

# Airlines Content Recommendations Based on Passengers' Choice Using Bayesian Belief Networks

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# Airlines Content Recommendations Based on Passengers' Choice Using Bayesian Belief Networks

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Additional information is available at the end of the chapter

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## Abstract

Faced with the increasingly fierce competition in the aviation market, the strategy of consumer choice has gained increasing significance in both academia and practice. As ever-increasing travel choices and growing consumer heterogeneity, how do airline companies satisfy passengers' needs? With a vast amount of data, how do airline managers combine information to excavate the relationship between independent variables to gain insight about passengers' choices and value system as well as determining best personalized contents to them? Using the real case of China Southern Airlines, this paper illustrates how Bayesian belief network (BBN) can enable airlines dynamically recommend relevant contents based on predicting passengers' choice to optimize the loyalty. The findings of this study provide airline companies useful insights to better understand the passengers' choices and develop effective strategies for growing customer relationship.

**Keywords:** consumer choice, Bayesian belief network, recommendation system

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## 1. Introduction

In a world of increasingly global competition, companies have to compete on the effectiveness and efficiency of their marketing strategies to capture new opportunities to satisfy customers' needs. In other words, having the greatest product at the lowest price is not competitive enough. Choice behavior is affected by a consumer's own preference for entire product categories and particular brands, allowing companies to collect market and industry data, learn about consumer preference, and change sales tactics. In general, companies must consider consumer choice and offer their customers varieties of differentiated products and different types of choices to meet consumer demand when they formulate revenue decisions

and marketing strategies. For instance, most airlines have different fare classes (e.g., economy class versus first class) that differ in the level of services and facilities available for customers. Companies have to understand the choices that consumers make when facing such a product assortment and provide appropriate contents for each consumer. Once individual choice has been modeled, the choice prediction would be of great value to managers for the estimation of the impact of a change in product formulation [1, 2].

What one cares most is choice, the selection of a suitable content from a set of available alternatives. Given the growing diversity of the purchasing channels and information media, companies are increasingly interested in modeling and understanding an actual process through which consumers choose products, in addition to measure consumers' future choices. Better understanding of consumer choices and predicting preference is important for enterprises to introduce new products and implement target marketing. Preference prediction could also be used more extensively by companies to guide decision optimization [3]. The researchers and managers are mostly interested in knowing human choice behavior, particularly the underlying choice mechanisms, and reveal and investigate fundamental reasons behind it. Choice behavior is complex and yet rational, as a result, decision makers seek to simplify the formulation of choice process. Capturing the consumers' choice decision, a method that estimates direct and indirect effects, the situation-specific variables and clear causal relationship could offer better representing choice behavior mechanisms. Based on choice mechanism, companies need to measure preference and predict consumer decision making to conduct market research to design products. In this chapter, we aim to investigate these concerns:

- How can we infer consumers' choice for content in the future?
- How to design a model using only current period choices to infer consumers' inter-temporal preferences?
- Is the process dynamic and it allows the researchers to analyze influences of effect changes?

With increasing awareness of transportation competition, if airline companies hope to survive and make profit, they have to realize that customer resource is the most valuable competitive advantage and try their best to satisfy the needs of their customers. Besides, Mowen (1988) emphasized that managers can reset promotional strategies to satisfy different types of consumers' desire most effectively, through the best channels [7]. Based on the above analysis, we decided to introduce a personalized content recommendation system to satisfy China air passengers' desire. As we all know, good relationship with customers is crucial for airline companies to keep advantage in competition and furthermore make profit in the long run. Using real history data from China Southern Airline and Bayesian network can fix best personalized contents to each individual passenger.

## 2. Consumer choice behavior and Bayesian belief network

This chapter introduces Bayesian belief networks (BBNs) for predicting air passengers' choice. On the basis of these choices, airlines can recommend best relevant content to passengers,

including products, service, tips, notices, feature introductions, and information sharing to improve their travel experience, satisfaction, and loyalty. The remainder of this paper is organized as follows. Section 2 briefly discusses a review of consumer choice behavior, provides some definitions, and illustrates advantages of Bayesian belief networks. In the next section, we establish BBN models by using the case of China Southern Airlines with real transaction data, including passengers' basic information, history decision options, and purchase characteristics to predict the possible contents which the consumer will choose, followed by model results and discussion.

## 2.1. Consumer choice behavior

When consumers face multiple alternative products, brands, and services, they tend to repeat the same choices that proved satisfactory in similar situations [4]. Information integration theory offers a specific mechanism to describe how individuals integrate separate pieces of available information into an overall index of preferences [5, 6]. The theory proposes that in situations where information about the products and brands are available in the marketplace, consumers tend to value and weight product attributes more often at the time of making a purchase decision. We formulated a comprehensive evaluation by combing consumers' values and weights under certain rules. Marketing managers should carefully study these decision-making processes and results to understand where consumers can collect relevant information, how consumers form beliefs, and what criteria consumers use to make product or service choices. As a result, companies can develop products that emphasize the appropriate attributes, and managers can reset promotional strategies to satisfy different types of consumers' desire most effectively, through the best channels [7]. Another interest issue to academia is in determining whether there are systematic differences in consumers' choice behavior. Identifying and understanding these differences are important for developing or formulating effective marketing strategies.

Consumer choice behavior has been mainly conceptualized as a combination of some socio-demographics and the attributes of alternatives [8]. Constructs, such as utility, attitude, or cognition, are used to map the attributes into one of the choice behavior. However, little research has been conducted about the choice process models considering the socio-demographic characteristics and the attributes of their decision alternatives in a recent study.

### 2.1.1. Consumer choice behavior in airline industry

In recent years, the airline industry faces the economic challenges, which are coupled with volatile fuel prices and pressure of environment protection. In addition, with increasing awareness of competition caused by the development of other transportation alternatives, if airline companies hope to survive and make profit, they have to realize that customer resource is the most valuable competitive advantage and try their best to satisfy the needs of their customers. Thus, good relationship with customers is crucial for airline companies to keep advantage in competition and furthermore make profit in the long run. Domestic and international airline companies have long shifted their attention to customer relationship management [9].

Relationship with passengers has been taken as one of the most important goals for every airline company to maximize passengers' loyalty and revenues. Besides good performance in airline operation and business management, another important key for success is leveraging power of customer relationship to attain superb performance. Those airline companies, who could correctly estimate trends and risks in the airline market and take necessary actions to satisfy their customers, could be much more successful in the industry.

Although understanding changing needs of passengers is of great importance for airlines, passengers' decision-making processes have received relatively little managerial attention. Therefore, further understanding of those decision-making processes is crucial for airline companies to improve their operations and business models [10].

With today's ever-increasing travel choices and growing consumer heterogeneity, numerous factors affect passengers' choices, for example, their socio-demographic status, decision-making patterns, cultural background, ticket cost, travel objectives, time schedule, and so on. The role of each factor is difficult to define, let alone the interaction between different factors. Leisure travelers are becoming more and more supply-oriented selecting airlines with most convenient schedules and best service experience. A change from selecting the travel destination and seeking for appropriate transportations to one, which a desirable airline service is initially set and the trip is arranged around in, will very likely alter the dominant social ideological trend of travel behavior.

## 2.2. Bayesian belief network

Belief networks are probabilistic graphical representations of models that capture relationship between different variables. Belief networks use either directed or undirected graphs to represent a dependency model. The directed acyclic graph (DAG) is more flexible and expressive. It is also able to investigate a wide range of probabilistic interdependency than undirected graphs. For example, induced and transitive dependency cannot be modeled accurately by undirected graphs, but can be easily represented in DAGs.

A causal belief network is made up of various types of nodes. An arc between two nodes represents a causal relation, an originating node of the arc is a parent node and the others are child nodes. A root node has no parents while a leaf node has no children. Each node has an underlying conditional probability table (CPT) that describes the option distribution for specific nodes associated with each possible combination of the parent nodes. Bayesian belief network (BBN) is a specific type of causal belief network, consisting of a set of nodes, where each node represents a variable in the dependency model and the connecting arcs represent the causal relationship among variables. **Figure 1** shows a simple BBN example about heart disease and heartache patients. The CPT's of the nodes is also illustrated in **Figure 1**. As for any causal belief network, the nodes represent stochastic variables and the arcs identify direct causal influences among the linked variables [11]. Each node or variable may take one of a number of possible states. The certainty of these states is determined from the belief in each possible state of all the nodes. The belief in each state of a node is updated whenever the belief

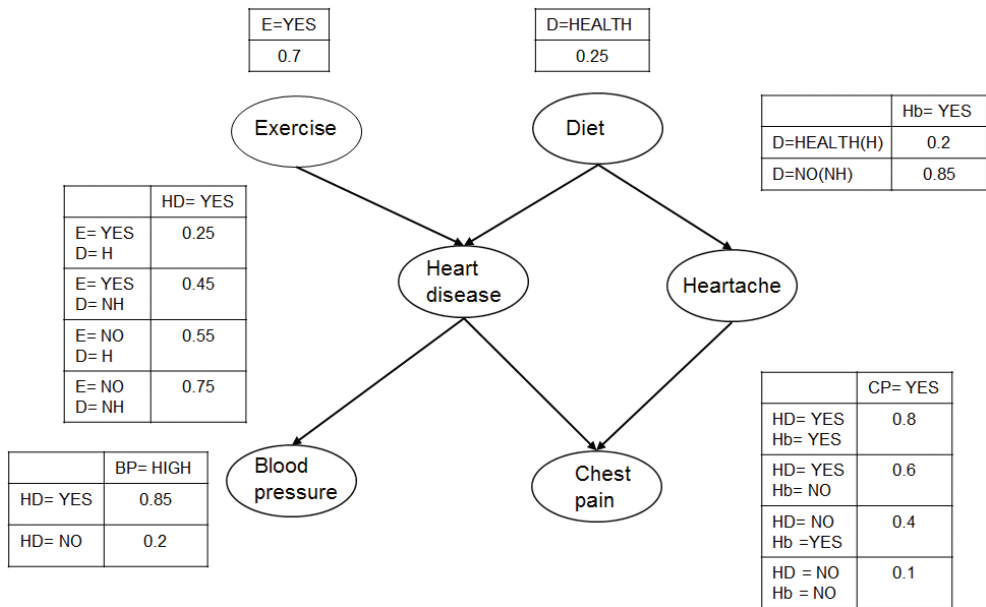


Figure 1. A Bayesian belief network depicting relationship among heart disease and heartache patients.

in each state of any directly connected node changes. The difference between Bayesian belief networks and other causal belief networks is that BBNs use Bayesian calculus to process the state probabilities of each node from the predetermined conditional and prior probabilities. The belief network is dynamic and their probabilities are subject to changes.

A Bayesian belief network is a graphical representation of a Bayesian probabilistic dependency within a knowledge domain [12], particularly appropriate for target recognition problems, where the category, identity, and class of target groups are to be recognized [13]. Bayesian belief networks have proven to be very useful, befitting to small and incomplete data collections. A Bayesian network can be, for example, used to save a considerable amount of space, explicit treatment of uncertainty, and support for decision analysis, casual relationship, and fast responses. Bayesian network is also suited to structural learning applications, and a combination of different sources of the preferred knowledge [14]. Besides, Bayesian approach finds the inclusion optimal model structure from data constructed by the a priori knowledge, and a constraint-based approach finds the optimal model structure from conditional dependences in each pair of variables. Given the ascertained information, Bayesian belief networks are used to determine or infer the posterior probability distributions for the variables of interest [11]. As such, they do not include decisions or utilities that typify the preferences of the users, but the user make decisions based on these probability distributions [11]. The causal relationships in Bayesian belief networks allow the correlation between variables to be modeled and predictions to be made. Comparing to classical statistical approaches, Bayesian belief networks have a distinct advantage [15]. BBN becomes not only a powerful tool for knowledge

representation but reasoning under conditions of uncertainty [16], frequently dealing with real-world problems such as building medical diagnostic systems, forecasting, and manufacturing process control for several decades [17]. Nowadays BBN has been extended to other applications including software risk management [18], ecosystem and environmental management [19], and transportation [20]. There is a great impact of key events on long-term transport mode choice decisions using Bayesian belief network, precisely Bayesian decision network, for the exploration of the suggested formalism in measuring, analyzing, and predicting dynamic travel mode choice in relation to key events and critical incidents [21]. However, seldom researches are found using BBN as an application in airlines marketing management. This paper introduces Bayesian belief networks using relative and contextual variables to estimate a logic relationship and test the causal mechanisms of current passengers' choice and predict their future preference.

### 3. Case study: BBN in China Southern Airlines

Air passengers make their choices using prior information available as well as information they obtain from the internal and external environments. Passengers integrate all the information actually available to them (including prior information and any information affect them) and turn them into preferences of a product. The basic aim is to support airline decision makers in their analysis of the impact of variables on passenger demand in the future. Prediction of passenger choice for the distant future is critical to guide managers in the specification of marketing strategies to be used. Such distant future predictions necessitate large-scale models of passenger choice but that pressing need contrasts sharply with the capabilities of traditional forecasting and modeling techniques. In this study, both qualitative and quantitative approaches are studied. Developed as such, the BBN is expected to guide airline managers in their future product decisions, facilitating analysis of specific decisions based on predicting the choice modes of passengers; highlighting the causal relationships among variables in the process and finally showing the impact of changes. To represent the dynamic nature of the causal relationship and to draw inferences based on the uncertainty concerning the states of the variables; this part constructs a Bayesian belief network for airline content recommendation mode using a case study of Chinese airline. A basic assumption of BBN is that when the conditional probabilities for each variable are multiplied, the joint probability distributions for all variables in the network are then calculated [22]. The structure is determined based on experts' judgments on content recommendation mode and a logic relationship.

Three components of a belief network are important: the nodes representing variables, the links among nodes, and states representing the expected utilities or probabilities. Therefore, the first step of the process is the development of a casual network. For this purpose, relevant variables and the logic relationship of this network should be determined. In the next stage, belief networks explore how the changes of states of variables (nodes) influence consumers' future choices and the needs of contents. Therefore, the static causal model is transformed into a dynamic one through the calculation of the Bayesian belief network. The resulting network is subjected to scenario analysis to help airline decision makers in their analysis on future product designs.

### 3.1. Determination of the basic variables and casual relations

To obtain a mutually, selectively exhaustive list of basic variables of the airline companies, interviews are conducted with airline domain experts, who are encouraged to identify the variables that might be relevant to the research. Thereafter, 35 variables are generated based on the situation of China and with weights of the expert judgments and estimation. The decision variables are classified into four groups:

1. Personal characteristics
2. Experience and behavior characteristics
3. Preference characteristics
4. Individuals' perceptions

Personal characteristics include airline passengers' demographic status and member information related to air travel. Experience and behavioral characteristics include passenger purchase behavior, decisions in choosing products, and attributes of particular experience. Preference characteristics include consumer preference and travel patterns. Individual perception describes the evaluation of passengers' loyalty, satisfaction, and comfort. After the identification of variables, the next step is the determination of the causal relations among all the variables. The use of this network is proposed to capture the knowledge and assumptions and to understand the mechanism of consumer choice processes'. The whole network is built up using Netica. The changes exist in the network are subjected to field tests using real world data from Chinese data sources.

### 3.2. Implementation of the BBN

The content recommendation is a new attempt in airline companies' new marketing strategies. After obtaining and integrating consumers' choice behavior, airline companies forecast and measure passengers' preference to predict intertemporal choices in the future. Based on the predicted choices, airline decision makers formulate relevant content and recommend it to target consumer groups. Passengers can get information about what they want to know which can improve their loyalty, satisfaction, and comfort with airlines. Better customer relationship, more market share in the fierce competition. Content recommendations include products, services, tips, notices, introductions, and information sharing. Products include popular routes; international and domestic hotels; duty free gifts, etc. Services include special assistance, baggage inquiry, online check-in, pre-paid luggages, and so on. Tips include travel guide, entertainment activities, lounge locations, and flight delays. News and promotions, mileage redemption, and offers are also included in notices. Introductions involve frequent flyer program, activities, flight and hotel, boarding and arrival procedure, and so on. Information sharing is a new measure applied to web search with the popularity of social media. Airline industry starts to realize this platform can further improve service experience. Passengers can link the data of Weibo (China popular social media) or WeChat to flight reservation process that is easy for them to know who are in the same flight [23]. The network in **Figure 2** shows airline content recommendations for given choices of passengers.



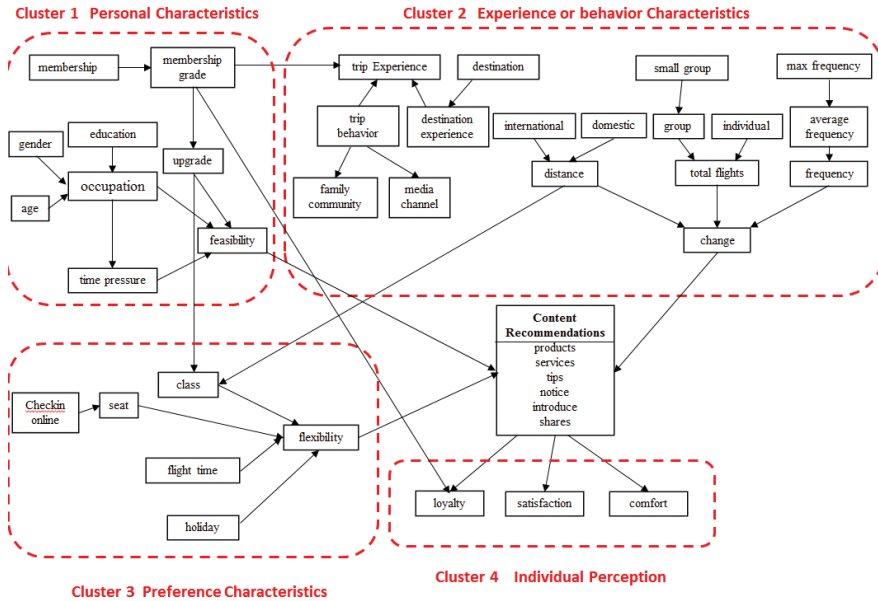


Figure 2. Network for content recommendation mode.

The first cluster illustrates personal information. Demographic data elements include gender, age, and education. By using these three attributes, one can speculate individual occupation and time pressure. Distinguishing leisure travelers and business travelers depends on time sensitivities. The node 'feasibility' indicates the air travel feasibility of each node combination, upgrade (yes or no), travel mode (leisure or business), and time pressure (yes or no). The second cluster depicts experience and behavior characteristic. The experience characteristic describes passengers' trip and destination experience. The third cluster represents passenger's preference such as fare class preference, seat preference, flight time preference, and holiday preference. It is worth to emphasize that distance and upgrade may lead passenger to change their class selections. Passengers will choose more comfortable classes when they take longer range flights. When it comes to membership upgrades, passengers are more likely to choose traveling first class to accumulate qualified miles. The fourth cluster describes individuals' perception evaluating the effect of variable changes on passengers' loyalty, satisfaction, and degree of comfort. This cluster refers to benefit variables that intend to cover the most significant perception. One of the benefit variables, namely, loyalty is affected by membership class. The higher the membership class, the higher level of stickiness to an Airline company. In this aspect, the outcome should take the weights of the benefit nodes into account.

### 3.3. Results and discussion

The data from airlines are used to complete all CPTs of the nature nodes. After completing all tables, we use Netica software to compile the network and determine the probabilities of six contents. Figure 3 shows the compiled decision network.

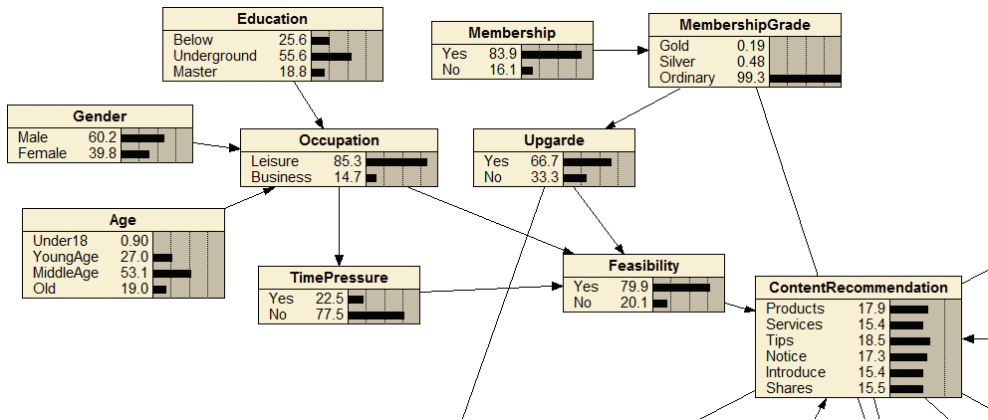


Figure 3. Compiled decision network (Cluster 1).

From **Figure 3**, the probability of tips is the highest, reaching 18.5% in total among all the contents decision options. Due to tips containing travel guide, entertainment activities, lounge caution, and delay calling, different kinds of hints remind passengers to have considerable experience. The probabilities of products and notice are around 17%. The other three contents are similar under the average level just over 15.4%. The beliefs and probabilities will be updated when evidence for certain nature nodes change. We will discuss some examples below.

After entering the evidence 'Yes' for the node 'Feasibility', which is colored gray in **Figure 4**, the belief for the decision nodes are auto-updated and recalculated. We find that only the probability of 'Introduce' option changed according to this new evidence. When air traveling is totally feasible for passengers no matter his or her travel purpose is holiday or business, the 'Introduce' is less useful to provide them flight information, boarding, and arrival procedure what they already know. They concern more about the services, delay caution, popular routes, holiday destination, and so on.

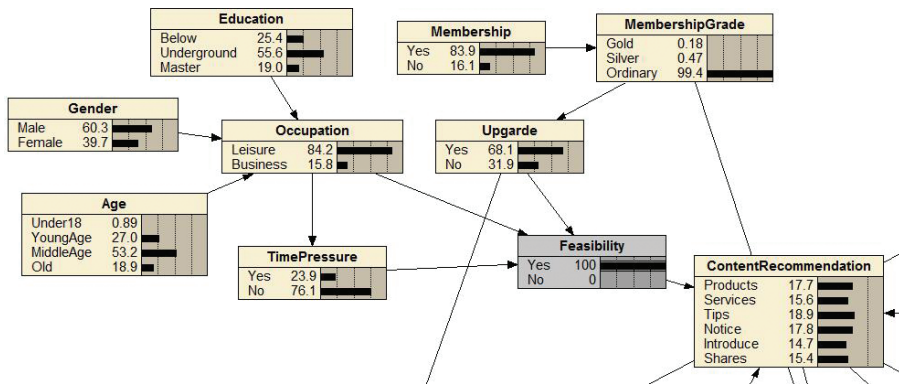


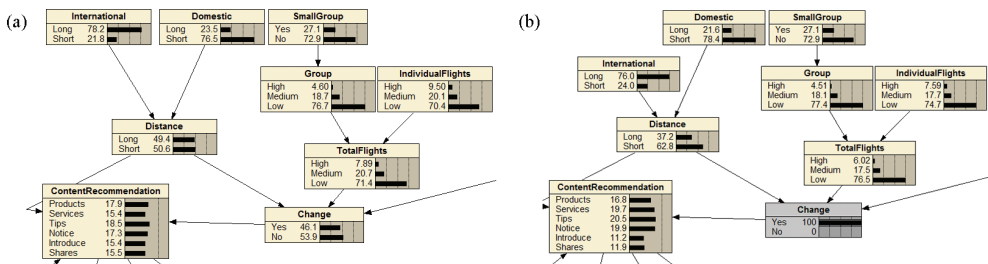
Figure 4. Compiled decision network ('Feasibility' = 'yes').

**Figure 5** represents the influence of the evidence ‘Yes’ for the nature node ‘Change’ on the decision options mode. The beliefs and probabilities updated automatically. The results illustrates if passengers change their purchase behavior or trip modes, for example, taking high-speed train, the effective method to retain their customers, airline managers could recommend relative tips and notice to them and give them more comfortable services.

We compiled network with the ‘Long’ for ‘Distance’, ‘High’ for ‘TotalFlight’, and ‘High’ for ‘Frequency’, respectively. The consequences are represented on **Figure 6 (a–c)**. The trends of three results are similar. The probabilities of ‘Products’, ‘Introduce’, and ‘Shares’ rise outstanding. However, what surprised us is that the probabilities of ‘Services’ decrease sharply. This result gives decision makers a good suggestion that passengers who have high frequency traveling behavior need products recommendation, destination introduce, web link to share when they experience long range journey. In the same way, the service is not as important as other aspects.

As each passenger has own preference. The information about preference is too diverse, so that we introduce a nature node ‘Flexibility’ to describe the overall variation of consumers’ preferences. Controlling states of these nodes, including seat, class, flight time and holiday, have no obvious effects on decision option modes. Therefore, we set ‘Flexibility’ to ‘Yes’ for sure in **Figure 7**. ‘Shares’ has the biggest change in the entire content recommendation options mode that means ‘Share’ is the most useful method to address flexibility problems whose regular pattern is hard to capture. Facing this situation, airline managers share links to their passengers on social media to release a service “meeting & sitting in the same flight” [23]. As the results shown in **Figure 8**, the membership class has significant influence on customers’ loyalty. Members with highest qualification are stickier to their choices of airlines; the probability of high loyalty ascends from 35.7 to 85.2% when we set ‘Yes’ for state ‘Gold’. Moreover, more than half of silver card owners remain loyal to their airline companies. For airlines, managers should better service loyal customers, reduce the loss of customers and mining new customers.

In the first part, we come up with three questions: How can we infer consumers’ choice for content in the future? How to design a model using only current period choices to infer consumers’ inter-temporal preferences? Is the process dynamic and it allows the researchers to analyze influences of effect changes?



**Figure 5.** (a) Compiled decision network (Cluster 2). (b) Compiled decision network ('Change' = 'Yes').

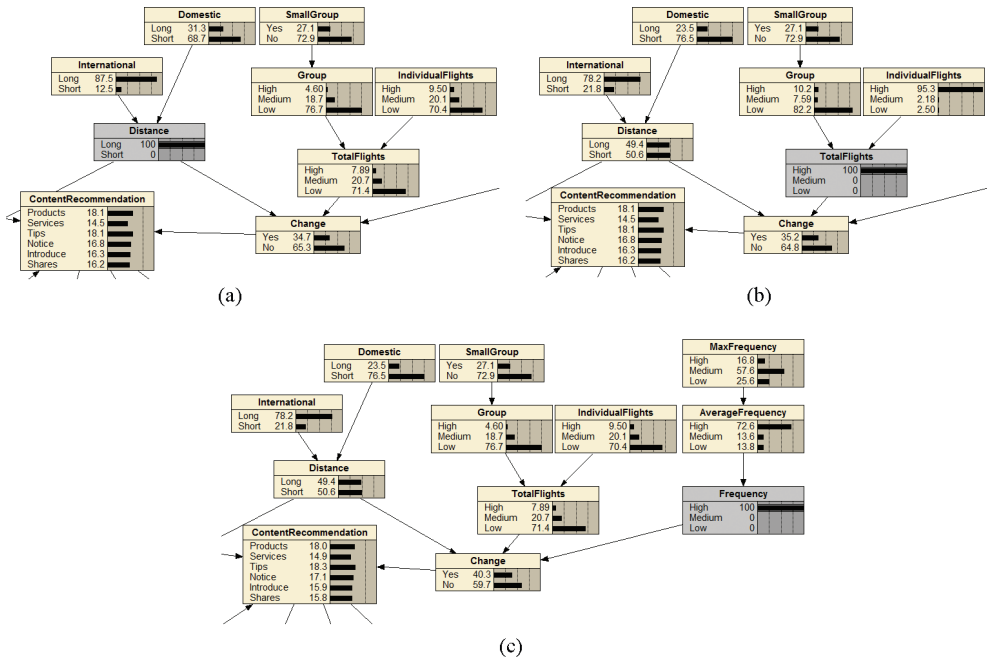


Figure 6. (a) Compiled decision network ('Distance' = 'Long'). (b) Compiled decision network ('TotalFlights' = 'High'). (c) Compiled decision network ('Frequency' = 'High').

This paper uses automatic updating process to explain the dynamics of belief networks. BBN model represents a complex network that constructs and model consumer choice process. From the examples above, we investigate clearly how the evidence of one state of a node change affects the probability of decision options. Based on China Southern Airline historical real data, we predict the passengers' choice and help airline managers recommend relative contents to satisfy passengers' needs.

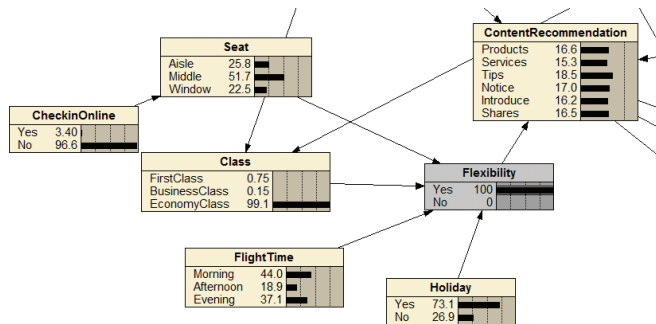


Figure 7. Compiled decision network ('Flexibility' = 'Yes').

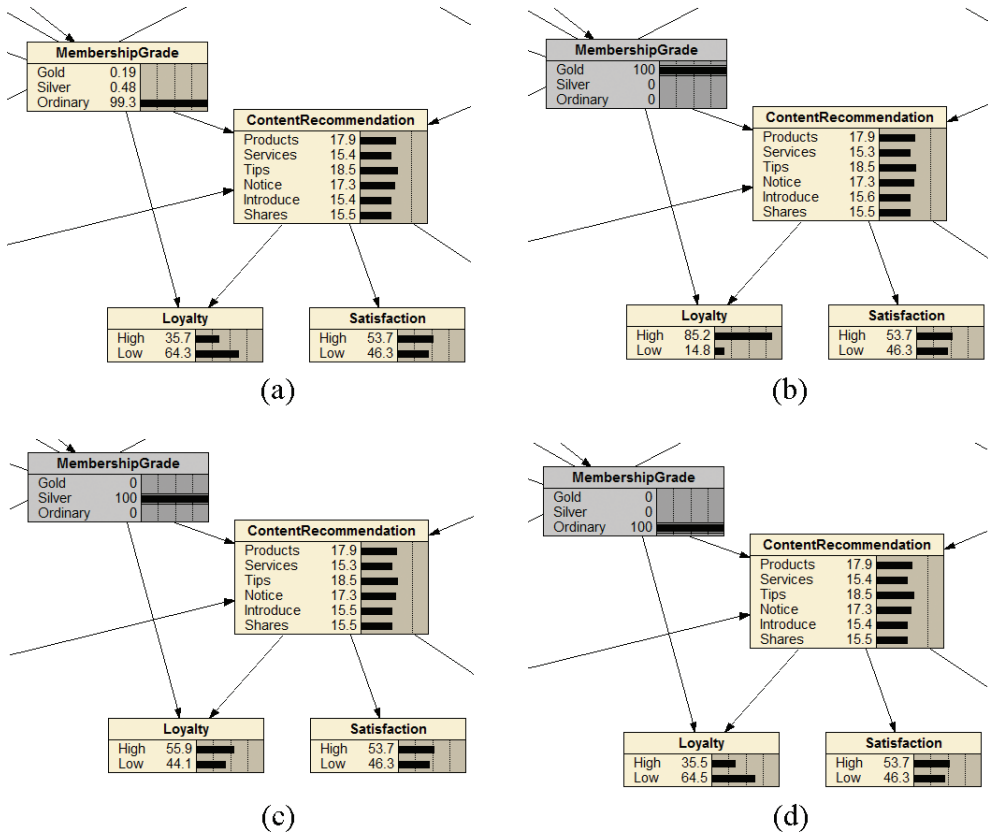


Figure 8. (a–d) Compiled decision network of Cluster 4.

### 4. Conclusion and implications

This article measures air passengers' preference and predicts their choices in the future based on current choice behavior using Bayesian belief network. This network can represent complex choice behavior and causal relationship among different variables, and the use of the probability of options can capture passengers' dynamic decision-making processes. The most powerful of the Bayesian network is that the probability of getting results from each stage is a reflection of mathematics and science. In other words, the network will infer reasonable results if we obtain enough information based on statistical knowledge.

We illustrate it by conducting a detailed empirical study of a data set from a Chinese Airline company. Our research demonstrates that understanding the extent to which the consumer choice behavior is beneficial for airline managers strategic decision making.

To help with formulating better marketing strategies, the airline companies may consider adoption of the following procedures.

1. To track detailed consumer behavior: inquiry of products, reservation, payment, ticket issue, check-in, waiting, cabin service, luggage claim, mileage accumulation.
2. To analyze consumer behavior: purchase behavior, tour experience, choice behavior, preference.
3. To set up high-level products: high-level customization; customized design and products design, relevant product support.
4. To use social media: share web link, extract information from social media and social network.

A good strategy should analyze passengers' trip behavior and preferences to conduct cross selling, filter unnecessary information, and to present consumer recommendations and offer the most valuable product portfolio to customers.

We expect that, together with the need for the more specific features; BBN combined with Artificial Intelligence and deep learning are of great value to addressing uncertainty problems and consumer choice behavior in the future.

## Author details

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