An Exploratory Comparison of Behavioural Determinants in Mobility Modal Choices

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Abstract. The rising demand for mobility in the 21st century creates a challenge for interdisciplinary researchers. As a result, the number of papers devoted to the application of agent-based technologies in the transportation engineering domain has grown enormously. However, there is still a need for modelling platforms that are capable of exploring the influence of different psychological factors on individual decision-making. By utilising our current mobility simulator - BedDeM, we propose an experimental method to test and investigate the impact of core determinants in Triandis' Theory of Interpersonal Behaviour on the usage of different transportation modes. Comparing the results with a calibrated population of Swiss household data, we conclude that *Intention* and *Affect* have a positive effect on the usage of private vehicles, while *Habit* and *Social factors* can encourage people to travel with public or soft transportation modes.

Keywords: Agent-based modelling · Modal choice simulation · Multi-agent system · Behavioural theory.

1 Introduction

Identifying the underlying mechanisms of decision-making is a fundamental challenge for social science researches. Under the subject of household mobility, different projects have been carried out to investigate the effects of individual determinants on modal choices of daily commuters (e.g. [11,13,20,27]). These often suggest that making travelling choices is a complex process, in which multiple aspects (such as cognitive, affective, social, habit etc.) should be considered in any future studies.

Agent-based modelling is a method of investigation of social phenomena that blend the knowledge of social sciences with the advantages of computational simulations. It allows an elegant treatment of heterogeneity in the population and enables the modelling of complex data processing while considering multiple factors and dynamic information [6]. In the domain of mobility however, most applications have been focusing on the topics of *traffic simulation* [4, 5] or *management and control systems* [19]. There is still a lack of research efforts that emphasise on understanding the roles of behavioural determinants and their relationships in daily transportation-related choices [6].

We have been developing an agent architecture that utilises the Triandis' Theory of Interpersonal Behaviour (TIB) [26]. Its implementation platform - Behaviour-Driven Demand Model (BedDeM) - offers a mechanism to measure the impact of different individual determinants on short-term transportation modal choices (i.e. car, bus, tram, trains, walking, biking). In this paper, we demonstrate this capability through a series of setups to activate/deactivate the core elements of TIB in agent's decision-making and compare the collective results after simulation. The current agent population contains a mapping of qualitative data in Swiss Household Energy Demand Survey (SHEDS) to all TIB's determinants, which is designed to reproduce the travelling patterns in Mobility and Transport Microcensus (MTMC) [17]. Hence, performing the experiment on this baseline can provide a practical insight into real-life situations where people often rely on a small set of factors to make their decision on modes of daily transport.

After considering some of the popular related projects in simulating mobility-related decision-making (see Section 2), we present a specification of BedDeM processes that are relevant to the case study in Section 3. Next, the experimental setup and its results are discussed in Section 4. We then conclude our experience suggest further development in Section 5.

2 Related work

In this section, we focus on the group of models that deal with mobility-related modal choices. Agent's goal is to select an option from a set of alternatives. The result of the deliberation process is a particular action or utilities/probabilities of all the options. In this case, the agent-based method is usually bottom-up: starting from evaluating an option using explicit individual determinants, then combine them to establish context-depending behaviours.

One popular approach is enhancing the agent's preferences, strategies and likelihood of making a particular decision with discrete choice models. The projects in the mobility domain often make use of *random parameters logit* [12] to assign predicted probabilities to outcomes of a set of alternative options. Examples include [1,9]. By incorporating empirical data (such as observed choices, survey responses to hypothetical scenarios or administrative records), it becomes a flexible framework for estimating the parameters of choice behaviour that is capable of capturing the statical patterns. However, without comprehensive support from a socio-psychological theory, these models cannot be utilised to explain the effect of each determinant on individual decisions. Non-computing experts often have difficulties understanding the underlying implications of different modelling scenarios and associated assumptions [14].

Another class of agent architectures aims to reproduce a more elaborate decision-making process by assigning agents with beliefs, values or world views that correspond to observation from ethnographic data or stakeholder's assessment. One of the most well-known architecture is the Belief-Desires-Intentions (BDI) [21] model. Padgham et al. developed a BDI system to allow agents to respond to the feedback from the environment instead of keeping predetermined modal choice [18]. Other works of Bazzan et al. [7] and Balmer et al. [3] also include a layer of BDI-based high-level component in the agent's decision-making. However, this architecture is often criticised for the lack of experimental grounding [10] and the agent choice of being homogeneous, completely rational and selfish [21]. From our present understanding, there is not a project that utilises more complex cognitive architecture, such as CLARION [24], ACT-R [25] or SOAR [15] for modal choice simulation. Nevertheless, we also not consider these to be sufficient options since none of them is currently covering all major aspects of human decision-making (i.e. cognitive, affective, social, norm and learning) [2]. Plus one would require knowledge in formal logic to interpret the result patterns, which is often not trivial for social scientists.

3 The Behaviour-Driven Demand Model (BedDeM)

As an effort to produce a more comprehensive agent architecture that can be utilised to capture qualitative data, we decide to implement Triandis' Theory of Interpersonal Behaviour (TIB) [26] in our platform - BedDeM. Its tri-level presentation (see Fig. 1) proposes a way to combine and evaluate different psychological aspects of decision-making, which is utilised to create an architecture that can calculate the likelihood of an agent to perform a particular action. We are developing BedDeM's first application for the domain of mobility using Repast library for agent-based modelling [22]. Its main purpose is to generate yearly demands at the individual household level that can be interpreted at the granularity of the historical evolution of mobility for Switzerland. At the current milestone, an agent population can be generated using qualitative questionnaires in SHEDS [23] and calibrated to the travelling patterns in MTMC [16]. More details of this procedure can be found in [17]. The two main mechanisms relevant to the experiment are described below.

3.1 Decision-making process

A full decision-making cycle is illustrated in Fig. 1. An agent first selects an isolated decision-making task from the list that is sequentially executed. Its personal desire/goal is then combined with means provided by the external environment to generate a set of possible options. For all determinants (d), each option (opt) is computed by comparing its property with other's ($R_d(opt)$). In the first level, this can be done using either a real numerical system (for determinants such as price or time) or ranking function (for determinants such as emotion). Both can be derived from empirical data (e.g. census/survey) or calibrated with expert's knowledge/stakeholder's assessment.

The results for these determinants are then normalised and multiplied with associated weights (called w_d); the sum of which becomes the reference value for the option in the next level (see Eq. 1). The weight, in this case, represents the importance of a decision-making determinant compare to others at the same level

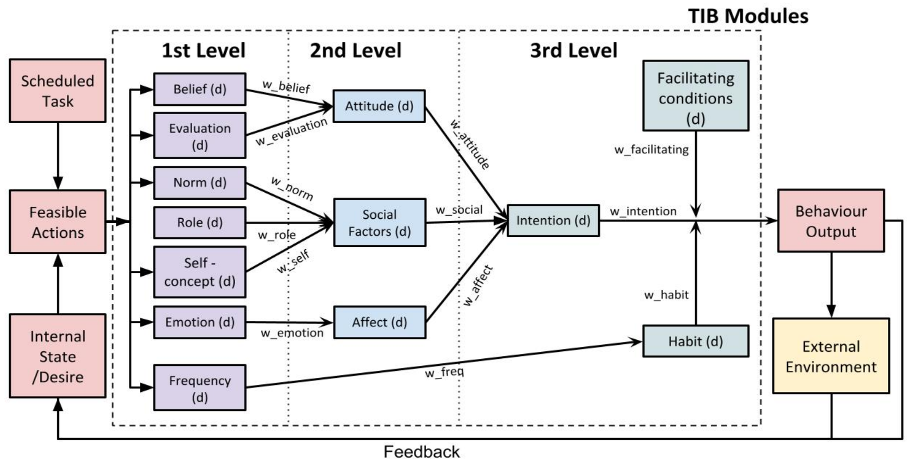

Fig. 1: Current agent's decision making mechanism with TIB Module

and emphasises on the heterogeneity of individuals. In the experiment setup, we can deactivate the irrelevant determinants by simply assign their weights to 0.

$$R_d(opt) = \sum_{a=1}^{A}(R_a(opt)/(\sum_{o=1}^{O} R_a(o)) * w_a)$$

where
- $R_d(opt)$ is the reference value of an option (opt) at determinant d.
- A is the set of the ancestors of d (i.e. determinants connects with d in the previous level).
- O is the set of all available options.
- w_a is the weight of ancestor determinant (a).

(1)

The combination process then continues until all options reach the behaviour output list; the reference value of which can be interpreted as the probabilities that a particular action is performed. If the agents are assumed to be deterministic, it would pick the option that is correlated to best-evaluated value. In case the options are given the same value, the agents would choose a random one.

3.2 The mobility simulation

An overview of BedDeM's application for mobility domain is shown in Fig. 2. After receiving processed information regarding the population and environment from the Configurator, the simulation process starts with a central controller creating all the agents with all their attributes and assigned them to their respective regions, from which information of agent's schedule and traffic are based on. As we use MTMC [16] and SHEDS [23] as inputs for the configuration phase, agents in this study represent households in Switzerland. Clustering these data entries also provides a way to calculate the recommendation for agents from the same network [8] (i.e. R_{role} - see Table 1).

Each agent then processes its individual schedule and creates decision-making events to be activated. At the time of simulation, the controller triggers these activities in an event-driven manner. In this current developing stage, no learning technique is applied for feedback loops inside the agent's decision-making process. Agents simply keep track of the number of times its used a vehicle for trips of the same purpose. In addition, After all the tasks finished, a reporter component collects the final results, which mainly consists of the kilometres for different modes (i.e. car, bus, tram, trains, walking, biking).

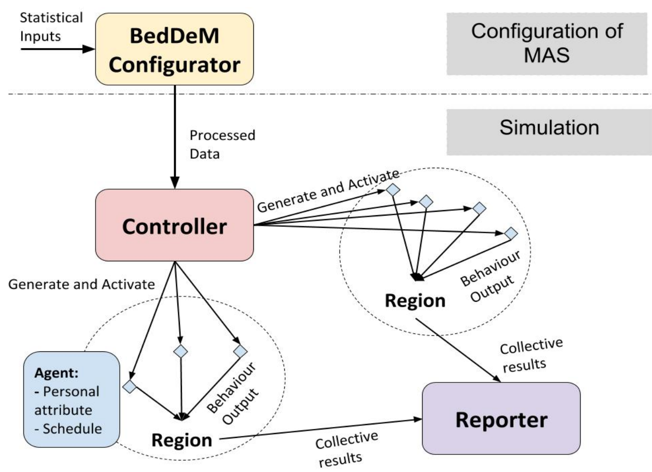

Fig. 2: An overview of BedDeM model

4 Experimental procedure

The experiment setup for the agent's decision-making procedure can be found on Figure 3. As mentioned in Section 3.1, the reference value of an option (opt) for each determinant (d) is calculated using Eq. 1 - $R_d(opt)$. It requires two components from determinants of the previous level - their reference values for that option ($R_a(opt)$) and weight(w_a). Since the first level determinants do not have any sub-connections, $R_a(opt)$ and w_a are derived from available properties that can be measured or ranked and qualitative questionnaire in SHEDS [23] (see the mapping in Table 1). The next few levels of mapping and calibration process of the reference population to MTMC [16] can be found in [17]. At this milestone, they are kept relatively simple to reflect the information in data sources and allow the impact of each determinant to be highlighted in the final results. More complicated mappings can also be configured similarly by adding/removing relevant nodes in the figure.

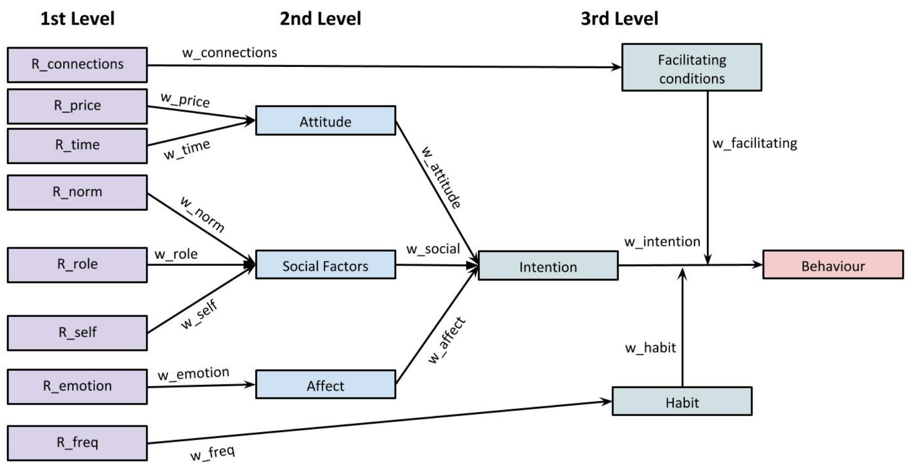

Fig. 3: Experiment setup in the agent's decision-making

4.1 Setup

In this paper, we want to focus on observing the impact of core determinants in TIB, i.e. attitude, social factors, affect, facilitating condition, intention, habit. This can be achieved by adjusting the corresponding weights in the models, i.e. *w_attitude, w_social, w_affect, w_facilitating, w_intention, w_ habit* (see Fig.3 and Table 2). This exercise is performed on the calibrated deterministic population described in [17]; in which mode, agents choose the best alternative for their trips. By keeping the weight(s) of the main determinant(s) as calibrated values and others to 0, the agent will only take into account that key determinant(s) in decision making and ignore the rest. In the first half of this setup, we focus on the second level of TIB, which connects to *intention* in the third level. Hence, w_intention is kept as in [17]. This is also applied similarly to w_attitude, w_social, w_affect in the second part to ensure *R_intention* remains non-zero. All trips are scheduled within one year so there is currently no difference in agents' accessibility to modes. Seasonal changes is planned for a future developing stage.

4.2 Results

After the simulation, the total kilometre results of all mobility modes can be obtained (i.e. walking, biking, bus/tram, train, car, others). Comparing reference results in [17] against the outcomes of each setup above would give us an idea

Determinant	**Measuring property/Ranking function (R_c)**	**Corresponding question in SHEDS** (w_c, i.e. importance of each determinant with scale 1-5)
Facilitating condition - *Inconvenient connections*	R_connections = Is the trip consist of multiple public connections (0/1 value)	w_connections = Inconvenient connections by public transport (e.g. long and/or multiple transfers)
Evaluation - *Price*	R_price = Cost of travelling	w_price = Choosing the cheapest option
Evaluation - *Time*	R_time = Duration of the trip (including the journey to station)	w_time= Travelling as fast as possible
Norm - *Environment Friendly*	R_norm = Motor type of the vehicle (Gas/Electric/No motor)	w_norm = In the Swiss society, it is usually expected that one behaves in an environmentally friendly manner
Role - *Environment Friendly*	R_role = Recommend from others in the agent's network (most used)	w_role = Most of my acquaintances expect that I behave in an environmentally friendly manner
Self-concept - *Environment Friendly*	R_self-concept = No data available - calibrated with historical data (see [17])	w_self = I feel personally obliged to behave in an environmentally friendly manner as much as possible
Emotion - *Enjoyment*	R_emotion = Vehicle's comfortableness/luxury	w_emotion = I enjoy this way of travelling
Frequency of past behaviours	R_freq = The number of usage over a certain period	w_freq = I am used to taking this means of transport

Table 1: Mapping of TIB's determinants and statistical data [17]

Main determinant(s)	**w_attitude**	**w_social**	**w_affect**	**w_facilitating**	**w_intention**	**w_habit**
Attitude (At)	as [17]	0	0	0	as [17]	0
Social Factors (SC)	0	as [17]	0	0	as [17]	0
Affect (Af)	0	0	as [17]	0	as [17]	0
At + SF	as [17]	as [17]	0	0	as [17]	0
SC + Af	0	as [17]	as [17]	0	as [17]	0
St + Af	as [17]	0	as [17]	0	as [17]	0
Facilitating Conditions (FC)	as [17]	as [17]	as [17]	as [17]	0	0
Intention (I)	as [17]	as [17]	as [17]	0	as [17]	0
Habit (H)	as [17]	as [17]	as [17]	0	0	as [17]
FC + I	as [17]	as [17]	as [17]	as [17]	as [17]	0
I + H	as [17]	as [17]	as [17]	0	as [17]	as [17]
FC + H	as [17]	as [17]	as [17]	as [17]	0	as [17]

Table 2: Experiment design

about the impact of the main determinants. The mapping in Table 1 and percent composition of the modes can then be used to interpret the meaning of the difference in each test.

Main determinant	**Car**	**Bus / Tram**	**Train**	**Walking**	**Biking**	**Others**
Reference population	73.09	4.07	23.2	2.67	4.91	4.42
Attitude (At)	45.77	16.0	33.86	6.22	5.9	4.58
Social Factors (SF)	40.57	17.34	45.1	2.45	1.85	5.03
Affect (Af)	82.32	1.51	15.55	2.32	6.37	4.29
At + SF	37.97	16.9	47.22	2.88	2.22	5.16
SF + Af	69.44	3.38	27.19	2.81	5.12	4.42
At + Af	77.84	3.45	17.95	2.96	5.87	4.29

Table 3: Result of comparing the second level of TIB's determinants (All units are in 10^9 kilometres)

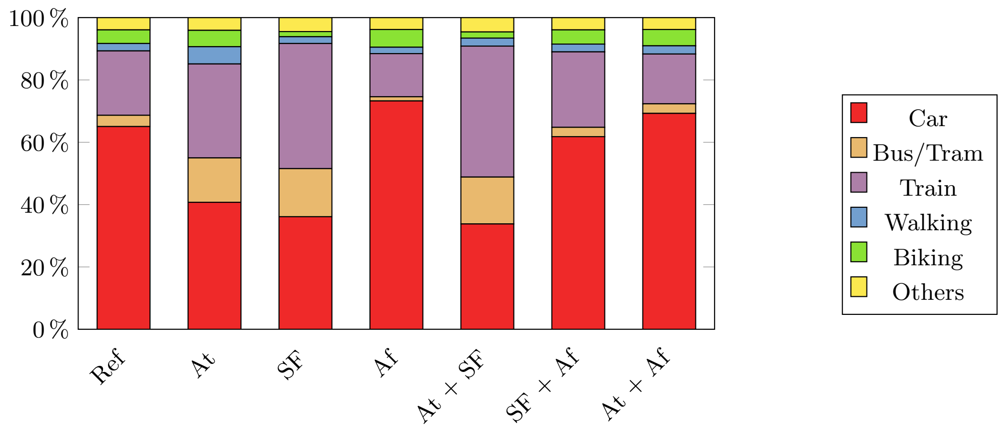

Fig. 4: Percent composition of modes in the tests of second level of TIB's determinants

Attitudinal, Affective and Social determinants: Table 3 and Fig. 4 show the results of running BedDeM with the reference population and with one or two determinants of the second level turned on. In the *Attitude(At)* test case, a large number of car users switched to the more cheaper options (bus/tram, train and walk). From Table 1, this determinant consists of 2 elements - time and cost. Although they are slower in speed, public modes do offer a more competitive price in the current market. The difference in time does not seem to play a major role in the agent's decision. This shift can also be observed in the *Social factors(SF)* test case with more than 40% decrease in car usage. As they provide the place for socialisation and are acceptable environmental friendly options, public transports see the most increase in number, whilst soft mobility usage sees a small decrease. When *Social factors* combines with other determinants (i.e. At + SF and SF + Af), we can observe a minor decrease in car's number. With the main focus on *Affect(Af)* determinant, more agents pick car than the other modes due to its convenience, comfortability and privacy. This also explains the figures when two determinants are combined. When *Affect* is not considered (i.e. At + SF), the car usage goes down. When it is put together with others, the number increases significantly (up to 40%). We conclude that *Affect* is the main driver for car, while *Social factors* can encourage people to use more public transport, especially for environmental reasons.

Intentional, Habitual and Facilitating condition determinants: The results of the third-level determinants' tests can be seen in Table 4 and Fig.5. Although we put the "inconvenience of public connections" as the criteria for *Facilitating Condition(FC)* (see Table 1), there is still a large number of households favour public transport and walking over car. It would mean this particular condition does not affect the final decision significantly. *Habit* test case also has a lower percentage of private vehicles compare to the reference. In contrast, *Intention* emerges as an important factor for car usage since the final figure of this mode is 10% larger than that of either *Habit* or *Facilitating condition*. It can be confirmed in the combination cases where *Intention* is present, i.e. FC + I or I + H. Both of them have a higher number of car trips than other scenarios with only *Habit* or *Facilitating condition*. In TIB, *Intention* refers to the deliberation process of human decision-making, as oppose to *Habit* which causes people to act on impulse. The simulation results at this level seem to indicate that the public and soft transports used to be popular in the past and only started to be replaced as more private vehicles became available in the studied year.

Main determinant	Car	Bus / Tram	Train	Walking	Biking	Others
Reference population	73.09	4.07	23.2	2.67	4.91	4.42
Facilitating Conditions (FC)	46.18	16.03	33.44	6.2	5.94	4.56
Intention (I)	67.72	4.12	28.12	2.77	5.21	4.42
Habit (H)	50.92	13.96	32.34	5.97	4.33	4.83
FC + I	67.82	4.16	28.0	2.76	5.2	4.42
I + H	69.23	3.45	27.73	2.63	4.9	4.42
FC + H	51.05	14.09	31.75	6.1	4.48	4.88

Table 4: Result of comparing the third level of TIB's determinants (All units are in 10^9 kilometres)

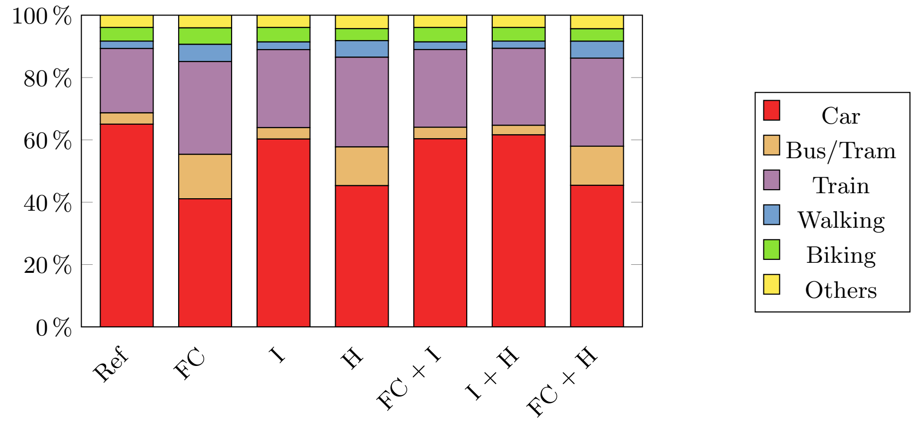

Fig. 5: Percent composition of modes in the tests of third level of TIB's determinants

5 Conclusion

In this paper, we demonstrate the ability of our simulation platform - BedDeM - to perform experiments that aim to capture the impacts of the core determinants in TIB on the usage of different transportation modes (i.e. car, tram/bus, train, walking, biking, others). Mapping in Table 1 is then used in conjunction with the differences between experimental outcomes to provide interpretations for all scenarios. The current preliminary results observe the figure of car increase when the agents invoke *Affective* factors in the second level of TIB. The same pattern can be found where the agents put their *Intention* first by performing the deliberation process rather than acting based on past behaviours. In the other hand, *Social factors* and *Habit* appear to be the reason why the majority of Swiss households choose public or soft transports.

The current model is still, however, missing some features, including *learning* and *variability*. Agents do not have self-learning ability and mostly rely on the frequency of past behaviours as *Habit* determinant. We are developing the agent's adaptability by changing its perception of certain values or determinant weights depend on the feedbacks (success/failure) received from environment. Coupling this along with traffic rate or different infrastructures in each Canton can provide a more realistic view of the shifts in behaviours of the agents. In term of model's variability, it involves expanding the mapping between the first level determinants with SHEDS and MTMC data (see Section 4). This can be accomplished through our collaboration with a sociologist to derive a more precise description of TIB's elements and generate more agent profiles in the current population. In addition, investigation on the effects of changes seasonal schedules and agent's accessibility to different modes (e.g. public transports do not work well in winter condition, new routes become available) is planned for the next stage.

There are also some promising research directions for our mobility platform. With the new innovation in technology and an increase in environmental awareness, it becomes more common for people to have access to electric or hydrogen vehicles. Using the same decision-making architecture, we can study the long-term transportation choices (such as purchasing a railcard or a new car), plus their influence on the daily routine. The model can provide a good indication of the roles of determinants in future scenarios (such as new infrastructures or government policies). In addition, the same experiment can be performed on different application domains (e.g. tourism) where TIB's determinants can potentially play a major role in the agent's decision-making.

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