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Using decision rules to achieve mass customization of airline services

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ABSTRACT

This paper uses the Dominance-based Rough Set Approach (DRSA) to formulate airline service strategies by generating decision rules that model passenger preference for airline service quality. DRSA could help airlines eliminate some services associated with dispensable attributes without affecting passenger perception of service quality. DRSA could also help airlines achieve mass customization of airline services and generate additional revenues by active or passive targeting of quality services to passengers.

1. Introduction

Lowering fares attracts more passengers, but an airline that engages in price competition usually does so by sacrificing investment in flight safety. Over time, this leads to a higher likelihood of a catastrophic event that causes financial loss and destroys an airline's reputation. This is why price competition alone is not a viable long-term strategy. Instead, an airline's competitive advantage lies in service quality (Chang and Yeh, 2002). Higher service quality leads to higher passenger satisfaction, better branding, and higher passenger demand, which in turn leads to higher revenue (Sim et al., 2006). In other words, an airline's reputation for quality service is what allows it to charge a premium over its competitor's price in the long run.

With the global economic downturn, most airlines are struggling just to survive. They are forced to cut costs and services as much as possible. What airlines need are ways to cut costs and generate more revenues while maintaining passenger's perception of airline service quality. Dominance-based Rough Set Approach (DRSA) could help airlines cut costs by identifying services that could be eliminated without affecting overall airline's service rating. DRSA could also help airlines generate additional revenues by providing excludable services for a fee to passengers who value quality service and are willing to pay for them.

Airline service quality is a complex mix of intangibles (Mazanec, 1995). It is a composite of various interactions between a passenger and airline employees as well as anything that is likely to influence passenger perception, such as an airline's image (Gursoy et al., 2005). Service quality can be defined as a consumer's overall impression of the relative efficiency of the organization and its services (Park et al., 2004). It can also be defined as a chain of services in which the entire service delivery is divided into a series of processes (Chen and Chang, 2005).

Previous studies in airline service quality used surveys to look at the disparity between expected service and perceived service received by passengers. Our study uses the data mining technique called Dominance-based Rough Set Approach (DRSA) to analyze a survey on airline service quality. A set of "if ***antecedent***, then ***consequent***" decision rules are induced from the passenger preference data that express the relationships between attributes values and the overall service ratings. There are several advantages of using DRSA. First, the airline service decision rules are formulated in natural language that is easy to understand. Second, services associated with dispensable attributes could be eliminated without affecting the airline's overall service rating. Third, decision rules that combine both personal and service attributes could be used to mass customize airline services to passengers.

This paper is organized as follows: Section 2 summarizes the previous studies on airline service quality. Section 3 introduces DRSA. Section 4 describes our empirical study. Section 5 presents our results and analysis. Section 6 concludes.

2. Evaluation of airline service quality

Previous studies on airline service quality were based on the idea that the quality of service is perceived and evaluated by

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passengers (Gronroos, 1990). The most widely used customer-perceived service quality model was proposed by Parasuraman et al. (1985). This model was further developed into what is known as SERVQUAL (Parasuraman et al., 1988). Gronroos (1993) suggested that measuring passenger experiences in airline service quality is a theoretically valid way of measuring perceived quality. This led to the use of survey questionnaires to collect data for analysis.

Based on SERVQUAL, Tsaur et al. (2002) proposed a five-aspect measurement for service quality. Each aspect includes two to four attributes. Assuming that attributes were independent, they used AHP to obtain attribute weights and used TOPSIS to rank the airlines. They concluded that the most important attributes are courtesy, safety, and comfort. Chang and Yeh (2002) used fuzzy multi-criteria analysis to describe the ambiguity between criteria weights and airline service quality rating. They proposed a list of 15 evaluation attributes to measure airline service quality and found that flight safety was the most important attribute.

Chen and Chang (2005) examined airline service quality from a process perspective. They measured the gap between passenger service expectation and actual service received and the gap between passenger service expectation and the perception of this expectation by frontline managers and employees. Importance–performance analysis was then used to construct evaluation maps of service attributes to identify areas for improvement. Their results revealed that gaps did exist, and passengers were more concerned about the responsiveness and assurance dimensions of airline's frontline staff. Gursoy et al. (2005) proposed a list of 15 service quality attributes to measure 10 major US airlines and examined their relative positioning using canonical correspondence analysis. They established a positioning map that helped airlines identify their closest competitors, their strengths and weaknesses, and areas for improvement. Liou and Tzeng (2007) applied a non-additive fuzzy integral model to investigate the inter-relations among service attributes. Lu and Ling (2008) used hypothesis tests to examine how different cultures lead to different passenger service perception.

While most studies used traditional statistical techniques to test their hypotheses, others applied multi-attributes decision making (MADM) models to look at an airline's integrated service level and make suggestions for improvement. Our paper takes a different approach. While previous studies employed methods that are more descriptive and inclusive in the number of service attributes, DRSA does the opposite by pruning away dispensable attributes that do not affect the overall service rating. Moreover, instead of modeling passenger preference explicitly in terms of importance weights, substitution rates, and other preference thresholds, DRSA induces the passenger preference model through classification examples given by passengers in a survey on airline services. The result is a set of decision rules that are actionable by airline managers and could be used to formulate an airline's service strategy. The basic concepts of DRSA are presented in the next section.

3. The basic concepts of DRSA

The classic rough set theory, first introduced by Pawlak (1982), is a valuable mathematical tool for dealing with vagueness and uncertainty (Pawlak, 1997). However, the use of the Classical Rough Set Approach (CRSA) as a data mining technique in general is restricted to classification problems where the data is either non-ordered or the ordinal nature of the data is ignored. Greco et al. (1998) proposed an extension of the rough set theory based on the dominance principle to incorporate the ordinal nature of the preference data into the classification problem. The resulting DRSA essentially substitutes CRSA's indiscernibility relation with the dominance relation in order to analyze preference-ordered data. An important consequence of the rough set theory is the possibility of modeling the preferences of a decision maker with easily understandable decision rules of the type ***if*** *antecedent* ***then*** *decision*. The main difference between CRSA and DRSA is that CRSA rules are restricted to expressing the antecedents of the rules with the equality relation "=" on attribute values, whereas DRSA rules can express the antecedents using the more general preference relations "$\succeq$" and "$\preceq$" instead. An example of a CRSA rule would be: *If (logo is crane) and (colors are blue and yellow), then (the airline is Lufthansa)*, whereas an example of a DRSA rule would be: *if* (*LCD screen size* $\geqslant$17") *and* (*price* $\leqslant$ \$250), *then* (*the product is a bargain*).

Yao et al. (2007) differentiates between two levels of knowledge represented by two kinds of rules. A low-order rule expresses connections between attribute values of the same object, whereas a high-order rule expresses connections between different objects in terms of their attribute values. Both CRSA and DRSA rules can be used to express low-order and high-order rules. In this study, we will focus on generating low-order DRSA rules.

The basic concepts of DRSA are summarized below. For more in depth theory, see the following references (Greco et al., 1998, 2001a, 2002; Pawlak, 1991, 1997; Slowinski et al., 2005; Blaszczynski et al., 2007; Yao et al., 2007; Kotlowski et al., 2008; Fortemps et al., 2008; Yao and Zhao, 2008).

3.1. Data table

DRSA uses an ordered information table. Each row represents an object, which in our case is defined as a respondent in our survey. Each column represents an attribute. A regular attribute has no preference-ordered domain, whereas a criterion is an attribute with preference-ordered domain. Thus the set of criteria is a subset of all attributes. Each cell in this table is an evaluation (quantitative or qualitative) by the respondent of that row about the attribute of that column.

Formally, the data table is in the form of a four-tuple information system $IS = (U, Q, V, f)$, where U is a finite set of objects (universe), $Q = \{q_1, q_2, \ldots, q_m\}$ is a finite set of attributes, V_q is the domain of attribute q, $V = \cup_{q \in Q} V_q$, and $f : U \times Q \to V$ is a total function such that $f(x,q) \in V_q$ for each $q \in Q, x \in U$. The set Q is usually divided into set C of condition attributes and set D of decision attributes.

3.2. Rough approximation by means of the dominance relation

Let $\succeq_q$ be an outranking relation on U with respect to criterion $q \in Q$, such that $x \succeq_q y$ means "x is at least as good as y with respect to criterion q". Suppose that $\succeq_q$ is a complete preorder, i.e., it is strongly complete (which means that for each $x, y \in U$, at least one of $x \succeq_q y$ and $y \succeq_q x$ is verified) and transitive binary relation defined on U. Thus, x and y are always comparable with respect to criterion q. Moreover, let $\boldsymbol{Cl} = \{Cl_t, t \in T\}, T = \{1, \ldots, n\}$, be a set of decision classes of U, such that each $x \in U$ belongs to one and only one class $Cl_t \in \boldsymbol{Cl}$. Assume that for all $r, s \in T$, such that $r > s$, each element of Cl_r is preferred to each element of Cl_s. In other words, assume that if $\succeq$ is a comprehensive outranking relation on U, then

$$[x \in Cl_r, y \in Cl_s, r > s] \Rightarrow x \succ y,$$

where $x \succ y$ means $x \succeq y$ and not $y \succeq x$.

Given the set of decision classes $\boldsymbol{Cl}$, it is possible to define upward and downward unions of classes, respectively, as

$$Cl_t^{\geqslant} = \bigcup_{s \geqslant t} s, \quad Cl_t^{\leqslant} = \bigcup_{s \leqslant t} Cl_s.$$

It is said that object x P-dominates object y with respect to $P \subseteq C$ (denoted by $xD_p y$) if $x \succeq_q y$ for all $q \in P$. Since $D_P = \bigcap_{q \in P} \succeq_q$, the dominance relation D_P is a partial preorder. Given $P \subseteq C$ and $x \in U$, let

$$D_P^+(x) = \{y \in U : yD_Px\},$$
$$D_P^-(x) = \{y \in U : xD_Py\},$$

represent respectively the P-dominating set and the P-dominated set with respect to x. We can use $D_P^+(x)$ and $D_P^-(x)$ as "granules of knowledge" to approximate a collection of upward and downward unions of decision classes. We define the P-lower and P-upper approximation of $Cl_t^{\geqslant}, t \in \{2,3,\ldots,n\}$, with respect to $P \subseteq C$ (denoted by $\underline{P}(Cl_t^{\geqslant})$ and $\overline{P}(Cl_t^{\geqslant})$, respectively) as

$$\underline{P}(Cl_t^{\geqslant}) = \{x \in U : D_P^+(x) \subseteq Cl_t^{\geqslant}\},$$
$$\overline{P}(Cl_t^{\geqslant}) = \bigcup_{x \in Cl_t^{\geqslant}} D_P^+(x) = \{x \in U : D_P^-(x) \cap Cl_t^{\geqslant} \neq \varnothing\}.$$

The P-lower approximation of an upward union $Cl_t^{\geqslant}, \underline{P}(Cl_t^{\geqslant})$, is composed of all objects x from the universe, such that all objects y that have at least the same evaluations for all the considered ordered attributes from P also belong to class Cl_t or better. In other words, if object y has at least as good an evaluation on the criteria from P as object x belonging to $\underline{P}(Cl_t^{\geqslant})$, then y belongs to class Cl_t or better. The P-upper approximation of an upward union $Cl_t^{\geqslant}, \overline{P}(Cl_t^{\geqslant})$, is composed of all objects x from the universe, whose evaluations on the criteria from P are not worse than the evaluations of at least one object y belonging to class Cl_t or better. Analogously, the P-lower and P-upper approximation of $Cl_t^{\leqslant}, t \in \{1,2,\ldots,n-1\}$, with respect to $P \subseteq C$ (denoted by $\underline{P}(Cl_t^{\leqslant})$ and $\overline{P}(Cl_t^{\leqslant})$, respectively) are defined as

$$\underline{P}(Cl_t^{\leqslant}) = \{x \in U : D_P^-(x) \subseteq Cl_t^{\leqslant}\},$$
$$\overline{P}(Cl_t^{\leqslant}) = \cup_{x \in Cl_t^{\leqslant}} D_P^-(x) = \{x \in U : D_P^+(x) \cap Cl_t^{\leqslant} \neq \emptyset\}.$$

The P-lower and P-upper approximations defined above satisfy the following properties for all $t \in \{1,\ldots,n\}$ and for any $P \subseteq C$:

$$\underline{P}(Cl_t^{\geqslant}) \subseteq Cl_t^{\geqslant} \subseteq \overline{P}(Cl_t^{\geqslant}), \quad \underline{P}(Cl_t^{\leqslant}) \subseteq Cl_t^{\leqslant} \subseteq \overline{P}(Cl_t^{\leqslant}).$$

Furthermore, the P-lower and P-upper approximations satisfy the following specific complementarity properties:

$$\underline{P}(Cl_t^{\geqslant}) = U - \overline{P}(Cl_{t-1}^{\leqslant}), \quad t = 2,\ldots,n,$$
$$\underline{P}(Cl_t^{\leqslant}) = U - \overline{P}(Cl_{t+1}^{\geqslant}), \quad t = 1,\ldots,n-1,$$
$$\overline{P}(Cl_t^{\geqslant}) = U - \underline{P}(Cl_{t-1}^{\leqslant}), \quad t = 2,\ldots,n,$$
$$\overline{P}(Cl_t^{\leqslant}) = U - \underline{P}(Cl_{t+1}^{\geqslant}), \quad t = 1,\ldots,n-1.$$

The P-boundaries (P-doubtable regions) of $Cl_t^{\geqslant}$ and $Cl_t^{\leqslant}$ are defined as

$$Bn_P(Cl_t^{\geqslant}) = \overline{P}(Cl_t^{\geqslant}) - \underline{P}(Cl_t^{\geqslant}),$$
$$Bn_P(Cl_t^{\leqslant}) = \overline{P}(Cl_t^{\leqslant}) - \underline{P}(Cl_t^{\leqslant}).$$

The accuracy of approximation of $Cl_t^{\geqslant}$ and $Cl_t^{\leqslant}$ for all $t \in \{1,\ldots,n\}$ and for any $P \subseteq C$ is defined respectively as

$$\alpha_p(Cl_t^{\geqslant}) = \frac{|\underline{P}(Cl_t^{\geqslant})|}{|\overline{P}(Cl_t^{\geqslant})|}, \quad \alpha_p(Cl_t^{\leqslant}) = \frac{|\underline{P}(Cl_t^{\leqslant})|}{|\overline{P}(Cl_t^{\leqslant})|}.$$

The ratio

$$\gamma_p(\boldsymbol{Cl}) = \frac{|U - (\cup_{t \in \{2,\ldots,n\}} Bn_p(Cl_t^{\geqslant}))|}{|U|} = \frac{|U - (\cup_{t \in \{1,\ldots,n-1\}} Bn_p(Cl_t^{\leqslant}))|}{|U|}$$

defines the quality of approximation of the classification $\boldsymbol{Cl}$ by means of the criteria from the set $P \subseteq C$, called in short the quality of classification, with $|\cdot|$ being the cardinality of a set. This ratio expresses the proportion of all P-correctly classified objects, i.e., all non-ambiguous objects, to all the objects in the data table. Every minimal subset $P \subseteq C$, such that $\gamma_p(\boldsymbol{Cl}) = \gamma_c(\boldsymbol{Cl})$, is called a *reduct* of C with respect to $\boldsymbol{Cl}$, and is denoted by $RED_{Cl}(P)$. A data table may have more than one *reduct*, and the intersection of all the *reducts* is known as the *core*, denoted by $CORE_{Cl}$.

3.3. Decision rules

The end result of DRSA is a representation of the information system in terms of simple decision rules of the type ***if*** *antecedent* ***then*** *decision*. For a given upward union of classes $Cl_t^{\geqslant}$, the decision rules induced under the hypothesis that all objects belonging to $\underline{P}(Cl_t^{\geqslant})$ are positive and the others are negative, suggest an assignment to "at least class Cl_t". Analogously, for a given downward union $Cl_s^{\leqslant}$, the rules induced under the hypothesis that all objects belonging to $\underline{P}(Cl_s^{\leqslant})$ are positive and the others are negative, suggest an assignment to "at most class Cl_s". On the other hand, the decision rules induced under the hypothesis that all actions belonging to the intersection $\overline{P}(Cl_s^{\leqslant}) \cap \overline{P}(Cl_t^{\geqslant})$ are positive and the others are negative, suggest an assignment to some class between Cl_s and Cl_t.

The following three types of decision rules can be considered:

1. $D_{\geqslant}$ -decision rules, which take the form

$$\text{If } f(x,q_1) \geqslant r_{q_1} \text{ and } f(x,q_2) \geqslant r_{q_2} \text{ and } \cdots f(x,q_p) \geqslant r_{q_p}, \quad \text{then } x \in Cl_t^{\geqslant}.$$

These rules are supported only by objects from the P-lower approximations of the upward unions of classes $Cl_t^{\geqslant}$. These "at least" type rules usually state conditions that, if satisfied, would lead to the assignment of objects to higher classes. Thus, the "at least" type rules can be viewed as a prescription for improvement.

2. $D_{\leqslant}$-decision rules, which take the form

$$\text{if } f(x,q_1) \leqslant r_{q_1} \text{ and } f(x,q_2) \leqslant r_{q_2} \text{ and} \cdots f(x,q_p) \leqslant r_{q_p}, \quad \text{then } x \in Cl_t^{\leqslant}.$$

These rules are supported only by objects from the P-lower approximations of the downward unions of classes $Cl_t^{\leqslant}$. These "at most" type rules usually state conditions that, if met, would lead to the assignment of objects to lower classes. Thus, the "at most" type rules indicate warnings or deteriorating threats and can be viewed as a list of do not's.

3. $D_{\geqslant\leqslant}$-decision rules, which take the form

$$\text{if } f(x,q_1) \geqslant r_{q_1} \text{ and } f(x,q_2) \geqslant r_{q_2} \text{ and} \cdots f(x,q_k) \geqslant r_{q_k}$$

and $f(x,q_{k+1}) \leqslant r_{q_{k+1}}$ *and* $\cdots f(x,q_p) \leqslant r_{q_p}$, *then* $x \in Cl_t \cup Cl_{t+1} \cup \cdots \cup Cl_s$. These rules are supported only by objects from the P-boundaries of the unions of classes $Cl_s^{\geqslant}$ and $Cl_t^{\leqslant}$, where $P = \{q_1,q_2,\ldots,q_p\} \subseteq C, (r_{q_1}, r_{q_2},\ldots,r_{q_p}) \in V_{q_1} \times V_{q_2} \times \cdots \times V_{q_p}, s,t \in T$ and $t < s$.

In general, the set of decision rules induced using the dominance relation of DRSA is a more comprehensive representation of the knowledge contained in the decision table than the set of rules induced via the indiscernibility relation of CRSA. This is due to the more general syntax of the rules where the preference relations "$\succeq$" and "$\preceq$" are used instead of the equality relation "=".

4. An empirical example

An empirical study is presented in this section to demonstrate the effectiveness of DRSA. Our goal is to induce a set of low-order decision rules that model passenger preference. We surveyed passengers directly to obtain their perceptions on airline services. The airline we focus on in this study is an international airline in Taiwan that flies to more than 60 destinations around the world. The main survey was conducted while passengers were at the

Table 1
Service attributes and their related items.

Factors in airline service quality	Related items
Employee service	Appearance of staff; promptness of service; courtesy of service
Safety and reliability	On time departure and arrival; safety record
Onboard comfort	Cleanliness of interior and seats; in-flight entertainment service; meal service; seating comfort; seat space and leg room
Complaint handling	Prompt handling of requests and complaints (e.g., flight delay or cancellation); having knowledgeable employees who can answer questions
Convenience	Convenient flight schedule; flight transfer; flight frequency; convenient reservation and ticketing; efficient check-in and baggage service; non-stop flights to various cities; in-flight internet/email/fax/phone; waiting lounge
Promotions	Frequent flyer program; availability of alliance partner's network; loyalty program; travel-related partners (e.g. hotels and car rentals)

waiting room or waiting lounge of Taiwan's Taoyuan International Airport, from June to October 2007.

4.1. Preliminary survey

Airline service quality is a complex system composed of many factors. To reduce the complexity in our study, we first proposed 24 related factors by consulting SERVQUAL, the managers of the airlines, and relevant literature. We then conducted a preliminary survey, with 82 passengers of the airline in question responding to our survey. The survey questions were designed for the airline, and the answers were measured on a five-point Likert scale. We used factor analysis to help us express the collected data with fewer but more representative factors. As a result we reduced the original 24 factors down to just six crucial factors. These six factors and their related items are shown in Table 1.

4.2. Primary survey

The results from the factor analysis indicate that six factors – employee service, safety and reliability, onboard comfort, complaint handling, convenience, and promotion are the most important in shaping passenger perception of airline service quality. We then prepared our primary survey, which is an expanded questionnaire, and approached different groups of passengers taking flights with the same airline in question and asked them for three types of information: (1) information on their personal profile, (2) their satisfaction level for each service factor, and (3) their overall satisfaction level regarding the service quality of the airline. In our study, the personal attributes are the regular attributes, and the service criteria are the criteria. For example, a passenger's age is considered a regular attribute since we have no preference with regards to age in this study, whereas passenger rating on employee service is considered a criterion since the rating denotes a preference order. The domain values of these personal attributes and service criteria for our primary survey are shown in Table 2. A total of

Table 3
Profile of respondents.

Distribution	Sample size	Frequency (%)
Total	473	
Female	264	55.8
Male	209	44.2
Marital status		
Married	269	56.9
Unmarried	204	43.1
Age		
Less than 30	138	29.2
30–40	135	28.5
40–60	177	37.4
60-above	23	4.9
Occupation		
Government employee	118	24.9
Private-sector employee	142	20.0
Student	51	10.8
Others	162	44.3
Education		
High school and below	111	23.5
College and above	362	76.5
Income (NTD/per month)		
Less than 30,000 ($1000)	144	30.4
30,001($1000)–70,000($2300)	225	47.6
70,001 ($2300) and above	104	22.0
Overall satisfaction levels		
Poor	91	19.3
Satisfactory	203	42.9
Good	179	37.8

Table 2
Description of attributes in the primary survey.

Attributes	Domain values	Value set	Preference
Personal attributes			
Gender	Female; Male	{F,M}	Non-ordered
Marital status	Married; Unmarried	{M,U}	Non-ordered
Age	Below 30; 30–40; 40–60; 60 and above	{1,2,3,4}	Non-ordered
Occupation	Government employee; Private-sector employee; Student; Others	{G,P,S,O}	Non-ordered
Education	High school and below; College and above	{J,C}	Non-ordered
Income	NTD 30000 ($1000) and below; NTD 30001 ($1000) $\sim$ NTD 70000 ($2300); NTD 70001 ($2300) and above	{1,2,3}	Non-ordered
Service Criteria			
Employee service	Poor; Satisfactory; Good	{1,2,3}	Ordered
Safety and reliability	Poor; Satisfactory; Good	{1,2,3}	Ordered
Onboard comfort	Poor; Satisfactory; Good	{1,2,3}	Ordered
Complaint handling	Poor; Satisfactory; Good	{1,2,3}	Ordered
Convenience	Poor; Satisfactory; Good	{1,2,3}	Ordered
Promotion	Poor; Satisfactory; Good	{1,2,3}	Ordered
Decision variable			
Satisfaction level	Poor; Satisfactory; Good	{1,2,3}	Ordered

473 respondents answered our primary survey. Their profiles are shown in Table 3.

5. Results of the DRSA analysis

We used the JAMM software (Slowinski, 2006) developed by the Laboratory of Intelligent Decision Support Systems (IDSS) at Poznan University of Technology to generate our decision rules. The induction of decision rules by the JAMM program uses the DOMLEM algorithm developed by Greco et al. (2001b). The program generates a set of ***if*** *antecedent* ***then*** *consequent* decision rules called minimal covering rules. Decision rules are minimal if they are complete and non-redundant. By complete we mean that the set of rules cover all the objects or respondents in the data set. By non-redundant we mean that there are no other rules with an antecedent of at least the same weakness and a consequent of at least the same strength. Thus for a set of minimal covering rules, the exclusion of any rule makes the remaining set incomplete. Our results are presented in the following sequence: results using reducts and core, decision rules generated with service attributes, and decision rules generated with both personal and service attributes.

5.1. Results using reducts and core

One way for airlines to reduce costs is to find airline services that might be eliminated without affecting passenger perception of airline service quality. We could do this by looking at the reducts and the core. According to Sai et al. (2001), if an ordered information table has one or more reducts, then attributes that are not part of any reduct are dispensable. These dispensable attributes could be removed from the data table without affecting the ordering of the objects. Analogously, airlines could eliminate the services associated with dispensable attributes without affecting passenger perception on airline service quality. However, our data table does not have any dispensable service attributes. The entire attribute set is the reduct and the core. This is because we had already used factor analysis to reduce the original 24 service attributes down to just six crucial service attributes for our primary survey. Thus, in this case we could not use the method of eliminating services associated with dispensable attributes to help airline reduce costs. But had we kept the original 24 service attributes in our primary survey, it is very likely that DRSA results would have shown that some service attributes are dispensable and could be eliminated to save costs.

5.2. Rules using service attributes

Our data table contains two types of attributes – personal attributes and service attributes. The first type is passenger's personal attributes, which cannot be controlled by the airline. The second type is airline's service attributes, which can be controlled by the airline. Since our goal is to find rules that are actionable by airline managers, we begin by focusing on rules whose antecedents are service attributes that can be controlled by the airline. Below is the set of minimal covering rules that we have generated using service criteria only (Table 4).

Table 4
Minimal covering rules using service criteria.

No.	Conditions	Decision	Strength
1	(Service $\leqslant$ 1)	$D \leqslant 1$	46 (0.51)
2	(Safety $\leqslant$ 1) and (Complaint handling $\leqslant$ 1)	$D \leqslant 1$	43 (0.47)
3	(Service $\leqslant$ 2) and(Safety $\leqslant$ 1) and (Promotion $\leqslant$ 1)	$D \leqslant 1$	47 (0.52)
4	(Safety $\leqslant$ 1) and (Convenience $\leqslant$ 1)	$D \leqslant 1$	67 (0.74)
5	(Safety $\leqslant$ 1) and (Comfort $\leqslant$ 1)	$D \leqslant 1$	41 (0.45)
6	(Safety $\leqslant$ 1)	$D \leqslant 2$	100 (0.34)
7	(Service $\leqslant$ 2) and (Convenience $\leqslant$ 2)	$D \leqslant 2$	178 (0.61)
8	(Comfort $\leqslant$ 1)	$D \leqslant 2$	49 (0.17)
9	(Safety $\leqslant$ 2) and (Promotion $\leqslant$ 1)	$D \leqslant 2$	64 (0.22)
10	(Convenience $\leqslant$ 1)	$D \leqslant 2$	77 (0.26)
11	(Comfort $\leqslant$ 1) and (Promotion $\leqslant$ 2)	$D \leqslant 2$	53 (0.18)
12	(Safety $\geqslant$ 2) and (Convenience $\geqslant$ 2)	$D \geqslant 2$	363 (0.95)
13	(Service $\geqslant$ 2) and (Comfort $\geqslant$ 3) and (Convenience $\geqslant$ 2)	$D \geqslant 2$	131 (0.34)

The value in the parentheses is the coverage of a given rule.

The rules are divided into three classes: "at most 1" rules, "at most 2" rules, and "at least 2 rules." The "at most 1" class of rules corresponds to an overall service rating of poor. The antecedents to this class of rules tell the airline what criterion ratings they should avoid. Hence, the "at most 1" rules read like a list of don'ts. Likewise, the "at most 2" class of rules tells the airline what not to do to avoid getting an overall service rating of 2 or lower. Lastly, there are the "at least 2" rules. The antecedents to this class of rules tell the airline what criterion ratings they need to meet to get an overall service rating of 2 or 3.

Given these three classes of rules, the airline could formulate a service strategy based on the "at least 2" rules (Rules 12 and 13). If the airline wants to achieve an overall rating of 2 or better, then it needs to achieve a rating of 2 in three service categories: *employee service*, *safety and reliability*, and *convenience*. It also needs to achieve a rating of 3 in the service category *onboard comfort*. Here, we note that the cover strength of a rule is the number of surveyed passengers supporting that rule. So since Rule 12 has a higher cover strength than Rule 13 (363 > 131), the airline should work on satisfying the conditions in Rule 12 first before it works on Rule 13. In other words, the cover strength of the decision rules can help the airline schedule the tasks it needs to do to achieve an overall rating of 2 or better.

So far the rules we have generated with just service attributes could only predict an "at least 2" rating for overall service; there are no rules that could predict an overall service rating of 3. Although "at least 2" rules are achievable by the airline's actions alone, what we would really like to find are rules that could help the airline achieve an overall service rating of 3.

5.3. Rules using service criteria and personal attributes

We now use both service criteria and personal attributes to generate a set of 76 minimal covering rules. We find 69 rules that use both personal attributes and service criteria, five rules that use only service criteria, and two rules that use only personal attributes. Again, the importance of an individual rule can be judged from its strength or coverage. The higher the coverage of the rule, the more important the rule is. Moreover, the performance of the decision rules was evaluated by a 10-fold-cross-validation. For the 473 responses, the overall classification error was 19%. Let us remark that the overall quality of classification was 0.958 and the accuracies of approximation for the unions of classes "at most 1", "at most 2", "at least 2", and "at least 3" were 0.97, 0.94, 0.99, and 0.90, respectively.

There are now four classes of rules: "at most 1" rules, "at most 2" rules, "at least 2" rules, and "at least 3" rules. However, since these rules use both personal attributes and service criteria, they can be difficult to interpret and use. Table 5 below lists all the "at least 3" rules. All these rules contain both personal attributes and service criteria, which means that when the airline tries to use an "at least 3" rule, it only has partial control over the overall service rating; getting a service rating of 3 would also depend on the identity and preference of the passengers. In what follows,

Table 5
The "at least 3" class of rules.

No.	Conditions	Decision	Strength
1	(Safety $\geqslant$ 3) and (Age $\geqslant$ 60)	$D \geqslant 3$	5 (0.03)
2	(Safety $\geqslant$ 3) and (Student) and (Service $\geqslant$ 3)	$D \geqslant 3$	24 (0.13)
3	(Safety $\geqslant$ 3) and (Age 30–40) and (Service $\geqslant$ 3)	$D \geqslant 3$	32 (0.18)
4	(Safety $\geqslant$ 3) and (Age 40–60) and (Complaint Handling $\geqslant$ 3)	$D \geqslant 3$	37 (0.21)
5	(Comfort $\geqslant$ 3) and (High school) and (Age $\leqslant$ 30)	$D \geqslant 3$	8 (0.04)
6	(Comfort $\geqslant$ 3) and (High school) and (Age 40–60) and (Convenience $\geqslant$ 3)	$D \geqslant 3$	6 (0.03)
7	(Convenience $\geqslant$ 3) and (Age $\geqslant$ 60) and (High school)	$D \geqslant 3$	6 (0.03)
8	(Comfort $\geqslant$ 2) and (Age $\leqslant$ 30) and (Public) and (Income = 1)	$D \geqslant 3$	4 (0.03)
9	(Comfort $\geqslant$ 3) and (Public) and (Complaint handling $\geqslant$ 3) and (Income = 2)	$D \geqslant 3$	16 (0.09)
10	(Convenience $\geqslant$ 3) and (Public) and (Age 30–40) and (Promotion $\geqslant$ 3)	$D \geqslant 3$	11 (0.06)
11	(Comfort $\geqslant$ 3) and (Age 40–60) and (Income = 3) and (Service $\geqslant$ 3)	$D \geqslant 3$	10 (0.06)
12	(Convenience $\geqslant$ 3) and (Income = 1) and (Private) and (Male)	$D \geqslant 3$	7 (0.04)
13	(Promotion $\geqslant$ 3) and (Other jobs) and (Income = 1) and (Male)	$D \geqslant 3$	4 (0.03)
14	(Promotion $\geqslant$ 3) and (Student) and (Comfort $\geqslant$ 3)	$D \geqslant 3$	12 (0.07)
15	(Convenience $\geqslant$ 3) and (Public) and (Service $\geqslant$ 3) and (College) and (Married) and (Promotion $\leqslant$ 3)	$D \geqslant 3$	16 (0.09)
16	(Income = 2) and (Safety $\geqslant$ 3) and (Other jobs) and (Comfort $\geqslant$ 3)	$D \geqslant 3$	14 (0.08)
17	(Age 40–60) and (Public) and (Female) and (Complaint handling $\geqslant$ 3)	$D \geqslant 3$	6 (0.03)
18	(Promotion $\geqslant$ 3) and (High school) and (Income = 3) and (Age 40–60)	$D \geqslant 3$	3 (0.02)
19	(Service $\geqslant$ 3) and (Other jobs) and (Age $\leqslant$ 30) and (Married)	$D \geqslant 3$	1 (0.01)
20	(Promotion $\geqslant$ 3) and (High school) and (Other jobs) and (Age $\leqslant$ 30)	$D \geqslant 3$	4 (0.03)
21	(Convenience $\geqslant$ 3) and (Age 30–40) and (Income = 1) and (Comfort $\geqslant$ 3)	$D \geqslant 3$	6 (0.03)
22	(Other jobs) and (Complaint handling $\geqslant$ 3) and (High school) and (Convenience $\geqslant$ 3)	$D \geqslant 3$	15 (0.08)
23	(Promotion $\geqslant$ 2) and (Private) and (Income = 2) and (Age 40–60) and (Male)	$D \geqslant 3$	2 (0.01)
24	(Convenience $\geqslant$ 3) and (Student) and (Female)	$D \geqslant 3$	5 (0.03)
25	(Convenience $\geqslant$ 3) and (Male) and (Age 40–60) and (Comfort $\geqslant$ 3)	$D \geqslant 3$	17 (0.09)
26	(Private) and (Income = 2) and (Convenience $\geqslant$ 3) and (Age 30–40) and (Married)	$D \geqslant 3$	4 (0.03)
27	(Age $\leqslant$ 30) and (Private) and (Safety $\geqslant$ 3) and (Income = 2)	$D \geqslant 3$	9 (0.05)

The value in the parentheses is the coverage of a given rule.

we will show how the airline could use the "at least 3" class of rules to achieve an overall service rating of good.

The "at least 3" rules show that when passengers are deciding whether or not to give the airline an overall rating of 3, they vary in the subset of service criteria that are important to them. Some passengers care more about *safety and reliability*. Others care more about *onboard comfort* and *promotion*. Unlike previous studies that try to identify one or few key service criteria that are the most important to all passengers, our results show that for any particular passenger, it is not the entire set of service criteria but a subset of service criteria that matters. The "at least 3" class of 27 rules show that safety might be the most important service criterion for some passengers, but safety is neither necessary nor sufficient to guarantee an overall service rating of "good" by all passengers. Other service criteria also matter, and the extent to which they matter really depends on individual passenger preference.

Of course, the airline could achieve an overall service rating of 3 simply by giving all passengers services that are worthy of a service criterion rating of 3 in all six service categories. But this would be too costly, because passengers only care if a subset of services merits a rating of 3 even though the airline would have to invest heavily to achieve a rating of 3 in all six service categories for all passengers.

Alternatively, the "at least 3" rules tell us that there is a cheaper and more efficient way to achieve an overall service rating of 3, and that would be to tailor the services to individual passengers. The airline could deliver to each passenger just the subset of services that passenger cares most about. But first, the airline needs to distinguish between baseline services that will be given to all passengers and excludable services that could be given selectively to each passenger. By excludability of a service we mean the ability of an airline to exclude a passenger from receiving that service, and by non-excludability of a service we mean the inability of an airline to exclude a passenger from receiving that service once that passenger is in the airport or onboard. Thus non-excludable services must be given to all passengers, and excludable services could be given selectively to passengers. Examples of non-excludable services are *safety and reliability*, *complaint handling*, and certain aspects of *convenience*. Examples of excludable services are *employee service*, *onboard comfort*, *promotions*, and certain aspects of *convenience*. An airline that aims for an overall service rating of 3 should definitely get a service criterion rating of 3 in non-excludable services. It should treat non-excludable services as baseline services.

Second, the airline needs to target the services at the passengers who are described by the rule. But the difficulty is how to identify these passengers. There are two ways to do this. One way is to actively target services at passengers. Airlines already collect passenger profile data from their frequent mileage programs so that they can target their promotional offers and services. Airlines can also target services at passengers through visual identification, once the passengers are at the check-in counter or on the plane.

Another way is to passively target the services at passengers. Most of the time, the airline does not need to identify the passengers; it just needs to offer these services for an additional fee. Passengers will select themselves when they choose to pay for these services. The airline just needs to make sure that the quality of these excludable services is worthy of an attribute rating of 3. Of course, this is what airlines already do when they offer different cabin classes with different levels of service quality. Even without knowing the DRSA rules, airlines are already doing what the DRSA rules tell them is the most efficient way of targeting services at passengers so that they can achieve quality service at a lower cost. The DRSA results merely spell out the decision rules explicitly for the airline.

In the current global recession, we see cash-strapped airlines trying to generate additional revenues by making passengers pay for excludable services such as meals, pillows, and blankets that used to be given for free. Yet we believe this is just market pressure forcing airlines to move away from mass production of services (equal treatment of passengers) to mass customization of services (different treatment of passengers). DRSA rules that combine both personal attributes and service criteria could help airlines actively or passively target passengers more accurately so as to deliver quality services at a lower cost. DRSA can help airlines achieve mass customization of airline services while generating additional revenue.

6. Conclusions

The first goal of decision analysis is to explain past decisions. The second goal is to give recommendations for future decisions. DRSA achieves both these goals. DRSA could help airlines eliminate some services without affecting an airline's overall service rating. DRSA could also help airlines actively or passively target quality services at passengers. In so doing, DRSA allows airlines to achieve mass customization of airline services while generating additional revenue for the airline. Unlike previous studies, our results have also shown that there is no single service criterion that dominates all others, and the extent to which a service criterion matters depends on the individual passenger preference.

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