The University of British Columbia (Okanagan Campus)
Faculty of Applied Science
School of Engineering

Towards an Agent-based Approach to Integrated Transit-Land Use Planning for Small and Rural Communities (SRC)

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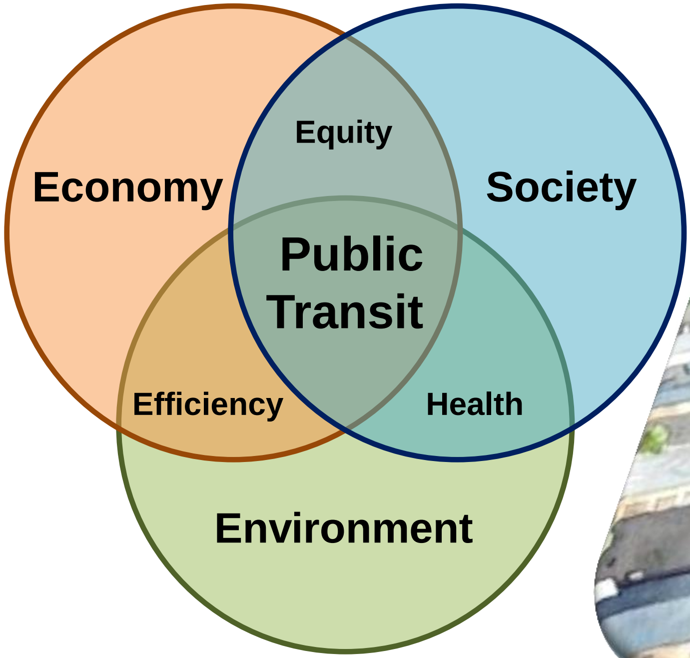
Public Transit

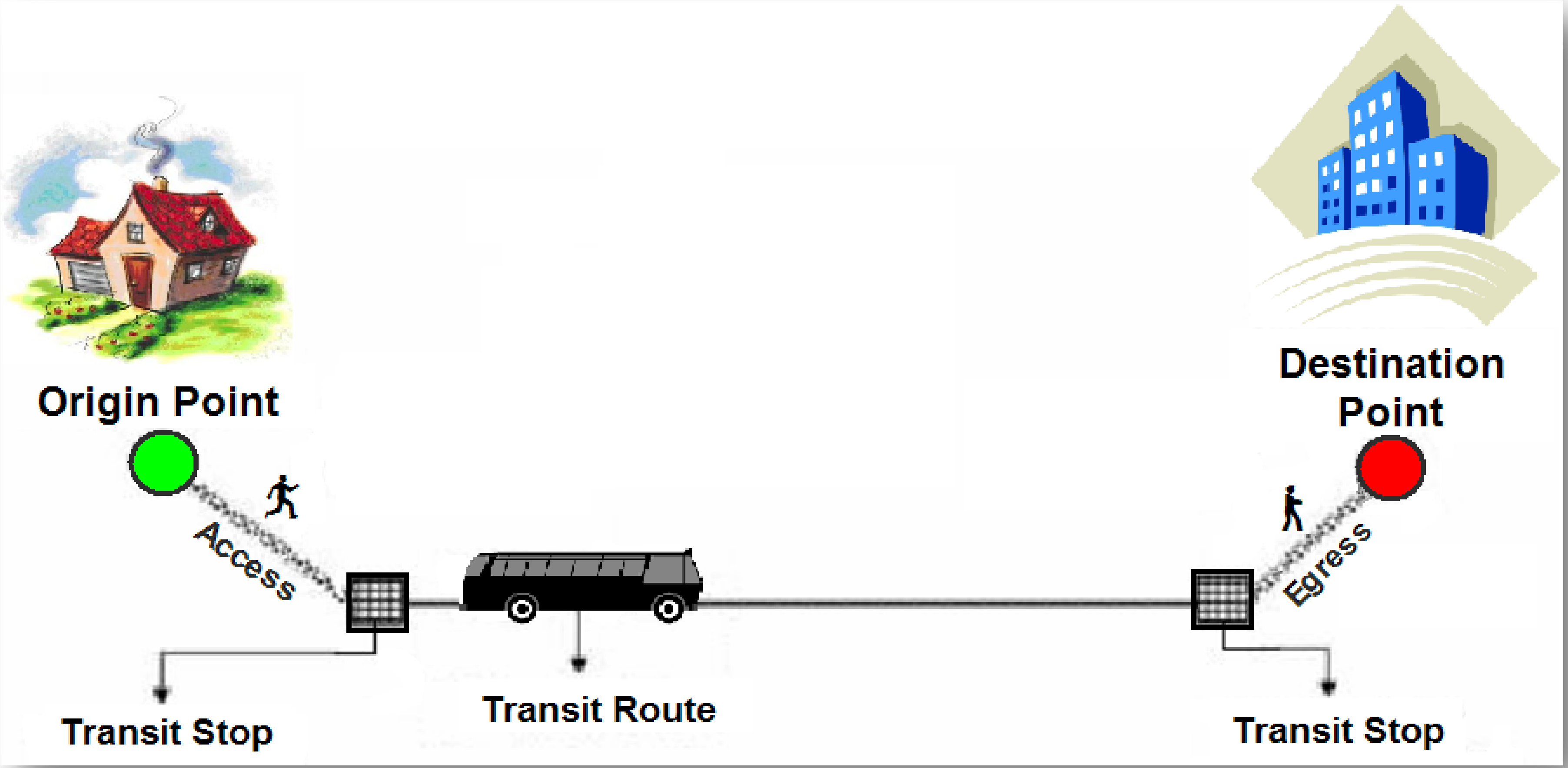
Unlike the car option, **public transit** affects the **social viability** of urban communities by **limiting** the adverse effects of **urban sprawl, congestion and emissions**.

It also supports the **economic viability** of the community by enhancing accessibility to major trip generators and CBDs where a mixed variety of activities are located.



The Transit Route Design Problem

Aim: to **define a transit route** which is **determined by a sequence of stops** and **associated with various design elements** which reflect the system performance requirements and resource limitations **in order to serve the demand** within a particular area.



The Transit Route Design Problem

Challenge

To achieve a compromise between the conflicting objectives of passengers and the operator.

Current Practice

Based on experience, the planner follows a set of service standards and practical guidelines, then generates and examines a number of design scenarios to select the best alternative.

Limitation

Yielding suboptimal designs where global optimality is not guaranteed.

A practical yet optimal transit route design approach is desirable.

The Need for a Practical Transit Route Design Approach

This need is supported by the limitations of the previous approaches in terms of:

Practicality

- Focusing only on theoretical problems without considering service planning guidelines, leading sometimes to operationally infeasible designs.

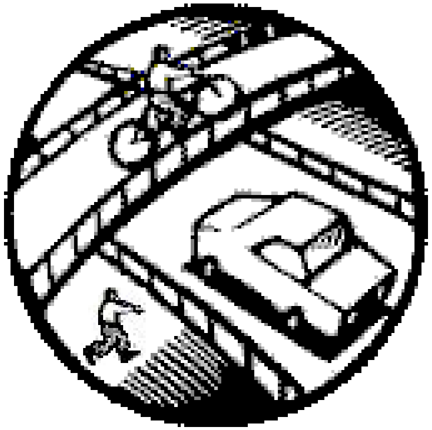
Demand Treatment

- Assuming fixed demand matrix, insensitive to route alignment & service quality.
- Aggregating demand in single points, although transit demand is scattered.
- Failing to capture the effect of design on existing demand along adjacent routes (mode shift vs. Route shift!).

Realism

- Ignoring some essential aspects of total transit trip travel time and focusing only on "in-vehicle" travel time.
- Assuming single path assignment & deterministic arrival / running times of TUs.

How Do We Choose a Mode for Travel?



Mode Choice Modelling

- Traditionally based on the Random Utility Maximization (RUM) theory, which originate in microeconomics.

- Assumes that people are "rational" and will examine the utility $V_m = \underbrace{\beta' X_m}_{\text{Observed Utility}} + \underbrace{\varepsilon_m}_{\text{Error Term}}$ and then choose the alternative m^* which maximizes their utility for a given trip.

Mode Choice Probability

LOGIT Models: Independent and Identically distributed (IID) errors with ***<u>type I extreme value distribution.</u>***

$$P_m = \frac{\exp(V_{m^*})}{\sum_m \exp(V_m)}$$

The Need for a Learning-based Mode Choice / Modal Shift Model

This need is supported by the following facts:

First, the decision process a passenger has to undertake while choosing an alternative mode is about the service quality which has to be examined.

Second, a distinguishing feature of mode switching decisions is being affected by some behavioural factors that can drive the choices.

Third, the stochastic and time-dependent nature of the transportation system may require more adaptive mode switching decisions by passengers.

Objectives

Given the needs for a practical transit route design approach and a learning-based mode shift model, the main objectives of this research are:

- Developing a modelling framework which can generate optimal transit route designs that maximize demand attraction (Design Tool).

- Considering modal shift barriers in terms of a threshold or inertia against shifting between modes (Evaluation Component).

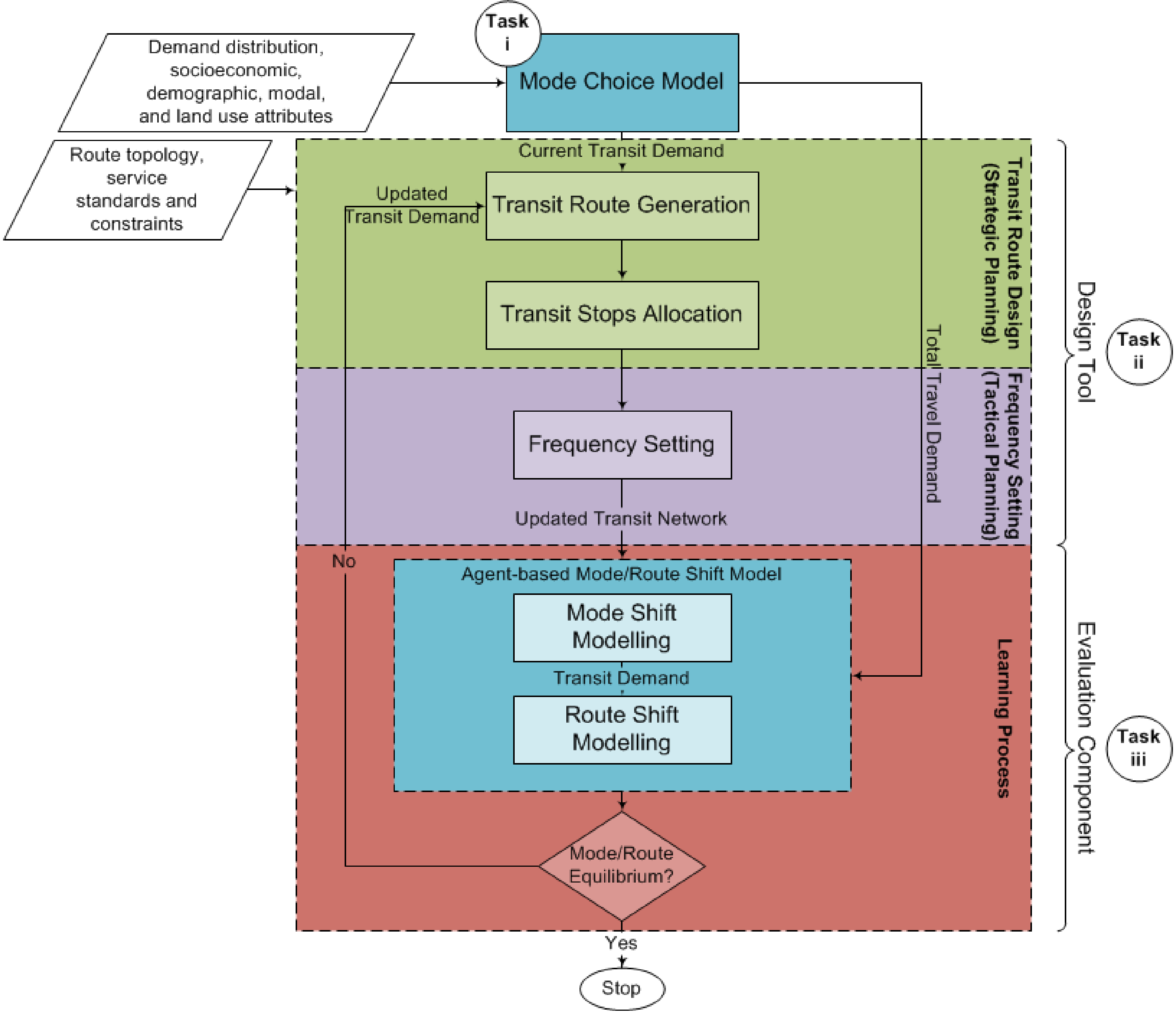
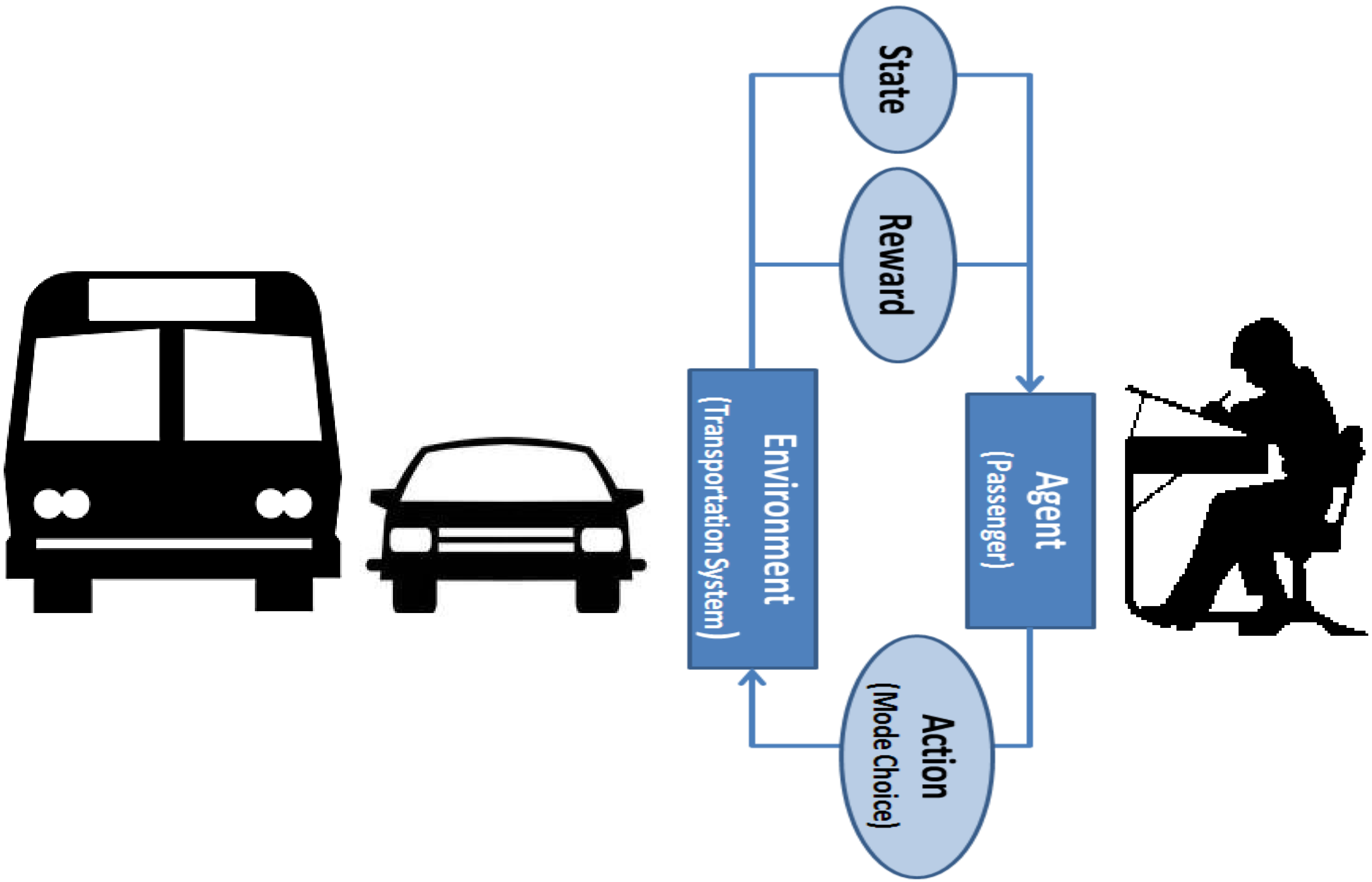


Figure 1. Agent-based Approach to Integrated Transit-Land Use Planning

Agent-based Mode Choice / Modal Shift Model

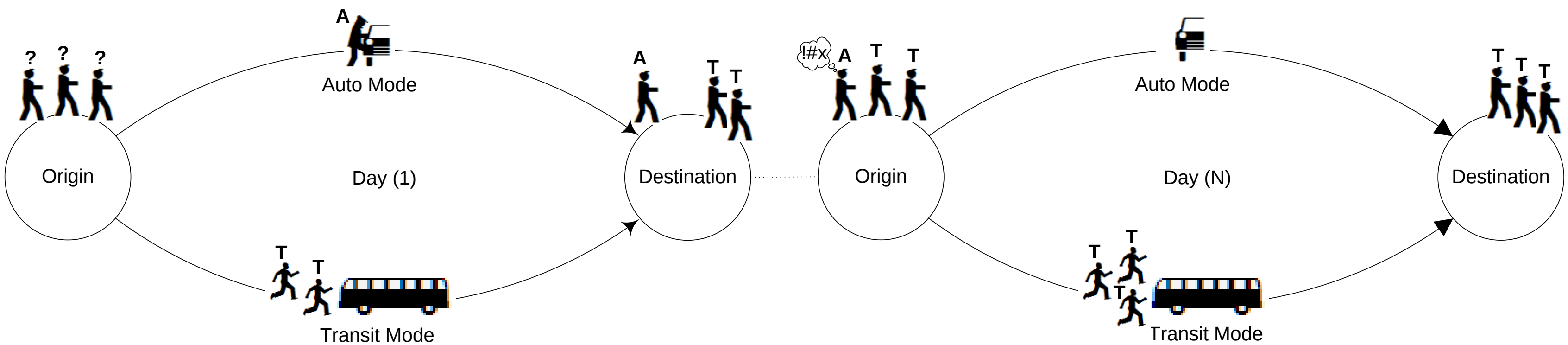


Learning-based Mode Choice / Modal Shift Model

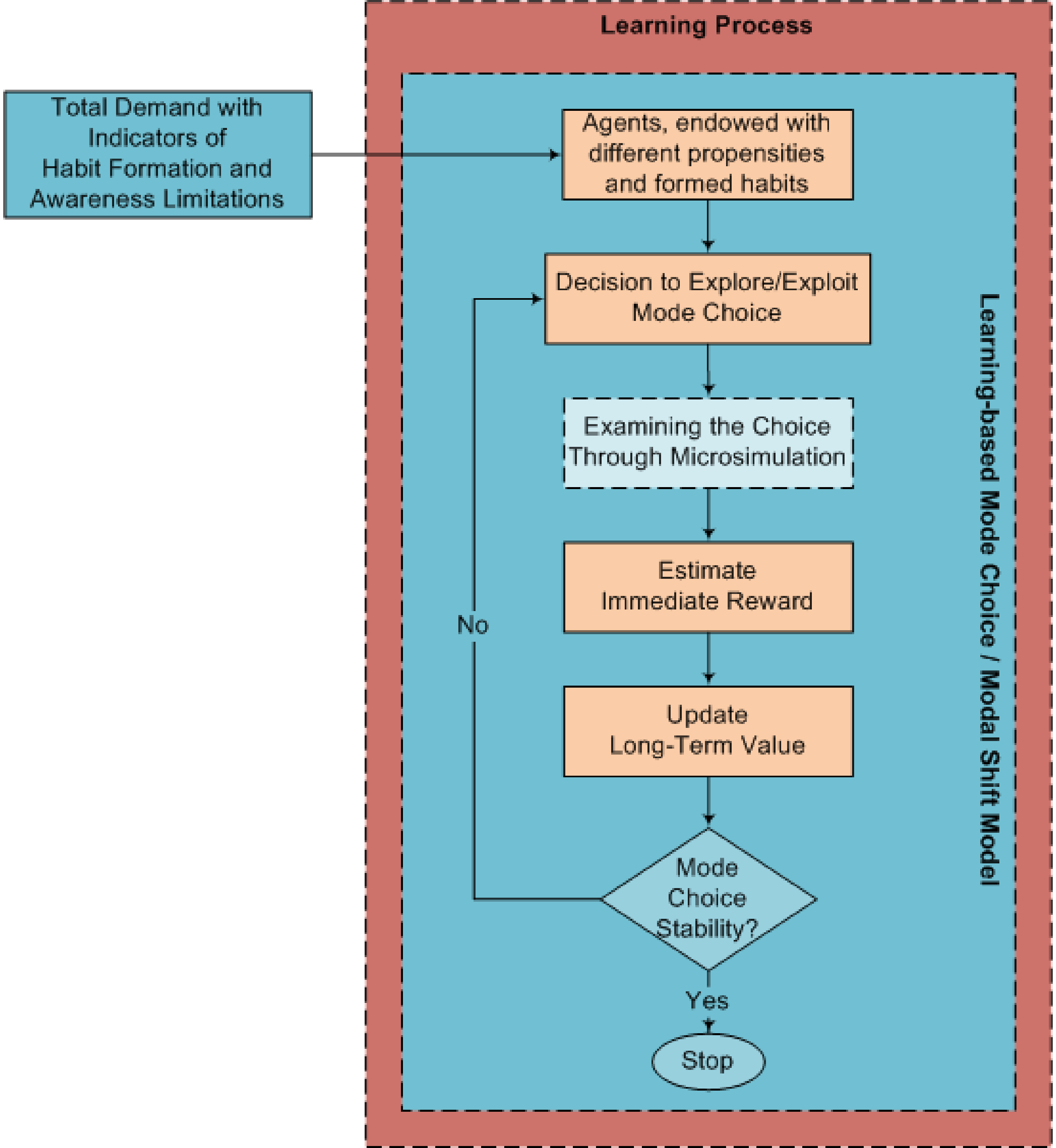
Consumers learn about the relative quality of products adaptively using learning rules.

Similarly, mode choice decisions can be addressed within an adaptive learning framework in which **passengers** are considered **consumers** and **modes** are considered **products**.

Mode Choice Decisions Under Reinforcement Learning Terminology



Agents adjusting their choices based on their previous experience with the system.


Learning Process
Total Demand with Indicators of Habit Formation and Awareness Limitations
Agents, endowed with different propensities and formed habits
Decision to Explore/Exploit Mode Choice
Examining the Choice Through Microsimulation
Estimate Immediate Reward
Update Long-Term Value
Mode Choice Stability?
No
Yes
Stop
Learning-based Mode Choice / Modal Shift Model

Learning-based Mode Choice / Modal Shift Model

Reinforcement Learning, Human Behaviour & Bounded Rationality

The rationality of passengers is bounded by the **information they could have**, the **cognitive limitations of their minds** and the **limited amount of time available** to them to make decisions.

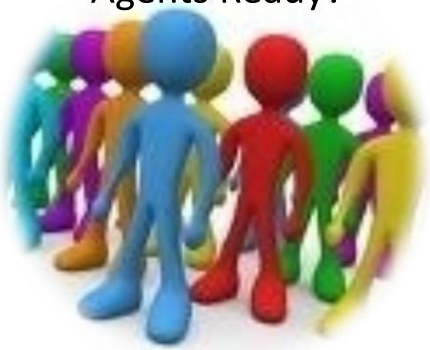
- Effect of Habit Formation on Step Size Parameter (α).
- Effect of Awareness Level on Exploration Rate (Є).
- Effect of Information Provision on Updating Rules.

Observing the Unobservable Component of Utility!!!

Effect of Habit Formation on Step Size Parameter (α)

Simple Updating Rule: $\boxed{V(s_{t+1}) \leftarrow V(s_{t-1}) + \alpha\, [R_t - V(s_{t-1})],}$

Where
$V(s_{t+1})$: Updated long-term value.
$V(s_{t-1})$: Previously estimated long-term value.
R_t : Immediate reward.
α : Step size parameter ($0 \le \alpha \le 1$).



$\alpha \rightarrow 0$, old experience from long ago still have a significant effect on current beliefs.
$\alpha \rightarrow 1$, only the very recent experience is remembered .

From a behavioural point of view, this learning mechanism is similar to the real choice behaviour which becomes insensitive to changes in the transport system, once habits are formed towards a specific mode of travel (i.e. $\alpha \rightarrow 0$).

Estimating the Value of the Step Size Parameter (α)

The choice rule that has attracted the most attention in choice decisions is the logit or exponential rule.

$$P_{im} = \frac{e^{V_{im}}}{\sum_{m} e^{V_{im}}},$$

where:

P_{im} : Probability that decision maker (i) selects alternative (m).

V_{im} : Utility that decision maker (i) obtains from alternative (m) (i = 1,…,I ; m = 1,…,M).

Research findings show that some explanatory variables such as car ownership, licence holding and car availability imply an indirect measurement of car use habits.

Hence, this research postulates that the choice probability of a particular mode can be considered as an indicator for habitual inertia towards it.

Knowing that habits act against learning new knowledge, the step size parameter is postulated to be an inversely proportional function of P_{im} **(e.g. $\alpha = 1 - P_{im}$),**

Where:

α : Step size parameter ($0 \leq \alpha \leq 1$).

P_{im}: Dominating previous choice probability.

Effect of Awareness Level on Exploration Rate (Є)

Balancing exploration and exploitation is an issue in reinforcement learning.

Obviously, awareness is required before exploring a new mode of transport.

Awareness can be direct and/or indirect and can be affected by:

- Strength of the formed habits.
- Impact of the system change(s) on the decision maker.

In this research, the exploration rate (Є) will be maintained to address the degree of awareness of the changes in the transport system.

Effect of Information Provision on Updating Rules

- **Belief-based Learning Rule (Partial Information)**

$$\underbrace{V_{im}(t+1) = V_{im}(t-1) + \alpha\,[R_{im}(t) - V_{im}(t-1)],}_{\text{Selected Mode (m)}} \qquad \underbrace{V_{in}(t+1) = V_{in}(t-1),}_{\text{Every Unselected Mode } (n \neq m)}$$

Agents will have adaptively formed beliefs about the quality of each of the alternatives, such that the utility of the unselected alternatives remains unaltered.

- **Reinforcement Learning-based Rule (Partial Information)**

$$\underbrace{V_{im}(t+1) = V_{im}(t-1) + \alpha\,[R_{im}(t) - V_{im}(t-1)],}_{\text{Selected Mode (m)}} \qquad \underbrace{V_{in}(t+1) = \alpha\, V_{in}(t-1),}_{\text{Every Unselected Mode } (n \neq m)}$$

Agents will have adaptively accumulated positive feelings, such that the utility of the unselected modes decays naturally as familiarity with those alternatives declines.

Effect of Information Provision on Updating Rules

- **Learning Rule (Perfect Information)**

Being in a state of perfect information might exist under the emergence of recent ITS technologies and advances in real time information provision capabilities. Hence, all utilities can be updated simultaneously using the following updating rule:

$$\overbrace{V_{im}(t+1) = V_{im}(t-1) + \alpha\, [R_{im}(t) - V_{im}(t-1)],}^{\text{Selected/Unselected Modes (M)}} \qquad \text{for } m = 1 \text{ to } M$$

Categories of Agents

- **Based on Car Availability and Transit Accessibility**

Agent Group	Car Availability	Transit Accessibility	Choice Possibilities	Suitable Updating Rule
G1 (Choice Users)	Yes	Yes	Mode/Route Choice	Belief-based (Rational-based Choice)
G2 (Captive Users)	Yes	No	Route Choice	RL-based (Familiarity-based Choice)
G3 (Captive Users)	No	Yes	Route Choice	RL-based (Familiarity-based Choice)

Numerical Simulation

- The modelling scenario considers a hypothetical mode choice / modal shift situation.
- 100 passengers face a daily mode choice between auto, transit and walk options.
- A simple conventional logit model is used to estimate the choice probabilities based on travel time and cost as explanatory variables.
- Based on the model / modal specification, the car alternative was the superior option on episode one.
- Between episode one and episode two, the transit travel time is reduced due to a significant change that favours the transit option.
- The assumption of exploration starts after the fifth episode at which the agents will become aware of the changes in transit mode by means of direct experience.

Traditional Mode Choice Model

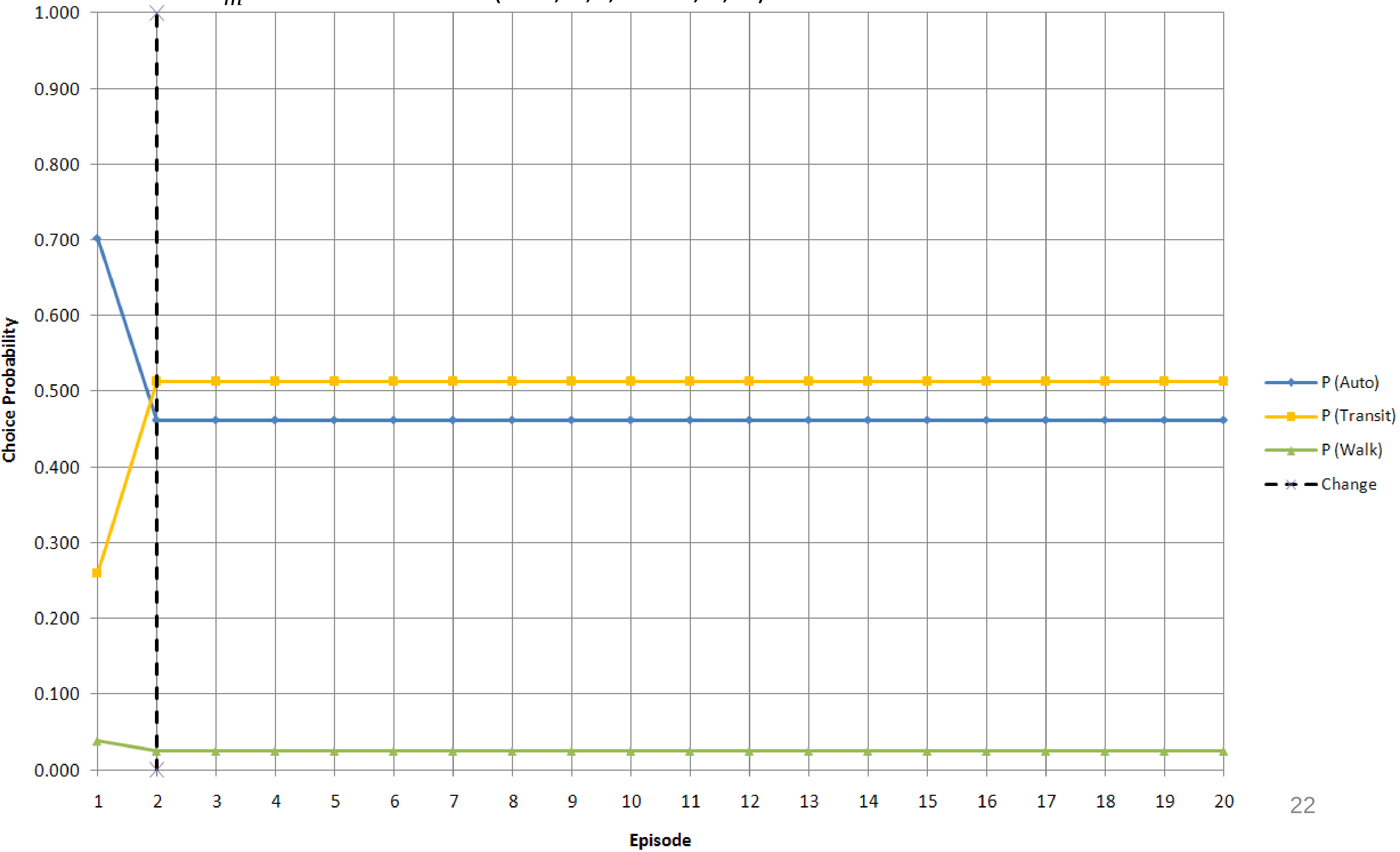
$$P_{im} = \frac{e^{V_{im}}}{\sum_m e^{V_{im}}},$$

where:

P_{im} : Probability that decision maker (i) selects alternative (m).

V_{im} : Utility that decision maker (i) obtains from alternative (m)

(i = 1,…,I ; m = 1,…,M).

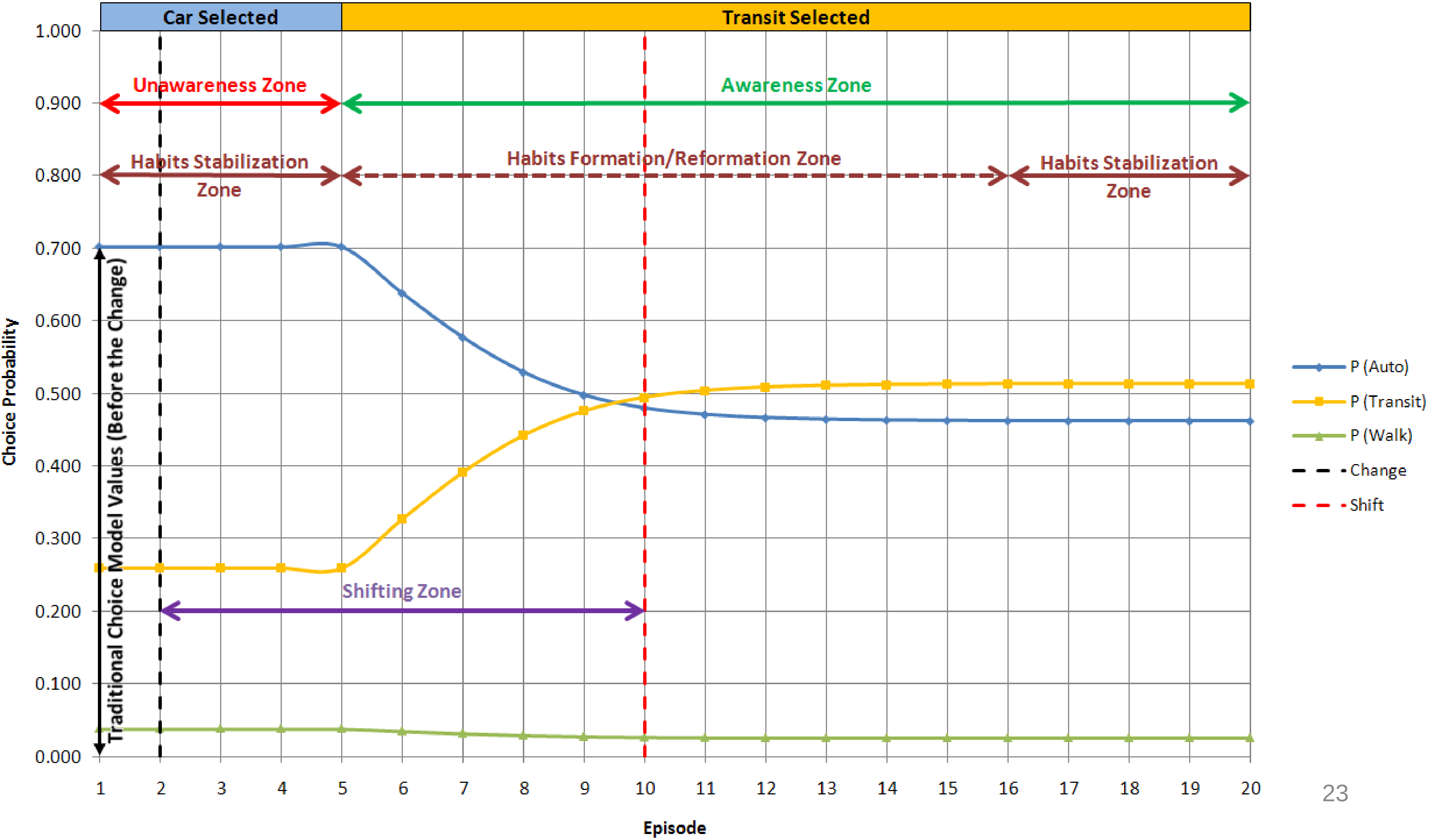


Learning-based Mode Shift Model, Partial Info., Belief-based Rule

Selected Mode (m)

Every Unselected Mode (n ≠ m)

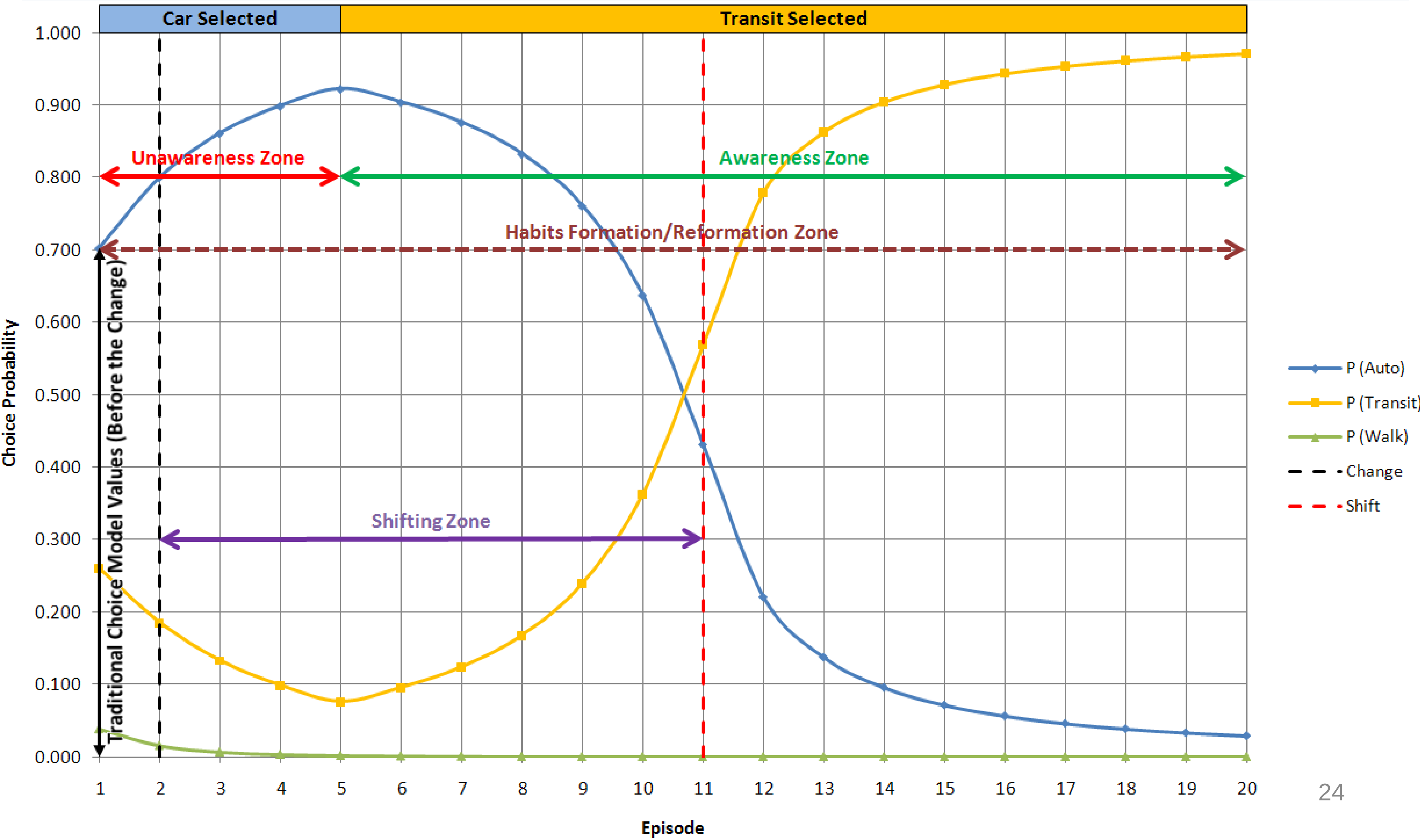
$$V_{im}(t+1)= V_{im}(t-1) + \alpha\,[R_{im}(t) - V_{im}(t-1)], \qquad V_{in}(t+1) = V_{in}(t-1),$$



Learning-based Mode Shift Model, Partial Info., RL-based Rule

Selected Mode (m) — Every Unselected Mode ($n \neq m$)

$$\underbrace{V_{im}(t+1) = V_{im}(t-1) + \alpha\,[R_{im}(t) - V_{im}(t-1)]}_{\text{Selected Mode (m)}}, \qquad \underbrace{V_{in}(t+1) = \alpha\, V_{in}(t-1)}_{\text{Every Unselected Mode } (n \neq m)},$$



Learning-based Mode Shift Model, Perfect Information

Selected/Unselected Modes (M)

$$V_{im}(t+1) = V_{im}(t-1) + \alpha\,[R_{im}(t) - V_{im}(t-1)], \qquad \text{for } m = 1 \text{ to } M$$