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Ngoduy, D, Watling, DP, Timms, PM et al. (1 more author) (2013) Dynamic Bayesian belief network to model the development of walking and cycling schemes. International Journal of Sustainable Transportation, 7 (5). 366 - 388. ISSN 1556-8318

https://doi.org/10.1080/15568318.2012.674627

Dynamic Bayesian belief network to model the development of walking and cycling schemes

D.Ngoduy*, D. Watling, P. Timms, M. Tight

*. Corresponding author, Institute for Transport Studies, The University of Leeds

LS2 9JT Leeds, United Kingdom

Phone: + 44 1133435345, e-mail: d.ngoduy@leeds.ac.uk

Abstract

This paper aims to describe a model which represents the formulation of decision making processes (over a number of years) affecting the step-changes of walking and cycling (WaC) schemes. These processes can be seen as being driven by a number of causal factors, many of which are associated with the attitudes of a variety of factors, in terms of both determining whether any scheme will be implemented and, if it is implemented, the extent to which it is used. The outputs of the model are pathways as to how the future might unfold (in terms of a number of future time steps) with respect to specific pedestrian and cyclist schemes. The transitions of the decision making processes are formulated using a qualitative simulation method, which describes the step-changes of the WaC scheme development. In this paper a Bayesian belief network (BBN) theory is extended to model the influence between and within factors in the dynamic decision making process.

Keywords: Dynamic Bayesian belief network, causal effects, walking and cycling (WaC)

1 Introduction

It is now generally recognized that the transport sector needs to play a key role in combating climate change and avoiding problems associated with limited supplies of fossil fuels (Tight et al., 2005). In such a context the advantages of walking and cycling (WaC) modes are obvious as they contribute to sustainable transport goals, to build healthier and more sociable communities, and to contribute to traffic reduction (Boschmann & Kwan, 2008). Bassett et al. (2008) have made comparisons between amounts of WaC in different countries and their results have indicated that many countries in Europe, North America and Australia have experienced a decline in WaC. According to Department for Transport (2009), in Britain, 67% of trips by all modes are under 5 miles in length, a distance which could be cycled by many people in half an hour; while 19% of trips are under 1 mile, a distance which could be walked by many in less than 20 minutes. Both modes, however, have been in long term decline. Cycle traffic declined from 23 to 5 billion passenger kilometres between 1952 and 2006, though there is evidence of an increase since the late 1990s (Department for Transport, 2007). Between 1995/7 and 2008 the number of trips per person made by bicycle fell by around 11% and the average distance travelled by 2% (Department for Transport, 2009). Furthermore, there is a wide geographical divergence in the use of cycling, with cities such as York, Cambridge and Oxford having much higher levels than the national average. These cities are all relatively flat, have good cycle facilities and high student populations and all have had the benefit of high levels of investment in WaC. In Britain walking accounted for 35% of all trips in 1975/76, but this fell to 22% in 2008. Despite this fall it is still an important mode of transport and in the UK it accounts for 76% of all trips under 1 mile (Department for Transport, 2009). Whilst most people walk on a daily basis, the amount of walking is not equally distributed across the population; for example households without a car walk on average 65% further than those with a car. In contrast, much higher levels of cycling are apparent in some parts of Northern Europe, with 28% of urban trips in the Netherlands made by bicycle (Pucher & Dijkstra, 2003), perhaps partly as a result of provision of high quality facilities and recent initiatives to promote policies such as bike and ride (Martens, 2006).

By its very nature walking is something that virtually everyone does, though households without a car walk on average 65% further than those with a car. Nearly 30 years ago Hillman and Whalley (1979,page 102) concluded that: ‘in both transport policy and practice, it [walking] has been overlooked or at the least, has been inadequately recognized‘. This may in part have been due to a feeling that walking ‘will take care of itself‘ (Litman, 2003) and that walking is a benign mode of transport in the sense of having few adverse impacts. Pucher and Dijkstra (2000) report that transport and land use policies have made walking ‘less feasible, less convenient, and more dangerous‘. Formidable obstacles to walking remain in many developed cities such as low density sprawl generating long trip distances, narrow or poor quality footways, inadequate crossing facilities and the continued growth of motor traffic. Whilst there have been many national and local initiatives to promote WaC, these often lack any kind of long term vision or strategy and can be piecemeal and inconsistent in their implementation such that their overall effectiveness is less than it might be. The time is now right to examine the means by which such a fundamental change both in the quantity of WaC, and in the quality of the experience can be achieved, which goes well beyond continuation of existing trends.

From a planning point of view, there is a general interest from transport planning authorities in developing schemes to make WaC modes more attractive. In order to plan the most effective means of implementation, it is desirable to be able to make predictions of the long-term future impacts of such schemes and to use a model for making such predictions. Any such model needs to take into account a number of specific factors of importance to the pedestrian and cyclist modes. Firstly, it is typically the case that pedestrian and cyclist schemes are implemented by local authorities in an incremental piecemeal fashion, with successive elements of the scheme only being implemented once previous parts of the scheme have proven to be "successful", in terms both of usage and overall public acceptability. It is therefore desirable for a model representing the step-changes of WaC in response to such schemes to be dynamic in nature, representing a number of sequential stages both in terms of the input of the stage on WaC use and the impact of WaC use on the likelihood of future stages being implemented. Secondly, since many causal factors affect, in complex interactive forms, both the attitudes of local authorities and (potential) pedestrians and cyclists, it is appropriate that such a model be based upon system dynamics principles incorporating causal chains and loops. Thirdly, if cycling and walking are to have significant impacts on climate change and transport energy usage, there needs to be a step change in the attitudes of trip makers who are currently using motorized modes if they are to switch to walk and cycle. Hence a system dynamics model representing pedestrians and cyclists should take into account that the behaviour of future (actual and potential) pedestrians and cyclists might be significantly different from the behaviour that can be observed at the current time. The combination of these three factors presents significant challenges to modelling. To this end, this paper puts forwards a causal modelling technique which represents the formulation of decision making processes (over a number of years) affecting the step-changes of WaC schemes. These processes, can be seen as being driven by a number of causal factors, many of which are associated with the attitudes towards a variety of factors, in terms of both determining whether any scheme will be implemented and, if it is implemented, the extent to which it is used. The outputs of the model are pathways as to how the future might unfold (in terms of a number of future time steps) with respect to specific pedestrian and cyclist schemes. The transitions of the decision making processes are formulated using a qualitative simulation method, which describes the step-changes of the WaC scheme development in an iterative and interactive manner. The details of the adopted modelling technique are described in the next sections. The main objectives of this paper are therefore twofold. On the one hand, we formulate causal mechanisms affecting the propensity to walk and cycle under a variety of driving factors and the causal links between them. On the other hand, we propose a Dynamic Bayesian belief network (DBBN) to mathematically model the causal relationships between driving factors and the propensity to walk and cycle over time.

This paper is organized as follows. Section 2 describes a causes and effects model for the step-changes of the perception of people to a number of walking and cycling schemes. Then we illustrate the concept of a Bayesian belief network (BBN) and how it is adopted to mathematically characterize the causes and effects model in Section 3. Section 4 presents a method to extend the BBN for a static causes and effects model to the DBBN for the dynamic nature of the step-changes of the perception of people over time. In this section we will describe an example of the performance of the DBBN for modelling the step-changes of the walking and cycling schemes over time. Section 5 illustrates a simulation result obtained from our developed model, followed by a discussion in Section 6 . Finally, we conclude the paper in Section 7 with a discussion of future research direction.

2 Causes and effects modelling

This section presents a model of the hypothesised causal mechanisms affecting the propensity to walk and/or cycle within pre-defined user-groups of the population. The causal factors will in some cases be measurable, but in many cases will be qualitative. The causal factors are influenced by implemented transport measures, but the population is also influenced at any time t by future plans of transport planning agencies to implement measures (if publicized), not just what has already been implemented by time step t ($t = 0, 1, 2, ...$) with each time step in the order of 1 or 2 years. As well as the implemented schemes and plans up to and including (the start of) time step t, the inputs to the model include any other causal factors, including any exogenous 'drivers'. The primary output from the model is the propensity to walk/cycle in time step t (disaggregated by user group), given the assumed causal mechanisms. The motivation of the model is to represent WaC as something quite distinctive from other transport modes.

There are many factors that influence an individual's physical activities through WaC. For example, the proximity of the destination, the availability and cost of other transportation modes, and the perceived safety of the route may influence an individual's propensity to walk and cycle (Hawthorne, 1989). In addition, WaC activities are also affected by the urban morphology of the site, the neighbourhood, and the metropolitan area (Handy et al., 2002). A survey by Walton and Sunseri (2010) has shown that several main factors influence the decision to walk such as fear of crime, trip-chaining, weather, distance or time, social pressure, fatigue and fitness, parking charges, enjoyment of walking, inconvenience, and geography. A study by Khisty (1994) found factors affecting the amount of walking activity to be attractiveness, comfort and convenience, population density, mixture of land uses, safety, system coherence, and continuity. Jennifer Bonham and Anne Wilson (2012) investigated the factors affecting changes in women's cycling patterns which are related to changes in housing, employment, health and family status.

In this paper, we focus on the group level demand model, shown in Figure 1 which summarizes the relationships between factors affecting the propensity to walk and cycle. The causes and effects between such factors will be modelled in Section 3. However, it is worth mentioning that the modelling technique in Section 3 can be applied to diagrams different from Figure 1 in which other causal factors could be added. If we consider a randomly selected individual within a certain 'user group', it is proposed that altogether the propensity to walk and cycle is directly conditioned by four main, multi-faceted factors:

- Perceived Comfort-Zone: A spatial representation of what an individual perceives to be their own personal physical limit of trips or trip segments that are possible by WaC.

- Environment: How attractive/conducive do individuals perceive the environment to be within which they could conduct WaC trips?
- Availability: How feasible is it to include WaC as part of an overall activity pattern?
- Group Social Norms: 'Intrinsic' values/beliefs, resulting from the era and location, and 'Conditioned' values, shaped by personal/others' experiences/beliefs of the transport system.

The general thinking behind the Perceived Comfort-Zone definition is to group together those factors that pertain to an individual's own perceived physical limitations as part of their normal weekly/daily activities. That is to say, it is not defined by the limits of human endurance, but is related to the perceived level of exertion that an individual is comfortable with expending as part of their normal activities.

The terms used in the four elements above are primarily meant to be groupings of causal factors, but on the other hand the groupings have been chosen with one eye on the mathematical mechanisms by which we might actually represent the propensity. Loosely speaking, we might think of the Comfort-Zone and Availability factors to define/restrict the travel choices available, and Environment and Group Social Norms to respectively define the individual-level and social group-level stimuli motivating the choice of travel option from those available. In this way, increasing the use of WaC is both about breaking down participation barriers to widen its perceived availability as an option, as well as about making the experience more pleasant for those who choose WaC.

In Figure 1, the causal factors underlying the four main conditioning elements of Group Social Norms, Perceived Comfort-Zone, Environment and Availability are proposed. The notation adopted is that a policy measure/lever is represented by italicised writing in a dashed box; a direct causal factor is represented by unitalicised text in an unbroken box. Each of the four major elements described are now considered in turn below.

2.1 Perceived Comfort-Zone

As noted earlier, the idea behind the notion of a Perceived Comfort-Zone is to reflect how the perceived comfortable level of physical activity that an individual is prepared to expend as part of their normal daily activity is reflected in the spatial 'network' they perceive to be available to them to conduct WaC activities. This has several causal factors. For example, distance separation of activities reflects the fact that as residential and other activity locations become more separated, this will have a potentially negative consequence on WaC. Clearly an individual will have a range of typical activities to perform, so a range of distances, thus the comfort-zone should reflect the range of activities the individual may want to perform.

- *Distance separation of activities*: Reflecting the fact that as residential and other activity locations become more separated, this will have a potentially negative consequence on WaC. Clearly an individual will have a range of typical activities to perform, so a range of distances.
- *Terrain*: Certainly for cycling, and for less able-bodied for walking too, the hilliness of the terrain has a major effect on the physical exertion. Generally we may not think we can affect this variable in any way, though since it is a measure of the terrain experienced by an individual as part of their normal trip pattern, there are potential indirect impacts from changes in residential location/land-use (though these are not reflected on Figure 1). This factor may be particularly useful in explaining issues of non-transferability of WaC propensity and experience between locations.
- *Technological assistance*: There is a whole range of possibilities in this category, including currently available devices used for storing energy and/or generating energy while cycling, to assist in climbing hills.
- *Health/fitness*: This is a reflection of both perceived and actual health/fitness levels of an individual,

in terms of a measure of the personal physical 'energy' they believe they can comfortably expend as part of a WaC activity. Note that by defining the limit in energy as opposed to distance terms, we are able to make connections to overall health/mobility levels, and subsequently relate overall WaC 'availability' to the terrain faced and measures that affect the separation of activities.

Several policy levers also may have a potentially significant impact on the factors above:

- *Land use policy/urban design*: Cervero et al. (2009) have shown that extensive network of bike lanes and set-aside street space for recreational cyclists and pedestrians along with other attributes of the built environment as urban densities, land-use mixes, accessibility, and proximity to transit are associated with WaC behaviour. As work, shopping, school and home activities have become more dispersed over recent decades, so the demands on travel have changed in terms of their pure separation. Thus future policies to encourage the provision of local shops, leisure facilities, jobs and schools have a potentially very positive impact on the possibilities to conduct shorter distance trips that are more amenable to walk and cycle (e.g. walk to the local shop rather than drive to out-of-town supermarket Tesco). A modern sense of 'local' might be local to place of work (e.g. provision of city centre health drop-in centres, provision of shopping at rail stations), not only local to home.
- *Health awareness/facilities*: Promoting healthy lifestyles as well as providing local facilities (e.g. swimming pools) also has the potential effect of producing more active and fit individuals across all age groups, which positively impacts on the perceived ability levels to perform WaC. Seefeldt et al. (2002) has argued that an individual's propensity to be active is determined by his or her perception of the consequences of a potential illness and the perceived benefits of using physical activity as a countermeasure to the risk of getting sick.

2.2 Environment

The heading of Environment is intended to reflect both the real and perceived attributes of the personal environment in which one engages in WaC. This has several factors:

- *Security, safety, comfort*: In many urban areas there are both real and exaggerated fears of personal security while walking, that vary by sex and age, as well as fears of accidents between pedestrians/cyclists and motorised vehicles. On the issue of comfort, the provision of shelters, not only at stops but also perhaps along a street, might greatly change the attitude to walking comfort during wet and/or windy conditions. For cyclists, security also refers to the availability of secure facilities for leaving bicycles at a destination. Studies by Taylor and Harrell (1996), King et al. (2002), Klinenberg (2002) have indicated that the presence of disorder and exposure to violence and crime can have a negative influence on an individual's willingness to use the public environment for WaC activities.
- *Speed, connectivity*: It is not only safety but also travel time that can be affected by the provision of appropriate facilities, whether pedestrian crossings or cycle-ways, particularly when interactions occur with motorized traffic. Perceived lack of connectivity of the network may be as a result of real or perceived barriers; for example, reserved cycle-ways may often stop just before major intersections or narrow busy roads, due to the difficulty/cost in fitting them in.

There are many policy measures that may be brought to bear on these factors:

- *Infrastructure*: Investing in the many measures that exist to improve both the security (cycle lanes, lighting, etc.) and connectivity of the network: car free housing developments, underground cycle parking in multi storey, retrofitting multi storey and petrol station for mobility hub, on-road cycle paths, reallocation of road space for on-road cycle paths, pavement widening, and maintenance of WaC infrastructure.

- *Traffic measures*: This comprises both reallocation of road space for the existing demand by alternative modes, and in suppressing or diverting motorized traffic in a desirable way. Examples include: strict liability legislation, fuel efficient cars, banning pavement parking, car clubs linked with smart card Dutch-style home zones, low emission zones, priority traffic signal for bicycles, advanced stop lines for cyclists, etc.

2.3 Availability

The third aspect related to WaC concerns real issues of availability of these modes as feasible travel alternatives (and ways in which this availability may be improved). Factors pertinent to this aspect include:

- *Cycle Provision*: This includes both cycle ownership (and incentives for this), and the provision of cycle hire facilities, including 'smart-card' facilities, and the cost of this provision, whether purchase/maintenance or hire cost. If WaC is an element of a choice between, say, walk+public-transport versus car, then the relative costs of the other transport modes may also be pertinent (Hawthorne, 1989).
- *Integration*: concerns the potential for integrating WaC with the use of other modes. This includes proximity of bus/train services to residential and activity locations (within walking distance?) and the accessibility of these services to the rest of the network. It may also include provision for carrying cycles on trains, cycle lockers, and pedestrian interchange facilities.

2.4 Group Social Norms

Attitudes of friends, family and work colleagues play a major factor in the perceived environment, over and above an individual's personal experiences. This includes both the positive potential for identifying WaC with environmental awareness, and in addressing real fears as well as dis-spelling myths about the perceived difficulties by non-WaC users. As described in Amesty (2003) and Stahl et al. (2001), supporting social networks as well as the availability of a companion for physical activity influence an individual's tendency to walk. In principle, there are at least two distinct facets of such norms, which are reflected in Figure 1:

- *Intrinsic Norms*: These norms are those unrelated to the transport system *per se*, but are more related to the generation, era and general political climate that individuals within a group are living. While we might consider the *Socio-political environment* as fixed for our transport system, there are potential ways for affecting change, such as a generally greater involvement of a group in the decision-making processes of a region or city (not just transport).
- *Conditioned Norms*: These norms are internal to the transport system, and something where careful attention is needed to produce positive images that will shape future decisions.

The main policy lever represented is thus *Travel awareness*, which communicates desirable outcomes to community groups, travel-plans, and public awareness campaigns about the negative energy/environmental impacts of dependence on motorised transport, and the positive experiences of walkers and cyclist. This factor includes all ways of shaping perceptions of the WaC environment.

3 Bayesian network theory

3.1 General concept

The concept of a Bayesian belief network (BBN) has been found in many applications described in the literature (Jensen, 1996; Neil et al., 1999). In principle, a BBN is a directed acyclic graph (DAG) which encodes the causal loops between particular factors represented in DAG as nodes (Figure 2). The arrow between nodes is modelled as a causal link. Nodes and causal links constitute a network in which arrows are pointing from parent nodes (causes) to child nodes (effects). Each node is associated with a probability (e.g. the technological assistance contributes to the Perceived comfort zone at which level of probability, either high or low). The Bayesian theory is adopted to compute the conditional probabilities associated with each node given a prior knowledge (i.e. specifications of WaC scheme to be implemented). The subjective conditional probabilities at each node may be defined by experts or focus groups combined with evidence (historical observations).

The causal effects between factors presented in Section 2 involve a network structure over the inferences of possible belief in each factor (e.g. high belief in better infrastructure provision leading to higher propensity to walk and cycle). Inter-relationships between factors are illustrated through conditional probabilities (e.g. how will hilly terrain affects the propensity to walk and cycle?). Note that 'probability' mentioned in this paper is not really about numbers but the structure of reasoning, that is the specific reason for the belief, assumptions which cause the belief to be held, sources of information to cause this belief to change, etc.

Before going into details about the BBN for modelling the causal loops in Figure 1, let us begin by giving some definitions and notation:

- x_i: random variable at node i, taking discrete states (e.g. high probability or low probability, etc.)
- $P(x_i)$: the probability of the random variable x_i in a particular state.

The relationship between joint and conditional probability is obtained from probability theory as:

$$P(x_1, x_2, ..., x_n) = \prod_{i=1}^{n} P(x_i|\pi(x_i)), \tag{1}$$

where $\pi(x_i)$ denotes the parents of random variable x_i at node i. A node with more than one parent must require their conditional probability distribution to be provided in a form of conditional probability table which specifies the conditional probability of the child node being in a particular state (i.e. high or low), given the states of all its parents. For example, equation (1) is applied for Figure 2 as:

$$P(x_5|x_1) = P(x_5|x_4, x_3)P(x_4|x_2, x_1)P(x_3|x_1)P(x_2|x_1) \tag{2}$$

The decomposition in equation (1) will provide a means for specifying the transitions of the decision process as in the context of a system dynamics which is detailed in the rest of this section.

3.2 Application of BBN to model the development of WaC schemes

To apply the BBN to model the development of WaC schemes, we propose to decompose the conceptual diagram in Figure 1 into the multi-layer diagram in Figure 3. In Figure 3, we have added layer 1 to present the potential WaC schemes to be implemented. For any given WaC scheme, the causal loops affecting the four main factors are modelled in layer 2. Each WaC scheme will influence different factors within four main factors. Such influence is modelled through arrows pointing from layer 1 and layer 2. The arrows pointing from layer 2 to layer 3 illustrate the causal loops between the four main factors and the propensity to walk and cycle given a specific WaC scheme. The thick arrow pointing from layer 3 to layer 1 models the response of the public to a specific WaC scheme. In our model, all probabilities associated with variables are assumed to take discrete values: high and low. We will describe how these variables could be measured in the numerical example (Section 5).

3.2.1 BBN to model the causal loops affecting the Perceived comfort zone

Figure 4 describes the causal loops between the Perceived comfort zone and a certain WaC scheme. From Figure 4, node Perceived comfort zone is the child of many parents such as Technological Assistance, Terrain, Individual Reinforcement, Health and Fitness, and Distance Separation of activities. Based on equation (1), the probability associated with the node Perceived comfort zone given the effects of other nodes under a certain WaC scheme is:

$$P(PCZ) = P(PCZ|TA, TR, HF, DS)P(TA)P(TR)P(HF)P(DS)P(HF|HAF)P(DS|LPUD), \tag{3}$$

where

- PCZ: Perceived comfort zone variable.
- TA: Technological assistance variable.
- TR: Terrain variable.
- HF: Health/fitness variable.
- DS: Distance separation variable.
- HAF: Health awareness/facilities variable.
- $LPUD$: Land use policty/urban design variable.

In equation (3) the probability associated with each parent node Technological Assistance, Terrain, etc. is determined directly from the impact of a certain WaC scheme on that node. For example, how does a WaC scheme reduce the negative impact on people's willingness to cycle in the hilly terrain of a city. Equation (3) allows the reasoning of the impact of a certain WaC scheme on the main factor, Perceived comfort zone, through many other factors.

3.2.2 BBN to model the causal loops affecting the Group social norms

Figure 5 describes the causal loops between the Group social norms and a certain WaC scheme. From Figure 5, node Group social norms is the child node of two parents, namely Socio-political environment and Conditioned norms. Based on equation (1), the probability associated with node Group social norms under a certain WaC scheme is:

$$P(GSN) = P(GSN|IN, CN)P(IN|SE)P(SE)P(CN|TrA)P(TrA), \tag{4}$$

where

- GSN: Group social norms variable.
- SE: Socio-political environment variable.
- CN: Conditioned norms variable.
- IN: Intrinsic norms variable.
- TrA: Travel awareness variable.

3.2.3 BBN to model the causal loops affecting the Environment

Figure 6 describes the causal loops between the Environment and a certain WaC scheme. From Figure 6, node Environment is the child node of two parents, namely Speed connectivity and Security, safety and comfort. Based on equation (1), the probability associated with node Environment under a certain WaC scheme is:

$$P(ENV) = P(ENV|SC, SeC)P(SC|IF, TrM)P(SeC|IF, TrM)P(IF)P(TrM), \tag{5}$$

where
- ENV: Environment variable.
- SC: Speed connectivity variable.
- SeC: Security, safety and comfort variable.
- IF: Infrastructure variable.
- TrM: Traffic measure variable.

3.2.4 BBN to model the causal loops affecting the Availability

Figure 7 describes the causal loops between the Availability and a certain WaC scheme. From Figure 7, node Availability is the child node of two parents, namely Cycle provision and Integration. Based on equation (1), the probability associated with node Availability under a certain WaC scheme is:

$$P(AVL) = P(AVL|CP, IT)P(CP)P(IT), \tag{6}$$

where
- AVL: Availability variable.
- CP: Cycle provision variable.
- IT: Integration variable.

The set of equations (3)-(6) determines the impact of a certain WaC scheme on the four main factors at a certain time, which is described by causal links between layer 1 and layer 2 in Figure 3. The effects of the four main factors on the Propensity to walk and cycle, that is the causal links between layer 2 and layer 3 in Figure 3, are modelled as below.

3.2.5 BBN to model the causal loops affecting the Propensity to walk and cycle

Figure 10 describes the causal loops between the Propensity to walk and cycle and the four main factors: Perceived comfort zone, Group social norms, Environment and Availability. Based on equation (1), the probability associated with node Propensity to walk and cycle under a certain WaC scheme is:

$$P(PWaC) = P(PWaC|PCZ, GSN, ENV, AVL)P(PCZ)P(GSN)P(ENV)P(AVL), \tag{7}$$

where $PWaC$ is the Propensity to walk and cycle variable.

Note that equations (3)-(7) are all computed at a certain time t. To model the causal loops between the Propensity to walk and cycle and the development of future WaC schemes (that is the causal link between layer 3 and layer 1 in Figure 3), the BBN is extended to the DBBN as detailed in the next section.

4 Dynamic Bayesian network theory

Since the standard BBN cannot be applied when there are closed loops in the causal diagram. As a result, it is not straightforward to apply the BBN for the multi-layer causal loops in Figure 3 because there is a feedback from the probabilities associated with the PWaC node to the probabilities associated at the WaC schemes node. To this end, we propose to extend the BBN to the DBBN which describes the evolution of causal loops in Figure 3 in discrete time steps. Let X^t denote a vector of random variables, representing probabilistic states of the network (driving factors) at time t, $X^t = \{x_1^t, x_2^t, ...x_n^t\}$ and $x_1^t, x_2^t, ...$ are random variables representing the factors described in Figures 4-10 at time t. The DAG network describing the time evolution of X^t is shown in Figure 9. Figure 9 describes the DBBN to deal with dynamic systems that evolve over time. Note that we have selected randomly a few factors to illustrate the causal effects in Figure 9 for the sake of simplicity. It is worth mentioning that the evolution of vector X^t does depend on many previous states (i.e. $t-1$, $t-2$, etc.). The vector of probabilities associated with each node X^t is:

$$P(X^t) \propto P(X^t|X^{t-1}, X^{t-2}, ...). \tag{8}$$

Let $Y^t = \{X^t, X^{t-1}, ..., X^1\}$, equation (8) becomes:

$$P(Y^t) \propto P(Y^t|Y^{t-1})P(Y^{t-1}), \tag{9}$$

where

$$P(Y^t|Y^{t-1}) = P(X^t|X^{t-1}, X^{t-2}, ..., X^1). \tag{10}$$

The key element now is to build up the causal links between time slice t and $t-1$ to compute $P(Y^t|Y^{t-1})$. Based on $P(Y^t)$ we determine what to do in the next time step $(t+1)$. Figure 10 shows a simple example of the causal links between the decision to implement a WaC and the previously computed probabilities associated with node Propensity to walk and cycle.

The following is an algorithm to determine the evolution of a set of WaC schemes over a number of years. Let S^t denote a set of discrete numbers $(0, 1, 2, ..., M)$ which represent the progress of the WaC schemes at time t, as indicated by the number of stages implemented. Note that $S = 0$ indicates the current situation. Define dS as being a variable which indicates whether a decision has been made to implement the next stage: it takes two values, 1 (if an implementation is to be made) and 0 (otherwise). The dynamic equation to represent the step-changes of WaC schemes is thus:

$$S^t = min(S^{t-1} + dS^t, M). \tag{11}$$

Equation (11) indicates that if the decision factor $dS^t = 1$ the next stage will be implemented, otherwise the scheme will stay in its current state. M is the maximum number of stages to be implemented. The key decisive element in equation (11) is dS^t, which is determined as

$$dS^t = 1 \quad If \;\; P(PWaC^{t-1}) = high \;\; and \;\; S^{t-1} < M, \tag{12}$$

$$dS^t = 0 \quad If \;\; P(PWaC^{t-1}) = low \;\; or \;\; S^{t-1} \geq M. \tag{13}$$

5 Numerical example

For the illustration purposes, the proposed modelling framework in this paper is implemented in VENSIM (Ventana Systems, Inc,). The VENSIM based model is simulated for 20 years (from 2010 to 2030). The time step is fixed at two years, which is long enough to get opinions of the public and experts over a WaC scheme to be implemented. Then conditional probabilities associated with each node in Figures 4-10 at each time step are calculated. We stress that all numerical values in the conditional probabilities are just assumed in order to show the numerical outputs from our modelling framework. Our ongoing work is to obtain evidence from historical facts and options from public in order to build up a database for such conditional probabilities.

For the illustration purposes, we will describe in detail below an example as how to measure the variables and define tables of conditional probabilities associated with those variables in order to numerically simulate our model.

- Measurement of Terrain variable (TR): this is based on the average slope length, where the slope angle is larger than 2%, over the whole network (defined as α). Accordingly, $P(TR) = high$ if $\alpha \geq 5\%$ and $P(TR) = low$ if $\alpha < 5\%$.
- Measurement of Distance separation variable (DS): this is based on the average maximum distance (L_{max}) to walk and/or to cycle: $P(DS) = high$ if $L_{max} \geq 2$ km and $P(DS) = low$ if $L_{max} < 2$ km for walking. Similarly, we can define $P(DS) = high$ if $L_{max} \geq 10$ km and $P(DS) = low$ if $L_{max} < 10$ km for cycling.

In order to apply our theoretical approach in any particular case-study, it will be necessary for the users of the approach to decide on an appropriate 'granularity' (level of detail) for the variables, and therefore a precise definition for them. This decision will be based on a combination of factors: the existence and level of detail of appropriate evidence (e.g. for the required transition probabilities), the subjective belief in the likely level of future uncertainty (based on expert opinion), and the level of detail required in the model forecasts for planning purposes. Based on the variable measurements, we can construct conditional probability tables. The example below shows in detail the conditional probability tables associated with Group social norms.

TABLE I

CONDITIONAL PROBABILITY TABLE $P(GSN|IN,CN)$.

	$IN = high$ $CN = high$	$IN = high$ $CN = low$	$IN = low$ $CN = high$	$IN = low$ $CN = low$
$P(GSN = high\|IN,CN)$	0.9	0.7	0.8	0.2
$P(GSN = low\|IN,CN)$	0.1	0.3	0.2	0.8

TABLE II

CONDITIONAL PROBABILITY TABLE $P(IN|SE)$.

	$SE = high$	$SE = low$
$P(IN = high\|SE)$	0.9	0.2
$P(IN = low\|SE)$	0.1	0.8

In Figure 5, the following unconditional probabilities are also inputs to the model: $P(SE = high) = 0.9$ and $P(TrA = high) = 0.8$. From Tables I-III and equation (4), we compute the probability associated with node Group social norms: $P(GSN = high) = 0.73$. The same procedure is used to compute the

TABLE III
CONDITIONAL PROBABILITY TABLE $P(CN|TrA)$.

	$TrA = high$	$TrA = low$
$P(CN = high|TrA)$	0.85	0.15
$P(CN = low|TrA)$	0.15	0.85

probabilities associated with node Perceived comfort zone, Environment and Availability. Finally, we determine the propensity to walk and cycle $P(WaC)$ using equation (7). The whole process will be applied at every time slice in which the computed $P(WaC)$ will be used for the decision making to implement the next WaC scheme (as described in equations (12)-(13) and Figure 10). In our example, a scheme is accepted if $P(PWaC = high) \geq 0.7$.

We assume that the local authority is planning to implement WaC schemes in three stages sequentially within the coming 20 years. A background overview of these WaC schemes is given in Timms and Tight (2010), Tight et al. (2011). The causal relationships of all factors are collected in the implementing process in order to decide what to do next: either continue to implement the other schemes or stop. Figure 11 shows the output of the model based on our assumed conditional probabilities given three schemes. It can be seen from the figure that there are three pathways to reach the final state in 2030, each of which is driven by many factors as indicated earlier and each pathway will happen given a certain probability associated with the propensity to walk and cycle. Due to the response from public views, a specific WaC scheme will not be implemented. For example, pathway 2 will reject scheme 2 but still reaches the target (i.e. scheme 3) whereas pathway 3 will reject scheme 3, which means that the target is not reached.

6 Discussion

- We are not modelling how individuals will decide between modes for a given particular journey; rather we are aiming to model the tendency of a city population to even consider walking and cycling as an option for a journey. This is the reason for our use of the word 'propensity'. So even if the propensity to walk and cycle is 0.5, this does not mean that we expect 50% of trips to be made by walking and cycling. In practice, the mode chosen for a particular trip will depend on many factors, including the existence of competing modes, but also on the trip length and purpose. Instead we are modelling something more that is more related to 'choice set generation', i.e. is walking/cycling even in the set of choices that travellers consider for a journey, even if they do not choose it. We believe that for many travellers, the option is not even considered, and our model hypothesises that this is something intrinsic to walking and cycling, rather than about its attractiveness relative to other modes. In fact, the theoretical model could be readily extended to consider the attractiveness of other modes, but we have chosen not to do this in our current paper. In general we consider the propensity to walk and cycle given a broad description of certain factors such as the average terrain, traffic measures, or the environment. The contribution of our approach is not to consider this in isolation (with the planner an abstract entity), but to explicit include the fact that as the propensity increases in response to policy measures, so the local authorities will have more political backing to implement further schemes to promote WaC activities. The mode choice for particular journeys is something that will be determined subsequently to WaC propensity (and could be incorporated in a future stage of our model, in which case competing modes would be important). So we might expect the actual number of people to walk and cycle will be less than the tendency of people to consider walk and cycle as an option.

- In our model, the variables could be defined at many different levels. At this first stage of the work we have made a compromise on detail by assuming that all such variables are represented at a common aggregate level. In fact it is no more complex for the theoretical model to be defined with different levels of detail for different elements. We have chosen not to do this for two reasons. Firstly, the more complex notation that would be required considerably complicates the mathematical presentation of the model (and the more detailed model is not so difficult to imagine, we believe, given our aggregate model). Already there is sufficient challenge in communicating our ideas about the aggregate model. Secondly, there is a question of whether we really have the evidence available at the levels of detail suggested, especially as the evidence we require is not that commonly used in existing transport models. Certainly it is possible to extend the model to address this issue, and should the data be available we can then exploit it. This will be left in our future research.
- Our model is looking at the long-term planning horizon (2030 and beyond). It is argued that the long-term future is uncertain and there is no evidence at this moment how the future looks like. Therefore, the model must contain many factors that reflect the uncertainty of the future. This is illustrated by the many possible probabilistic pathways that our model generates to the future (see Figure 11 for a sample of such pathways). Based on the model, we can identify the key bifurcation points in the most likely pathways and the factors which are most important in influencing them, and thereby allow the planner a degree of influence in choosing a most desirable and/or most plausible/robust pathway to follow.
- The numerical example in our paper is only used to illustrate how the model is simulated. We are currently in the process of determining the existence of evidence and data from cities that have experienced major changes in walking/cycling over time (e.g. Delft and Copenhagen) in order to understand how the pathways are built up. Table IV describes as how all variables provided in our model are measured and what data collection method is needed to put a value on each variable in a particular city. Based on the table, we aim to determine the values of each variable for a particular city and show how the model could actually be applied to such a specific city. However, the use of such evidence (and its potential transfer to plan in other locations) is a complex issue that would need a paper of its own to address and therefore left in our future work. In principle, the table shows that the model variables can be measured on a qualitative scale. The scale would have to be clearly defined by the modeller. For example, if GIS data helps us to make a judgement whether a city is flat, hilly or very hilly using the average slope length, then we could decide the Terrain variable can be low, medium or high, respectively. Another example is if a survey suggests that northerners are not as fit as southerners, we could decide the Health and Fitness variable of a northern city is low while that of a southern city is high. Nevertheless, the choice of such a qualitative scale and meaning assigned to the variables is decided by the modeller, so our suggestions are only meant to be an example, but it is definitely not intended to be a universal scale. It has been found there are similarities and differences in attitudes and beliefs about decision to commute by bicycle between the two bicycling-oriented cities (Eva Heinen and Susan Handy, 2012). However, the authors indicated that large-sample studies are needed to understand attitudes towards bicycling attitudes. The investigation of how to validate our model using such empirical studies will be left in our future work.

7 Conclusion

This paper has presented a method to represent the causal factors affecting the decision making process for the development of WaC schemes. First of all, we have adopted a Bayesian belief network to model the causal loops affecting the propensity to walk and cycle. Then we extended the Bayesian belief network to aid a planning authority to implement a WaC scheme over time and its interaction with the propensity to walk and cycle. It could be used to foster important partnership with other agencies (such as health, transport, local authorities) to ensure that a WaC scheme is supported and promoted within the community. In the model, the casual loops are facilitated through a Vensim based model in which users can easily design the casual factors to drive the decision making process. The outcomes of the model are the pathways, each of which will happen given a certain probability associated with the propensity to walk and cycle computed from the causal loops.

Nevertheless, the model will not be complete without validation. We are currently in the process of determining the existence of evidence from cities that have experienced major changes in walking/cycling over time (e.g. Delft and Copenhagen) in order to understand how the pathways are built up. However, the use of such evidence (and its potential transfer to plan in other locations) is a complex issue that would need a paper of its own to address. It is beyond the scope of our present paper, which we feel already is sufficiently long, instead our focus in this paper has been on the theoretical development and its illustration with examples.

Acknowledgments

This paper is based on work being undertaken as part of an ongoing research project funded through the UK Engineering and Physical Sciences Research Council on 'Visions of the Role of Walking and Cycling in 2030' (Grant reference: $EP/G000468/1$). We would like to thank researchers and practitioners involved in the project for comments on the draft of this paper.

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TABLE IV
MODEL VARIABLES.

Variables	Description	Equation	Definition	Data collection method
Technological assistance	TA	3	The provision of high tech devices to support WaC activities	Oservational/Interview survey of bicycle users in a particular city
Terrain	TR	3	The average slope length, where the slope angle is larger than 2%, over the whole network	Using GIS data (to make a judgement whether the city is hilly, very hilly or flat)
Health and Fitness	HF	3	The average maximum energy to expand as a part of WaC activity	Regional and city based survey of the fitness of population
Distance separation	DS	3	The average maximum distance to walk and/or to cycle for a particular activity	Regional and city based survey
Health awareness/facilities	HAF	3	The perceived benefits of using physical activity	National survey
Land use policy/urban design	LP/UD	3	The provision of local facilities and WaC networks	Using GIS data
Conditioned norm	CN	4	Norms internal to and conditioned by the transport system	Qualitative social surveys done at a local level
Intrinsic norm	IN	4	Wider societal norms which do not relate specifically to transport	Qualitative social surveys done at a local level
Speed/connectivity	SC	5	The provision of infrastructure facilities to support WaC activities	Analysis of walking/cycling network
Security, safety and comfort	SeC	5	Understanding of how walkers and cyclists perceive safety, security and comfort	Social surveys of walkers and cyclists
Cycle provision	CP	6	The provision of cycle ownership and hire facilities	Regional and city based survey for cycle ownership
Integration	IT	6	The potential integration level of cycles with other public transport modes	Using GIS data to look at the relationship in space between individuals and bus stops, train stations, etc

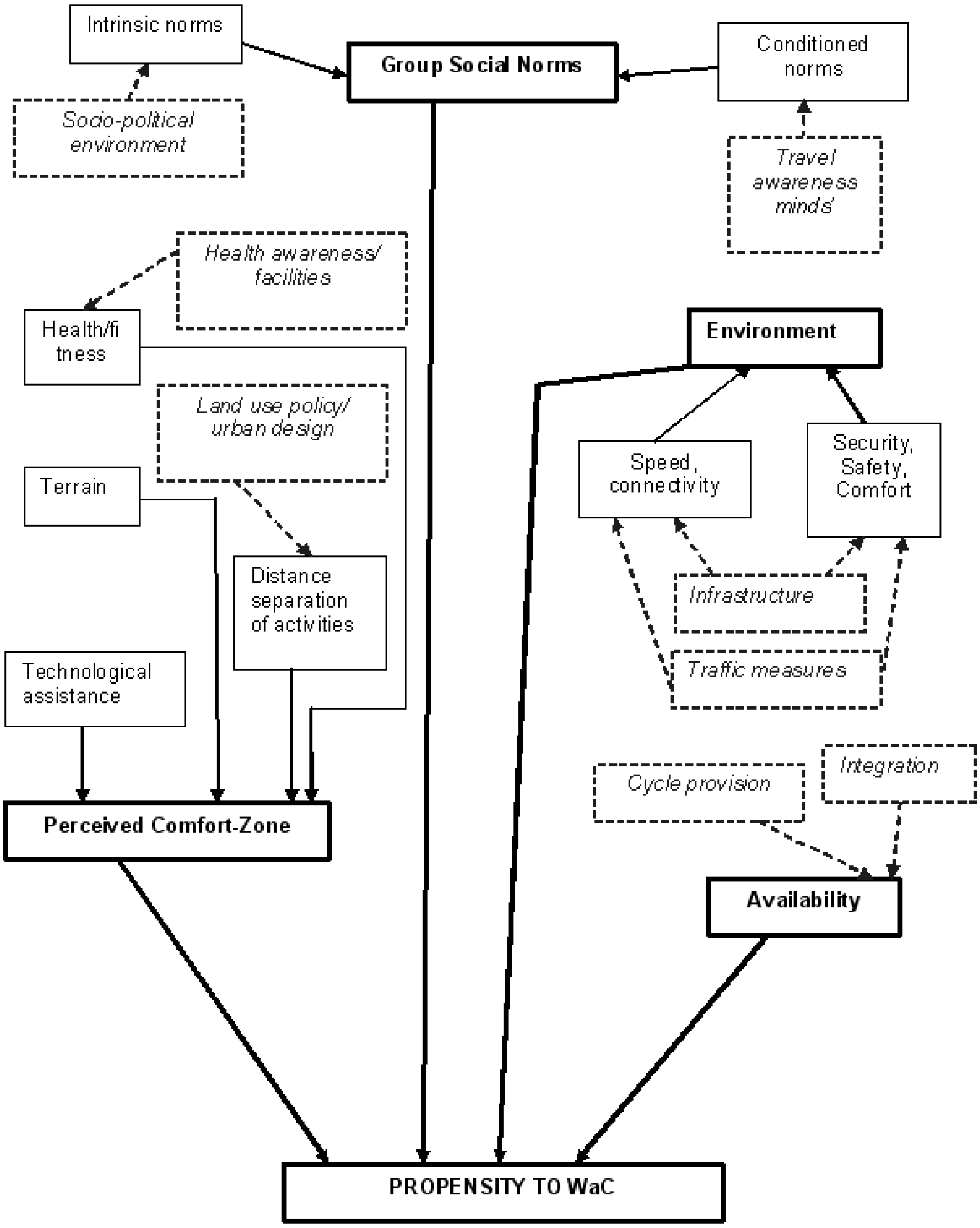

Fig. 1. Conceptual model of propensity to walk and cycle within a 'group'

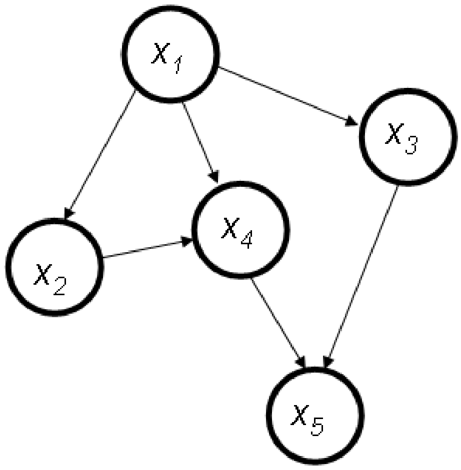

Fig. 2. Example of a directed acyclic graph

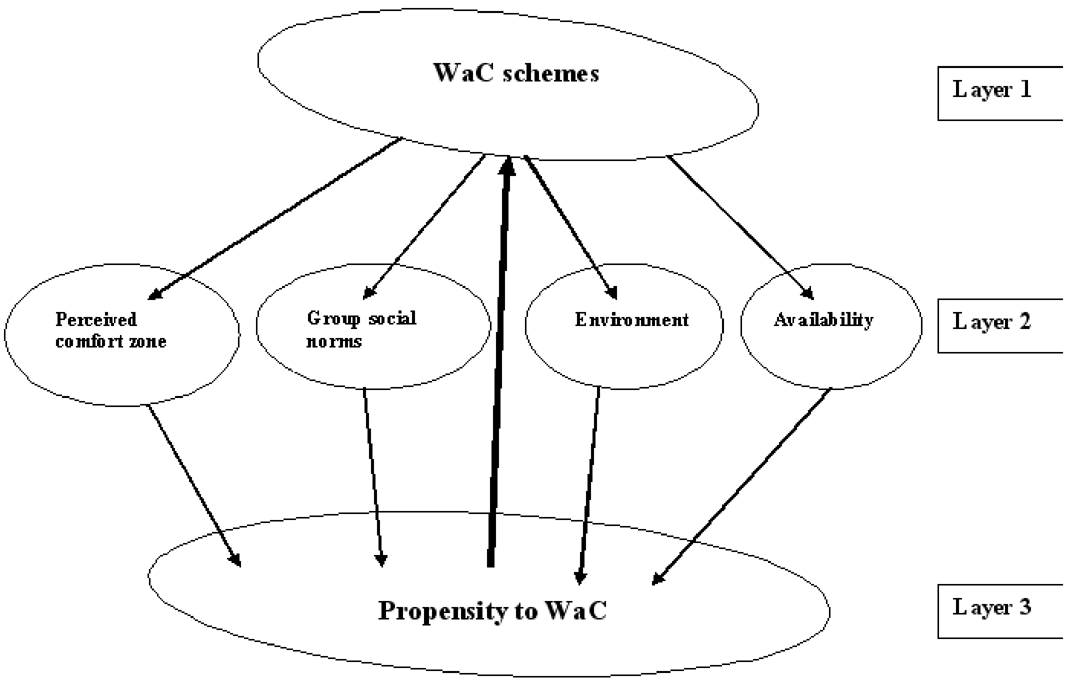

Fig. 3. Multi-layer causal loops for the development of WaC schemes

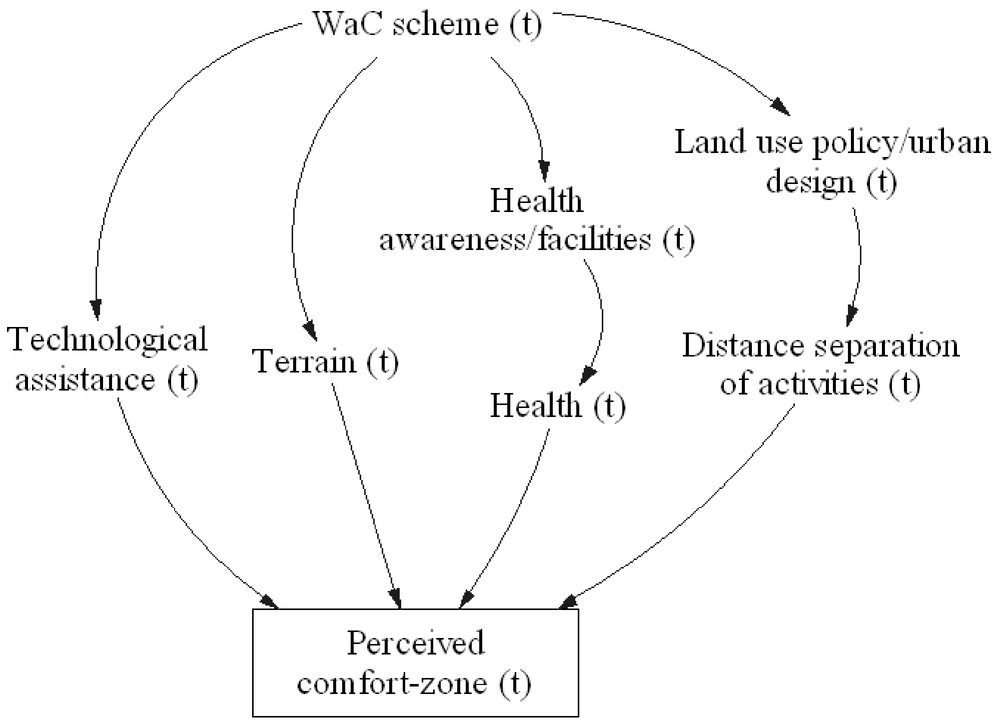

Fig. 4. Causal loops to determine P(PCZ) from a WaC scheme at time t

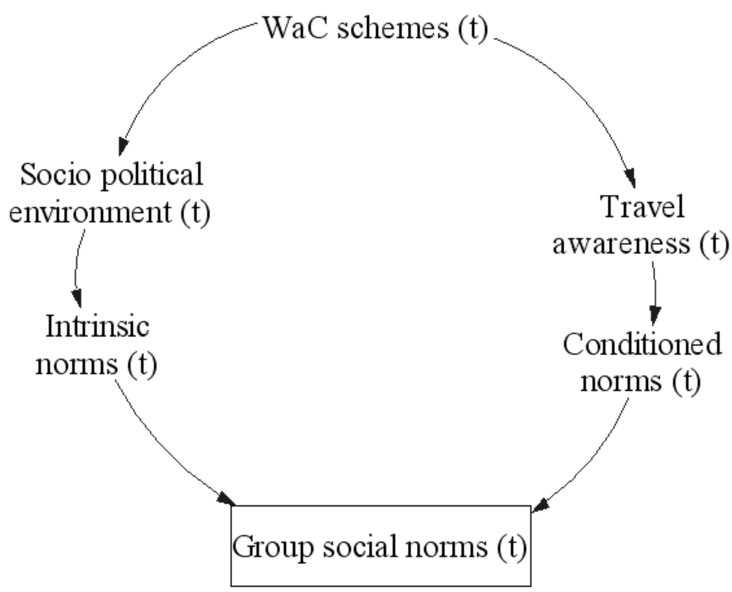

Fig. 5. Causal loops to determine P(GSN) from a WaC scheme at time t

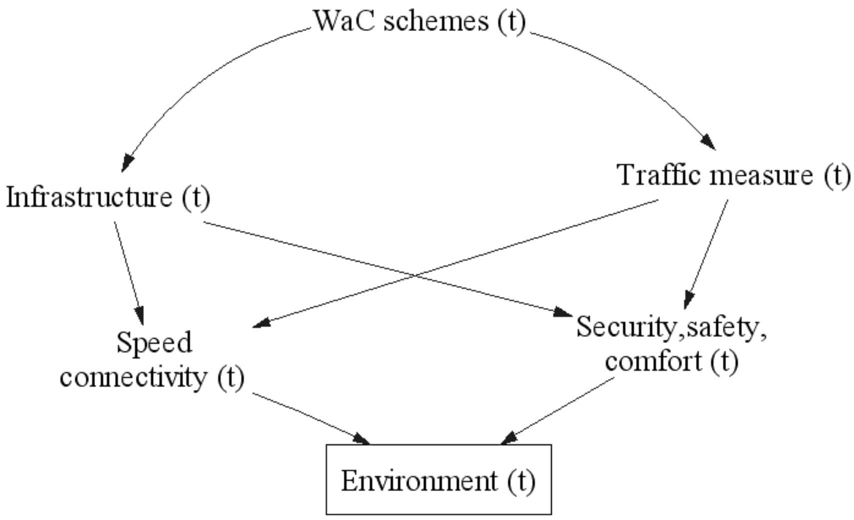

Fig. 6. Causal loops to determine P(ENV) from a WaC scheme at time t

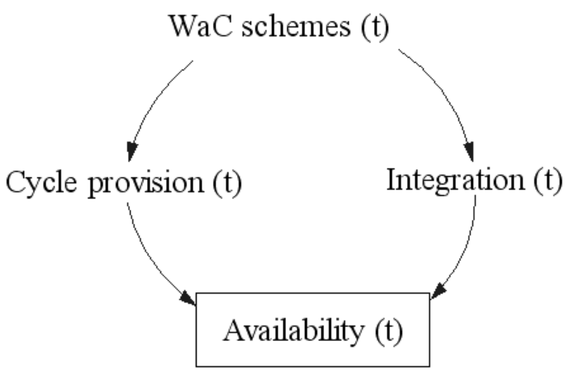

Fig. 7. Causal loops to determine P(AVL) from a WaC scheme at time t

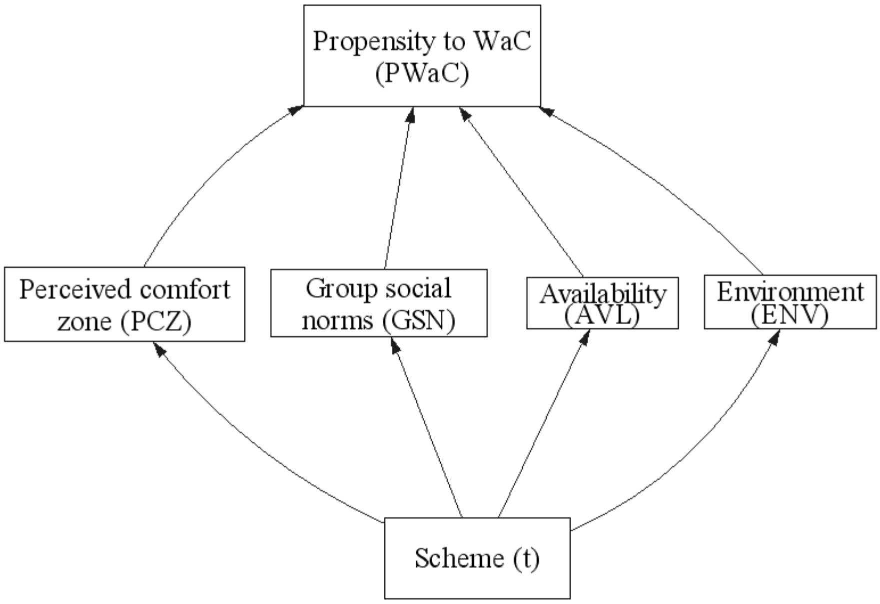

Fig. 8. Causal loops to determine P(PWaC) from a WaC scheme at time t

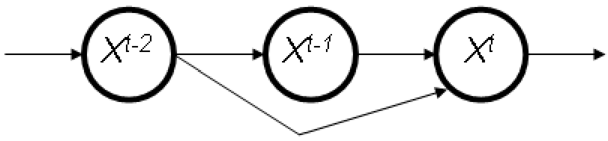

Fig. 9. Dynamic directed acyclic graph network

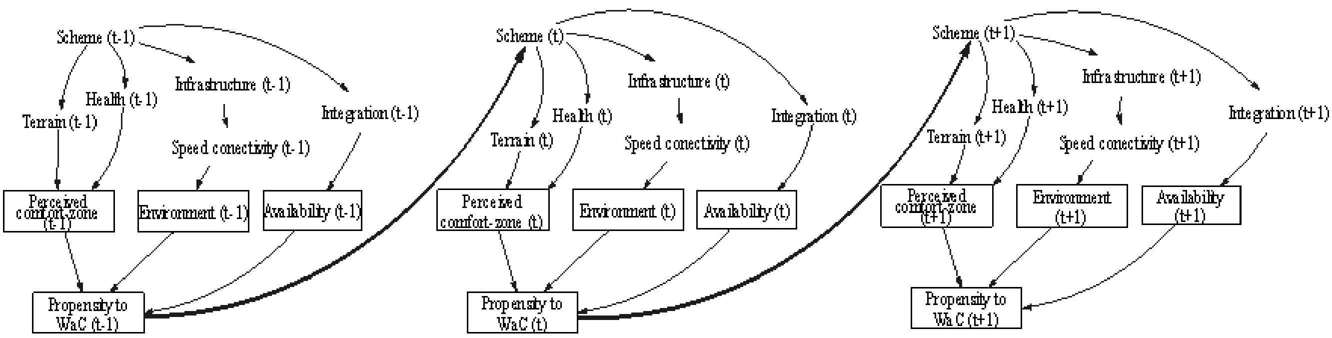

Fig. 10. Evolution of WaC schemes in a DBBN

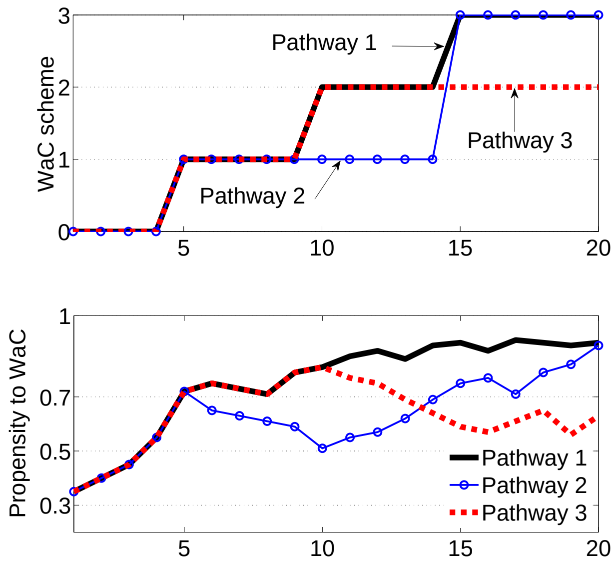

Fig. 11. Pathways of WaC schemes over 20 years