

A Novel Modal Shift Modelling Framework for Transport Systems

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Abstract

The challenges from transport modes on human environments, health and economy, have called for investigations into how behavioural changes can be achieved for better resource utilisation. Trip makers' travel demands have been identified, and they include cognitive, physical and affective aspects. Presently there is a shortage of models that integrate all those demands. In addition, trip maker's context during decision making and social interaction structures are not addressed. These gaps have made it difficult to stimulate behavioural changes for modal shift effectively. This paper introduces a novel modal shift framework (MOSH framework) to support research on how to best stimulate trip makers' behaviour changes to adopt less preferred transport modes. MOSH framework encompasses the Consumat model, which integrates social-psychological theories, coupled with a cognitive work analysis. These two (consumat and cognitive work analysis) were chosen to incorporate all travel demand factors into trip maker's decision-making process. A hypothetical case study model of the shift from road to rail was developed using the framework to demonstrate its applicability for such investigations.

Keywords: Modal Shift, Modelling, Transport System, Consumat, Cognitive work analysis.

1 Introduction

Human activities and their lifestyle have impacted negatively on the ecosystem to such an extent that its existence is threatened. Prominent among these activities is transport system. A transport system consisting mainly of road, rail, air and waterways is fundamental to growth in an industrialised society. Transport sector according to Stanton (2013) remains the fastest growing, and it is characterised with environmental, economic, social and health challenges.

Stakeholders have approached these challenges using different world-views, which include technological innovations, expansions and construction of new road links and policy initiatives, such as advocating for individual behavioural change. While some of these approaches can be capital intensive and subject to limitations Steg (2007), a behavioural change approach towards a mode of transport shift can be achieved with less costs and provide immediate impacts on curbing the challenges (Chapman 2007; Steg 2007; Roberts *et al.* 2014). However, insights into the usefulness and effectiveness of these approaches could be gained through model representations.

There are a plethora of models for studying trip maker's mode choice. There is, however, shortage of models for behavioural change in modal shift. Modal shift as described by Rodrigue (1998) occurs when a transport mode has a comparative advantage in a similar market over another mode. Hence, the mode with better advantage attracts more users than the other. To our knowledge, most mode choice models available have centred on the modal split, which looks at the proportion of passengers using a particular transport mode. These models are not useful for policy makers who wish to understand motives behind trip maker's mode choice behaviours. Hence, to achieve behavioural change, several factors that drive trip maker's behaviour in mode choice have to be considered for proper stimulation of behaviour towards the desired mode.

In order to contribute to overcoming those limitations, we introduce a novel modal shift (MOSH) framework that captures the nonlinear and heterogeneous characteristics of trip makers. The characteristics includes aspects such as their cognitive, physical and affective differences during mode choice decision-making process. MOSH framework aims at providing modelling techniques that allow investigations into individual actor's attributes, behaviour and interactions. The application of MOSH framework is demonstrated through a hypothetical case study, focussing on the modal shift from road to rail. In this case study, we employ agent-based modelling to explore the autonomous features of individual agents and observe the emergent behaviour arising from their interactions. We were able to observe that the model conceptualised from the framework is capable of assisting policy makers to gain insight into modal shift problems and provide guides on how to effectively stimulate their behaviours.

The remainder of the paper is organised as follows: Section 2 discusses the background to the study which includes research on modal shift, factors and constraints to modal shift, approaches to modelling mode choice, and agent-based modelling. Section 3 gives the overview, explain the components and

process flow of the MOSH framework. A hypothetical case study to address a specific modal shift problem is developed and implemented as presented in Section 4. Finally, Section 5 presents the conclusions and proposes further ideas for future research.

2 Background

2.1 Modal Shift

Several studies conducted on modelling mode choice have focused on the modal split (e.g. Sakano & Benjamin (2011), Nurddin *et al.*, (2007)). These models are non-behavioural and employ aggregate approaches which are only good for planners and engineers to make predictions (Barff *et al.* 1982) and not for understanding factors responsible for individual mode choice. Moreover, the majority of modelling studies available on modal shift have mainly been on freight and shipping transports (e.g. Islam *et al.*, 2016; Blauwens *et al.*, 2006). There are few available models on passengers travel patterns. Most of these few models based their behavioural architecture on limited socio-psychological theories of human behaviour. For instance, Heath & Gifford (2002) use theory of planned behaviour to predict the use of public transport hence, failed to represent human behaviour adequately.

2.2 Factors and Constraints to Modal Shift

Social, psychology and human factors researchers have been at the centre of studies on constraints to mode choice. Wardman *et al.* (2001) broadly conceptualised travel demands in terms of physical ability, cognitive efforts and affective (i.e. the subjective emotional assessment of individual circumstances) required to make a trip. In addition, some utility factors such as cost and value for money, punctuality and reliability, frequency of the mode, comfort/cleanliness, travel time, bus stop/interchange/station facilities, etc. have been identified in several studies (e.g. Derek Halden Consultancy (2003), DfT (2009)) as major constraints preventing car travellers from shifting to other modes. These factors have also been identified in social and psychology studies to have consequences on travel demands. Mann and Abraham (2006) observed that utility beliefs influence decisions through their affective impact.

Attitudes and perceptions in addition to the utility factors have also been investigated. Atasoy *et al.* (2012) and Chee & Fernandez (2013) incorporated these two factors into the mathematical models presented in their studies to investigate mode shift problems. Apart from the factors mentioned, other modal shift constraints with significant effects are experiential and personal affective. Gardner and Abraham (2007) and Mann and Abraham (2006) found out that journey-based affect and personal space/autonomy are common affective barriers in mode shift to public transport. In a recent study, Ryan *et al.* (forthcoming) used thematic analysis method to understand the functional and affective aspect of a commuters' journey to a university using Herzberg's Hygiene-Motivation theory. Their study revealed some motivational factors (e.g. a sense of being valued as a passenger; excitement in the journey), and hygiene factors (such as rule and policies; impact on personal status) as factors that affect mode choice. Also, Ryan study confirmed Stanton *et al.*, (2013) system based analysis findings, which state that there are interrelationships between constraints that impact on mode choice and travel decisions.

From our point of view, and as revealed in the literature on constraints to modal shift, it is clear that effective modelling of modal shift problems requires complete representation of travel demand factors as identified by social, psychology and human factors studies. At present, this not easily achievable because most of the existing models' behavioural architectures were based on few socio-psychological theories of human behaviour, and are implemented using mathematical approaches. Recent studies including Osman Idris *et al.* (2015), Tudela *et al.* (2011)) used traditional mathematical choice models such as classical logit Domarchi *et al.* (2008); probit Atasoy *et al.* (2012) and hybrid Temme *et al.* (2007) mode choice models in their studies. These approaches impose limitations on the models' capabilities to include many relevant theories of human behaviour in choice making. Attempts to include all attributes and interrelated features of different passengers would therefore, result in multiple complex equations, which are difficult for non-experts to comprehend. More importantly, social interaction structures among the actors and their immediate environments are not emphasised or explained in the methodologies provided by these models. Furthermore, real-time and dynamic observations of trip makers' behaviour are not possible due to the static nature of the mathematical approaches. Therefore, to address these limitations, an agent-based modelling technique is explored in this study.

2.3 Agent Based Modelling

Agent-based modelling (ABM) has become a widely used technique to model complex systems composed of interacting, autonomous "agents" (Macal & North, 2010). Agents have behaviours, interact

with and influence each other, learn from their experiences, and adapt their behaviours. Furthermore, individual modelling of agents allows full effects of the diversity that exists among agents with respect to their attributes and behaviours to be observed. Individual agents disaggregate behaviour within an environment give rise to emergent and observable system effects. The features provided by this technique will be explored in this study.

As revealed in the reviewed literature, the existing mode choice models lack the capabilities to achieve the objective of stimulating trip makers' behaviour for the mode shift due to the following limitations:

- There is no reference to trip makers' context (situation) during decision-making process
- Existing models are often purely mathematical and hence, give limited room for actors' multiple and heterogeneous characteristics to be observed
- The effect of social interactions among individuals and with the environment is not emphasised
- There are no clues provided on how trip maker behaviour can be stimulated to encourage modal shift

To effectively address the problems highlighted, a framework is introduced in the next section that presents a new methodology for dynamic and comprehensive investigations into various trip makers' features and mode choice factors.

3 The MOSH Framework

3.1 Overview

The focus of this framework is to provide support for understanding how best to stimulate individual trip makers' behaviour, to enable them to adopt less preferred but greener modes of transport as a result of mode usage challenges on human life style. It considers the heterogeneity in trip makers' physical, cognitive and affective characteristics and accounts for actors' context in the process of trip making within an uncertain and dynamic socio-technical system.

To achieve this, our proposed modal shift framework (depicted in Figure 1) brings together integrated theories of human behaviour in choice making and human factors' formative task analysis models.

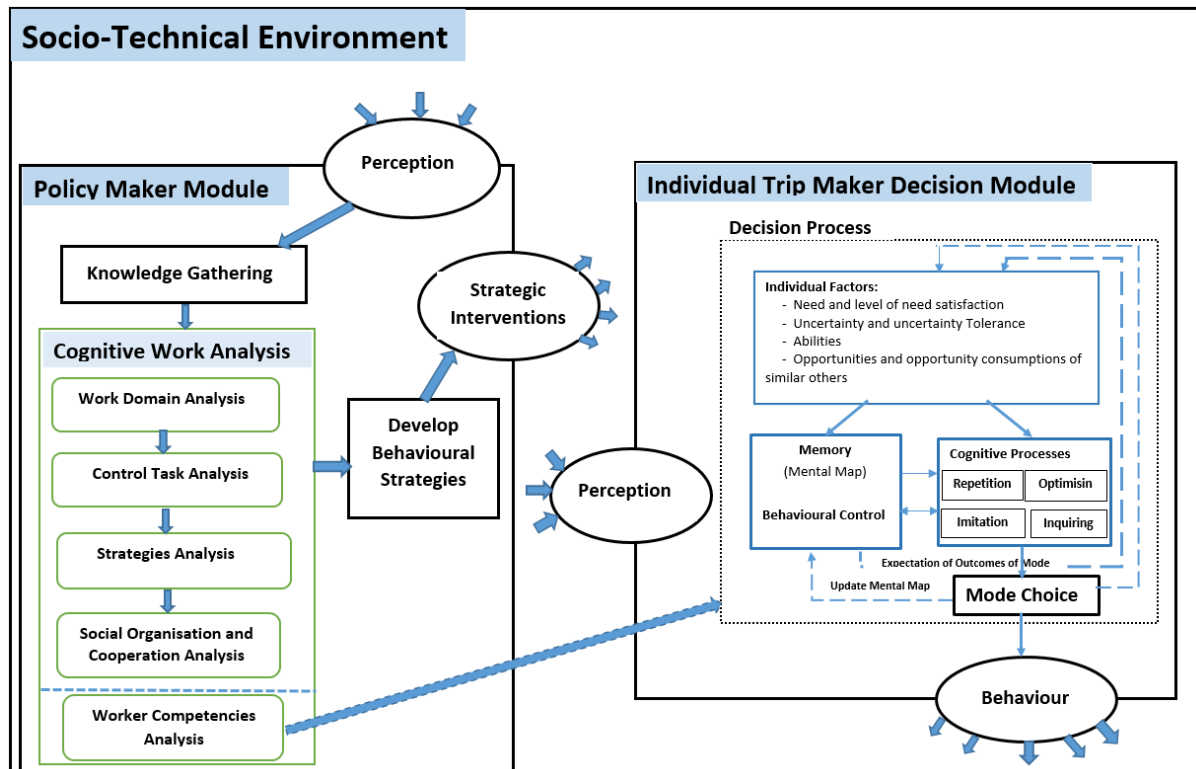


Figure 1: Modal Shift (MOSH) Framework (inspired by Jager and Janssen, 2012; Jager, 2000; Rasmussen *et al.*, 1994; Vincente, 1999; Schlüter *et al.*, 2017)

The framework consists of three major components: The outer box in the figure represents the **socio-technical environment**. It consists of technology, economy, demography, cultures, institutions, within which the two inner boxes (policy makers and individual trip makers) operate. According to Jager

(2000), the sociotechnical environment is a human-induced environment that is derived from, and operating within the larger natural environment. Sociotechnical resources are available and are applicable to all actors within the system irrespective of status, thereby making the environment the decision context of actors.

The **policy maker module** consists of three activities: *Knowledge Gathering*, *Cognitive Work Analysis (CWA)*, and *Develop Behavioural Strategies*, and two processes: *Perception* and *Strategic Interventions*. The CWA is a well-established human factors formative task analysis tool developed by Rasmussen *et al.* (1994) and Vincente (1999). It focuses on how human-system interactions are conducted within a given domain, rather than how it currently works or how it should operate. CWA allows policy makers to gain insights into those factors influencing trip makers' behaviour and their relationships. The activities and processes in the diagram are connected with solid arrows indicating the flow of information.

The **Individual trip maker decision module** centres on the "Consumat" approach. Consumat is a well-researched and cognitively-inspired conceptual model that integrates several known social-psychological theories. It was developed originally by Jager (2000) to model consumer behaviour and market dynamics; it was later revised by Jager and Janssen (2012) to accommodate more realistic behaviours in choice making. Consumat provides our framework with social-oriented heuristics, possible network structures for agents' interactions and cognitive processes in human decision making.

3.2 Components of the MOSH Framework

The challenges of transport systems on various aspects of human life lead stakeholders to the process of fact finding (knowledge gathering) their causes. The outcome of the knowledge gathering is further analysed with CWA, which is a five-phased framework that focuses on how system constraints limit functionality in specific situations within a socio-technical system. Most of the illustration on the description of CWA in this section is obtained from (Stanton *et al.*, 2013). Following is a detailed description of the different phases of the CWA framework:

- **Work Domain Analysis (WDA):** Uses its abstraction hierarchy (AH) shown in Figure 2 to provide investigative access to the system's components and environments at different levels of granularity (refer to Jenkins *et al.*, (2009) for details). In our case, the WDA reveals the fundamental set of constraints that the modes' components, the process of using the components and their purposes impose on the actions taken by the trip makers. The AH describes a system based on five different levels, ranging from physical objects (the physical components of the system) at the bottom, up to overriding functional purpose at the top (the system's reason for existence). It makes use of the 'why-what-how' triad to provide guidance by giving answers to why the system exists, what functions can be conducted within the domain as well as how these functions can be achieved. Figure 2 shows an extract from a larger AH. For instance, provisions of 'what' communication facilities can be derived from 'how' access to telephony network while on board. These two (i.e. what and how) answer the question of 'why' cater for needs of the trip maker. Investigators may be interested in asking and answering questions at any level of these details.

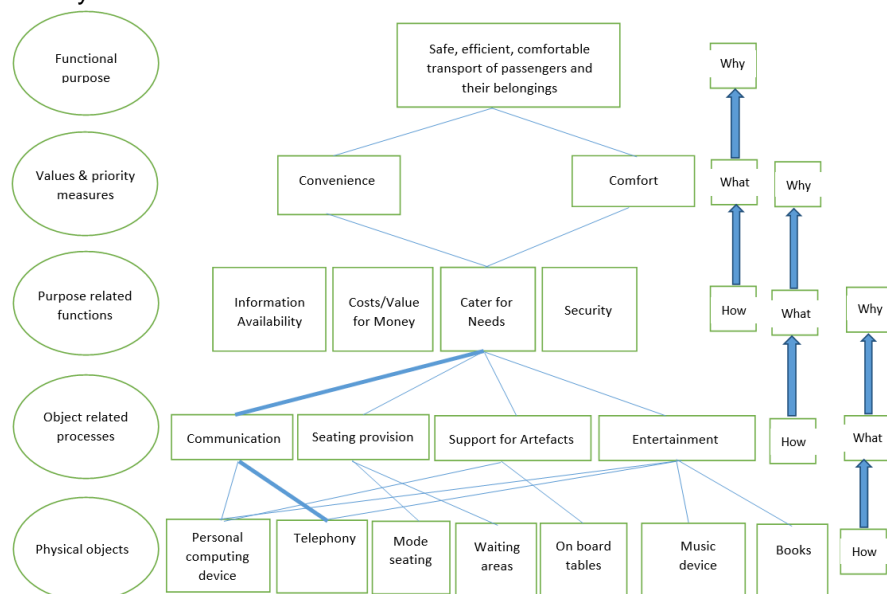


Figure 2: Work Domain Analysis (Abstraction Hierarchy): An example

- Control Task Analysis (ConTA):** Accounting for the decision maker's context is one of the gaps this framework sought to address. Hence, the ConTA is an important phase that models the context of the trip maker. It uses contextual activity templates (CAT) introduced by Naikar *et al.* (2006) (see Figure 3) to model known recurring activities within the system. It focusses on which activity can be achieved independently of how it is conducted or who undertakes it. Constraints to performing a required activity have significant influence on the decision maker. For instance, on a long haul train journey, connections with telephone network are an issue for a trip maker who needs to be in constant touch with business partners or for other purposes. Consequently, in the contextual activity template for a rail user example shown in Figure 3, situations are placed in the horizontal axis representing various stages of a trip maker's journey. These situations are subsequently mapped to functions that occur under each situation. A function in this context is the activity a user can perform in a given situation. Functions are taken from object-related processes of the AH (see the second row of figure 2) and form the vertical axis of the templates. The cells with ball and whiskers in the template indicate situations where functions can and typically do occur; while cells surrounded by dotted line indicate the function is able to occur in this situation but typically does not, and Empty cells without ball or dotted lines indicate the function is not possible in that situation.









Situations Functions	Origin/ Destination	En-route to transport	At Station	On train	Rail interchange	En-route to destination
Seating Provision						
Support for artefacts						
Entertainment						
Communication						

Figure 3: Contextual Activity Template for the rail system (Source: Stanton *et al.*, 2013)

With the information provided by the template, policy makers can make provisions for situations where functions can be performed but are not yet adopted.

- Strategies Analysis (SA):** There are different ways to carry out the same activity by the trip makers. SA looks at known recurring activities as presented in CAT and considers different strategies that are likely to be used to complete them. For instance, to ensure constant communication networks in a long haul train travels, wireless technologies can be installed on the train coaches. While CTA focuses on what needs to be done, SA focuses on the flexibility of doing it in different ways, in that context. The freedom and flexibility allow the user to adapt and select a way of achieving an end-state that is most appropriate in a given situation.
- Social Organisation and Cooperation Analysis (SOCA):** Focuses on constraints imposed on individual trip maker's needs and requirements. It indicates where each trip maker can perform a given function rather than where they typically perform or should perform the function. For instance, a mobility impaired trip maker may not have the same flexibility in accessing a train as an abled bodied trip maker. SOCA uses CAT to show how each of the functions and situations can be examined with respect to individual differences (e.g. physical, cognitive abilities, etc.).

The outcome of the first four phases (i.e., Focussing on what activity can be achieved independent of how it is conducted or who undertakes it; strategies that are likely to be used to complete the activities; and identifying individual trip maker limitations in using the mode) gives the policy maker enough insights about the system and various trip maker possible stereotypes. Hence, assist in the "Develop

Behavioural Strategies” activities stage to establish new strategies to extend the system flexibility. The results of the strategies are presented as interventions into the environment.

- Worker Competencies Analysis (WCA): Lastly, the skill level needed by a trip maker to effectively choose a suitable mode for the trip is determined at this stage. This skill is a function of individual cognitive, physical, tolerance and affective capabilities. The activities within this analysis stage are mapped to and detailed in the decision process of the *Individual Trip Maker Decision Module* as depicted in Figure 1.

The second inner box in Figure 1 named *Individual Trip Maker Decision Module* consists of two states and two processes. The states are the *Decision Process* and the *Mode Choice*, while the processes are the *Perception* and the *Behaviour*. The *Decision Process* contains three boxes including (i) *Individual Factors*, which are the decision making driving factors. (ii) The *Memory and Behavioural Control* that consists of the trip maker's own characteristic, previous experiences of using various modes, available mode's characteristic, and similar others experience; as well as ability has by the trip maker, and the ability demanded (physical, cognitive, and affective) to make the trip. And (iii) possible *Cognitive Processes* the trip maker adopts in selecting mode. The two dotted lines within the decision process box represent the updating and evaluation processes. The outer dotted box updates the memory with the trip experience, and the inner one evaluates how well the mode meets user's expectation. The solid lines are the flow of information between the major states.

3.3 Process Flow through the MOSH Framework

The process flow diagram in Figure 4 provides a guide to understand the framework better. Processes and decisions in the diagram are labelled with numbers. To make a trip, an individual has certain personal characteristics and journey purpose which influence the choice of mode for the journey (elements 2 and 3 in Figure 4). The decision for mode choice is determined by the individual driving factors which refer to the trip maker's internal state; behavioural control; and memory contents.

The decision making is based on the ratio of trip maker's *Level of Need Satisfaction and Aspiration Level* (LNS/AL), and/or *Behavioural Control* (BC) with the ratio of *Uncertainty and Uncertainty Tolerance* (U/UT). The outcome of which determines the engagement of trip maker in any of the four cognitive processes of *Repetition*, *Optimising*, *Imitation*, and *Inquiring* (elements 7,9,13 and 15 in Figure 4).

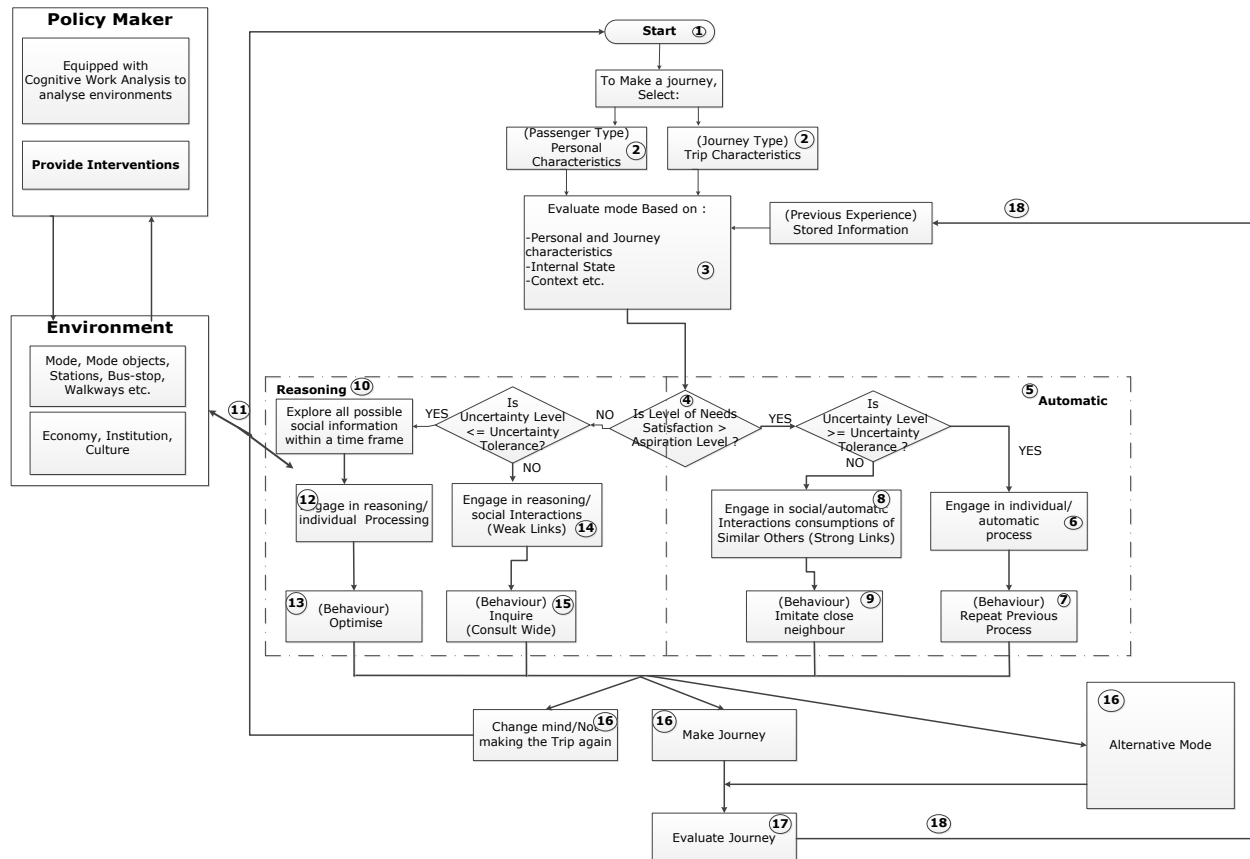


Figure 4: Modal Shift Process Flow

Cognitive processes are identified along two dimensions of *reasoned* versus *automatic* (elements 5 and 10 in Figure 4) and *individual* versus *social* (elements 6, 8, 12, and 14 in Figure 4). A trip maker engages in individual behaviour when its level of uncertainty is low (i.e. $U < UT$), and engages in social when uncertainty is high ($U > UT$). The automatic process occurs when its preferred mode of transport regularly satisfies its need. Automatic behaviour can be individually or socially executed; it is individual when a trip maker *repeats* previous ways of making trips without consulting others or engaging in the cognitive evaluation. It is social when other similar trip makers are *imitated*. However, *reasoning* processes occur when there is dissatisfaction i.e. ($LNS < AL$ or/and $BC \leq 0$). Then, the trip maker would need to elaborate on alternative travel modes in order to make the journey. This process can also be individually or socially executed. It is individual when reasoned within itself by making use of information from the environment to deliberate on the mode to use; it is social when a trip maker consults similar and non-similar other trip makers in order to find better alternatives. At some points during the reasoning process, individual trip maker consults the environment for more information among other means. In the process, it encounters any improvements or nudges provided by the policy maker through the insight gained from analysing the system. This may affect its ability required to make use of the desired mode and hence, affect either its behavioural control or level of need satisfaction.

Lastly, when a mode is chosen and the trip made, the aggregated effects of individual trip makers' behaviour in mode usage go back into the environment. The trip maker's perception of the environment is represented by the equation below:

$$P(it) = \emptyset U_{it}^{\alpha 1} * \alpha F_{it}^{\alpha 2} * \gamma O_{it}^{\alpha 3}$$

Where:

- P is the perception based on the change in environment at time t for mode i
- U is the improvements perceived on utility factors, and \emptyset is the coefficient of the improvements for mode i.
- F is the improvement perceived on psychological factors, and α is the coefficient of improvements for mode i
- O is the improvements perceived of other factors (cognitive, physical, etc.) and γ is the coefficient of improvements for mode i
- α is the Cobb-Douglas type utility weighted function (Janssen & Jager, 1999) to factor the perception such that the quantity of each factor contributes to the total perception.

4 A Hypothetical Case Study

In the following, we use the MOSH framework to conduct a hypothetical case study for modelling and simulating road to rail shift. This will help to demonstrate the feasibility and applicability of the framework.

4.1 Case study description

For this case study, we assumed the "perception" process and "knowledge gathering" stage of the MOSH framework had been undertaken before the generation of data made available to us by the UK National Rail Passenger Survey (Transport Focus, 2016) detailed in section 4.4.

In this case study, there is a given population of heterogeneous passengers with many attributes including the purpose of the journey, the category of passenger, disabilities and demographics.

4.2 Model Design

In the model design, some assumptions and simplifications are made. The assumptions include: there are differences between the expected satisfaction and the actual satisfaction levels from a mode; limited mode's attributes considered in this model provide enough insights regarding the functionality of the model. While the simplifications are: distance travelled by the passenger to the nearest bus stop and the train station as well as period to go out and come back are not modelled; all transportation system run 24 hours a day. The simplification is to keep the model simple, while still maintaining satisfactory results and reasonable outputs from the model design.

The considered mode's attributes are obtained from the purpose related functions level in the WDA of the cognitive work analysis (see the middle row of Figure 2). The attributes (cater for need, security, information availability, and costs/value for money) are chosen to enable incorporation of passengers' physical, economic, cognitive and affective views of a mode.

Cater for need is about how well the transport mode satisfies the needs of trip makers. While the Security assesses how safe is the mode at the time of the trip. Information availability focusses on the

ability of a passenger to access needed information at any point of the trip. Cost/Value for money attribute is an economic and utility variable that has strong effects on trip maker's decisions. Each of the mode's attributes is appropriately evaluated based on users' level of need satisfaction, this is represented by index varying between 0 (fully unsatisfied) and 1 (fully satisfied), as shown in the equation below:

$$LNS_t = LNS_1^{\alpha_1} * LNS_2^{\alpha_2} * LNS_3^{\alpha_3} * \dots * LNS_n^{\alpha_n}$$

Where:

- LNS_i is the level of need satisfaction for need *i* at time *t*
- α is the Cobb-Douglas type utility weighted function that factors the total level of individuals need satisfaction such that the quantity of each of the needs contributes to the total LNS (Janssen and Jager, 1999).

The passenger's cognitive and user experience behaviours are captured by the state machine diagrams in Figures 5 and 6 respectively. A state machine diagram captures the different states of an entity as well as the possible transitions between these states. For more information about state machine diagrams (see Bersini (2012); Siebers & Onggo (2014)). In Figure 5, a trip maker can be in any of the four cognitive states shown in the diagram (repetition, optimising, imitation, or inquiring) depending on the determining factors (the ratios of LNS/AL, BC, and U/UT). Figure 6 shows the adoption transitions pattern from car to train. The inner single state on the left shows a trip maker as a car mode user, while the inner composite state on the right side of the figure shows a trip maker as a train user. Each state within the Train Users Experience state represents a class of train usage.

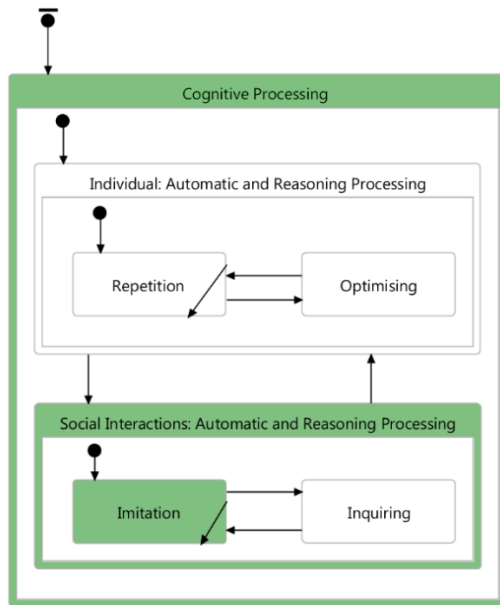


Figure 5: Passenger Agent: Cognitive Processing State Machine Diagram

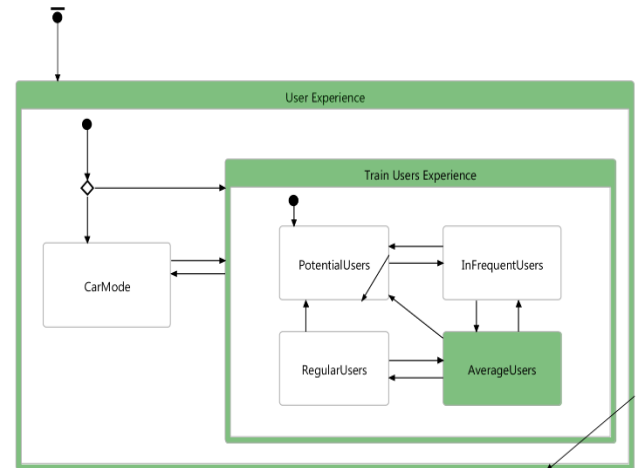


Figure 6: Passenger Agent: User Experience State Machine Diagram

4.3 Implementation of the Model

The model was simulated in the Recursive Porous Agent Simulation Toolkit (REPAST) Symphony version 2.3.1. REPAST is a free, open source, and Java-based simulation toolkit for ABM. There are three classes of active objects in the simulation: the passenger, the mode, and the policy maker.

Two stereotype categories are considered for the passenger agent, "the passenger type" and "the user experience level". The passenger type includes old age pensioner, youth, able-bodied person, and family. Each embarks on different kinds of journeys which include commuting (education, apprentice, and work), leisure (holiday, shopping, visiting) and business. There are also different levels of journey familiarity for various passengers based on journey types. The user experience stereotype has passengers as road users who have no rail usage experience and rail users with different level of rail usage experiences such as potential users, infrequent users, average users and regular users (Figure 6). The two travel modes modelled are car and train. The car is considered to be the highly preferred

mode and train as the less preferred mode. 80% of the population are car users, while 20% are train users. The policy maker agent develops and provides interventions to improve passenger's experience. Passenger satisfaction is focused on each of the four mode's attributes mentioned in the model design (Section 4.2).

A population of 6700 passengers is simulated, which is distributed as follows: 2500 able bodied adults, 1000 families, 2000 youth, and 1200 old age pensioners. The simulation runs for a period of 240-time steps (where one model time step is equivalent to one hour in a continuous model). The uncertainty tolerance and aspiration level are randomly generated. Passengers 'initial experience' is set to zero for all the mode attributes at time $t=0$. Social agreeability is calculated based on social settings given as follows: the maximum allowed difference between interaction initiator (interactor) and the chosen partner (interactee) is set to 0.5. Two interacting passengers with maximum difference higher than this value are not qualified to interact. Because, their level of conformity and similarity (social, previous experience, journey type, etc.) are assumed to have large variations to interacting passengers. The social interaction is set to 2% of entire population. The above settings are based on informed guesses made through consultation with experts in rail transport research and agent-based simulation.

4.4 Parameterisation and Validation

The model's variables are calibrated based on the set of descriptive data acquired from the UK's National Rail Passenger Survey (NRPS Spring 2015: Wave 32) (Transport Focus, 2016). The NRPS data is supported by car usage data from the DfT Report on "Understanding the drivers of road travel" (DfT, 2015). Corresponding values from the datasets relevant to our chosen mode's attributes are selected, aggregated (as shown in Table 1) and used for the calibration. In addition, experts in rail passenger research and agent-based simulation are consulted to verify the simulation settings assumptions made. The model is validated at various stages of the simulation using techniques such as independent review, continuous code debugging, model run with known characteristics, and animation.

Table1: Spring 2015: Wave 32 Descriptive Data

Satisfaction level	Information Availability	Cater For Need	Security	Value for Money
Very satisfied	0.26032	0.2666747	0.29843262	0.163797895
Fairly satisfied	0.437919	0.38659769	0.4765658	0.282060143
Neither satisfied nor dissatisfied	0.193382	0.14026273	0.19086208	0.209335071
Fairly dissatisfied	0.073792	0.10339568	0.02196016	0.204737609
Very dissatisfied	0.034587	0.1030692	0.01217934	0.140069282

The values in Table 1 show the percentage of total population that perceived each of the mode's attributes on the scale ranging from "very satisfied" to "very dissatisfied". The values are used in the simulation. Corresponding output for each of the attributes is observed from the simulation model and recorded as shown in Table 2.

Table 2: Modal Shift Simulation Values

Satisfaction level	Information Availability	Cater For Need	Security	Value for Money
Very satisfied	0.195789326	0.169994382	0.232050562	0.088030899
Fairly satisfied	0.365980337	0.28561236	0.454356742	0.194101124
Neither satisfied nor dissatisfied	0.202598315	0.121174157	0.204617978	0.165044944
Fairly dissatisfied	0.091570225	0.125393258	0.027207865	0.194710674
Very dissatisfied	0.086567416	0.240331461	0.024272472	0.300617978

Following this, a correlation study is carried out on the NRPS data (Table 1) and the simulation model's output (Table 2) for the selected mode's attributes. The result of the comparison is shown in Figure 7 and Figure 8 below.

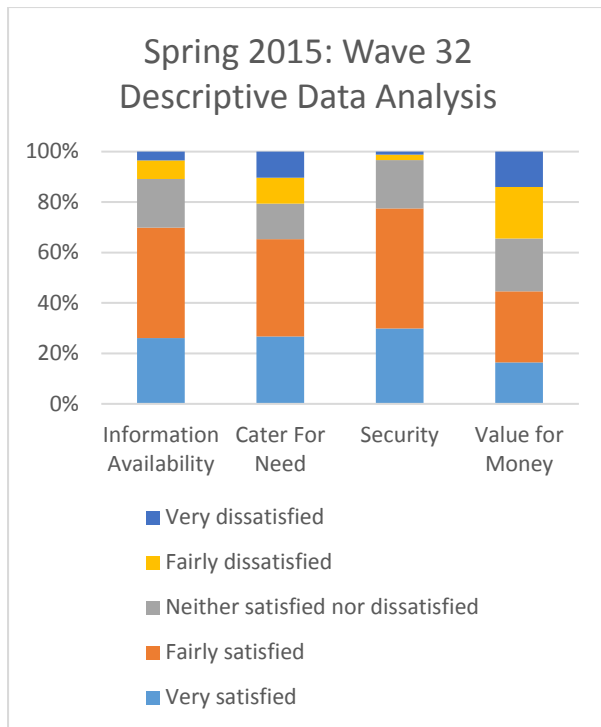


Figure 7: NRPS Descriptive Data (Spring 2015: Wave 32)

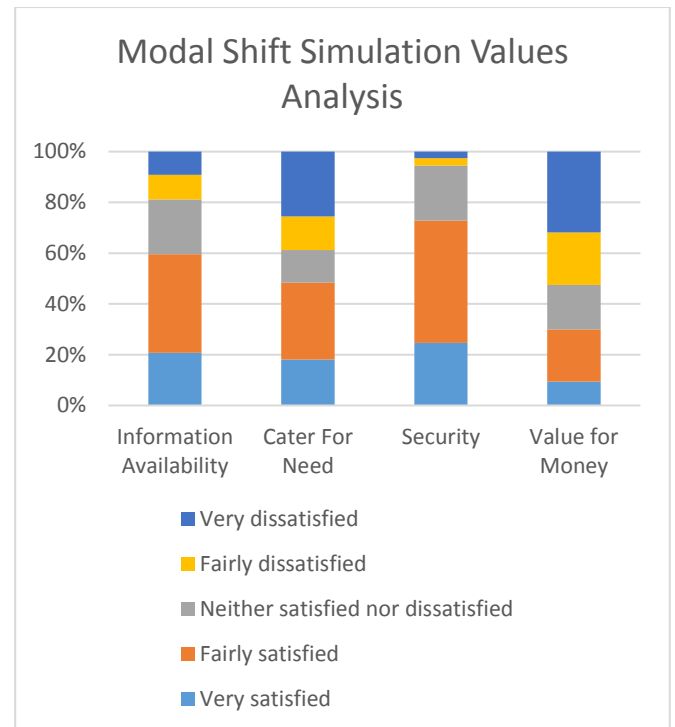


Figure 8: Simulation Model Values

Figures 7 and Figure 8 show strong correlations between each of the corresponding attributes of the descriptive data and the output data of the simulation. However, there are some variations in the "cater for need" and "value for money" attributes, which might be due to the assumptions we made, but for our purpose to demonstrate the application of the framework, the output of the simulation is sufficiently accurate. We will use this simulation result later as our base case result that we are comparing against.

4.5 Experimentation

The following hypothetical experiment should provide some insight into the operation of the simulation. In this experiment, we look at the changes that occur in a passenger's travel mode adoption patterns as well as in their cognitive processes in the process of making travel mode choice. We consider two scenarios:

- Base scenario: employs the output from the validation experiment
- Experimental scenario: investigates behavioural changes as a consequence of providing interventions to reduce car usage. The only intervention provided in this experiment is the introduction of parking space tax policy for car users. The base scenario started without intervention, a parking space tax of £2.5 is introduced at 120 hours, and the behaviour is observed up till 240 hours. Another simulation run based on the same previous settings is carried out, in which parking space tax of £5 is introduced from 120 hours up to 240 hours.

The users' adoption patterns for the two experimental scenario runs are observed and compared with the base scenario output.

4.6 Results

The observed outputs from the simulation show a plot of passengers' mode adoption patterns and cognitive processing behaviour depicted in Figure 9 and Figure 10 respectively. The behaviours of the two experiments are observed from time 0 to 240 hours. The simulation runs became stable after 24 hours and remained constant up to time 120 hours when interventions are applied.

The overall stable behaviour from the beginning of the simulation reflects the present situations as captured from the NRPS dataset used for parameterisation. Figure 9 and Figure 10 show the number of adopters (y-axis) against the time steps (x-axis). In the first simulation run shown in Figure 9, a parking space tax policy of £2.5 is introduced at 120-time steps when the numbers of car users and train users are 2967 and 3733 respectively.

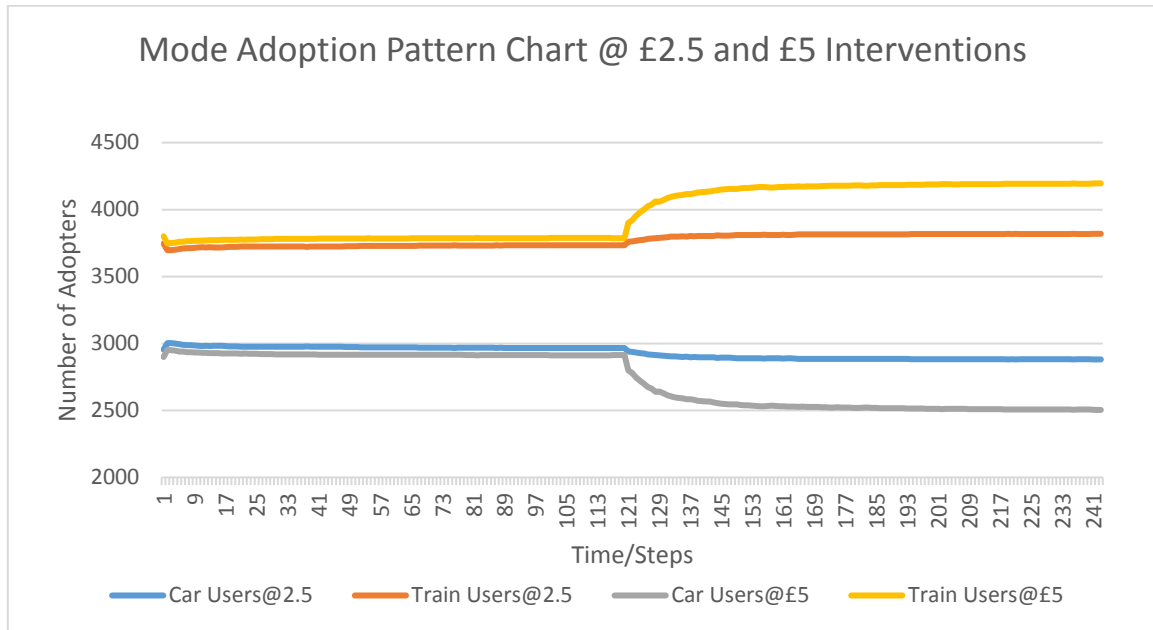


Figure 9: Passengers' Mode Adoption

This intervention gave a slight increase of 2.3% in the numbers of train users at 240 steps when the behaviour became stable again. The number of car users reduced by the same percentage. In the second simulation run also shown in Figure 9, the parking space tax policy of £5 is introduced at 120-time steps as the first run, to allow direct comparison. The numbers of car and train users are 2913 and 3787 respectively. The simulation is observed up to step 240 when the pattern became stable. The output shows that the number of train users has increased by 14.0% while that of the car users has reduced by the same percentage.

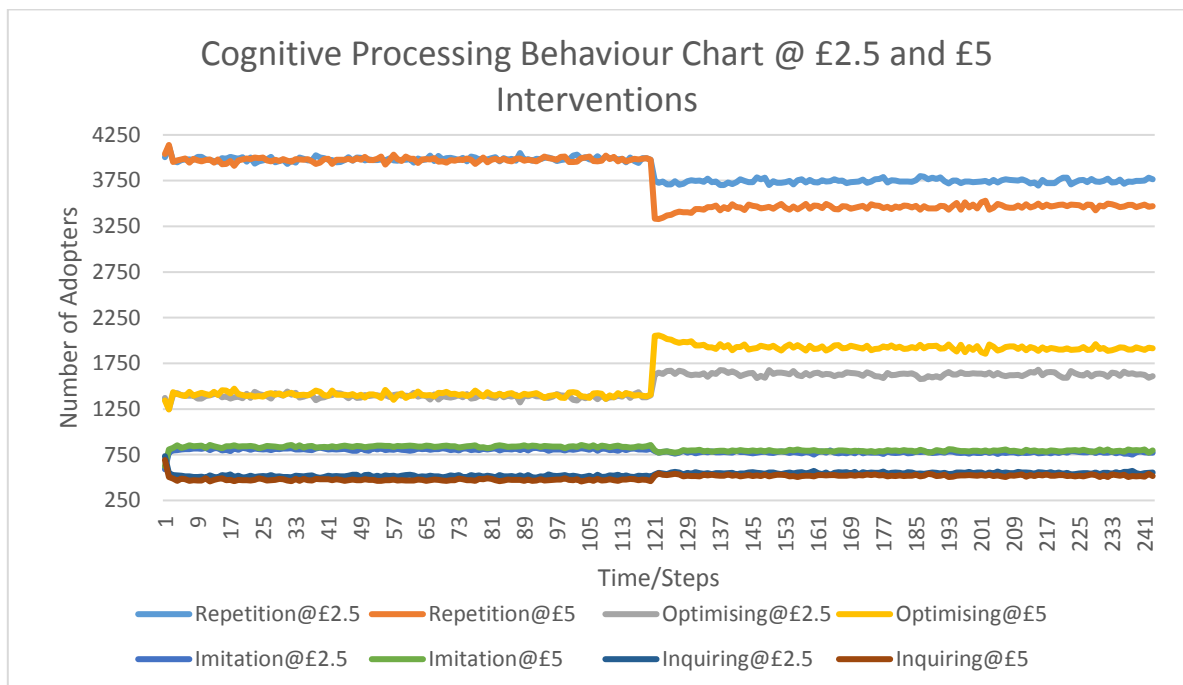


Figure10: Passengers' Cognitive Behaviour

Figure 10 shows the number of passengers engaging in different behaviours before and after the £2.5 and £5 tax policy interventions. Before the interventions are introduced at 120-time steps, the

results indicate that 59.5 % of all the passengers are found repeating their previous behaviours (either using car or train as mode). 20.8 % of the passengers are found optimising their behaviour, while 7.6% are engaging in making inquiries about better alternative modes, and the remaining 12.1 % were involved in imitating their happy neighbours. After the interventions have been applied, the simulation is observed at step 240 when the behaviours are found stable. For £2.5 intervention, the percentage of passengers repeating their previous behaviour has reduced by 3.4%, while optimisers have increased by 3.5% and those engaging in inquiring have increased by 0.4% and those engaging in imitation has reduced by 0.4%. For £5 policy intervention, a reduction of 7.5 % is recorded for passengers repeating their previous behaviour, while optimisers have increased by 7.6%; those engaging in inquiring have increased by 0.84% while imitators also reduced by 0.86%.

4.7 Discussion

It was observed from the experiment that the proportion of the number of adopters when £2.5 and £5 tax policies were applied was not linear. With £2.5 parking tax policy, 2.3% car users adopted train transport as their new mode. While 14.0% of the car users changed to train transport when parking tax policy of £5 was applied (see Figure 9). This implies that most car users having weighed their needs and benefits of using cars under the new tax policy regime of £2.5 still prefer making trips with cars to using train transport. However, changing the tax policy to £5 for the same set of trip maker gave a considerable decrease in the number of car users by 14.0%.

Furthermore, the gradual rise in the number of adopters (train users) and decrease in the numbers of defectors (car users) over a period of time between 120-time steps and 193-time steps when the graph became stable (see Figure 9) was as a result of social interactions going on among passengers who are dissatisfied with the new policy hence, seeking better alternatives from happy neighbours. This explains the variability in cognitive processing behaviours shown in Figure 10. There was a reduction in the numbers of mode users repeating their previous behaviour and those imitating other users, which give rise to increase in the number of optimisers and the Inquirer mode users (see Figure 10).

From the case study model, it is evident that the framework is capable of giving insight into the development of appropriate interventions that can be used to influence passengers' mode shift behaviour. However, the models need to be tested against more real-world cases and for different modes of transport. Also, it is worthwhile to note that there are some scenarios where trip maker's behaviour might be practically impossible to stimulate due to location situations. For instance, a trip maker whose residence or workplace is not on the route of policymakers' preferred mode, may find it unreasonable to change the current preferred mode. The MOSH framework is not presently applicable in such exceptional cases.

5 Conclusions and Further Work

This paper introduced a novel modal shift framework called MOSH to support research on how to best stimulate individual trip maker's behaviour to adopt less preferred transport modes. It addressed some gaps in existing works, such as limited use of necessary socio-psychological theories of human behaviour, no distinct social interaction structures among trip makers, and no reference to trip makers' context in decision making. The MOSH framework addressed these gaps by exploring agent-based modelling method to investigate individual trip maker's attributes. It achieves that by employing the Consumat approach for social interaction structures coupled with the CWA for trip maker's contextual factors in decision making.

A hypothetical case study for investigating car to train mode shift was carried out to demonstrate the applicability of the framework in the transport domain. The result showed that the model conceptualised from the framework is capable of assisting policy makers to gain insight into how to effectively stimulate trip makers' behaviour towards adopting a less preferred mode. However, limitations in exceptional cases such as where trip maker's behaviour might be practically impossible to stimulate due to location (residence or workplace) do exist at present in the framework. Such situation and more accurate methods of measuring perception will be looked into in the future.

In the future, we intend to look further into the concept of measuring passenger's affective effects on mode choice which forms components of spatial and temporal context that determines individual attitude. In this respect, we hope to research into the application of intelligent fuzzy-decision components to achieve this objective.

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