

Modeling the influence of structural lifecycle events on activity-travel decisions using a structure learning algorithm

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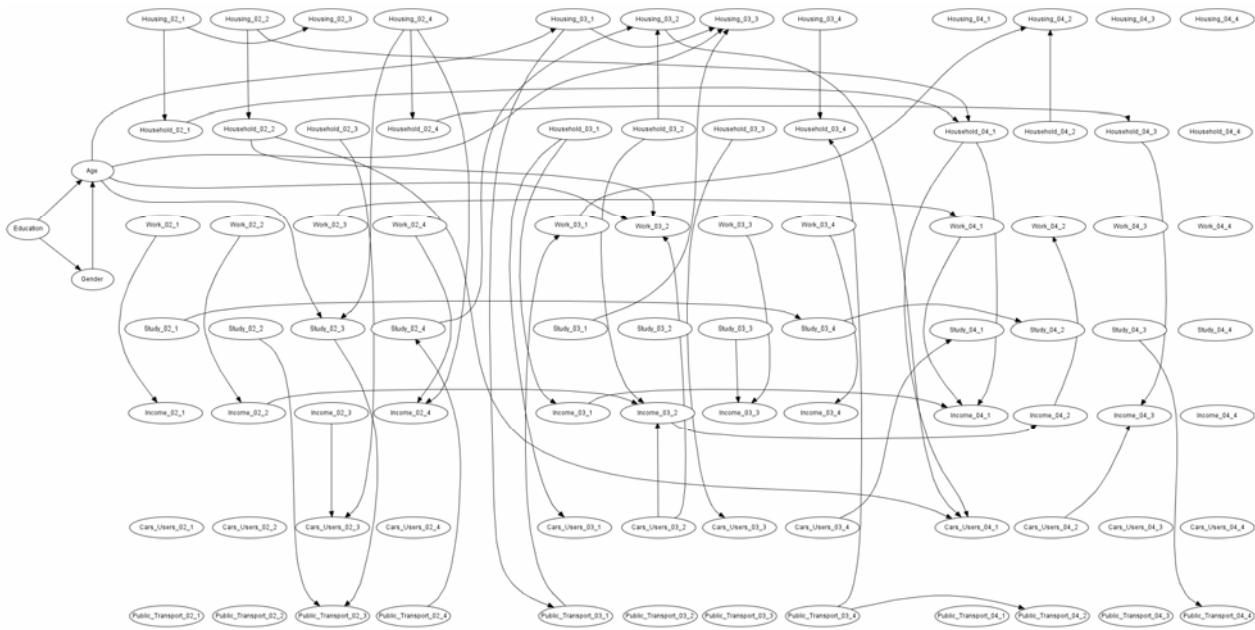
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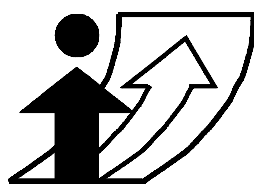
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Verhoeven, Eindhoven University of Technology
 Arentze, Eindhoven University of Technology
 Timmermans, Eindhoven University of Technology
 van der Waerden, Eindhoven University of Technology

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Marloes Verhoeven
Urban Planning Group
Eindhoven University of Technology
The Netherlands
Phone: 040-247 28 61
Fax: 040-243 84 88
E-mail: m.verhoeven@bwk.tue.nl

Theo Arentze
Urban Planning Group
Eindhoven University of Technology
The Netherlands
Phone: 040-247 22 83
Fax: 040-243 84 88
E-mail: t.a.arentze@bwk.tue.nl

Harry Timmermans
Urban Planning Group
Eindhoven University of Technology
The Netherlands
Phone: 040-247 22 74
Fax: 040-243 84 88
E-mail: h.j.p.timmermans@bwk.tue.nl

Peter van der Waerden
Urban Planning Group
Eindhoven University of Technology
The Netherlands
Phone: 040-247 46 84
Fax: 040-243 84 88
E-mail: p.j.h.j.v.d.waerden@bwk.tue.nl

Abstract

This paper describes the results of a study on the impact of lifecycle events on activity-travel choice decisions of individuals. An Internet-based survey was designed to collect data concerning structural lifecycle events. In addition, respondents answered questions about personal and household characteristics, possession and availability of transport modes and their current travel behavior. In total, 710 respondents completed the online survey. The complexity of transport mode choice is modeled using a Bayesian Belief Network. Previous papers describe the conceptual framework underlying the model and the temporal effects of lifecycle events on mode choice. This paper focuses on influences of structural life trajectory events on each other and on changes in resources that impact activity-travel decisions. We investigate the

extent to which causal relations exist between these events and their direct and indirect effects on changes in transport mode availability and the possession of transit passes. A structure learning algorithm is used to build a Bayesian Belief Network of interdependencies between these events from the data.

Keywords

Structural lifecycle events, Bayesian Belief Network, Structure Learning and Parameter Learning.

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1. Introduction

The increasing interest in encouraging public and slow transport modes has stimulated the need for further research about transport mode choice decisions. The effectiveness of transport policies in decreasing car use and stimulate alternative transport modes such as bike and public transport will benefit from a better understanding of the decision process underlying transport mode choices. It is generally believed that decision processes underlying transport mode choice are much more complex than traditional models reflect. Traditional transport mode choice models typically assume that the probability that an individual will choose a particular transport mode is a function of attributes of the choice alternatives and a set of socio-demographics (Verhoeven *et al*, 2005a).

However, transport mode choice decisions are not made in isolation. Choice behavior is often context-dependent, implying that conditions beyond socio-demographics and attributes of the choice alternatives influence the outcome of the decision. Moreover, the dynamics of transport mode decisions are often ignored. We assume that other aspects in addition to socio-demographics and attributes of the choice alternatives influence the transport mode choice decision. In particular, structural lifecycle events that occur during an individual's and household's life course could trigger shifts on activity-travel choice decisions of individuals. Traditional models often take changes in attributes into account. However, these changes are not modeled in a dynamic network. In this context, structural lifecycle events are defined as major events in a person's life such as moving house, an increase or decrease in the number of persons in a household, and changing job or job location.

We assume that an individual is more likely to reconsider his/her current mode choice after or in anticipation of the occurrence of a structural lifecycle event. Some structural lifecycle events, for instance moving to another residence, may dramatically change the spatial context within which travel mode choice decisions have to be made. A consequence of this change could be a shift in characteristics, like accessibility, distance and travel time relationships, and with it a shift in the utilities an individual derive from alternative travel modes. Such structural lifecycle events may also trigger other events, such as a change in car possession, that may expand or reduce a choice set. The change in situation may trigger learning processes so that the implications for choice behavior may materialize gradually over time after the event.

The aim of the study is to analyze the influence of structural lifecycle events on activity-travel decisions with a special focus on changes in resources influencing transport mode decisions using a Bayesian Belief Network (BBN). BBN is a powerful knowledge representation and reasoning tool, depicting the direct and indirect effects between probabilistic variables. A BBN takes into account the (inter)dependencies among the variables which are involved in the complex decision making process without imposing a hierarchy of importance on the variables of the model. The advantage of using a network structure is that both direct and indirect effects of events can be measured and modelled.

This paper describes the first results of a study that examines the causal relationships between structural lifecycle events and their effect on activity-travel decisions. First, we will discuss our perspective of taking structural lifecycle events influence activity-travel choice. Next, we will discuss briefly how Bayesian Belief Networks can be used to model the problem at hand and

how the structure and parameter learning algorithms work. After that, our modeling approach is illustrated and the data collection, which is used to build the network, is introduced. Finally, the core contribution of the paper will be discussed: the application of a structure learning algorithm to derive the causal structure of the Bayesian Belief Network. The paper will be concluded by discussing the potential of the suggested approach and some avenues of future research.

2. Structural Lifecycle Events and Activity-Travel Decisions

Activity-travel choices are not made in isolation, choice behavior is often context-dependent. The dynamics of activity-travel decisions are often ignored in traditional models. Van der Waerden, *et al* (2003a, b) argued that critical incidents and key events may be relevant concepts for studying the dynamics of activity-travel. Structural lifecycle events are the main events they considered. Later, Prillwitz and Lanzendorf (2006) described the impact of life course events on car ownership, while Beige and Axhausen (2006) described long-term mobility decisions in terms of a life course. To model the effects of key events, Verhoeven, *et al* (2005a, b) argued that a Bayesian Network may constitute a valuable approach. More recently, Xie *et al* (2006) also applied this approach in modeling travel mode choice behavior. Their explanatory variables were personal characteristics, such as household income, household size, dwelling type, travel time etc.

In this study, we explore the causal relations between structural lifecycle events at different moments in the past and activity-travel choice, with special reference to car changes in ownership and transit pass. A structural lifecycle event is defined here as a major event in a person's life such as a marriage or move that may trigger a process of reconsideration of current behavior. Some events may dramatically change the space-time context within which travel decisions have to be made. Moving house implies a shift in characteristics such as accessibility, distance/travel time relationships and perhaps also the utility an individual derives from alternative travel modes. An event such as changing jobs may also lead to changes in these characteristics. A final example is the birth or adoption of a child, which may induce new activities (e.g. day care).

This new perspective is modeled in terms of a Bayesian Belief Network. The advantages of this method are that it allows representing a complex network with direct and indirect causal relationships between a set of variables and that it is based on probabilistic distributions among the various states of a variable. This BBN method is explained briefly in the next section.

3. Bayesian Belief Networks

Bayesian Belief Networks (BBN) developed in overlapping 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. A Bayesian network is a network representation of the interrelationships and conditional dependencies between a set of variables (Neapolitan, 1990).

Bayesian networks are directed acyclic graphs (DAGs) in which the nodes represent variables, the arcs signify the existence of direct causal influences between the linked variables, and the strengths of these influences are expressed by the forward conditional probabilities (Pearl 1988). The directed acyclic graphs do not allow undirected or bidirectional arcs and cyclic feedback loops are neither permitted. A Bayesian network consists of two components: 1) a structure component (i.e., the DAG), which specifies the structure of cause-effect relationships between variables; and 2) a parameter component, which consists of a set of conditional probability distributions that provide the statistical interpretation of the cause-effect dependence relationships depicted by the graphical structure.

Thus, 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 relation, the node from which the arc originates is called the parent node and the other node is called the child node. 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 sum of all chances is of course equal to 1.0 (for each row). The CPT of a child node is more complicated; the conditional probability table expands with the possible state configurations 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). Each node has a certain probability distribution, which represents posterior probabilities 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 in the CPT. The probabilities of a child node depend on the probabilities regarding the parent nodes.

A Bayesian network is denoted by $B(G, \Theta)$, in which $G=(N, A)$ is a DAG where N , the set of nodes, represents a set of variables $X = \{X_1, X_2, \dots, X_n\}$ and A is a set of arcs representing the directed dependency relationships from parent nodes to child nodes, and Θ denotes a set of CPTs associated with the node set N and the arc set A , where $\theta_i \in \Theta$, where $i = 1, 2, \dots, n$, is the CPT of variable X_i , $\theta_i = P(X_i | \Pi_i)$, given the parent variable set Π_i of X_i . In a given Bayesian network B , marginal and conditional independencies encoded by its DAG structure provide the following factorization of the joint probability distribution:

$$P(X_1, X_2, \dots, X_n) = \prod_{i=1}^n P(X_i | \Pi_i) \quad (1)$$

Standard algorithms can be used to compile the network and update probabilities when evidence for certain nodes becomes available and is entered to the network. The BBN can handle uncertainty in the sense that it uses probability distributions across states. If evidence for a certain node becomes available it can be entered in the network and all probability distributions can be updated by automated procedures.

4. Learning Networks

Until now we assumed that the structure and conditional probabilities necessary for characterizing the network were provided externally, say by an expert or an intelligent agent

capable of encoding real-world experience in such terms. Our task has been to draw inferences from the network but not to challenge its authenticity. It is not always easy to construct a complicated network based on the literature and/or common knowledge. Fortunately, nowadays, methods are available that support the derivation of a network automatically from direct empirical observations, thus bypassing the human link in the process known as *knowledge acquisition*.

Pearl (1988) describes that the task of finding a generic model of empirical data usually falls under the category of learning. Learning can be thought of as the process of acquiring an effective internal representation for the persistent constraints in the world, i.e., generic facts and rules, as well as assembling the computational facilities by which predictions and explanations are produced. Learning is comprised of two subtasks; *structure learning* and *parameter learning*. Taking Bayesian belief networks as the basic scheme of knowledge representation, the learning task separates nicely into two additional subtasks; learning the numerical parameters (i.e., the conditional probabilities) for a given network topology and identifying the structure itself, specifically, the links and the directionality of the arrows. These subtasks are clearly not independent because the set of parameters needed depends largely on the structure assumed, and conversely, the structure of the network is formally dictated by the joint distribution. Still, it is more convenient to execute the learning process in two separate phases: *structure learning* and *parameter learning*.

Hugin, a software program for learning Bayesian networks (Hugin Expert, 2005), uses the PC or NPC algorithm for structure learning and the EM algorithm (Estimation-Maximalisation) for parameter learning. The PC algorithm, which Hugin uses, is a variant of the original PC algorithm (Spirtes *et al*, 2000) and it belongs to the class of constraint-based learning algorithms. The basic idea of these algorithms is to derive a set of conditional independence and dependence statements by statistical tests. The PC algorithm consists of the five following steps (Spirtes *et al*, 2000 and Jensen *et al*, 2002):

1. Statistical tests for conditional independence are performed for all pairs of variables (except for those pairs for which a structural constraint has been specified).
2. An undirected link is added between each pair of variables for which no conditional independences were found. The resulting undirected graph is referred to as the skeleton of the learned structure.
3. Colliders are then identified, ensuring that no directed cycles occur. (A collider is a pair of links directed such that they meet in a node.) For example, if we find that A and B are dependent, B and C are dependent, but A and C are conditionally independent given S, not containing B, then this can be represented by the structure $A \rightarrow B \leftarrow C$.
4. Next, directions are enforced for those links whose direction can be derived from the conditional independences found and the colliders identified.
5. Finally, the remaining undirected links are directed randomly, ensuring that no directed cycles occur.

The first two steps are repeated until all the possible pairs are tested. First only pairs are tested (no conditional relations), after that pairs are tested conditional on a third variable and so on until all pairs are tested conditional. The following independence testing procedure is used for the first step in the PC algorithm: If variable X causes variable Y , it implies a probabilistic dependency, $P(Y|X) \neq P(Y)$. Thus, if the null hypothesis of marginal independence of X and Y ,

$H_0 : P(Y | X) = P(Y)$ or $P(X, Y) = P(X)P(Y)$ is rejected, the directed dependence $X \rightarrow Y$ is supported.

One important thing to note about the PC algorithm is that, in general, it will not be able to derive the direction of all the links from data, and thus some links will be directed randomly. This means that the learned structure should be inspected, and if any links seem counterintuitive the NPC algorithm, which allows the user to interactively decide on the directionality of undirected links, could be used instead. Another possibility is to import constraints in the structure learning process. Constraints describe where no directed or undirected link could appear.

The EM algorithm (Lauritzen 1995, Cowell and Dawid (1992)) tries to find the model parameters (probability distribution) of the network from observed (but often not complete) data that maximizes the log-likelihood of the current joint probability distribution on the case data (for details of the method readers are referred to Lauritzen (1995) and Cowell and Dawid (1992)).

5. Modeling Approach

The assumed effect of events on activity-travel decisions is inspired by the theory of learning and adaptation. According to this theory, individuals develop and continuously adapt choice rules while interacting with their environment. Transport systems, urban environments are highly dynamic, non-stationary and uncertain. People are also very dynamic; they adapt to all kind of changes (Arentze *et al*, 2003).

The reinforcement learning approach assumes that individuals' choices in complex environments are driven by rules that are formed and continuously adapted through learning while the individual is interacting with the environment. Through search an individual explores choice opportunities in his or her environment and keeps a memory record of the varying rewards associated with his actions. Actions that produce positive rewards are reinforced and have a higher probability of being repeated in future choice situations under similar conditions, while actions with negative outcomes tend to be avoided. In stationary environments, reinforcement learning implies that random behavior will ultimately evolve into habitual behavior.

In non-stationary environments, a gradually changing environment or discrepancies between the changing environments and changing personal or household circumstances may imply that the behavior of interest is no longer adequate to cope with the new situation. An individual may then have to change one or more facets of his habitual behavior, and/or change household resources such as number of available cars or transit passes that influence such patterns. Structural lifecycle events may have a similar, but attenuated effect. A dilemma for any individual, who has limited knowledge about new circumstances, is the choice between exploration and exploiting current knowledge. Selecting actions that have not been tried before gives the opportunity of discovering new choices that may yield higher rewards than the currently best action. However, this comes with the risk of negative experiences. Individuals who wish to avoid such risks may stick to the currently best choice. Thresholds for reconsidering current choices and the thoroughness of search will vary depending on the

individual’s tendency to take or avoid such risks.

The link with this general theory of learning and adaptation and lifecycle events is that by learning and adaptation individuals have adapted to some extent to their environment, and are therefore in some state of equilibrium (exhibit habitual behavior) until an event causes such an amount of change that an individual feels the need to start exploration, implying they may reconsider their current choices and/or resources. Such behavior may be reactive or proactive. Learning would imply that adaptation to new circumstances takes time and, hence, that current behavior cannot be fully understood in terms of the current state of the individual and the environment. Besides learning processes, other mechanisms may produce temporal effects such as delayed responses (people respond to a change only after some time), accumulation of stress (people avoid too many changes in a short amount of time), etc.

The existence of temporal effects of lifecycle events on mode choice was tested in a previous paper (Verhoeven *et al*, 2005b). The results of a regression analysis indicated that all identified events had significant temporal effects. Moreover, the effects were interpretable in terms of particular temporal patterns of adaptation. We assume that a structural lifecycle event changes a certain personal situation, i.e., state. Figure 1 illustrates such influences in a graph. In this example, the events describe changes in residential location and the substates describe the different residential conditions. This graph represents (a part of) the life course of one individual. For instance an individual lives with his parents (substate C) and he/she moves in the first quarter of 2004 to his/her first dorm room (substate B). Soon after this change he/she moves again and starts living together (substate A). This example illustrates transitions between different substates, which describe the residential condition of an individual; substate A = living on your own, state B = living in a dorm room and state C = living with parents. The event describes changes in residential situation. Several different type events are possible; for example first dorm room, another dorm room, living on your own, renting a house, buying a house, etc.

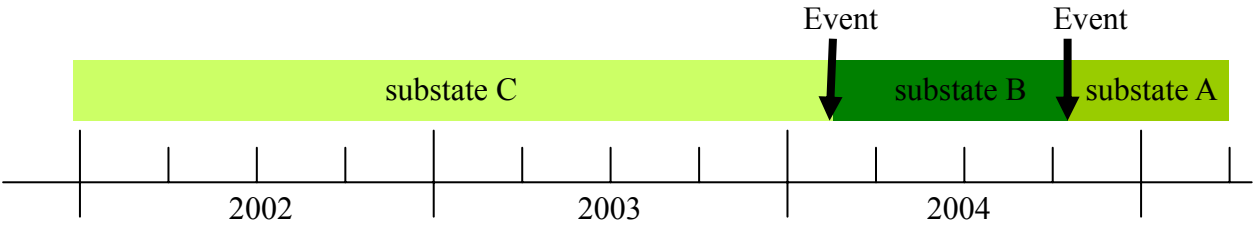


Figure 1: Effects of events on one state dimension

Figure 2 illustrates another example of changes in states caused by a structural lifecycle event. In this case the structural lifecycle event describes changes in household composition. There are different aspects of household composition and, hence, dimensions of states, namely the number of household members (state 1), the number of children (state 2) and the marital state (state 3). Figure 2 illustrates the changes in household composition and the corresponding substates for one individual. In this example the event in the third quarter of 2002 is a birth/adoption of a child. This results in a change in state 1, from two persons (substate B) to three persons (substate C). State 2 changes from no children (substate A) to 1 child (substate B), while state 3, the marital state stays the same, i.e. married (state C). The second change, the event in the third quarter of 2004, is also a birth/adaptation of a child. These two changes have

no effect on state 3, marital state, this state stays the same. In case of a change such as getting married, it will only affect state 3 and states 1 and 2 will stay the same.

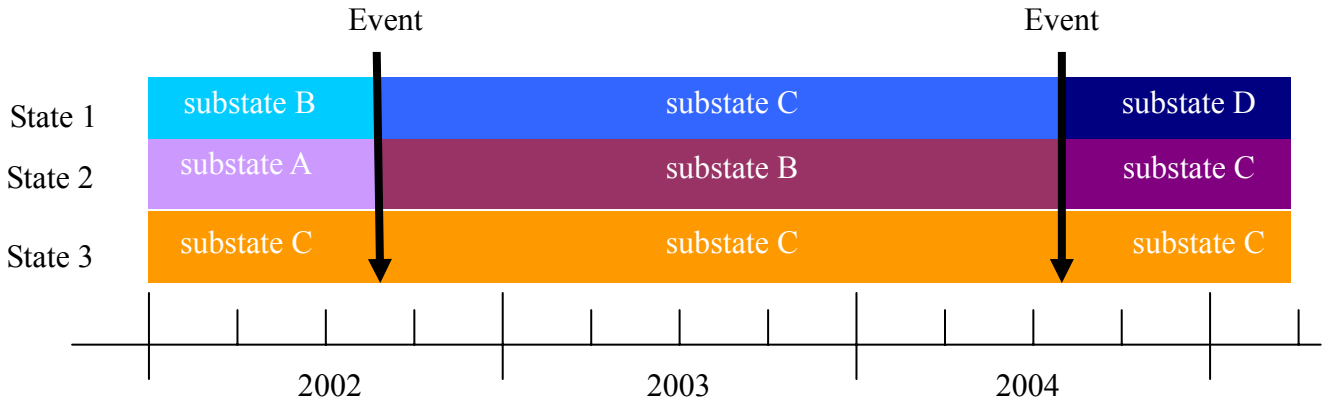


Figure 2: Effect of changes of an event on more states

Figures 1 and 2 represent parts of a life course for one individual. Events may however be interrelated and have complex relationships with (aspects of) activity-travel behavior and attributes of the person that are not influenced by events (e.g., education, age, gender, etc.). In order to describe those influences of events for more individuals and take the complexity into account a Bayesian network is constructed. Figure 3 illustrates one component of this conceptual model describing the influences of events on states in time on a single dimension. The first row corresponds with a structural life cycle event, for example change in residential location. The first possible change in residential location for the time period $t=1$ is illustrated with node E_1 , the second possible change in residential location for the time period $t=2$ is illustrated with node E_2 , and so on until time period t . For every time period there is a corresponding state, which describes a personal situation. The logical causal relationships are represented with arrows; from Event to State within the same time period and from a prior State to the next State.

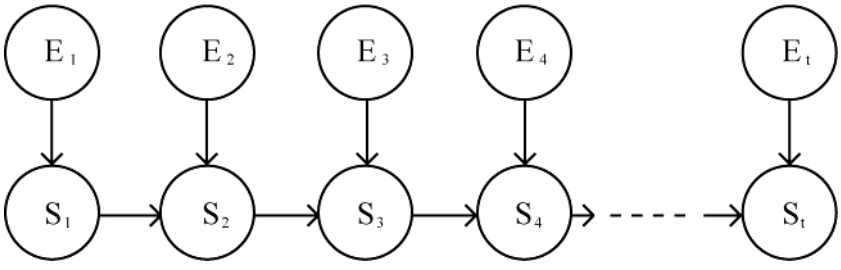


Figure 3: Assumed conceptual model of the influence of an event on a state (E is event and S is state)

This conceptual model could of course be extended with more events and corresponding states. Besides the assumption that a structural lifecycle event changes a person or household-level state, we also assume that events could influence each other. When an individual starts with a new job in a different location he/she might consider moving to that new location soon or late. In that case the occurrence of a change in work location could trigger a change in residential location. Another example of influences between structural lifecycle events could be the effect

of a change in work on income.

Figure 4 illustrates the extended conceptual model. Besides the event i and the corresponding substate, an event j is included with the three corresponding substates 1, 2 and 3. Personal characteristics, such as age, education and gender, are included as well. Since they are not influenced by events, these characteristics are not represented in a state which corresponds with an structural lifecycle event. The continuous links represent the logical relationships, thus between event and state (in the same time period) and between prior state and the next state. The dashed lines represent possible relations among events and between events and personal characteristics, the existence and direction are still uncertain. The structure learning algorithm will decide if a relation exist and which direction the link should have. Every dashed line represents one of four categories of possible relations; (1) within event i , across time periods; (2) between event i and event j during the same time period, (3) between event i and event j across time periods and (4) between event i and personal characteristics.

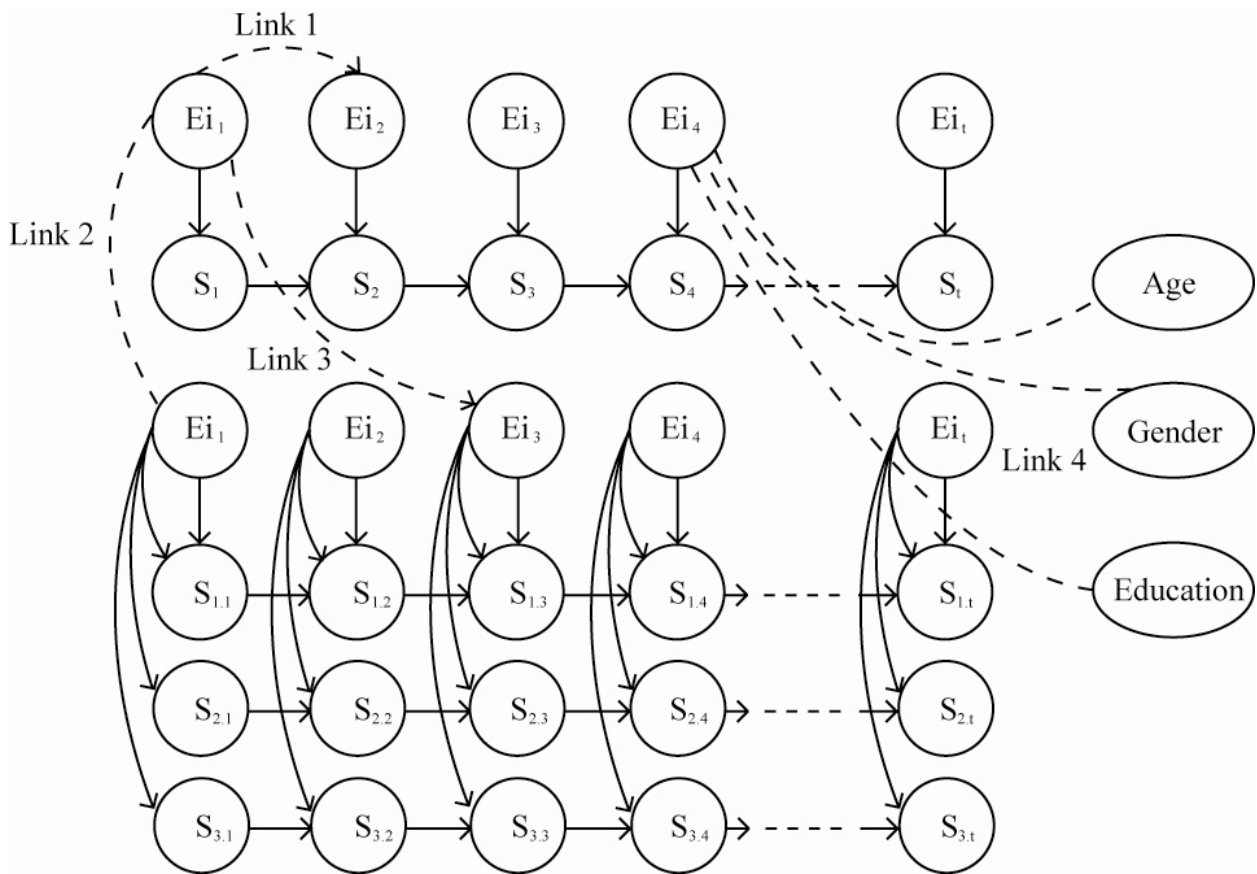


Figure 4: conceptual model of the influence of event on each other

Depending on the purpose of the model, two alternative approaches are relevant to structure those assumed event influences, namely by time period (i.e., quarter) or in a life course (i.e., age classes). The first approach can visualize influences between different events and the corresponding states in time, direct or with a certain delay in time. This first approach is time specific, while the second approach visualizes influence between events that could occur during a (general) life course at a certain age (period). According to the first approach the subscript in Figure 4 corresponds with a certain time period (for instance a quarter), but the subscript could

also represent a certain age period in the second approach (for example 1 = younger than 20 years old, 2 = 20-30 years old, 3 = 30-40 years etc.). Obviously more structural lifecycle events could be included in the model, as well as corresponding states. Of course the model becomes more complicated when more variables are included in the model.

In this paper, the result of the first approach, time period structure, will be described. In particular, we wish to analyze the influence of structural lifecycle events on each other and on changes in resources, influencing activity travel decisions. Given this focus, the events without corresponding states are included in the network structure. As mentioned before, the structure learning algorithm in Hugin will be used to discover which causal relationships exist between the five structural lifecycle events and the events, representing changes in resources. An Internet-based survey was designed to collect data concerning the events. First the data collection is described in more detail and after that the results of the structure learning will be discussed.

6. Data Collection

Existing data collections often do not exactly match the necessary data for a particular research. For that reason researchers collect more and more data. These days especially internet-based questionnaires are popular compared to questionnaires distributed by post. The advantages of an internet-based questionnaire are rather simple distribution among respondents by e-mail, the costs are low compared to the cost for postal distribution and the processing of data is less time consuming. For this particular study various personal information is needed: structural lifecycle information, transport mode choice and of course personal characteristics. Unfortunately, no known existing data set provides this required information. For that reason an Internet-based questionnaire, based on a conceptual network model (Verhoeven *et al*, 2005a), was designed to collect data for this study.

In total, 710 respondents completed the whole survey in the end of 2004. The survey was designed to collect data concerning five important structural lifecycle events and changes in resources influencing activity-travel behavior. Respondents indicated whether they experienced these events, and, if so, they indicated in a matrix the timing of the event (month and year), the cause of the change (i.e., the specific type of event) that took place and the before and after situation for every change.

In addition, respondents answered questions about their current situation in terms of personal and household characteristics, possession and availability of transport modes, their current travel behavior and their perception and preference of certain trip conditions. The total questionnaire consisted of the following components:

1. Household and personal characteristics;
2. Availability of transport mode;
3. Occurance of lifecycle events: (a) Change in residential location, (b) Change in household composition, (c) Change in work location, (d) Change in study location, and (e) change in household income;
4. Change in resources, influencing activity-travel decisions: car possession and availability; availability of public transport pass;

5. Current travel behavior per trip purpose: (a) work, (b) study, (c) grocery, (d) shopping and (e) sports;
 6. Perception of trip conditions: comfort, safety, privacy, environmental damage, expenses, and time;
 7. Stated preference part for evaluation of the selected trip conditions.
- In this paper, only data of parts one, three and four are used.

Each respondent who experienced one of the events filled in the matrix up to ten changes. The data concerning the events was recoded into new (time) variables for each respondent. For the present purpose, only the last three years (2002, 2003 and 2004) are taken into account, because changes longer ago probably will have no impact on the current situation (Fearnley and Bekken, 2005). Every event has 12 new (time) variables which correspond with the quarters in these years.

7. Results and Analysis

For every event the questionnaire used a classification of the more specific changes that were involved. Across events, the number of changes (i.e., classes) distinguished varied from three to ten. The calculation time of the learning algorithm increases when the number of classes of variables increases. The size of the CPTs also expands if there are more classes involved. For these reasons and for a better comprehension of the network we reduced the number of classes into three; no change, the change with the highest frequency for the event under concern and other change. The class with the highest frequency for each event was determined over all three years. The most frequent classes were buying a house (residential location), birth/adoption of a child (household composition), other job (work location), start with (new) study (study location) and increase in income (household income). For the change in resources there are two classes beside no change, namely increase or decrease (car possession and availability) and start or stop with PT pass (public transport pass).

This data collection was used for constructing the Bayesian Belief Network. The whole network is empirically derived through structure and parameter learning using the PC and EM algorithms in Hugin. First, structure learning was used to determine the structure of the network that best fits the data and after that we applied parameter learning. The input for the structure and parameter learning is a file with the new (time) variables. Table 1 shows the frequencies of the changes of all seven events, first in total, second subdivided into the years 2002, 2003 and 2004 and after that the years are divided into quarters.

Table 1: Frequencies of the seven structural lifecycle events

<i>change in residential location</i>															
<i>total changes</i>															
2535															
< 2002	2002					2003					2004				
2232	118					120					65				
	<i>1st</i>	<i>2nd</i>	<i>3rd</i>	<i>4th</i>	<i>missing</i>	<i>1st</i>	<i>2nd</i>	<i>3rd</i>	<i>4th</i>	<i>missing</i>	<i>1st</i>	<i>2nd</i>	<i>3rd</i>	<i>4th</i>	<i>missing</i>
	26	31	31	30	0	33	19	38	30	0	24	29	9	3	0

<i>change in household composition</i>															
1538															
1314	81					79					64				
	15	25	20	18	3	20	10	26	22	1	30	23	10	0	1
<i>change in work location</i>															
2535															
2264	111					103					57				
	28	25	25	28	5	24	29	30	19	1	26	23	7	0	0
<i>change in study location</i>															
684															
595	52					22					15				
	5	4	36	6	1	3	3	12	4	0	5	3	7	0	0
<i>change in study location</i>															
684															
595	52					22					15				
	5	4	36	6	1	3	3	12	4	0	5	3	7	0	0
<i>change in household income</i>															
1034															
801	72					97					64				
	15	15	18	17	7	31	16	21	19	10	31	25	6	0	2
<i>change in car possession and availability</i>															
812															
597	65					87					63				
	7	13	21	10	14	20	16	27	13	10	27	31	4	0	1
<i>change in availability of public transport pass</i>															
890															
721	67					67					35				
	9	12	28	14	4	20	10	21	14	2	13	10	8	3	1

The table shows that only a part of all changes occurred in 2002/2003/2004. Missing values are caused by missing information of a change, like year of month. Those missing values do not affect structure learning. Due to the moment of data collection, that took place in the end of 2004, only a few changes occurred in the fourth quarter of 2004. The effect of this could be less causal relations with the variables that represent the last quarters in 2004.

The PC algorithm was used for the structure learning with the significance level of 0.05. Figure 5 represents the learned network, with causal relations between the events. Every row represents all time-related variables of one event, the columns represent a time period (i.e., quarter of a year). In total Hugin produces 61 links in this network. A disadvantage of the PC algorithm is that it will not be able to derive the direction of all the links from data. Some links will be directed randomly. Constraints were included in the structure learning to prevent that directions of links are back-in-time.

All causal links found during the structure learning are represented in the complex network in Figure 5. To distinguish the different links (group 1 – 4), the total learned network is divided into four networks, see Figure 6 – 9. Each network only displays the links of one group. The causal links of the first group are ordered horizontal, the links of the second group are ordered vertical and the other links, third and fourth group, are ordered diagonal.

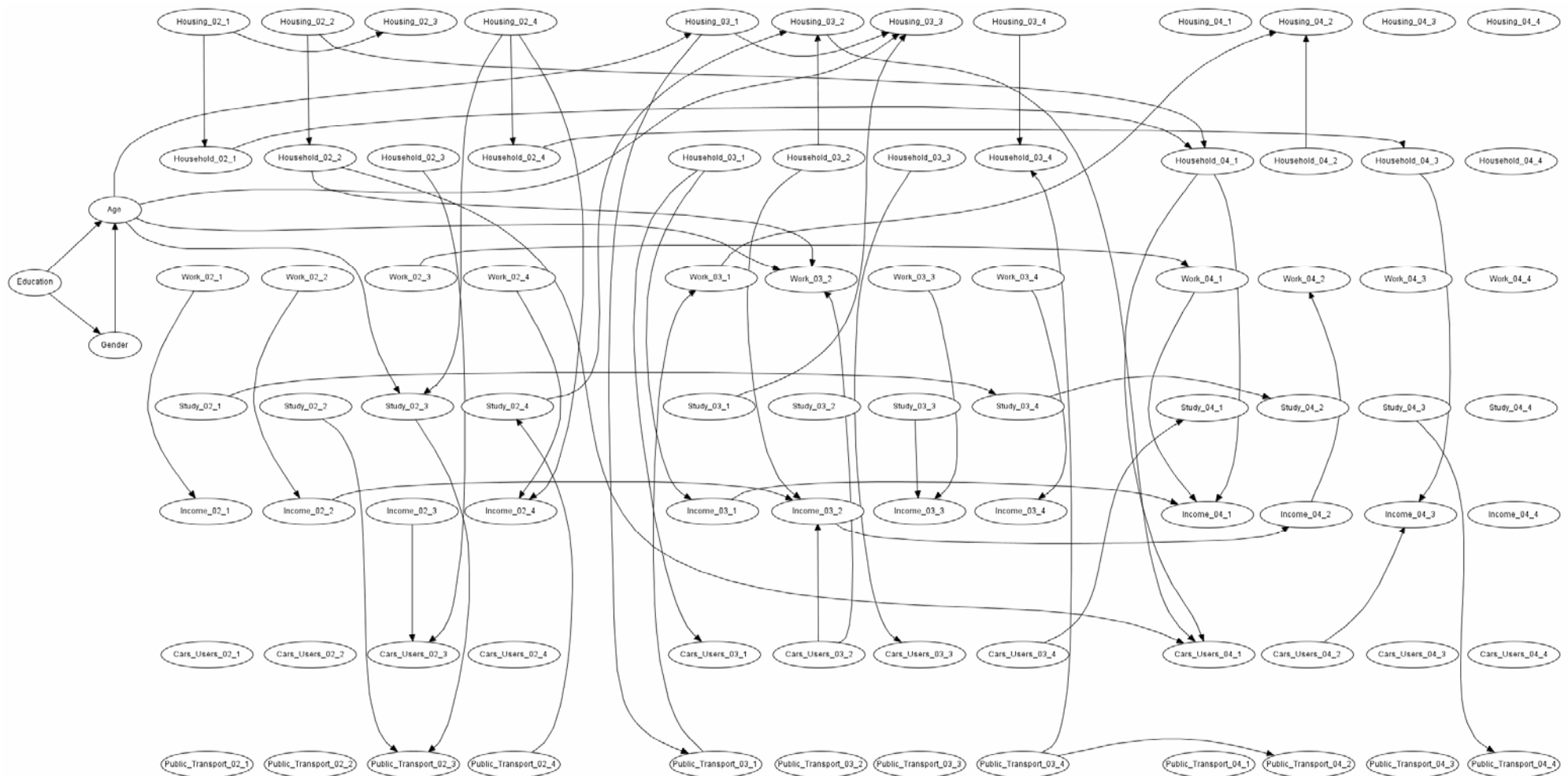


Figure 5: Learned network with all causal relations between the events and personal characteristics

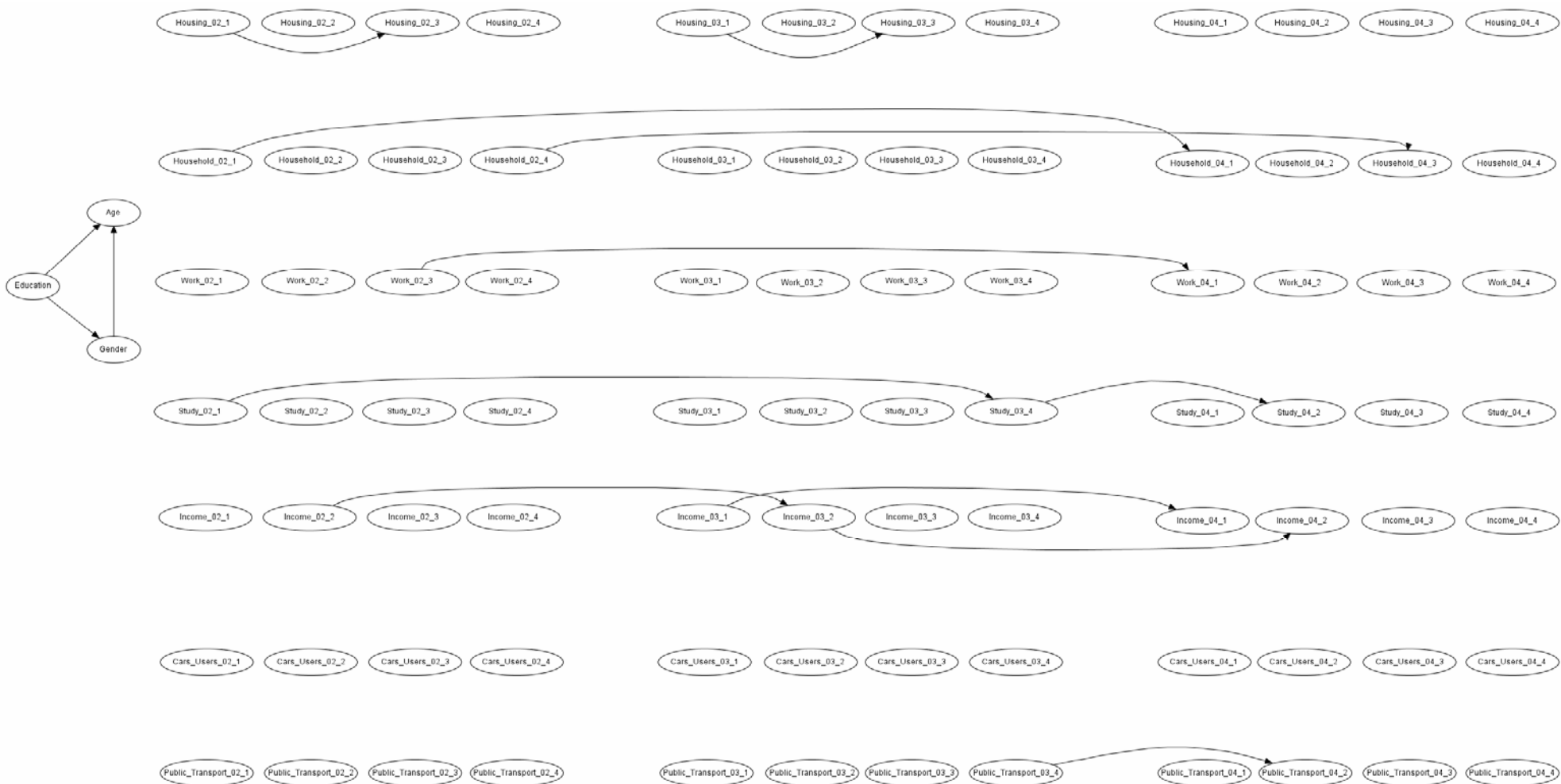


Figure 6: Learned network with all links of group 1

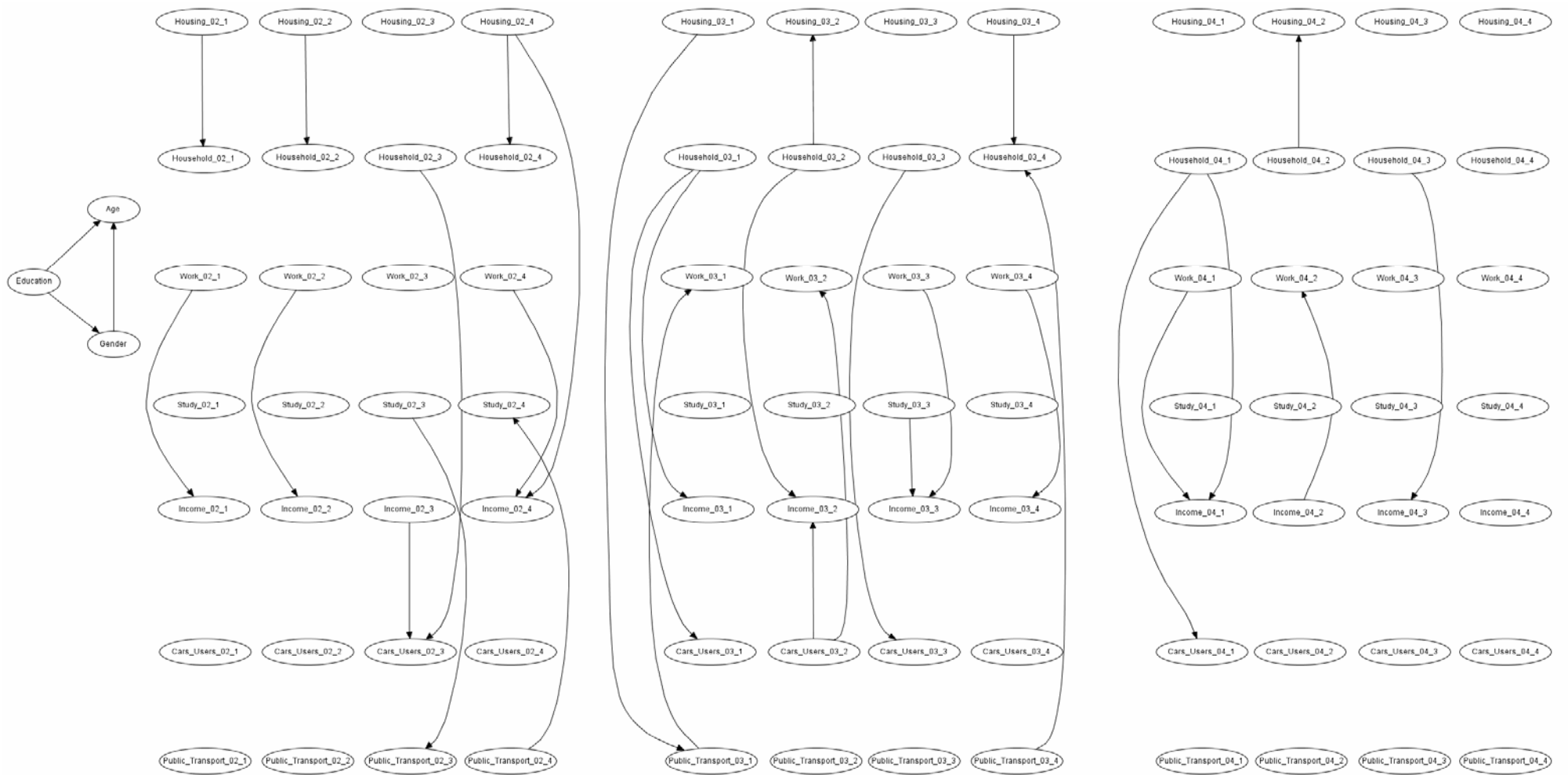


Figure 7: Learned network with all links of group 2

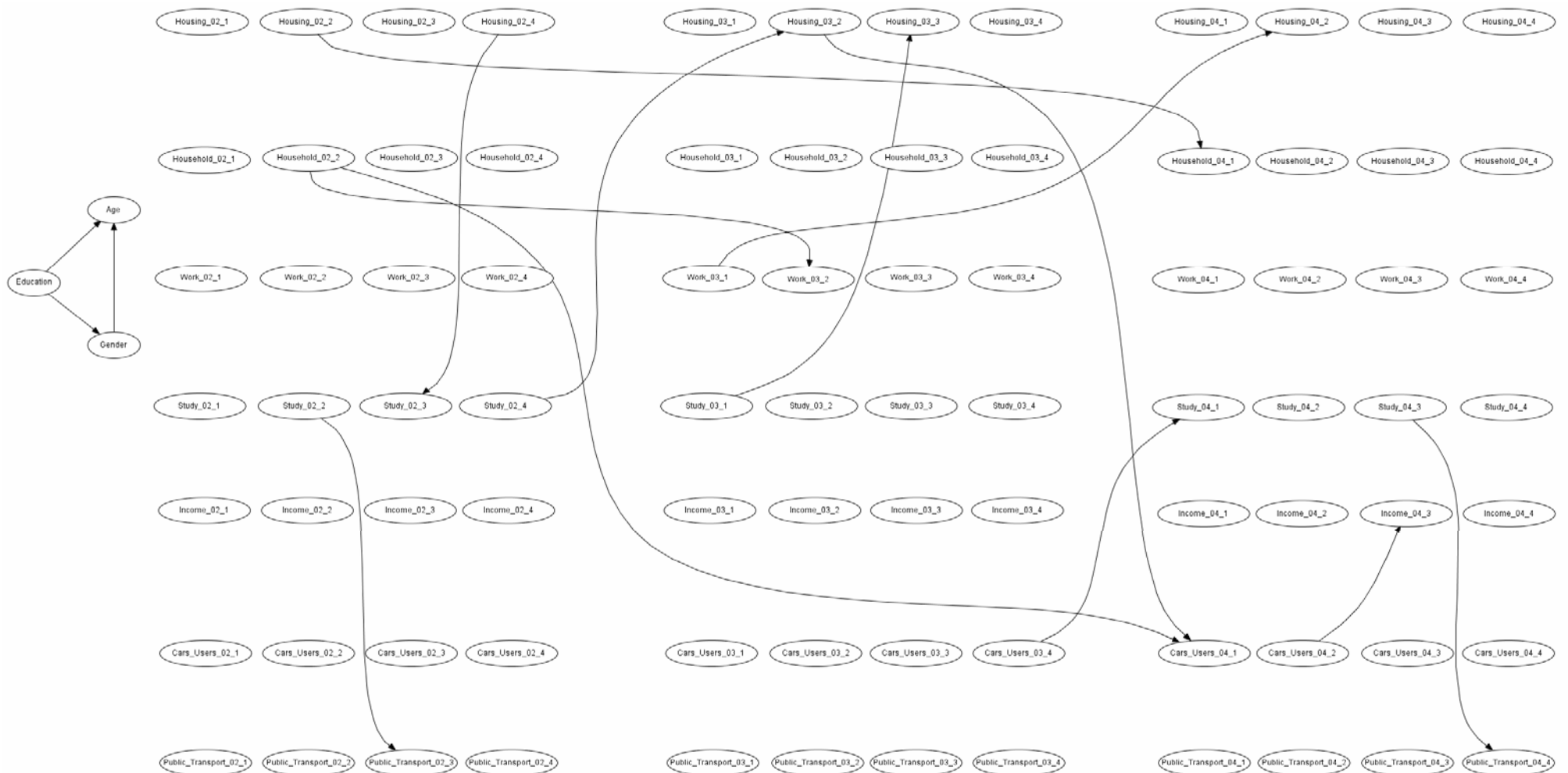


Figure 8: Learned network with all links of group 3

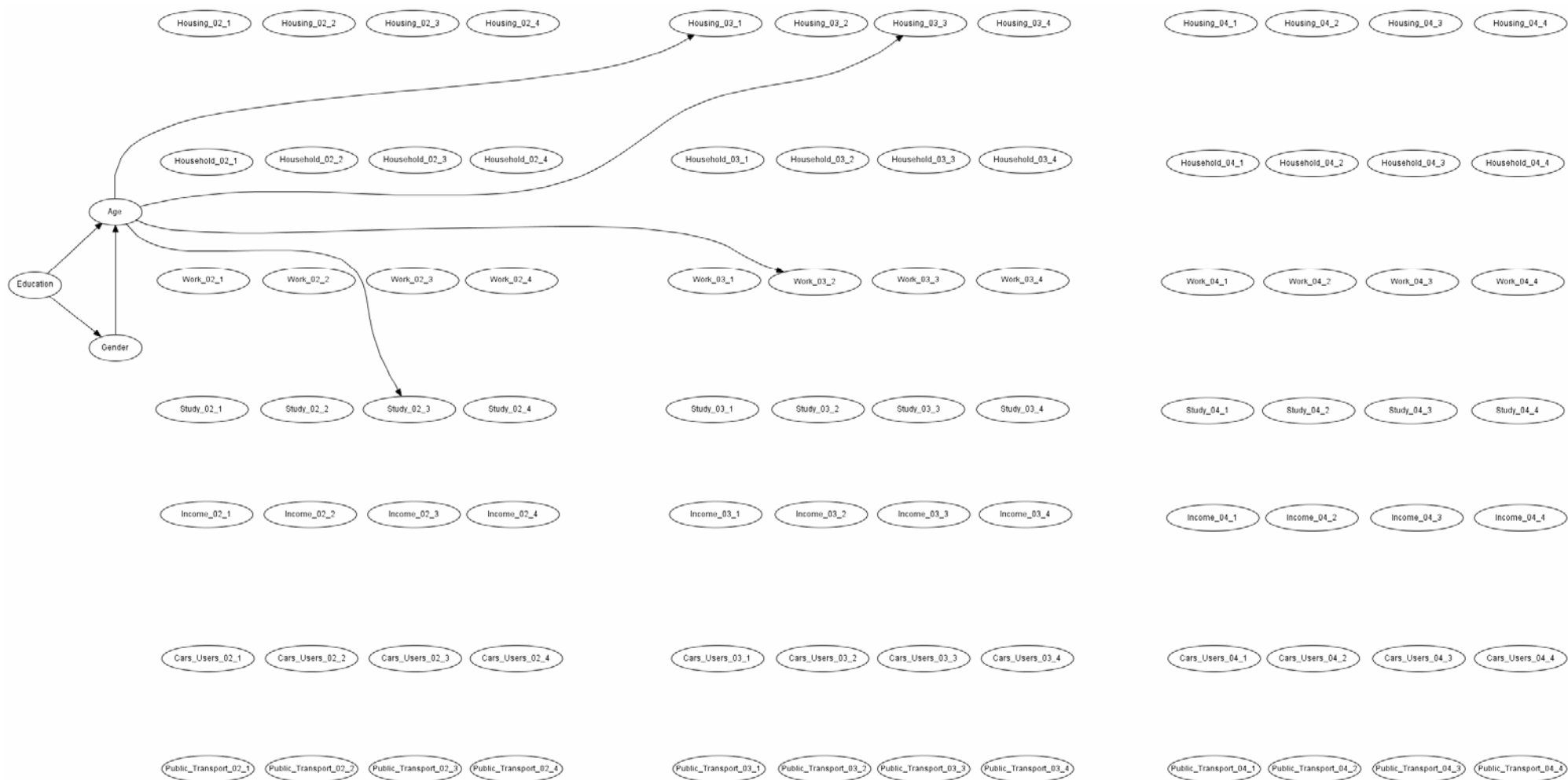


Figure 9: Learned network with all links of group 4

Based on this learned network we can conclude that there are influences among the five structural lifecycle events and between the structural lifecycle events and the events, which correspond with changes in resource variables. The occurrence of one event could trigger another event. In general we can say that most links in the learned network, Figure 5, are in the second group, links between events in the same time period. In the total network most links are in the middle of the figure, around 2003. The data collection was held in the end of 2004, this can explain that less links exist in this year. The causal links are a result of the structure learning. Besides structure learning, parameter learning was also executed. The result of parameter learning is that all influences are quantified in conditional probability tables (CPTs) based on the data. Two links of group one and three will be discussed in detail to illustrate their influence. Both examples involve the impact on the resources.

All links in Figure 6, group 1 (temporal links within event group), go beyond a quarter. This shows that there is a certain “time span” between events. The “time span” for events varies from half a year to two years. These temporal links do not necessarily mean that one change influences another change. The causal relation could also mean that a change lead to no change or the other way around, underlying CPTs quantify these links. For instance there exist a link between the node ‘Public Transport_03_4’ and ‘Public Transport_04_2’ with a time span of half a year. All CPTs are filled out in the parameter learning part, based on the data. The compiled network in Netica (Norsys Software Corp., 1997) represents probabilities for all nodes. Figure 10 illustrate a small part of this compiled network. The probabilities for the classes no change, Stop with PT pass and Start with PT pass of the node ‘Public Transport_03_4’ are respectively: 98.6, 0.99 and 0.42. The probabilities of the node ‘Public Transport_04_2’ are respectively: 98.6, 0.42 and 0.99.

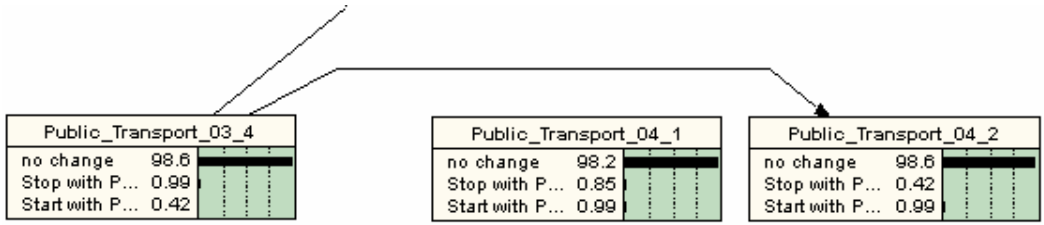


Figure 10 Small part of the compiled network without evidence

The BBN can handle probabilistic reasoning under uncertainty. If evidence for a certain node becomes available it can be entered in the network and all conditional probabilities will be updated automatically. For example, the evidence ‘Stop with PT pass’ for the node ‘Public Transport_03_4’ is entered and the conditional probabilities for the classes of the node ‘Public Transport_04_2’ change. Figure 11 illustrates the BBN when the evidence is entered into the network.

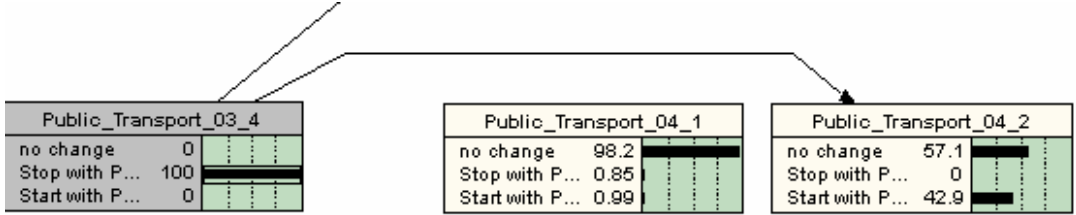


Figure 11 Small part of the compiled network with entered evidence

The conditional probability of classes ‘no change’ and ‘Stop with PT pass’ of the node ‘Public Transport_04_2’ decreases, respectively from 98.6 to 57.1 percent and from 0.42 to 0 percent. While the probability of the class ‘Start with PT pass’ increases from 0.99 to 42.9 percent. Figure 12 illustrates the CPT of the node ‘Public Transport_04_2’, which shows the probability distribution across the classes of this node for each class of the parent node.

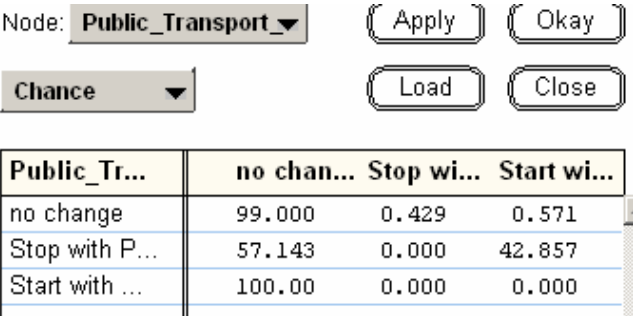


Figure 12 CPT of the node ‘Public Transport_04_2’

Figure 7 shows that causal links between structural lifecycle events also exists. In general the following relations can be distinguished, often in both directions: Housing – Household, Housing – Income, Household – Income, Work – Income and Study – Income. More importantly, the learned network also depicts causal links between changes in lifecycle events and changes in the resource variables, influencing activity-travel behavior. Example are Housing – Public Transport, Household – Cars and Users, Household – Public Transport, Work – Cars and Users; Work – Public Transport, Study – Public Transport and Income- Cars and Users. All relations, as quantified in the underlying CPTs (not shown), are well-interpretable.

The third network, Figure 8, portrays the links between structural lifecycle events across quarters. In total 12 links were found between: Housing – Household, Housing – Work, Housing – Study; Housing – Cars and Users, Household – Work, Household – Cars and Users, Study – Cars and Users, Study – Public Transport and Income – Cars and Users. All links show a certain response time, not every event immediately triggers another event. All links, as quantified in the underlying CPTs, are plausible and can be explained. For example the link between ‘Study_02_2’ and ‘Public Transport_02_3’: in the Netherlands all students receive a public transport pass which they can use during their study period. After ending a study (succesfully or unsuccesfully) they have to return the pass within a certain period. Figure 13 shows the probabilities for these nodes and Figure 14 shows the probabilities after the evidence ‘Other change’ for the node ‘Study_02_2’ is entered. This supports the causal relations described before.

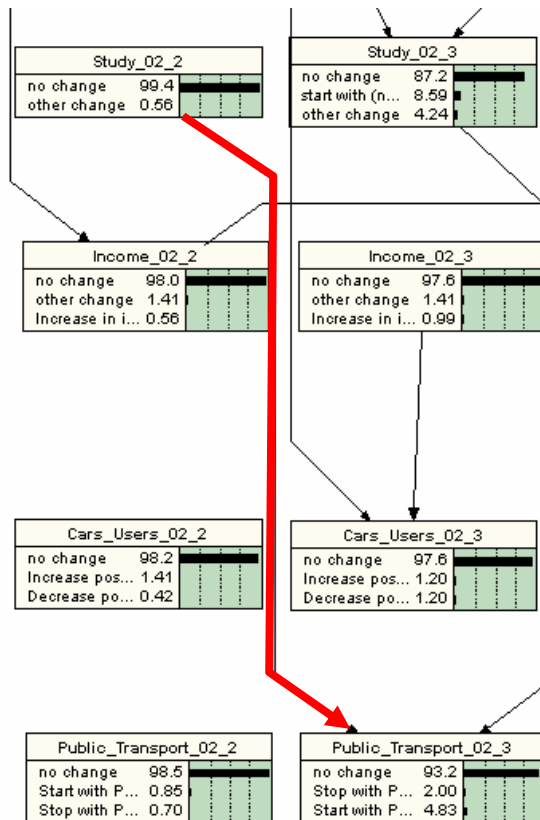


Figure 13

Small part of the compiled network

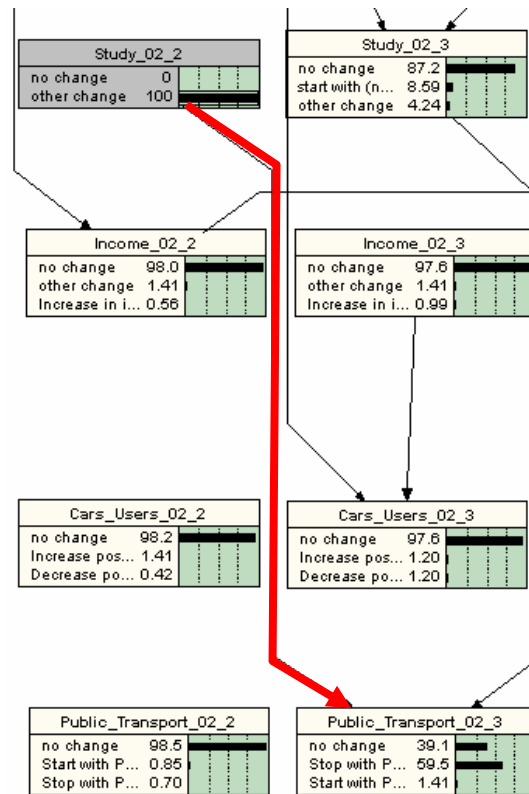


Figure 14

Compiled network with evidence

The last network, Figure 9, represents the links between events and personal characteristics. In total, three links between the personal characteristics were found and four links between events and the personal characteristics. No direct link exists between personal characteristics and the variables related to resource changes. However, all groups were described separately, but the total network represents of course all causal links. Sometimes there are also indirect links between variables, which means that event A also influences event C through event B ($A \rightarrow B \rightarrow C$). For example, the link between Age and Public Transport; $Age \rightarrow Study_02_2 \rightarrow Public\ Transport_02_3$. All links, as quantified in the underlying CPTs (not shown), are reasonable and intuitively correct.

The links in the total network are not identical for all years, whereas one could expect that this would be the case. There are two possible explanations; (1) the links are not structural but coincidental, (2) the links exist in general, but only a few are learned based on this specific sample. Further analysis is necessary to examine this. One option is to cluster the three years in one year and learn the structure again with structure learning. In this case the sample will be three times bigger. Another option is decrease the temporal resolution and cluster the quarters into years. This will probably result in less distorted distributions in the CPTs and probabilities.

8. Summary and Conclusion

As part of a wider study, which seeks to apply Bayesian networks in estimating direct and indirect effects of lifecycle events on activity-travel decisions, and transport mode choice in particular, in this paper we have reported the first results of such an approach, which aimed at providing evidence that structural lifecycle events influence each other and in isolation or combination affect resource decisions that influence transport mode choice decisions.

The framework showed how the influence of structural lifecycle events on personal states could be modeled in a Bayesian belief network. The BBN represents the causal relationships between nodes, which represent the structural lifecycle events and the corresponding personal states. Certain characteristics of this BBN method, such as representing a complex network with direct and indirect causal relationships between variables, 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.

The learned network proves that indeed structural lifecycle events influence each other and resource decisions.. Four different influences are distinguished: (1) within one event, across time periods; (2) between one event and another event during the same time period, (3) between one event and another event across time periods and (4) between one event and personal characteristics. The occurrence of one event triggers another event with some probability. There is a certain “time span” between changes within an event, this varies from half a year to two year. This does not necessarily mean that one change influences another change, for example a change can also ‘cause’ no change. The links between events within a time period indicates that one event influences another event, all links are logic. Links across a time period suggest that there is a certain response time between events. Not every event immediately influence another event, some changes take time.

Not all changes from the data collection are included in the network. Only the changes in the last three years were taken into account. Fearnley and Bekken (2005) argued that it makes little sense to try to estimate effect that materialise 10 or more years after a change. Too many other factors will have changed during the same period, which are impossible to include. However, another way to include more changes in a network is the structure of the second approach, life course (i.e., age classes).

These results imply that we will continue future research by estimating networks. The next step is to add state variables and transport mode to the network. Besides that, we will also explore the second approach of structuring the lifecycle events (age classes) to find out which causal relations could be learned. Ultimately, the results of this approach will be embedded into a more comprehensive dynamic system of activity-travel behavior. The Bayesian Network can be linked to a demographic forecasting or simulation model, which allows us not only to simulate the probabilistic relationships between demographic and other structural life cycle events, but also how such events directly and indirectly influence key facets of activity-travel behavior, not only transport mode choice decisions, but also activity-type participation. A long term model such as this can then be combined with short term activity-travel simulation models.

In this study, the analysis has been restricted to reactive behavior, based on the notion that

individuals may physically experience change in their behavior. However, adjustment may also be proactive in the sense that people knowing that an important event will happen in the future anticipate its likely consequences and mentally search for the best coping strategy and decide to adjust certain facets of their activity patterns proactively. In principle, a similar approach can be adopted to study any such proactive effects. We hope to report the findings of such further extensions and alternative specifications in the near future.

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