1	2	1	2	O
28	2	2	2	1	2	2	1	2	2	2	2	O
29	2	1	2	2	3	2	2	2	1	2	2	O
30	2	2	2	2	3	2	2	1	2	2	2	O

Note: X express the object is not match with decision rules. O express the object is match with decision rules. The blank express the object cannot find the matching rules.

original attribute specification was detailed in Table A.3 of Appendix A. The approximation of decision class was shown in Table 2. The accuracy of the entire was 89.23%. This implies that low dependence on agents, medium dependence on agents and high dependence on agents were characterized exactly by those data in the decision table and the quality of the entire classification was 96.39%. Herein, decision class 1 was selected as an example in this empirical study.

In this study, 44 rules were generated by ROSE2. The decision rules were shown in Table B.1 of Appendix B. If the new object matched more than one logical rule, we could use strength to distinguish from these matching rules [39]. Thus, two hit testes that incorporate 30 and 36 validation sample object to check the feasibility of the decision rules in this study. The result in Tables B.2 and B.5 of Appendix B show that the hitting rate reach 90%. The results of the empirical study indicate that the generated decision rules can cover most new objects.

The rules from number 1 thru number 9 of low dependence on agents (decision class 1) shown in Table 3 can be translated into one decision algorithm represented by the decision flow graph shown in Fig. 1. In this figure only explored the *throughflows* (Supports) and omitted the strength, and coverage factors which associated with branch. The decision rules numbered from 42 to 44 were approximate rules, which means that the rule do not belong to a specific decision class and may overlap more than one decision class. Therefore, those rules did not consider in this step.

By correlating their decision to the preference of consumption with the basic attributes, including the consumption habits and personal characteristics/attributes, our analysis of low dependence on agents (decision class 1) was match up closely to the present financial market in Taiwan: (1) a higher moral crisis costs (c_{21}), (2) a lower customer satisfaction (c_{41}), (3) a lower behavioral loyalty (c_{51}), (4) a lower attitudinal loyalty (c_{61}), (5) male (c_{71}), (6) college education (c_{82}), (7) age between 31 and 40 (c_{92}), (8) married status (c_{101}), (9) engaged in financial industry (c_{111}). The above results show that there were clearly characteristics of the customer preference among financial companies and agents in Taiwan.

Therefore, using the flow graph, we identified that medium dependence on agents (decision class 2): (1) a lower Moral Crisis Costs (c_{22}), (2) a lower asset specificity costs (c_{31}), (3) satisfied with agents (c_{42}), (4) a low behavioral loyalty (c_{51}), (5) a medium attitudinal loyalty (c_{62}), (6) college education (c_{82}), (7) aged less than 30 years old (c_{91}), (8) married status (c_{101}), (9) engaged in non-financial industry (c_{112}). The high dependence on agents (decision class 3) have the characteristics: (1) a lower moral crisis costs (c_{22}), (2) satisfied with agents (c_{42}), (3) a higher behavioral loyalty (c_{52}), (4) a higher attitudinal loyalty (c_{63}), (5) female (c_{72}), (6) college education (c_{82}), (7) age between 31 and 40 (c_{92}), (8) single status (c_{102}), (9) engaged in financial industry (c_{111}). The relative decision table for class 2 and 3 were shown in the Tables B.3 and B.4 of Appendix B, respectively. And the relative decision flow graph for class 2 and 3 were shown in the Figs. B.1 and B.2 of Appendix B, respectively.

3.1.2. Results of the post-process

The purpose of this study use FCA to aggregate rules and to diagnose the relationship among attributes belonging to the rules in the specific class. From the lattice diagram, association rules and implication sets can retrieve general information for each category. Table 4 shows the context table, which converted 9 rules of decision class 1 representing the attributes in the rules into a binary form [37]. The Java-based open source tool-ConExp [14] was used in this study to generate the lattice diagram shown in Fig. 2. The formal concept tool also produced the association rules and implication sets to aid decision making.

Table B.3
Decision table for decision rule of decision class 2 as example.

Rule #	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	Support	Strength (%)	Coverage (%)
10			2	2	3		2		1	2	7	6.54	17.50
11	1					1		1			5	4.67	12.50
12		2	2				2	1		2	4	3.74	10.00
13	2	1		1						2	5	4.67	12.50
14	2		1	2						1	3	2.80	7.50
15			2		1	2				1	2	1.87	5.00
16			1					3			4	3.74	10.00
17		2				1	1			2	4	3.74	10.00
18				1	2			2			6	5.61	15.00
19		1	2				1				3	2.80	7.50
20	2					2		4			7	6.54	17.50
21				2	1		3				1	0.93	2.50
22		1	2		1						2	1.87	5.00
23							1	2	2		2	1.87	5.00
24	1			1	2						5	4.67	12.50

Table B.4
Decision table for decision rule of decision class 3 as example.

Rule #	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	Support	Strength (%)	Coverage (%)
25		1		2				2	2		6	5.61	33.33
26	2						1		1	1	3	2.80	16.67
27					2	2	3				4	3.74	22.22
28			2			2	1	3			1	0.93	5.56
29	1	2						2		2	5	4.67	27.78
30					3	2	1		2		1	0.93	5.56
31	2		2		3	1	2			1	5	4.67	27.78
32			2	1			3				1	0.93	5.56
33		2		1		2				2	1	0.93	5.56
34		1	2	2			2		2		5	4.67	27.78
35			1	2	1		1				1	0.93	5.56
36	1		2					3			1	0.93	5.56
37			1		1	2	2	2			1	0.93	5.56
38		2			3		3				4	3.74	22.22
39		2	1	2				4		2	1	0.93	5.56
40			1	2	3	2	2				1	0.93	5.56
41	1				3	2			2		2	1.87	11.11
42	2	2		2	2	1	3				1	0.93	5.56
43	2				3	2	2			1	1	0.93	5.56
44	2	1	2		2					2	1	0.93	5.56

Table B.5
The second hit test of new sample object.

Sample	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}	D	Hit
1	2	2	2	2	3	1	2	2	1	1	3	O
2	1	1	1	1	2	2	1	2	1	1	1	O
3	1	1	2	1	2	2	2	1	2	1	2	O
4	2	1	2	2	2	1	1	1	1	1	2	O
5	2	2	2	2	3	2	1	2	2	1	2	O
6	1	2	1	1	2	1	2	1	1	1	2	O
7	2	2	1	1	1	2	1	2	1	1	3	O
8	1	2	2	2	3	2	2	4	1	2	1	X
9	1	2	2	2	2	2	3	4	1	2	3	O
10	2	2	2	2	3	2	2	4	1	2	3	X
11	1	1	1	1	3	2	2	3	1	2	2	O
12	2	1	2	2	2	1	2	2	1	2	1	O
13	2	1	2	2	2	1	1	2	1	2	2	O
14	2	1	2	2	3	2	3	2	2	2	1	X
15	2	1	2	1	2	1	4	3	1	2	1	X
16	2	1	2	2	3	2	3	2	2	2	1	X
17	1	1	1	1	2	1	3	4	1	2	1	O
18	2	2	2	2	2	2	1	4	1	1	2	O
19	1	2	2	1	2	2	3	1	1	2	3	O
20	1	1	1	1	2	1	3	1	2	2	1	O
21	2	1	2	2	2	2	1	2	1	2	2	O
22	1	1	1	1	2	2	2	2	1	1	1	O
23	2	2	2	2	3	1	2	4	1	1	3	O
24	1	1	1	1	2	1	2	3	1	1	1	X
25	1	1	1	1	2	1	3	2	1	2	1	O
26	2	2	2	2	2	1	2	2	2	1	3	X
27	2	2	2	2	3	1	2	3	1	2	2	O
28	2	2	2	2	3	2	1	2	1	1	3	O
29	1	1	2	2	3	1	2	1	2	1	2	O
30	1	2	2	2	3	1	1	2	2	1	2	O
31	1	2	2	1	2	1	2	2	2	1	1	O
32	1	1	1	1	1	1	2	2	1	1	1	O
33	2	2	2	2	3	1	1	4	1	1	3	O
34	2	2	2	2	3	1	2	2	2	1	3	O
35	1	2	2	2	2	2	1	2	2	1	3	O
36	1	2	2	1	3	1	3	1	1	2	2	O

Note: X express the object is not match with decision rules. O express the object is match with decision rules.

In Fig. 2, the concepts were more general when the lines go up, and the concepts were more specific when the lines go down. From the result could retrieved general information, such as: (1) higher Asset Specificity Costs (c_{32}) may be engaged in a financial industry (c_{111}), i.e. ($c_{32} \rightarrow c_{111}$); (2) a lower behavioral loyalty (c_{51}) might come out a low attitudinal loyalty (c_{61}), i.e. ($c_{51} \rightarrow c_{61}$); (3) some customers with a lower asset specificity costs (c_{31}) might have college education (c_{82}) and under 30 years old (c_{91}), i.e. ($c_{31} \rightarrow c_{82}$, c_{91}); and (4) a customer was a male (c_{71}) maybe aged between 31 and 40 (c_{92}), i.e. ($c_{71} \rightarrow c_{92}$). The more details would present in the next section.

Table C.1
The implication sets for decision class 1.

Implication sets	
1 < 2 > c_{32} ==> c_{111}	17 < 1 > c_{71} c_{92} ==> $c_{51}c_{61}$
2 < 2 > c_{51} ==> c_{61}	18 < 1 > $c_{82}c_{92}$ ==> $c_{52}c_{62}c_{101}$
3 < 1 > c_{21} ==> $c_{41}c_{63}c_{81}$	19 < 1 > c_{94} ==> $c_{31}c_{42}$
4 < 1 > $c_{31}c_{42}$ ==> c_{94}	20 < 1 > c_{61} c_{101} ==> $c_{32}c_{111}$
5 < 1 > c_{52} ==> $c_{62}c_{82}c_{92}c_{101}$	21 < 1 > $c_{62}c_{101}$ ==> $c_{52}c_{82}c_{92}$
6 < 1 > $c_{31}c_{61}$ ==> $c_{51}c_{82}c_{91}$	22 < 1 > $c_{82}c_{101}$ ==> $c_{52}c_{62}c_{92}$
7 < 1 > $c_{31}c_{62}$ ==> $c_{72}c_{82}c_{111}$	23 < 1 > $c_{92}c_{101}$ ==> $c_{52}c_{62}c_{82}$
8 < 1 > $c_{42}c_{62}$ ==> $c_{32}c_{102}c_{111}$	24 < 1 > c_{102} ==> $c_{32}c_{42}c_{62}c_{111}$
9 < 1 > c_{63} ==> $c_{21}c_{41}c_{81}$	25 < 1 > $c_{31}c_{111}$ ==> $c_{62}c_{72}c_{82}$
10 < 1 > $c_{61}c_{71}$ ==> $c_{51}c_{92}$	26 < 1 > $c_{42}c_{111}$ ==> $c_{32}c_{62}c_{102}$
11 < 1 > c_{72} ==> $c_{31}c_{62}c_{82}c_{111}$	27 < 1 > $c_{61}c_{111}$ ==> $c_{32}c_{101}$
12 < 1 > c_{81} ==> $c_{21}c_{41}c_{63}$	28 < 1 > $c_{82}c_{111}$ ==> $c_{31}c_{62}c_{72}$
13 < 1 > $c_{61}c_{82}$ ==> $c_{31}c_{51}c_{91}$	29 < 1 > $c_{101}c_{111}$ ==> $c_{32}c_{61}$
14 < 1 > c_{91} ==> $c_{31}c_{51}c_{61}c_{82}$	30 < 1 > $c_{32}c_{62}c_{111}$ ==> $c_{42}c_{102}$
15 < 1 > $c_{61}c_{92}$ ==> $c_{51}c_{71}$	31 < 1 > c_{112} ==> $c_{41}c_{71}c_{83}$
16 < 1 > $c_{62}c_{92}$ ==> $c_{52}c_{82}c_{101}$	32 < 1 > $c_{41}c_{71}$ ==> $c_{83}c_{112}$
	33 < 1 > c_{83} ==> $c_{41}c_{71}c_{112}$

3.2. Discussions

In this section, the details of low dependence on agents, medium dependence on agents, and high dependence on agents were presented in Sections 3.2.1–3.2.3, respectively.

3.2.1. Low dependence on agents

Comparing the lattice diagram and context table, attributes with the least frequency in the context table will be posited at the bottom of the lattice diagram, and the concepts (attributes) were more specific. This means that those attributes were not important in determining the characteristics of the low dependence on agents, such as higher behavioral loyalty (c_{52}), high attitudinal loyalty (c_{63}), female gender (c_{72}), high school education (c_{81}), graduate (c_{83}), aged under 30 years old (c_{91}), aged between 51 and 60 (c_{94}), single status (c_{102}), and engaged in non-financial industry (c_{112}).

In Table 4, the higher frequency of the sub-attribute can find the main characteristics for each attribute, such as a higher lower asset

Table C.2
Context table for decision rules of decision class 2 as example.

Rule #	(c_2)		(c_3)		(c_4)		(c_5)		(c_6)			(c_7)		(c_8)			(c_9)				(c_{10})		(c_{11})	
	c_{21}	c_{22}	c_{31}	c_{32}	c_{41}	c_{42}	c_{51}	c_{52}	c_{61}	c_{62}	c_{63}	c_{71}	c_{72}	c_{81}	c_{82}	c_{83}	c_{91}	c_{92}	c_{93}	c_{94}	c_{101}	c_{102}	c_{111}	c_{112}
10						×		×			×				×						×			×
11	×											×					×							
12				×		×									×		×							×
13		×	×				×																	×
14		×			×			×															×	
15						×			×				×										×	
16					×														×					
17				×								×		×										×
18							×			×								×						
19			×			×								×										
20		×											×							×				
21								×	×							×								
22			×			×			×															
23														×				×				×		
24	×						×			×														
Frequency	2	3	3	2	2	5	3	3	3	2	1	2	2	3	2	1	2	2	1	1	1	1	2	4

specificity costs (c_{31}), unspecified customer satisfaction, lower behavioral loyalty (c_{51}), college education (c_{82}), age between 31 and 40 (c_{92}), marriage status (c_{101}), engaged in financial industry (c_{111}), and the gender was male (c_{71}) for the low dependence on agents.

From the lattice diagram, association rules and implication sets generated by the tool-ConExp which also deduced the attribute relationship. For example, attributes c_{52}, c_{72}, c_{82}, c_{92} implied attribute c_{62}, and attribute c_{52}, c_{31}, c_{61}, c_{62} implied attribute c_{82}. The relative information about implication relation among attributes was shown in Table 5. The relative implication sets were shown in Table C.1 of Appendix C.

In Table 5, the highest frequency was c_{62} and c_{82}, meaning that the attribute was the most superconcept implied by other subconcepts. The concept of c_{62} was inherited by all its subconcepts, such as c_{31}, c_{42}, c_{52}, c_{72}, c_{82}, c_{92}, c_{101}, c_{102}, c_{111}. The concept of c_{82} was the same. The second tier attributes were c_{51}. Those highest frequency superconcepts expressed the most important information (the common characteristic) for the low dependence on agents, which was a medium attitudinal loyalty (c_{62}), college education (c_{82}) and lower behavioral loyalty (c_{51}), which should contain some relationship, such as low attitudinal loyalty and higher education. The results were reasonable because a customer with a higher education level or a lower behavioral loyalty was usually independent in investment of financial market; therefore, most of these attributes/characteristics may not rely on agents.

3.2.2. Medium dependence on agents

There were 15 rules of the decision class 2. The general information about the attributes relationship were (1) a customer with a medium attitudinal loyalty (c_{62}) might have a lower behavioral loyalty (c_{51}), i.e. ($c_{62} \rightarrow c_{51}$); (2) a customer was more satisfied with the agent (c_{42}) and engage non-financial industry (c_{112}) maybe with a college education (c_{82}), i.e. (c_{42}, $c_{112} \rightarrow c_{82}$); (3) a customer with a higher asset specificity costs (c_{32}) might be engaging non-financial industry (c_{112}), i.e. ($c_{32} \rightarrow c_{112}$); and (4) a customer with a higher moral crisis costs (c_{21}) and a lower behavioral loyalty (c_{51}) might have a medium attitudinal loyalty (c_{62}), i.e. (c_{21}, $c_{51} \rightarrow c_{62}$).

From the higher frequency of the context table, we found the main characteristics for each attribute of the medium dependence on agents, such as: lower moral crisis costs (c_{22}), lower asset specificity costs (c_{31}), satisfied with agents (c_{42}), low attitudinal loyalty (c_{61}), high school education (c_{81}), aged under 40, engaged in financial industry (c_{112}), and unspecified behavioral loyalty, gender and marriage. The most important information was satisfied with agents (c_{42}), and the least important information was attributes c_{63}, c_{83}, c_{93}, c_{94}, c_{101}, and c_{102}. The relative context table and lattice diagram were shown in Table C.2 and Fig. C.1 of Appendix C.

The most implied attribute was non-financial industry (c_{112}), followed by satisfied with agents (c_{42}), and lower Moral Crisis Costs (c_{22}). The attribute relationship, such as attribute c_{22}, c_{32} implied attribute c_{112}, attribute c_{82}, c_{72} implied attribute c_{42}, and attribute c_{41}, c_{52} implied attribute c_{22}. The relative information about implication relations among attributes was shown in Table C.3 of Appendix C.

3.2.3. High dependence on agents

There were 20 rules of the decision class 3. The general information were (1) the customers engage in financial industry (c_{111}) might be with a lower moral crisis costs (c_{22}), i.e. ($c_{111} \rightarrow c_{22}$); (2) a customer had a college education (c_{82}) might be with a high attitudinal loyalty (c_{63}), i.e. ($c_{82} \rightarrow c_{63}$); (3) a customer aged between 41 and 50 (c_{93}) might be more satisfied with agents (c_{42}), i.e. ($c_{93} \rightarrow c_{42}$); and (4) married status (c_{102}) female (c_{72}) customer might had a high attitudinal loyalty (c_{63}), i.e. (c_{72}, $c_{102} \rightarrow c_{63}$).

The main characteristics for each attribute were lower moral crisis costs (c_{22}), higher asset specificity costs (c_{32}), satisfied with agents (c_{42}), higher behavioral loyalty (c_{52}), high attitudinal loyalty (c_{63}), female (c_{72}), college (c_{82}), aged between 31 and 40 (c_{92}), single (c_{102}), and non-financial industry (c_{112}). The most important information was female (c_{72}) and the least important information were attributes c_{91} and c_{101}. The relative context table and lattice diagram were shown in Table C.4 and Fig. C.2 of Appendix C.

The most implied attribute was a higher behavioral loyalty (c_{52}) and higher asset specificity costs (c_{32}), followed by college (c_{82}) and female (c_{72}). Other relative information about implication relation among attributes was shown in Table C.5 of Appendix C.

The reduct process was used in RST to reduce the superfluous attribute, to produce the reduct attribute set and the most important core attribute set, which may be the most important decision factors for decision making. However, in this study, the reduct attribute set and core attribute set were of the same set $\{c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9, c_{10}, c_{11}\}$. Under this situation, we could not find the relationships between attributes, the most important attribute, or the least important attribute. However, FCA can help with the retrieval of this information. From the table of the implication relation between attributes, we could summarize the highest frequency of implied attribute as the most important factor, followed by other the higher frequency of implied attributes as important factors affecting personal consumption pattern. FCA could provide more knowledge from the suitable rules. Table 6 was the informa-

Table C.3
Implication relation between attributes for class 2.

Imply super concept	c_{51}	c_{82}	c_{112}	c_{42}	c_{52}	c_{62}	c_{41}	c_{111}	c_{22}	c_{83}	c_{91}	c_{94}	c_{61}	c_{31}	c_{81}	c_{92}	c_{72}	c_{63}	c_{101}	c_{32}	c_{71}	c_{21}	c_{102}
Sub concept	c_{62} $c_{22}c_{112}$ $c_{31}c_{112}$ $c_{22}c_{31}$	$c_{42}c_{112}$ $c_{52}c_{112}$ $c_{91}c_{112}$ $c_{42}c_{52}$ c_{63} $c_{42}c_{91}$ c_{101}	c_{32} c_{82} $c_{22}c_{31}$ $c_{22}c_{51}$ $c_{31}c_{51}$ $c_{42}c_{52}$ c_{63} $c_{71}c_{81}$ $c_{42}c_{91}$ c_{101} c_{112} c_{32}	c_{82} $c_{31}c_{61}$ $c_{61}c_{72}$ $c_{31}c_{81}$ $c_{61}c_{111}$ $c_{72}c_{111}$ $c_{52}c_{112}$ $c_{91}c_{112}$ c_{63} c_{101}	$c_{22}c_{41}$ c_{83} $c_{22}c_{111}$ $c_{41}c_{111}$ c_{63} c_{101}	$c_{21}c_{51}$ $c_{51}c_{92}$	$c_{22}c_{52}$ c_{93} $c_{22}c_{111}$ $c_{52}c_{111}$	$c_{22}c_{41}$ $c_{22}c_{52}$ $c_{41}c_{52}$ $c_{42}c_{72}$ $c_{61}c_{72}$	$c_{41}c_{52}$ c_{94} $c_{41}c_{111}$ $c_{52}c_{111}$ $c_{31}c_{112}$ $c_{51}c_{112}$ $c_{31}c_{51}$	$c_{52}c_{61}$	$c_{21}c_{71}$ $c_{32}c_{42}c_{82}c_{112}$	$c_{22}c_{72}$	$c_{42}c_{72}$ c_{83} $c_{42}c_{111}$ $c_{72}c_{111}$	$c_{42}c_{81}$ $c_{22}c_{112}$ $c_{51}c_{112}$ $c_{22}c_{51}$	c_{102} $c_{71}c_{112}$ c_{94}	c_{102}	$c_{42}c_{111}$ $c_{61}c_{111}$	$c_{52}c_{112}$ $c_{42}c_{52}$ c_{101}	$c_{52}c_{112}$ $c_{42}c_{52}$ c_{63}	$c_{71}c_{112}$ $c_{81}c_{112}$ $c_{91}c_{112}$ $c_{71}c_{81}$ $c_{42}c_{91}$	$c_{81}c_{112}$ $c_{21}c_{91}$	$c_{71}c_{91}$	$c_{81}c_{92}$
Frequency	7	12	18	17	9	4	7	10	13	2	6	2	7	8	4	1	4	5	5	10	4	2	2

Table C.4
Context table for decision rules of decision class 3 as example.

Rule #	(c_2)		(c_3)		(c_4)		(c_5)		(c_6)			(c_7)		(c_8)			(c_9)			(c_{10})		(c_{11})	
	c_{21}	c_{22}	c_{31}	c_{32}	c_{41}	c_{42}	c_{51}	c_{52}	c_{61}	c_{62}	c_{63}	c_{71}	c_{72}	c_{81}	c_{82}	c_{83}	c_{92}	c_{93}	c_{94}	c_{101}	c_{102}	c_{111}	c_{112}
25			×					×									×				×		
26		×												×						×		×	
27										×			×			×							
28						×							×	×				×					
29	×			×													×						×
30											×		×	×							×		
31		×				×					×	×			×							×	
32						×	×									×							
33				×			×						×										×
34			×			×		×							×						×		
35					×			×	×					×									
36	×					×												×					
37					×				×				×		×		×						
38				×							×					×							
39				×	×			×											×				×
40					×			×			×		×		×								
41	×										×		×								×		
42		×		×				×		×		×				×							
43		×									×		×		×							×	
44		×	×			×				×													×
Frequency	3	5	3	5	4	6	2	6	2	3	6	2	8	4	5	4	3	2	1	1	4	3	4

Table C.5
Implication relation between attributes for class 3.

Imply super concept	c_{22}	c_{102}	c_{41}	c_{82}	c_{63}	c_{111}	c_{72}	c_{42}	c_{52}	c_{31}	c_{62}	c_{71}	c_{83}	c_{93}	c_{81}	c_{32}	c_{101}	c_{61}	c_{92}	c_{51}	c_{94}	c_{21}	c_{112}
Sub concept	c_{111}	$c_{31}c_{52}$	c_{61}	$c_{22}c_{63}$	$c_{22}c_{82}$	$c_{22}c_{82}$	$c_{42}c_{82}$	c_{93}	$c_{31}c_{102}$	$c_{52}c_{102}$	$c_{22}c_{32}$	$c_{22}c_{32}$	$c_{22}c_{32}$	$c_{21}c_{42}$	$c_{41}c_{52}c_{61}$	$c_{22}c_{52}$	$c_{22}c_{81}$	$c_{41}c_{81}$	$c_{41}c_{61}c_{71}c_{82}$	$c_{42}c_{83}$	$c_{52}c_{112}$	$c_{92}c_{112}$	$c_{22}c_{31}$
	c_{71}	$c_{42}c_{52}$	$c_{52}c_{63}$	$c_{42}c_{52}$	$c_{72}c_{102}$	$c_{22}c_{63}$	$c_{63}c_{102}$	$c_{31}c_{82}$	$c_{22}c_{32}$	$c_{42}c_{52}$	$c_{22}c_{52}$	$c_{22}c_{52}$	$c_{42}c_{51}$	$c_{42}c_{72}$	$c_{42}c_{72}$	$c_{52}c_{62}$		$c_{52}c_{81}$	$c_{21}c_{112}$	$c_{72}c_{112}$	$c_{32}c_{41}$	$c_{32}c_{92}$	$c_{21}c_{32}$
	$c_{32}c_{62}$	$c_{21}c_{63}$	$c_{52}c_{72}$	$c_{41}c_{63}$	$c_{22}c_{42}c_{71}$	$c_{42}c_{63}$	$c_{21}c_{63}$	$c_{51}c_{83}$	$c_{32}c_{62}$	$c_{52}c_{92}$	$c_{22}c_{83}$	$c_{32}c_{62}$	$c_{22}c_{52}$	$c_{42}c_{81}$	c_{101}	$c_{22}c_{62}c_{71}$		$c_{41}c_{92}$	$c_{21}c_{32}$	$c_{32}c_{72}$	$c_{41}c_{112}$		$c_{32}c_{41}$
	$c_{52}c_{62}$	$c_{21}c_{72}$	$c_{52}c_{81}$	$c_{42}c_{63}$	$c_{21}c_{72}$	$c_{22}c_{42}c_{71}$	$c_{41}c_{63}$	$c_{82}c_{102}$	$c_{41}c_{63}$	$c_{42}c_{102}$	$c_{52}c_{83}$	$c_{52}c_{62}$	$c_{32}c_{62}$			$c_{22}c_{83}$		$c_{72}c_{92}$					$c_{32}c_{51}$
	$c_{42}c_{63}$	$c_{63}c_{81}$	$c_{72}c_{92}$	$c_{52}c_{63}$	$c_{22}c_{72}$	$c_{22}c_{72}$	$c_{52}c_{63}$	$c_{22}c_{71}c_{111}$	$c_{22}c_{62}c_{71}$	$c_{82}c_{102}$	$c_{72}c_{83}$	$c_{42}c_{63}$	$c_{52}c_{62}$			$c_{52}c_{83}$		$c_{82}c_{92}$					$c_{31}c_{62}$
	$c_{52}c_{83}$	$c_{31}c_{82}$	$c_{82}c_{92}$	$c_{22}c_{42}c_{71}$	$c_{52}c_{72}$	$c_{22}c_{81}$	$c_{63}c_{81}$	$c_{22}c_{112}$	$c_{41}c_{81}$	$c_{92}c_{102}$	$c_{22}c_{112}$	$c_{22}c_{83}$	$c_{32}c_{63}$			$c_{63}c_{83}$							$c_{42}c_{62}$
	c_{101}	$c_{31}c_{92}$	$c_{52}c_{112}$	$c_{22}c_{72}$	$c_{21}c_{102}$	c_{101}	$c_{41}c_{92}$	$c_{31}c_{112}$	$c_{31}c_{82}$	$c_{22}c_{112}$	$c_{31}c_{112}$	$c_{52}c_{83}$	$c_{22}c_{62}c_{71}$			$c_{21}c_{112}$							$c_{32}c_{72}$
	$c_{31}c_{112}$	$c_{52}c_{92}$	c_{94}	$c_{52}c_{72}$	$c_{81}c_{102}$		$c_{21}c_{102}$	$c_{22}c_{31}$	$c_{22}c_{83}$	$c_{42}c_{112}$	$c_{42}c_{112}$	$c_{22}c_{42}c_{111}$	$c_{62}c_{72}$			$c_{41}c_{112}$							$c_{51}c_{72}$
	$c_{42}c_{112}$			$c_{41}c_{92}$	$c_{22}c_{42}c_{111}$		$c_{82}c_{92}$	$c_{31}c_{62}$	$c_{31}c_{92}$	$c_{62}c_{112}$	$c_{22}c_{31}$					$c_{51}c_{112}$							$c_{21}c_{92}$
	$c_{62}c_{112}$			$c_{72}c_{92}$	$c_{22}c_{71}c_{111}$		$c_{81}c_{102}$	$c_{62}c_{112}$	$c_{42}c_{102}$	$c_{42}c_{62}$						$c_{52}c_{112}$							$c_{32}c_{92}$
	$c_{31}c_{62}$			$c_{42}c_{102}$			$c_{51}c_{112}$		$c_{92}c_{102}$							$c_{72}c_{112}$							c_{94}
	$c_{42}c_{62}$			$c_{22}c_{42}c_{111}$			$c_{32}c_{51}$		$c_{41}c_{112}$							$c_{92}c_{112}$							
				$c_{22}c_{71}c_{111}$			$c_{42}c_{81}$		$c_{82}c_{102}$							$c_{51}c_{72}$							
									$c_{32}c_{41}$							$c_{21}c_{92}$							
									c_{94}							c_{94}							
Frequency	21	16	14	29	23	14	26	20	30	20	18	17	17	6	6	30	2	10	8	6	6	4	21

tion of the attribute relationship for each personal preference for agents; moreover, we found that the most important factors were as same as the result of flow graphs. For this reason we believed that this customers' preference model was more credible.

In this study, we discovered that FCA was not only used to detect the principal attribute but also was used to explore the relationships between these attributes. Hence, FCA can complement the flow graphs perfectly.

4. Conclusions

In this study, RST generated 44 rules. These rules can be explored further to gain additional information through FCA, such as the most important factors/attributes affecting the relationship between personal preference for agents and its result was same as flow graphs. Therefore this attributes relationship can give decision makers *a priori* prediction.

The main characteristics of the low dependence on agents were with medium attitudinal loyalty (c_{62}), college (c_{82}), and lower behavioral loyalty (c_{51}); and the other features were such as engaged in financial industry (c_{111}) and married status (c_{101}). The main characteristics of the medium dependence on agents were engaged in non-financial industry (c_{112}), satisfied with agents (c_{42}), and lower moral crisis costs (c_{22}); the following features were lower asset specificity costs (c_{31}), aged under 30 years old (c_{91}), and lower behavioral loyalty (c_{51}). The main characteristics of the high dependence on agents were with a higher behavioral loyalty (c_{52}), higher asset specificity costs (c_{32}), college (c_{82}), and female (c_{72}); the following features were with lower moral crisis costs (c_{22}), satisfied with agents (c_{42}), and single status (c_{102}).

In summary, we have shown that the combined rough sets with flow graph and FCA approach was a promising method for discovering important facts hidden in data and minimal sets of relevant data (data reduction) for the customers' preference. We believe that FCA can assist decision makers in finding more information. It also can help determined the relationships between these attributes. Regardless of the type of soft computing generating the decision rules, FCA may be applied to get more information.

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Appendix A

See Tables A.1–A.5.

Appendix B

The original rules generated from ROSE2 were described in Table B.1. The rule syntax represents as follow:

Rule #. (attribute ^ relation ^ value) ^ & ... ^ (attribute ^ relation ^ value)) (decision = value) ^ OR ... OR ^ (decision = value); [support, strength, relative strength, level_of_descrimination] [support_class1, support_class2, ..., support_classN] [{class1_objects}, {class2_objects}, ..., {classN_objects}].

The line begins with sequence of "Rule no" – Rule #. Attribute is the name of conditional attribute, value is its value and relation is one of the following: "=", ">", "<", ">=", "<=", "in". Following are the decision part of the rule which assign to the decision class (es). Others details about the rule syntax can check the manual of the software ROSE2.

Appendix C

See Tables C.1–C.5.

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