

# Modelling Consumer Choice Behaviour with Bayesian Belief Networks

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## 1 INTRODUCTION

Human behaviour is complex and often not transparent. Nevertheless, one would like to understand human behaviour and especially the underlying choice mechanisms and reasoning. Understanding choice behavior is of utmost importance in both the private and public sector. In the business world, companies are interested in consumer choice behaviour because a better understanding of consumer choice behaviour allows them to introduce more successful products and increase their market share. Public agencies introduce different policies to stimulate a certain (desirable) behaviour. The effectiveness of such policies will improve as their understanding of the decision processes underlying those choices increases.

Choice behaviour is often context-dependent: conditions beyond socio-demographics and the attributes of the choice alternatives influence the outcome of the decision. The typical choice models, developed in marketing and urban planning, capture statistical relationships between the dependent and a set of independent variables. To capture the complexity of daily decision-making, a modelling approach that allows estimating direct and indirect effects, the inclusions of contextual and situation-specific variables and the specification and testing of causal mechanisms may offer (some) advantages in better representing the mechanisms leading to a particular choice.

The aim of this paper is to illustrate the use of Bayesian Belief Networks (BBN) for modelling consumer choice behaviour problems. The advantages of this method are that it allows representing a complex network with direct and indirect causal relationships between a set of variables, that it can handle uncertainty in the reasoning process, and that it is based on a probabilistic chance distribution among the various states of a variable.

This paper will first briefly discuss some existing models of consumer choice behaviour, followed by a summary of Bayesian Belief Networks. Next, the input for a network and two different approaches to build a network will be described. The following section illustrates the use of Bayesian Belief Networks for modelling transport mode choice, which can be seen as an example of consumer choice behaviour. The paper will be concluded by discussing the potential of the suggested approach.

## **2 CONSUMER CHOICE BEHAVIOUR AND BBN**

Over the years, a wealth of studies on consumer choice behaviour has accumulated in the literature. The different theories about consumer choice behaviour are mainly influenced by economics, later on theories were also influenced by psychology and sociology. Most choice models include only a limited number of variables to keep the model simple and easy to understand. However, to model complex behaviour we should include more variables, and consequently the model becomes complex and may be difficult to comprehend. The Bayesian Belief Network method (BBN) is a strong tool to model complex decisions and might be useable in this context.

### **2.1 Theories of Consumer Choice Behaviour**

In our daily life we are all consumers, sometimes we make conscious choices and other decisions are habitual. For example when a person is shopping for products in the supermarket he/she probably will have a standard route and the choice of products is often an automatic process, like a habit. The choice was made before and it is not necessary to make this choice over and over again. Only if something important to the customer, such as the price, taste of the product or the addition of a new brand, changes people may reconsider their decision. In some cases, which do not happen that often, like the purchase of a car, consumers may become heavily involved in the decision making process and really consider many possible alternatives and make a well considered decision. The business world is very interested in these decision processes, because it helps them to understand consumers' choice behaviour and consequently they could anticipate in order to stimulate desired behaviour, for example purchase of a specific product.

Wierenga *et al* (1987) describe consumer choice behaviour as all personal actions that are part of acquiring, using or discarding products or services in order to satisfy their own needs. The actual purchasing of a product is important just like the corresponding actions. Those actions could involve parts of the decision process, like orientation, obtaining advice from other consumers or consulting a consumers' magazine. Three theories of consumer choice behaviour are explained; economic theory, classical economic utility theory and the characteristic approach. The economic theory is based on the distribution of income among saving and purchasing products. The classical economic utility theory assumes that the consumer is familiar with all possible choice options and will choose the option, in this case a product, which corresponds to the highest satisfaction or in other words, utility. Effects of possible changes in price or income could be analysed with this theory. The characteristic approach is based on the assumption that consumers evaluate characteristics that describe the products. Different decision rules can be used to make the actual choice, a combination of different rules is possible as well. Some rules are compensatory, which means that one (bad) characteristic can be compensated by an other (good) characteristic.

Admittedly, these theories are only few of many others. Many other theories of consumer choice behaviour, stemming from disciplines other than economics, could be mentioned. Psychology has identified constructs like motivation, perception, attitude and

expectations. Sociology acknowledged the influence of a social network; consumers operate in a certain social environment. Other persons in that social network may influence purchasing decisions. However, as implicitly indicated by Wierenga *et al*, most theories have in common that consumer choice behaviour has been mainly conceptualized as a function of the attributes of the choice alternatives and some socio-demographics. Constructs such as utility, satisfaction, attitude or motivation have been used to map the attributes into one of these constructs and subsequent choice behaviour. However, choice behaviour is often context-dependent: conditions beyond socio-demographics and the attributes of the choice alternatives influence the outcome of the decision. Moreover, process models and models accounting for inherent uncertainty in the choice process are still rare.

These limitations of most existing and frequently applied theories and models of consumer choice behaviour imply that it may be worthwhile to consider other approaches that allow decision making under uncertainty and context-dependent choice. This paper will explain the possibilities of Bayesian Belief Networks that allow estimating direct and indirect effects, the inclusions of contextual and situation-specific variables and the specification and testing of causal mechanisms.

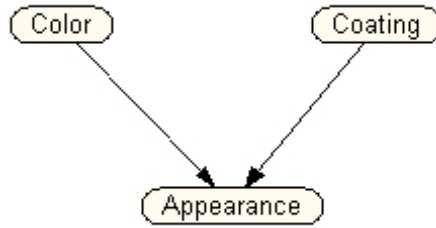
## 2.2 Bayesian Belief Networks

Bayesian Belief Networks (BBN) developed in fields such as Artificial Intelligence and Machine Learning represent a powerful approach for combining different knowledge sources with various degrees of uncertainty in an efficient and structured way. Surprisingly, BBN have not yet found major application in consumer choice behaviour. An exception is Arentze *et al* (2005), they empirically estimated behavioural models using BBN, more precisely decision networks, to structure mental maps for shopping scheduling decisions. The Bayesian learning was also used by Erdem (1996) in a theoretical framework to derive brand choice probabilities depending on past usage experience and advertising.

A Bayesian network is a network representation of the interrelationships and conditional dependencies between a set of variables (Neapolitan, 1990). The network consists of several nodes, which represent variables, and arcs, that connect nodes and represent causal relationships between the nodes. The representation of variables (nodes) have several states; which correspond with the classes or options of the concerning variable. For example the variable (node) 'color' could have several options (states): red, green, yellow, blue etc. Each node has an underlying conditional probability table (CPT) that describes the chance distribution across the states of that specific node for each possible combination of states of the parent nodes. An arc between two nodes represents a causal relationship, the node from which the arc originates is called the parent node and the other node is called the child node.

A simple BBN is designed to illustrate the use of Bayesian belief models, see figure 1. In this case the network represents the influence of color and coating on the appearance of a car. This network consists of three nodes, with the following states: color (red, green, yellow or blue), Coating (metallic or not metallic) and Appearance (shining or not

shining). The nodes Color and Coating are the parent nodes for the Appearance node, which is also called the child node.



**Figure 1:** Simple BBN example

The CPT of a node that has no parents is simple, it only contains the states of this node and the chance distribution across the states. The CPT's of the nodes color and coating are illustrated in table 1 and 2. In this example, the chance that the color is red is 0.30, the chance that the color is green is 0.2 and the sum of all chances is of course 1.0 (for each row).

**Table 1:** CPT of the node Color

Red	Green	Yellow	Blue
0.3	0.2	0.1	0.4

**Table 2:** CPT of the node Coating

Metallic	Not Metallic
0.4	0.6

The CPT of a child node is more complicated; the conditional probability table expands with the states of the involved parent node(s). The CPT describes the chance distribution across the states of that specific child node for each (combined) state of the parent node(s). Table 3 shows the CPT of the child node appearance.

**Table 3:** CPT of the node Appearance

Color	Coating	Shining	Not shining
Red	Metallic	0.7	0.3
Red	Not Metallic	0.2	0.8
Green	Metallic	0.9	0.1
Green	Not Metallic	0.5	0.5
Yellow	Metallic	0.95	0.05
Yellow	Not Metallic	0.8	0.2
Blue	Metallic	0.6	0.4
Blue	Not Metallic	0.1	0.9

Each node has a certain probability, which represents conditional beliefs about the likelihood of possible outcomes for each node. The initial probabilities for a node that has no parents are simple, they exactly correspond with the chance distribution across the states as shown in table 1 and 2. The probabilities of a child node depend on the belief of the parent nodes.

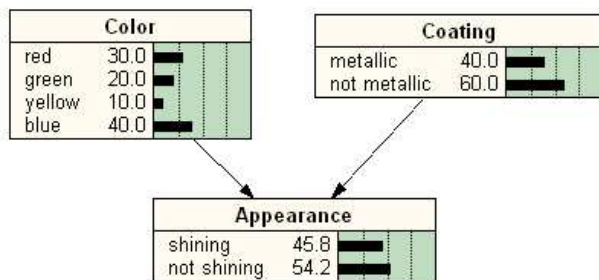
Standard algorithms can be used to compile the network and determine the expected belief of each node state. Using the same algorithms, beliefs can be updated when evidence for certain nature nodes becomes available and is entered to the network. Figure 2 illustrates the beliefs for the three nodes. Using the numbers of tables 1, 2 and 3, the belief for the states 'shining' of the 'appearance' node can be calculated as follows:

**Belief state 'shining'** = (chance 'red' x chance 'metallic' x chance 'red & metallic') + (chance 'red' x chance 'not metallic' x chance 'red & not metallic') + (chance 'green' x chance 'metallic' x chance 'green & metallic') + (chance 'green' x chance 'not metallic' x chance 'green & not metallic') + (chance 'yellow' x chance 'metallic' x chance 'yellow & metallic') + (chance 'yellow' x chance 'not metallic' x chance 'yellow & not metallic') + (chance 'blue' x chance 'metallic' x chance 'blue & metallic') + (chance 'blue' x chance 'not metallic' x chance 'blue & not metallic') =

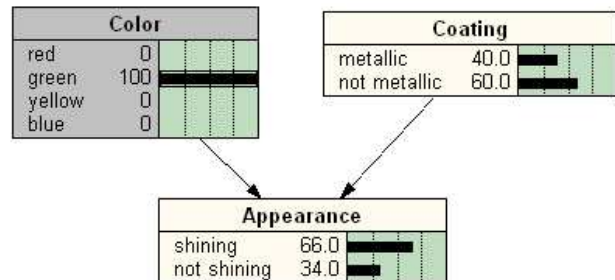
$$(0.3 \times 0.4 \times 0.7) + (0.3 \times 0.6 \times 0.2) + (0.2 \times 0.4 \times 0.9) + (0.2 \times 0.6 \times 0.5) + (0.1 \times 0.4 \times 0.95) + (0.1 \times 0.6 \times 0.8) + (0.4 \times 0.4 \times 0.6) + (0.4 \times 0.6 \times 0.1) = \mathbf{0.458}$$

**In addition the belief for the state 'not shining' is equal to:  $1 - 0.458 = 0.542$**

This is also called forward reasoning; the beliefs of a child node depend on the beliefs of the parent node(s).



**Figure 2:** compiled BBN



**Figure 3:** entered evidence parent node

The BBN can handle uncertainty, in other words it can calculate the beliefs for several states. If evidence for a certain node becomes available it can be entered in the network and all the beliefs will be updated automatically. For example, the evidence 'green' for the node 'color' is entered and the beliefs for the states of the node 'appearance' change. Figure 3 illustrates the belief of the BBN when the evidence is entered to the network. The evidence exists of a 100 percent certainty that the color is green.

Again the beliefs of the ‘Appearance’ node can be calculated in the same way, the changed numbers are bold:

$$\text{Belief state 'shining'} = (0 \times 0.4 \times 0.7) + (0 \times 0.6 \times 0.2) + (1 \times 0.4 \times 0.9) + (1 \times 0.6 \times 0.5) + (0 \times 0.4 \times 0.95) + (0 \times 0.6 \times 0.8) + (0 \times 0.4 \times 0.6) + (0 \times 0.6 \times 0.1) = \mathbf{0.66}$$

In addition the belief for the state ‘not shining’ is equal to:  $1 - 0.66 = \mathbf{0.34}$

Besides forward reasoning, calculate the beliefs of child nodes, there is also backward reasoning which allows calculation of the beliefs of a parent node(s), the other way around. Therefore the well-known Bayes formula is used:

$$P(A | B) = \frac{P(B | A) \cdot P(A)}{P(B)} \tag{1}$$

where:

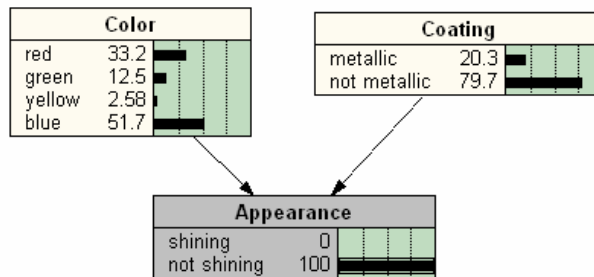
$P(A)$  is the prior probability or marginal probability of A. It is ‘prior’ in the sense that it does not take into account any information about B.

$P(A | B)$  is the conditional probability of A, given B. It is also called the posterior probability because it is derived from or depends upon the specified value of B.

$P(B | A)$  is the conditional probability of A, given B.

$P(B)$  is the prior or marginal probability of B.

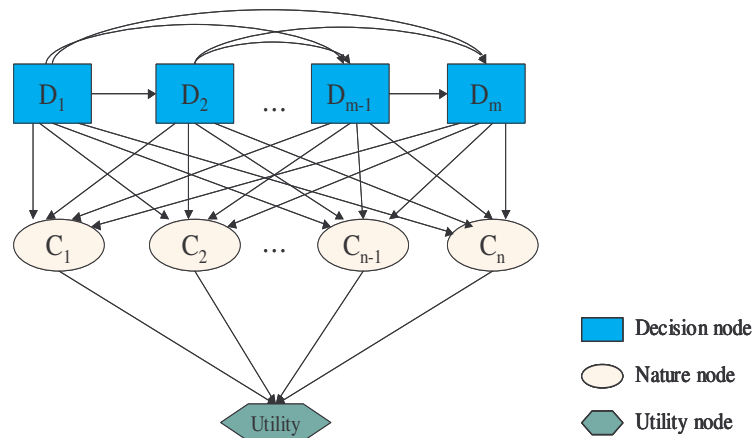
Figure 4 illustrates the result of the entered evidence ‘not shining’ for the child node ‘appearance’. The beliefs of the parent nodes ‘color’ and ‘coating’ are automatically updated. The beliefs for ‘red’ and ‘blue’ of the nature node ‘color’ increases even as ‘not metallic’ of the nature node ‘coating’.



**Figure 4:** entered evidence child node

A decision network is an extended Bayesian belief network. The nodes in a BBN are actually called nature nodes in terms of Bayesian Belief Networks. A decision network (DN) consist of three different node types; nature node(s), decision node(s) and utility node(s). The possible states of a decision node represent the options for that decision (i.e., a choice set). Since the decision maker is free to decide which option to choose, the initial probability distribution across states of a decision node is uniform and,

therefore, no CPT needs to be defined at the level of decision nodes. As basic belief networks, the links represent causal relationships between the nodes. Typically, a nature node represents a situational variable or a direct or indirect consequence of decision options that are relevant for making a choice. A utility node represents preferences of the decision maker. A so-called conditional utility table (CUT) is associated to each utility node. This table has a similar format as a CPT. However, rather than a probability distribution, it defines a utility value for each combined state of the parent nodes indicating how the decision maker evaluates that state.



**Figure 5:** General structure of Bayesian Decision Networks

The DN shown in Figure 5 has an idealized form. In reality, not necessary all decision and nature nodes are interconnected, nature nodes may be interconnected mutually, there may exist links directly between decision nodes and the utility node and the network may include multiple utility nodes. Links between decision nodes are special as they do not represent cause-effect relationships. Rather, they indicate the sequence in which decisions are to be made. For that reason the links are called ‘non-forgetting’ links. The only restrictions include that the graph is a-cyclic and that directions of the links are consistent with the direction of the causal relationships.

Standard algorithms can be used to compile the network and determine the expected utility of each decision option. Using the same algorithms, beliefs and expected utilities can be updated when evidence for certain nature nodes becomes available and is entered to the network. In case of a single decision node, the expected utility of a decision option is calculated as the sum of the products of probability and utility across the possible direct and indirect outcomes of the decision option. In case of multiple decision nodes, the expected utility of a decision option is defined as the expected utility of that decision option under the condition of the best decisions on the next decision variables.

### **3 CONSTRUCTING A BAYESIANS BELIEF OR DECISION NETWORK**

We argue that a Bayesian Belief Network or a decision network constitutes an adequate formalization to represent direct and indirect causal mechanisms. In this paper we will illustrate the use of Bayesian Belief Networks to conceptualize a complex (decision) network of choice behaviour.

#### **3.1 Construction**

There are two possible approaches to construct a network; expert knowledge and learning algorithms. The first approach is to use existing knowledge (e.g, literature, expertise, etc.) to build and structure the network. The input for a network consists of a set of variables and their direct and/or indirect causal relationships. In the case of a Bayesian Belief Network the variables are all represented by nature nodes. If a Decision Network is constructed the variables could be represented by nature nodes, decision nodes and utility nodes. Common knowledge, logic or statistical data can be used to complete the conditional probability table(s) and the conditional utility table(s).

The second approach is to use a learning algorithm to construct a network. Learning bayesian belief networks has traditionally been divided into two categories: structural and parameter learning. Structural learning determines the dependence and independence of variables and suggests a direction of causation, in other words, the position of the links in the network. Parameter learning assumes the structure of the network as given and determines the conditional probabilities at each node of the network, given the link structures and the data. Data is necessary to use a learning algorithm.

Both approaches could also be mixed, experts can provide the structure of the network using domain knowledge and the CPT's can be extracted from empirical data using parameter learning. Two networks, one based on (expert) knowledge and the other based on structural (and parameter) learning, could be compared in order to test the (dis)similarities.

#### **3.2 Complex Network**

The Bayesian technique is a strong tool to structure a complex (decision) problem. A structural learning algorithm can guide the process of constructing a belief network, but also common knowlegde or literature can be used to structure an network. It is recommended to divide all variables into groups or clusters. Start with one group or cluster and construct the causal relations between the variables. If you immediately visualize the CPT's you can decide if the relation between those variables make sense.

As mentioned before human behaviour is complex and not transparant. Nevertheless, one would like to understand human behaviour and especially the underlying choice mechanisms and reasoning. BBN supports reasoning about direct and indirect relations between involved variables, which would eventually end in a result of a well structured visualisation of the (decision) problem.

A lot of choice problems deal with the same variables, or the same group of variables. A general structure could speed up the construction process. For example consumer choice problems always include a decision variable, which is the product or service considered and several characteristics or variables that influence the decision variable. Those characteristics could be grouped into;

- 1) personal characteristics
- 2) product / service characteristics
- 3) context characteristics
- 4) individuals' perceptions and evaluations

Personal characteristics (1) describe a person, like socio-demographics. But they also could describe an existing 'product state'. For example, describing the electronic devices in the states 'already owned; not owned, but interested; not owned and not interested'. Product or service characteristics (2) describe several characteristics of that particular product or service. For example, when a consumer wants to buy wine he/she will consider characteristics like color, taste, brand and price. Characteristics of a store could be context characteristics (3), but in case of drinking wine the context could also be described in terms of dinner; for example the choice of wine could depend on the choice of main course. Individuals' perceptions and evaluations (4) describe the characteristics that are important for the decision. The perceptions could be represented as nature nodes and for evaluation utility nodes could be included. The following part of this paper illustrates a decision network for transport mode choice, which can be seen as an example of consumer choice behaviour.

## **4 TRANSPORT MODE CHOICE DECISION NETWORK**

In this part the construction of a decision network for transport mode choice will be described and illustrated. Transport mode choice is an example of consumer choice behaviour, where the consumers choose a transport mode out of a set of available transport modes. The first section describes the structure of the network, the second section explains the data collection method (including the questionnaire) that was used to complete the CPT's and CUT's. Finally the compiled network will be illustrated with the expected utilities for the decision options.

### **4.1 Decision Network Structure**

The decision network in figure 6 models the transport mode decision for a given trip of an individual. Hence, the network includes only a single decision node that concerns the transport mode choice for the trip. The structure was determined based on the general literature on transport mode choice and common knowledge about logical relationships. The nature nodes are grouped in three clusters.

The first cluster deals with personal characteristics, in this case the availability of certain transport modes. The links in this cluster represent logical relationships. For examples: the nature node 'feasibility' indicates the feasibility of every state combination of mode

choice, bike possession (yes or no), drivers license (yes or no) and car possession (yes or no). The utility node in this cluster 'utility feasibility' defines a penalty (a strongly negative utility) for an infeasible state and a zero utility for a feasible state, to make sure that infeasible choices are never made.

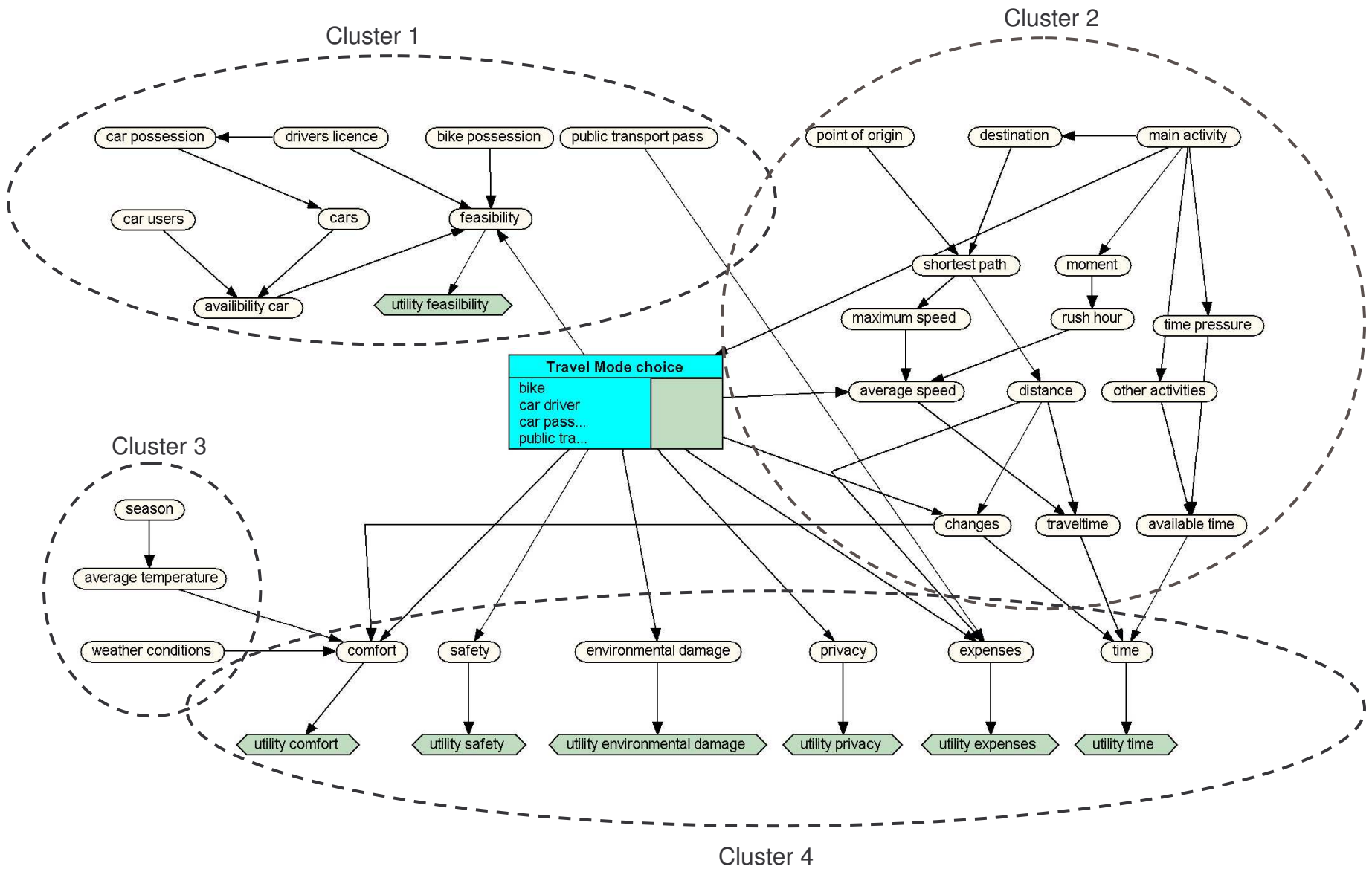
The second cluster describes product or service characteristics. For transport mode decisions this could be trip characteristics such as origin location, destination location, trip distance and trip purpose. Again, the structure in this cluster represents logical relationships. If no uncertainty would be involved, the beliefs would be represented by zero/one probabilities.

The third cluster represents context characteristics, like some situational variables. In this particular application, only weather conditions are taken into account. Depending on the application, other situational factors could be added such as available time for the activity and day of the week.

The fourth cluster deals with the individuals' perceptions and evaluations of different aspects for the trip considered. The aspects refer to benefit variables, such as safety, comfort, privacy and costs. The nature nodes represent the subjective assessments for the given trip on these benefit dimensions. Each benefit variable is dependent on the choice of transport mode. Other benefit variables are in addition influenced by situational factors or trip attributes. Related to each nature node is a utility node representing the subjective evaluation (a utility value) of each outcome of that benefit variable. In a decision network, the total (expected) utility is defined as the sum of (expected) utilities across utility nodes and, therefore, the utilities defined for each benefit outcome should take the relative weight of the benefit variable into account.

The benefit nodes included in the network intend to cover the most important considerations individuals generally have in making a choice between transport modes.

The whole network is built up in the software program Netica (Norsys Software Corp., 1997). We emphasize that the links included in the network are based on literature and our knowledge about transport mode choice. Whether or not the influences exist is subject to testing based on data about transport mode choice behavior.



**Figure 6:** Decision Network for transport Mode Choice

## 4.2 Questionnaire

It is convenient to complete the CPT's and/or CUT's of a decision network with data. This is not always an option; a complex network demands an extensive and rather particular data collection. In this case an Internet-based questionnaire was designed to collect data for this decision network. The questionnaire consisted of the following components:

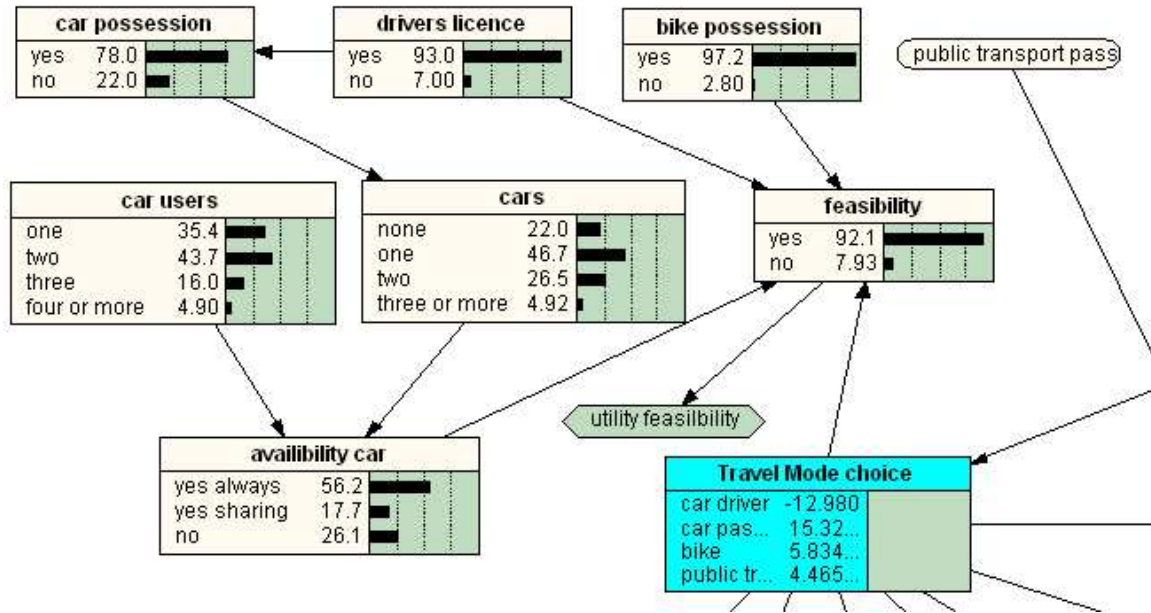
1. Household and personal characteristics;
2. Availability of transport mode;
3. Current travel behavior per trip purpose: work, study, shopping, and sports;
4. Perception of trip conditions: comfort, safety, privacy, environmental damage, expenses, and time (CPT-part);
5. Stated preference part for evaluation of the selected trip conditions.

The second part of the questionnaire provides information for the CPT's of the first nature node cluster (figure 5). The current travel behaviour data was used to complete most of the labels of the nature nodes of the second cluster. To complete the CPT's of the third cluster statistical data and logic was enough. The respondents completed in the fourth part of the questionnaire the CPT of each nature node of the fourth cluster network model. The stated preference part of the survey used an orthogonal fraction of a full factorial design to generate profiles in terms of the benefit variables. Respondents were asked to indicate their preference for each profile on a 0-100 scale. Based on this data, utility functions can be estimated which then can be used to define the utilities in the CUT's of the fourth cluster.

To collect the required data a sample was drawn using an Internet-based survey. E-mail addresses were collected from a set of colleges and universities in the Netherlands. Approximately 2400 emails were sent with a request to participate and to send the mail to three other persons. In total 710 respondents finished the whole survey.

## 4.3 Compiled Decision Network

Transport mode choice was conceptualized in a decision network, based on general literature and common knowledge. The data was used to complete almost all conditional probability tables of the nature nodes and all the conditional utility tables of the utility nodes. If all the tables are completed, Netica compiles the network and determines the expected utility of each decision option. The expected utility of a decision option is calculated as the sum of the products of probability and utility across the possible direct and indirect outcomes of the decision option. Figure 7 presents the compiled decision network.



**Figure 7:** Compiled Decision Network with expected utilities

The expected utility for the different choice options is in this case calculated for the whole sample of respondents. The expected utility of the choice option 'car driver' is negative (-12.98), the utilities of the other choice options are positive; 15.32 for 'car passenger', 5.834 for 'bike' and 4.465 for 'public transport'. The negative utility of 'car driver' is a consequence of the uncertainty in the personal characteristics cluster; it is not certain if there is a drivers license, if there is a car available etc.. Moreover the utility node in this cluster 'utility feasibility' defines also a penalty (a strongly negative utility, in this case -100) for an infeasible state and a zero utility for a feasible state, to make sure that infeasible choices are never made. The beliefs and expected utilities can be updated when evidence for certain nature nodes becomes available and is entered to the network. This is also called 'hard evidence'.

For example the evidence 'yes' for the nature node 'feasibility' is entered (see Figure 8). This change means that instead of the probabilistic chance distribution across the states 'yes' and 'no' from the node 'feasibility' now the model deals with the deterministic evidence of 'yes' for the node 'feasibility'. The beliefs and the expected utilities for the the decision node options are automatically recalculated. Figure 8 represents the decision network with this new evidence. The nature node 'feasible' is coloured grey, this illustrates that 'hard evidence' is entered for this node. The new expected utility for the 'car driver' option is now positive; 15.93. Of the other choice options, only the expected utility of the 'bike' option changed according to this new evidence. The entered 'hard evidence' also influenced the beliefs of the bike possession node. Those beliefs are automatically updated with backward reasoning. The beliefs of the bike possession node change from yes = 0.972 and no = 0.028 in the begin situation to yes = 0.9704 and no = 0.0206 after entering the evidence of feasibility is yes. The other transport mode options, car passenger and public transport, are always available. Moreover the feasibility of

those two transport modes don't depend on the causal relations with the nature nodes bike possession, car availability and drivers license. The deterministic CPT of feasibility node therefore always has the option feasible if the transport mode is public transport or car passenger.

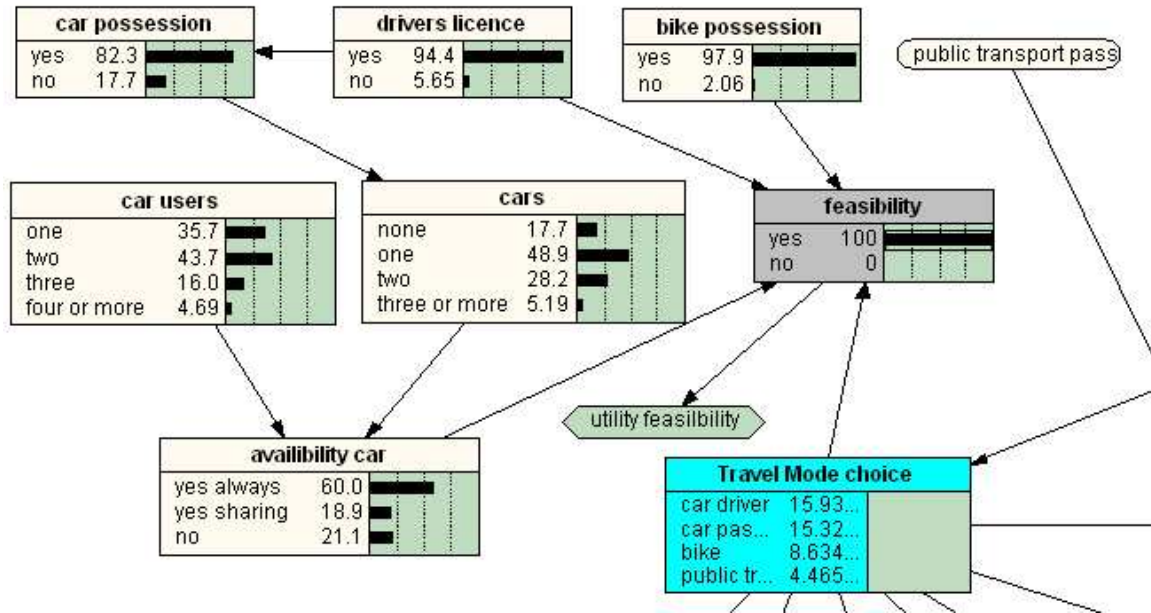


Figure 8: Compiled Decision Network with entered evidence (feasibility = yes)

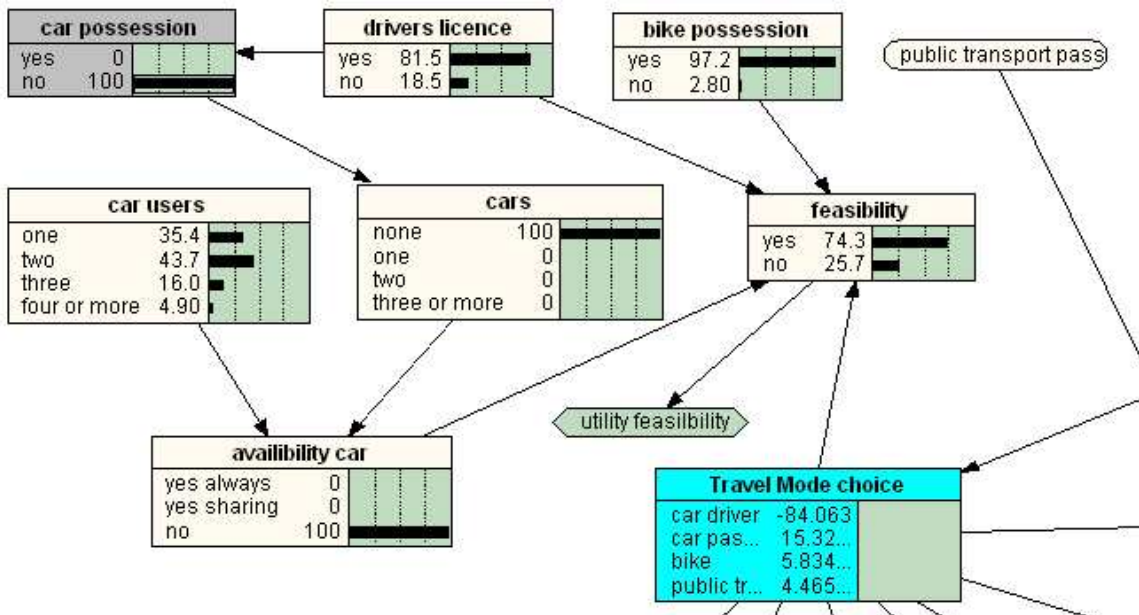


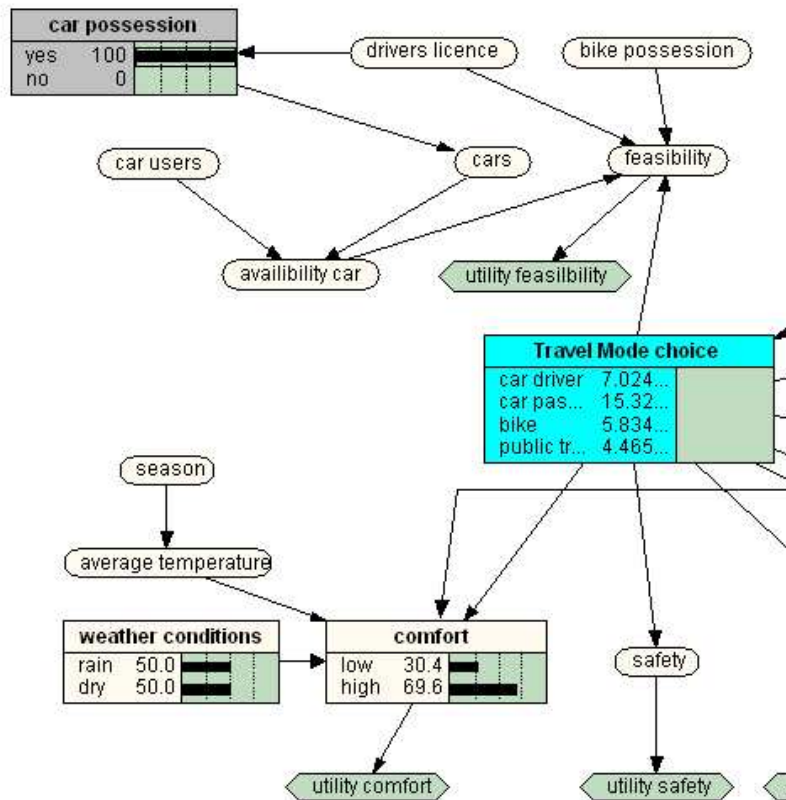
Figure 9: Compiled Decision Network with entered evidence (car possession = no)

Figure 9 illustrates the impact of the evidence 'no' for the nature node 'car possession' on the expected utilities of the mode options. The beliefs and expected utilities are automatically updated. The expected utility for the mode option car driver decreases and becomes more negative; from -12.98 in the begin situation (figure 6) to - 84.063 after entering the new evidence. The beliefs of the nodes with are causally linked with the node 'car possession' are also updated. For example the beliefs of the nodes 'cars' and 'availability car' change into 'none' and 'no'. This is of course the result of the CPT's of these nodes. The conditional probability table of the node 'cars' is presented in table 4.

**Table 4:** CPT of the node Cars

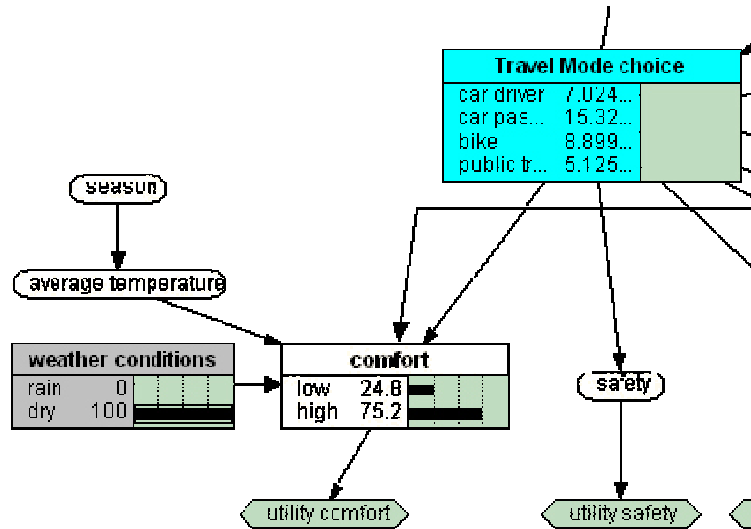
Car possession	None	One	Two	Three or more
Yes	0.000	0.598	0.339	0.063
no	1.000	0.000	0.000	0.000

The examples mentioned above only illustrated the effects of the personal characteristics part on transport mode choice. With one other example we also explain the effects of changes in the context part and the individuals' perceptions and evaluations part. Figure 10 illustrates the compiled network with the evidence 'yes' for the nature node 'car possession'. In this case all the expected utilities are positive.



**Figure 10:** Compiled Decision Network with expected utilities (car possession = yes)

There is no certainty about the weather conditions, the chance that it will rain is 0.50. The beliefs for the 'comfort' nature node are based on the data collection. The respondents filled in the exact CPT's of these individuals' perceptions node in part 4 of the questionnaire. The CUT of these evaluations nodes are based on the questionnaire part where the respondents filled in the stated preference. Figure 11 illustrates the effects of the evidence 'dry' for the nature node 'weather conditions'.



**Figure 11:** Compiled Decision Network with entered evidence (car possession = yes and weather conditions= dry)

The expected utilities of the mode options bike and public transport change, they increase. For the mode options car driver and car passenger there is no difference in weather conditions, the chance distribution in the CPT of the node 'comfort' doesn't depend on those conditions. The increase of the expected utilities for the bike and public transport options is a result of the change in beliefs for the nature node 'comfort'. The beliefs of a high comfort level increased because of the dry weather conditions.

This automatic updating process illustrates the dynamics of an decision network. This transport mode decision network is based on a specific data collection. So, it describes the effects, changes and preferences for this sample. For that reason this decision network could not be used in general.

## 5 CONCLUSION AND DISCUSSION

This paper described the technique of Bayesian Belief Networks and explored its possibilities for modelling consumer choice problems. The advantages of this promising method, such as representing a complex network with direct and indirect causal relationships between variables, including uncertainty, the use of a probabilistic chance distribution among the states of a variable and the dynamic updating of the network in

case of entering new evidence, can offer some advantages compared to other methods to capture the complexity of consumer decision making.

A decision network for transport mode choice was discussed in more detail. Transport mode choice behaviour is also a kind of consumer behaviour, the product is the transport mode and the product characteristics at benefit level, on which consumers evaluate the product, are comfort, safety, environmental damage, privacy, (travel)expenses and (travel)time. This network could be translated into a consumer choice network for any other consumption product.

A Bayesian belief network could be used to structure or model consumer choice behaviour. A compiled network is very dynamic and it allows the user to analyze influences of changes. For example if hard evidence is entered for a certain node all beliefs will be updated and in the case of a decision network the expected utilities for the choice options are recalculated. This could be very useful if you want to know which impact a new product could have on consumer choice behaviour. Further research could focus on structuring consumer choice behaviour in a general network or construct a network for a specific branch or product. An existing data collection or results from a questionnaire could help compile the network in order to predict consumer choice behaviour/preferences in terms of choice probabilities (for BBN) or expected utilities of the choice options (for DN).

BBN are relatively new to the consumer choice literature in general and retailing and services in particular. The potential advantage of the approach is that BBN takes direct and indirect relations between probabilistic variables into account.

The aim of this paper was to illustrate the use of Bayesian Belief Networks (BBN) for modelling consumer choice behaviour problems. The intention was an eye-opener for a new powerful and promising modelling method. Hopefully this paper will convince people to explore the possibilities of this approach in their study of consumer choice behaviour.

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