A Revision and Experience using Cognitive Mapping and Knowledge Engineering in Travel Behavior Sciences

Maikel León, Gonzalo Nápoles, María M. García, Rafael Bello, and Koen Vanhoof

***Abstract*—All modern society investigates in the field of Travel Behavior because of the significance for all social and economical process of a country. The problems related with travel behavior are not structured; the Artificial Intelligence techniques have a high interest in its solution, specially related with the knowledge representation and the uncertainty. The use of advanced computer techniques like Knowledge Engineering and Cognitive Mapping is also relevant from diverse points of view. A crucial role is played by the process of modeling and defining what will be taken into account in this kind of problems, for that reason in this paper are described some important ideas of how to understand and extract the mental representation of individuals in the decision making and planning of trips, related to daily travels, because this is useful information that can be used in transport demand prediction, analysis and studies.**

***Index terms*—Travel behavior, knowledge engineering, cognitive mapping, mental representation, daily travel.**

I. Introduction

IN the process of transportation planning, travel demand forecast is one of the most important analysis instruments to evaluate various policy measures aiming at influencing travel supply and demand. In past decades, increasing environmental awareness and the generally accepted policy paradigm of sustainable development made transportation policy measures shift from facilitation to reduction and control [1].

Objectives of such Travel Demand Management (TDM) measures are to alter Travel Behavior without necessarily embarking on large-scale infrastructure expansion projects, to encourage better use of available transport resources and to avoid the negative consequences of continued unrestrained growth in private mobility.

As this policy approach is shifting from rather simple supply-oriented measures to more complex TDM measures, the need to effectively analyze, evaluate and implement a range of policy scenarios is giving rise to the awareness that an improved understanding of individual travel choices and behavior is essential to accomplish reliable and policy responsive forecasts.

Therefore, the advanced travel demand models need to embody a realistic representation and understanding of the travel context and the decision-making process of individuals in order to mimic their sensitivity to a wider range of transport policy measures.

Mental representation is a simplified and subjective reconstruction of the reality. It is for that reason critical to understand how individuals construct these representations to mentally simulate possible decisions and choices under specific expected situational conditions [2]. Because individuals hold their mental representations in working memory, and the capacity of that memory is restricted, individuals will experience restrictions on the amount of information that can be represented.

So, mental representations will in general engage a major overview of reality [3]. The term Cognitive Map refers to the internal mental representation of environmental information. Cognitive mapping is essential for spatial behavior and decision-making whether traveling across a continent or traversing an urban area.

The principal purpose of cognitive mapping is to facilitate individuals to make choices related to the spatial environment. Some transportation researchers have begun to engage with cognitive mapping to a restricted scale, acknowledging that travel and transportation systems are influenced by and they influence spatial cognition [4].

To this point, much of the focus in transportation research has been positioned on how cognitive mapping influences path selection, the routes selected by travelers.

However, the relationship between travel and spatial cognition extends beyond route choice. Cognitive mapping encompasses individuals' knowledge not only of potential travel routes but also of destinations themselves, as well as their proximity, purpose, desirability, and familiarity as such, spatial cognition shapes each person's access to opportunities in the urban environment [5].

Modeling approaches have shifted from trip and tour based models of travel demand to activity based models in which the context of daily travel (i.e. the need to perform activities, household interactions, etc.) is accounted for.

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At the same time, a dramatic increase in computational capacity has enabled modeling techniques to evolve from aggregated approaches to large scale microsimulation of individual travel behavior [4].

In order to transfer and transform the knowledge source from individual minds to some explicit knowledge representation, usually denoted as Knowledge Base (KB), that enables the effective use of the knowledge, it is necessary to explore knowledge acquisition methods in organized approaches, to extract from persons a better understanding of the complex relationships between spatial cognition, travel, and other factors, such as socio-economic status, culture, and individual abilities.

All of this with the intention of helping to guide transportation policymakers, seeking to improve accessibility to important resources such as jobs, healthcare, and other amenities. It is essential to capture true individual decision mechanisms in order to improve behavioral realism of these models [3].

II. Mental Representations, Cognitive Maps and Travel Behavior

At the same time as the literature on theories and measurement of cognitive maps is fixed, the links between cognitive maps and travel behavior is less perceptive. Specifically, research on cognitive mapping and travel has tended to focus primarily, in fact almost exclusively, on the fourth and final part of the traditional travel demand analysis process: route choice. In contrast, the first three steps: trip generation, trip distribution, and in particular, mode choice, have been given far less attention by cognitive mapping researchers [6].

Existing opinion appears to specify that, because factors such as cognitive mapping facility, cognitive map knowledge of possible alternatives, navigation and way finding strategies, and preferences for path selection criteria all are supposed to have a considerable impact on travel choices, there is a rising need to include spatial cognition explicitly in models [7].

Cognitive mapping and travel behavior research has centered on how information on what is known about the location, probable destinations, and viable alternatives for any option affects what is known about the network over which travel must take place. The links between cognitive maps and travel choices are essential to comprehend travel behavior.

The scientific literature on household activity modeling, as a conceptually sound and robust way to forecast travel behavior than traditional travel demand modeling is large and increasing. Activity modeling could be enhanced significantly with better information on how modal experience shapes individuals' cognitive maps (see Fig. 1).

In other words, the cognitive maps of people who mostly walk and use public transit may vary systematically from those who are mostly chauffeured in private vehicles, and from those who usually drive [8].

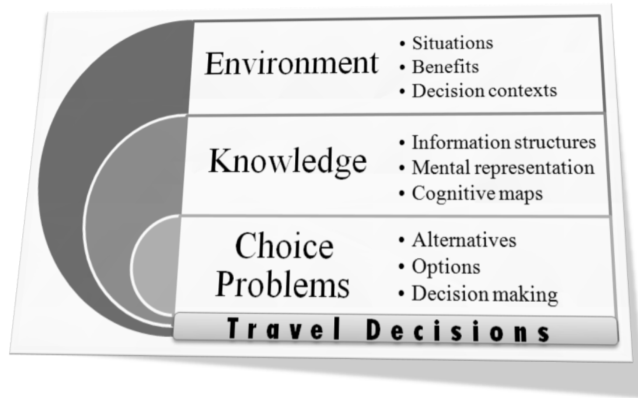

Fig.1. Abstraction levels of mind related to Travel Behavior.

This line of way of thinking is dependable with study on job explore behavior among low salary workers. Those with regular access to private vehicles tend not only to search larger geographic areas work for work, but tend to perceive job opportunities in less spatially constrained ways.

In order to remedy such cognitive barriers to job opportunities experienced by those without regular access to autos, compensatory solutions such as trip planning services, guaranteed ride home services, and overall progresses to transit service could be applied [9].

Another means of compensating for limitations in individuals' cognitive maps could be the dissemination of Intelligent Transportation Systems (ITS). Such systems decrease individuals' overall dependence on their own cognitive maps potentially rising access to recognized destinations. However, ITS would not necessarily influence how prior spatial knowledge informs the initial portions of the travel behavior sequence, trip generation and trip distribution [10].

Persons would still rely on their cognitive maps when choosing to make a trip and selecting a meticulous purpose for that trip. Public transit planning could potentially profit from cognitive mapping study in at least two other ways.

First, the well-documented body of research showing that different people tend to construct and interpret cognitive maps in systematically different ways such as isolated route knowledge as compared to broader configurationally knowledge of a region suggests that the representation of transit networks, routes, transfer points, and schedules might best be consistently represented in redundant ways to be user-friendly to different types of spatial learners [11].

Second, if street and transit networks, while overlapping in space, tend to be constructed completely unconnectedly in the minds of most travelers, this might give details why large shares of personal vehicle drivers never use, or still think using, public transit. While drivers may prefer private vehicle travel over transit, they may never consider using transit, even if a particular transit trip may be competitive in time and cost with an auto trip, if the transit network is, for all intents and purposes, transparent.

However if marketing programs are doing well in encouraging drivers to use transit once or twice, consciousness of transit may cause drivers to change their cognitive maps to include transit as a possibility for a number of trips. Given that high percent of all trips after year 2000 were made in private vehicles, efforts to encourage drivers to occasionally use transit could bear substantial fruit for transit systems anxious to attract more riders.

While cognitive mapping researchers have recognized the connection between travel and spatial learning, little is known yet about how the existing transportation infrastructure itself shapes cognitive maps and, in turn, affects route selection as well as other aspects of travel including trip frequency, trip purpose and destinations, and mode choice.

Nevertheless, the incomplete accessible study suggests that transportation communications and, in particular, way finding on overlapping, up till now distinct, modal networks, sidewalks, bike lanes, local streets and roads, affects the increase of cognitive maps and, in turn, travel behavior [12].

Individual activity travel choices can be considered as actual decision problems, causing the generation of a mental representation or cognitive map of the decision situation and alternative courses of action in the expert's mind. This cognitive map concept is often referred to in theoretical frameworks of travel demand models, especially related to the representation of spatial dimensions.

Actual model applications are scarce, mainly due to problems in measuring the construct and putting it into the model's operation. The development of the mental map concept can benefit the knowledge by individual tracking technologies [4].

At an individual level it is important to realize that the relationship between travel decisions and the spatial characteristics of the environment is established through the individual's perception and cognition of space. Because a person observes space, for instance during travel, the information is added to the individual's mental map.

Among other things, the mental map subsequently shapes the individual's travel decisions, since it reflects what an individual knows and thinks about the environment and its transportation systems (spatial planning).

Although this concept is often referred to in theoretical frameworks of travel demand models, actual model applications are scarce, mainly due to problems in measuring the construct and putting it into the model's operation [13].

III. Knowledge Engineering, Knowledge Acquisition and Knowledge Base

Knowledge Engineering (KE) is defined as the group of principles, methods and tools that allow applying the scientific knowledge and experience to the use of the knowledge and their sources, by means of useful constructions for the human. It faces the problem of building computational systems with dexterity, aspiring first to acquire the knowledge of different sources and, in particular, to conclude the knowledge of the expert ones and then to organize them in an effective implementation.

The KE is the process to design and make operative the Knowledge Based Systems (KBS); it is the topic concerning Artificial Intelligence (AI) acquisition, conceptualization, representation and knowledge application [14].

Traditionally the KE has been related with the software development in which the knowledge and the reasoning play a primordial piece. As discipline, it directs the task of building intelligent systems providing the tools and the methods that support the development of them.

The key point of the development of a KBS is the moment to transfer the knowledge that the expert possesses to a real system (see Fig. 2). In this process they must not only capture the elements that compose the experts' domain, but rather one must also acquire the resolution methodologies that use these [15].

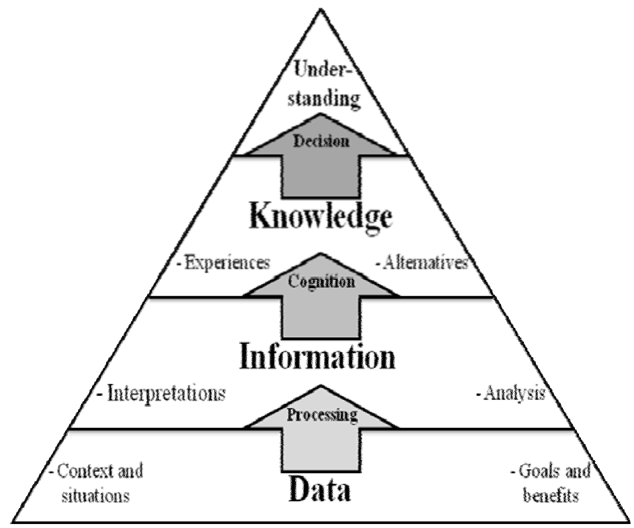

Fig.2. Data, Information and Knowledge Acquisition.

The KE is mainly interested in the fact of "to discover" inside the intellectual universe of the human experts, all that is not written in rules and that they have been able to settle down through many years of work, of lived experiences and of failures.

If the KE can also be defined as the task of to design and build Expert Systems (ES), a knowledge engineer is then the person that carries out all that is necessary to guarantee the success of a development of project of an ES; this includes the knowledge acquisition, the knowledge representation, the prototypes construction and the system construction.

The fundamental problems in the construction of the KBS are [16]:

- Knowledge Acquisition: How to transfer the human knowledge to an effective representation abstract, denominated conceptualization.
- Knowledge Representation: How to represent the knowledge in terms of information structures that a computer can later process.
- Inferences Generation: How to use those information structures to generate useful information in the context of a specific case.

A Knowledge Acquisition (KA) methodology defines and guides the design of KA methods for particular application purposes. Knowledge elicitation denotes the initial steps of KA that identify or isolate and record the relevant expertise using one or multiple knowledge elicitation techniques. A KA method can involve a combination of several knowledge elicitation techniques which is then called knowledge elicitation strategy (Of course these terms are used differently by different authors).

There are several characteristics of KA that need to be considered when applying KA methods [17]. KA is a process of joint model building. A model of expertise is built in cooperation between a domain expert (i.e., the knowledge source) and a knowledge engineer. Appropriate knowledge elicitation techniques are needed to make it plain.

The results of KA depend on the degree to which the knowledge engineer is familiar with the domain of the knowledge to be acquired and its later application. Also, it is noticed that the results of KA depend on the formalism that is used to represent the knowledge. KA is most effective if knowledge representation is epistemologically adequate (i.e., all relevant aspects of expertise can be expressed) and usable (i.e., suits all later usage needs).

These characteristics of KA provide guidance for the design of KA methods. For example, they imply that KA methods must assure that the knowledge engineer becomes familiar with the application domain.

The KA also takes into account the transfer and transformation of the potential of experience in the solution of a problem from several sources to a program. The sources are generally expert human but it can also be empiric data, books, cases of studies, etc.

The required transformation to represent the expert knowledge in a program can be automated or partially automated in several ones [18].

There are different ways of KA:

- The expert interacts with the knowledge engineer to build the KB:
  [Expert] → [Knowledge Engineer] → [KB]
- The expert can interact more directly with the ES through an intelligent publishing program, qualified with sophisticated dialogues and knowledge about the structure of the KBs:
  [Expert] → [Intelligent Program] → [KB]
- The KBs can be built partially by an induction program starting from cases described in books and past experiences:
  [Books] → [Induction Program] → [KB]
- A method of acquisition of the most advanced knowledge is the direct learning from books:
  [Books] → [Data Processing] → [KB]

General requirements exist for the automation of the KA and they should be considered before attempting this automation, such as independence of the domain and direct use of the experts without middlemen, multiple accesses to sources of such knowledge as text, interviews with experts and the experts' observations.

Support to diversity of perspectives including other experts, to diversity of types of knowledge and relationships among the knowledge, to the presentation of knowledge of diverse sources with clarity, in what refers to their derivation, consequences and structural relationships, to apply the knowledge to a variety domain and experience with their applications and to validation studies.

The automated methods for the KA include analogy, learning like apprentice, learning based on cases induction and analysis of decision trees, discovery, learning based on explanations, neural nets, and modification of rules and tools and helps for the modeling and acquisition of knowledge that have been successful applied; they seem to depend on intermediary representations that constitute languages of modeling of problems that help to fill the hole between the experts and the implementations of programs [15].

Diverse causes have taken to the construction of the Automated Knowledge Engineers (AKE), the descent in the cost of the software and hardware for ES, it has favored the development of the same ones. This has increased the demand of ES, greater than the quantity of AKE, and able to support ES.

The movement toward an extensive human activity, as the KE, is contrary to all the industry tendencies, in particular the industry of the software.

The Knowledge Engineer's role, as middleman between the expert and the technology, sometimes is questioned. Not only because it increases the costs but also for their effectiveness, that is to say, it can get lost knowledge or it can influence subjectively on the KB that is making (see Fig. 3).

The automated knowledge acquisition keeps in mind in what measure belong together the description of the application domain that has the expert and the existent description in the KB and how to integrate the new information that the expert offers to the KB.

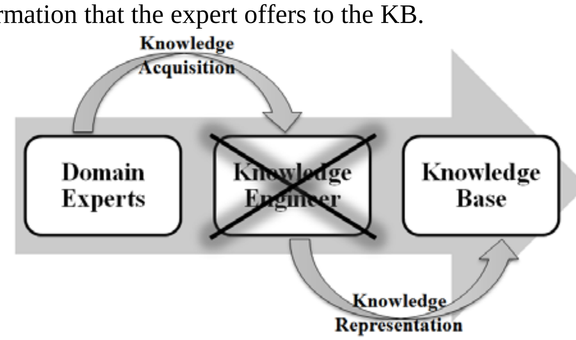

Fig.3. Automated Knowledge Engineer.

The AKE, if it is possible, should be independent of the experts' domain, to be directly applicable for the experts without middleman able to ascend to diverse sources of knowledge, including texts, interviews with the experts, and other features.

Also, it should be able to embrace diverse focuses, even different experts' partially contradictory approaches, and to be able to embrace diverse forms of knowledge representation.

Diverse methods of implementation of AKE exist [17], some of the most significant can be:

- Generation of rules starting from a database whose fields correspond to the attributes or conditions and the last field corresponds to the conclusion. Each article of the base becomes a rule.
- Dialogue with the experts. The AKE should guide the expert, but with certain flexibility.
- Learning for similarity. Given a group of objects which represent examples and opposite of examples of a concept, the AKE generalizes a description that covers the positive examples and not the negatives. The positive examples generalize and the negatives specialize the objects (the concepts can be described as rules).
- Adjustment of numeric parameters of certain parts of the knowledge, as the coefficient of the expressions that conforms the production rules.

Most of the existent methods to acquire the knowledge automatically, work with a fixed representation language, developed by the designer. The training data (examples) for these methods can contain non prospective errors using the knowledge domain to guide the learning. Some methods of automated learning are not strong to select the appropriate generalization of the data, among all the possible ones [19].

IV. Automated Knowledge Engineer for acquiring Individuals Mental Representation about Travel Behavior

While faced through complex choice problem like activity-travel option, persons generate a mental representation that allows them to understand the choice situation at hand and assess alternative courses of action.

Mental representations include significant causal relations from realism as simplifications in people's mind. We have used for the capture of this data, in the knowledge engineering process, an Automated Knowledge Engineer (see Fig. 4), where the user is able to select groups of variables depending of some categories, who characterize what they take into account in a daily travel activity. There are diverse dialogues, trying to guide the user, but not in a strict way or order.

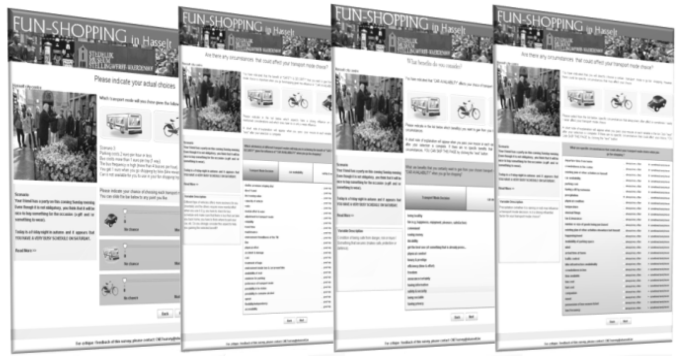

Fig.4. Automated Knowledge Engineer.

In the software there are 32 different ways to sail from the beginning to the end, due to the flexibility that must always be in the data capture process, trying to adapt the Interface as much as possible to the user, guarantying then that the given information will be as natural and real as possible, never forcing the user to give an answer or to fill a non-sense page.

For each decision variable selected a matrix with attributes, situational and benefit variables exist, in this way respondents are asked to indicate the causal relations between the variables.

Fig. 5 shows a segment of the definition file that is automatically generated with the flat representation of a cognitive map. This process is totally transparent to the user (that´s way is called Automated Knowledge Engineering).

```
First-decision
TM/SL

Second-Decision
SL/TM

Start-normally-TM/SL
Yes, XXX/No

Relations-variables-TM/SL
'normally'-'atribute'-'benefit'
-
-
-
'situation'-'atribute'-'benefit'

Car/Zone1
XX (value in 0..1)

Bus/Zone2
XX

Bike/Zone3
XX

Considerations
XXXXXXXXXXXXXXXXXX
```

Fig.5. Definition file segment of the generated KB.

Fig. 6 shows a possible and simple real map of a person after the selection of the variables and the relationship that was considered. Because of individual differences in the content of cognitive maps, different motivations or purposes for travel and different preferences for optimizing or satisfying decision strategies, human travel behavior is difficult to understand or predict.

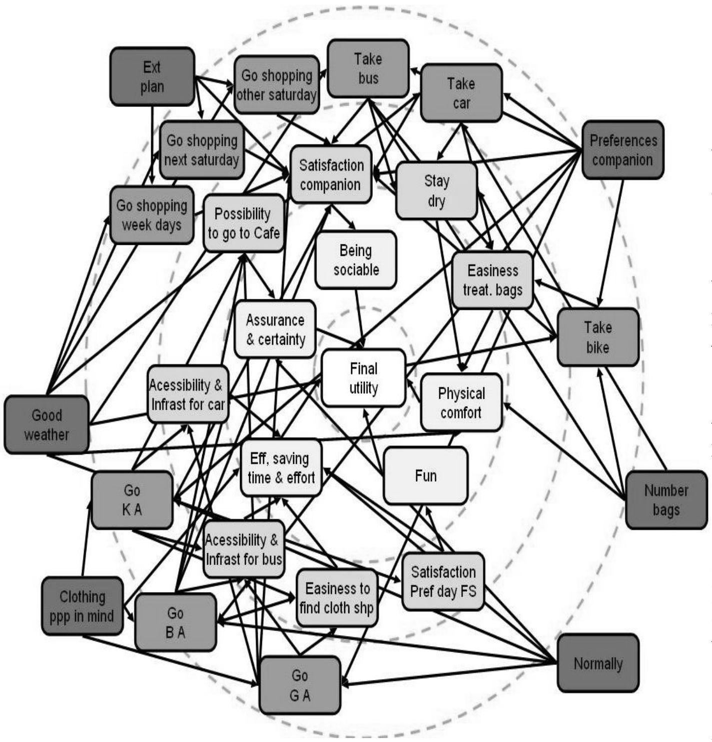

Fig.6. Possible individual cognitive map for a shopping activity.

The problem facing future study is that of combining travel demand with network provide with an understanding of how persons choose on where they prefer to go and how they prefer to get there. Emphasizing cognitive mapping values may give a stage of imminent that has not so far been completely supplied.

In a case study 223 persons were already asked to use the software, and the results are really promising given that the 99% of individuals (see Fig. 7) were able to interact complete along with the Automated Knowledge Engineer, generating their own cognitive map about a shopping activity scenario that was given.

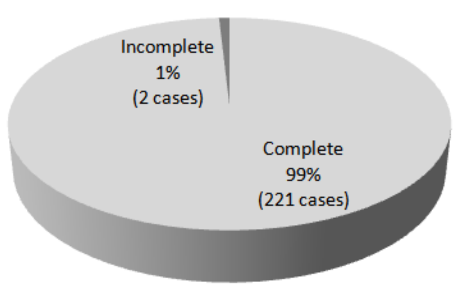

Fig. 7. Percent of complete generated KBs.

V. Conclusions and Future work

We have argument in this paper that cognitive mapping research has the possibility to address the continuing focus on accessibility in transportation studies.

While accessibility has traditionally been conceived as proximity of (or cost of travel between) one location and others, cognitive mapping research shows that physical distances are only one factor shaping how individuals make choices in a spatial context.

Human being differences, including past modal travel experiences, cultural preferences, and spatial abilities, form the cognitive map and, in this manner, influence the cognitive immediacy and openness of latent destinations in a region.

The automated methods used in the Knowledge Engineer in occasions can end up being more competent than the humans to acquire and to refine certain types of knowledge. They can reduce the high cost significantly in human resources that it wraps the construction of Knowledge Based Systems.

It had been taken into account the satisfactory use of the Automated Knowledge Engineering to extract mental representations and as an interesting way of make automatic a cognitive map formalizing.

Considering this, an Automated Knowledge Engineer to acquire Individuals Mental Representation about Travel Behavior was developed, and from a generated Knowledge Base is directly built a Fuzzy Cognitive Maps that characterize the way of thinking of a person, giving us the possibility of simulate the behavior of individuals, to infer and predict future situations that can be considered in the transport planning process.

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