Simple Heuristics as Mental Model for Staple Food Choice: An ABM Exercise

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Abstract. Our model employs simple heuristics as rules of thumb for binary staple food choices: rice and non-rice. We compare the behaviour of fast-and-frugal tree (FFTree) and tallying models to learn their suitability to model staple food choices. The dynamics that emerge from the uncertain nature of food choice, systematic preference change, and social interactions are presented. With some explainable behaviours, we believe that simple heuristics are effective for capturing more extensive staple food choice dynamics.

Keywords: Heuristics · Fast-and-Frugal Tree · Mental Model · Tallying · Staple Food Choice.

1 Introduction

Staple food choice is a more specific phenomenon in food choice study – more limited options, a higher consumption volume. Therefore, imbalanced staple food consumption and production system can cost global hunger. Among the Sustainable Development Goals (SDGs), staple food discussion appeared in three goals: SDG 2—Zero Hunger, SDG 3—Health, and SDG 12— Responsible Consumption and Production. These goals emphasised food sustainability, promoting awareness of responsible consumption within regional and global scopes.

There is a growing concern about climatic volatility, droughts, floods, and salinity in regions where staple crops are rain-dependent. Despite the possible impact, staple food choice runs by default – people tend to consume one dominant staple from where they live, showing an attachment to one particular staple amidst their production capacity in the regions.

We take Indonesia as our case study in staple food choices. As one of the most extensive rice producers among Southeast Asian countries, rice consumption in Indonesia had reached 139 kg per capita per year, exceeding the FAO rice consumption standard of 60-65 kg per year. The consumption outnumbered fellow rice-producer countries in Southeast Asia, averaging 65-70 kg per capita annually [2].

An agent-based model (ABM) has been extensively applied in the general food supply chain context [13], but not in staple food choices. Interestingly, previous food choice studies dominantly adopted rational assumptions in the agent's mental model, with all information required to make a food decision and resources to process the information.

Some examples are the Theory of Reasoned Action (TRA) to study meat consumption behaviour [11], the Theory of Planned Behaviour (TPB; [1]) as a predictive model of organic food consumption, and the Weight and Additive model (WADD) to study preferential choice mechanism in the milk substitution [5]. These mechanisms are known as complex decision models.

Contrary to the rationality assumption in the complex decision models, Gigerenzer et al. [6] observed simple rules (or heuristics) in how people decide. Instead of considering all factors, people rely on a few critical pieces of information (or cue) to make food choices [12]. These heuristics signalled that food choice is contextual–one factor may dominate in one situation but not the other. Despite its simplicity, studies have confirmed that heuristics in daily tasks with limits in time, information, computation, and pressure to risk and uncertainty work as accurately as complex decision models.

Katsikopoulos et al. [7] classified two simple strategies on how people transform cues into a choice: counting (Tallying) or by ordering (Fast-and-Frugal Tree, FFTree). Tallying examines whether there are enough reasons for assigning an instance to a target class, while FFTree looks at the reason one at a time, in a given order. Both are simple models that involve a small number of cues combined in a simple way and require fast and transparent reasoning.

In this paper, we develop an ABM where agents are supported with the cognitive skills necessary to make food choices between rice and non-rice using simple models: Tallying and FFTree. We aim to study the simple models' performance when applied as our agent mental model in the staple food choice context.

2 Methods

We collected primary data from our ethnographic diary collection method: a three-day food diary record and a post-diary survey of 44 respondents aged between 20 to 65 years ($M = 32.58, SD = 12.09$) between November 2020 and March 2021. From the data, we identified the six most informative staple food choice cues in the decision model stage of this simulation: mealtime, ease, taste, attitude, situation, and familiarity. Feature importance measures were drawn by fitting the data using simple (tallying, FFTree) and complex decision models (logistic regression, decision tree, and random forest).

Agent Attributes. In our model, six attributes determine the agent's preference for staple food. Random numbers with a uniform distribution between 0 and 1 were generated to represent the preferences according to mealtime, ease, taste, attitude, situation, and familiarity. These preferences can be translated into single-cue choices through simple thresholding in which the population-level thresholds become model parameters.

For instance, for agent i, the preferences are 0.46 (mealtime), 0.96 (ease), 0.77 (taste), 0.84 (attitude), 0.54 (situation), and 0.39 (familiarity). If the thresholding rule is choosing rice if preference $<$ threshold of 0.7, then agent i will have the following single-cue choice: rice (mealtime), non-rice (ease), non-rice (taste), non-rice (attitude), rice (situation), and rice (familiarity).

Additional two random numbers were generated to represent the influenceability and persuasiveness of agents. When the interaction in social networks is activated, the preferences of agents with high influenceability tend to be affected by agents with high persuasiveness as long as they are connected in the networks. The associated mechanism will be described in the subsection Social Networks.

In the initial part of the simulation, we defined the attributes of the agents. Cue thresholds are defined as the simulation parameter at the population level. Based on the defined attributes and parameters, the agent makes decisions using the following decision processes.

Decision Process. Empirical decision-making models can be established, fitted, and tested with the available data. The simplest one is a univariate or single-cue decision where the food choice is assumed to be taken after considering only one factor.

In a higher degree of deliberation, processing multiple factors into a decision can be done through many schemes, among which can be represented by a simple tallying course [6]. In this scheme, multiple influencing factors are identified as the basis of the decision. The single-cue decision is estimated for each factor based on the agent's attributes. The final decision is made by tallying all single-cue decisions without ranking or weighting. It is straightforward that the final decision has the highest tally. When an even number of cues are being considered, a tie may occur (refer to the example in subsection Agent Attributes). In such cases, the default choice selected is rice.

Instead of considering all six cues, an agent can also consider a subset of the cues, e.g., attitude, familiarity, and situation. The size of the cue subset can be an additional degree of freedom in the model that simulates the variation among agents.

Next, FFTree [8] is a simple decision-making model consisting of a sequence of decision nodes. In contrast with a more complex decision tree, only one factor is considered at a time. Simple, easy to understand, robust, insensitive to noisy data, and working well in small-size data are critical characteristics of FFTree that make it an excellent alternative model for some classification tasks. Practical tools like `FFTrees` package in `R` [10] can help understand the empirical data from the perspective of the fast-and-frugal decision model.

For our case, fitting the data using FFTrees produced a simple decision tree as depicted in the left panel of Figure 1. This tree is dependent on the data supplied for the fitting. Fitting a subset of the data may produce a different decision tree even though the tree's elements (decision node or single-cue decision) are the same. Each decision node can either be type P (positive decision or continue to the lower node), type N (negative or continue), or type E (the edge with either positive or negative decision). How the factors are arranged in a tree's

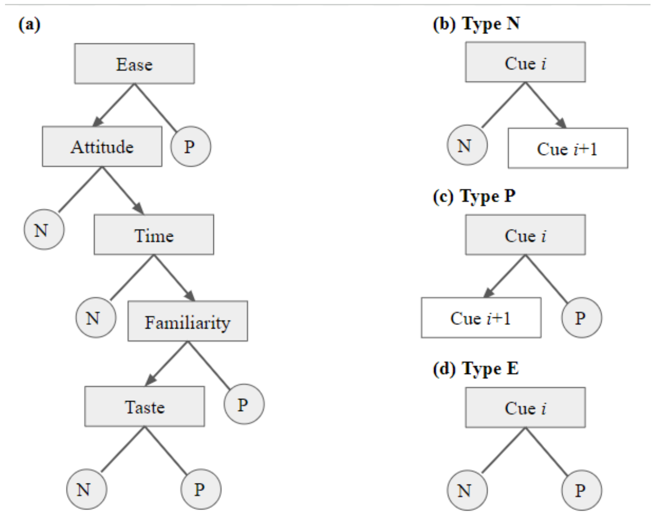

Fig. 1. (a) FFTree that fits the empirical data drawn from food diary and post-diary survey. This tree consists of decision nodes with three possible types (b, c, d).

nodes depends on the factors' predictive capability. Yet, the sequence can also be random because of the uncertain nature of food choice. Different people may have different decision trees, and the trees may change over time (due to the influence of social networks).

The agents' decision process is modelled using tallying or FFTree in the next step. In the first decision model, a subset of single-cue decisions is randomly selected and tallied. The decision with the highest tally becomes the final decision for each mealtime. To represent the uncertain nature of choice, the size of the subset mentioned above is randomly selected from $[1, 2, \ldots, 6]$ where 6 is the maximum number of cues to consider.

In the FFTree model, a random decision tree is grown by randomly sequencing the decision nodes, each with its type (see Figure 1). The actual depth of the tree is determined by how the type-E node is positioned. This node will be the end of the decision tree. After the tree is grown, the single-cue decisions from the previous stage are evaluated sequentially.

Social Network. People's preference for staple food may change over time. For instance, people can increase familiarity with non-default staple food by absorbing information and knowledge from society. The dynamics of social influence in the social network can be modelled using one of three classes of social influence models, namely assimilative social influence models, similarity-biased influence models, and repulsive influence models [3].

Among the three, the similarity-biased influence is deemed suitable for modelling the diffusion of values in the network because an individual is likely to share opinions and influence others with a certain degree of similarity. The degree of similarity or confidence level in [3] may vary from agent to agent. When simulated using a population with initially diverse opinions, the typical size of the degree of similarity affects the final state of the simulation, either convergence toward consensus or clustered opinions.

Following the interaction within the social network, the single-cue preference of an agent i will be affected by the injunctive norm exerted by its neighbours with relatively similar preferences. This diffusion can be formulated as follows [3]:

$$a'_i = a_{i,t} + \mu \sum_{i \neq j} f_{ij} \quad \text{with} \quad f_{ij} = \begin{cases} (a_j - a_i), & \text{if } |a_j - a_i| \leq \epsilon, \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where μ with a typical value between 0 and 0.5 is the rate of opinion convergence while ϵ_i is the confidence threshold of agent i. The latest parameter can also be described as the degree of influenceability with the higher value means a broader tolerance of an agent for different insights. Note that f represents the similarity measure among agents' opinions. Using this expression, one may expect that agent i will not significantly change its preference if its neighbours have symmetrically distributed preferences around a_i.

In the ABM, a small value of μ was initiated at the agent level while ϵ is set to 1 (agent barely ignores similarity). The degree of persuasiveness is included in the model such that social influence emerges from only neighbouring agents with enough persuasiveness. When social interaction is activated, an agent checks the preferences of its neighbours and slowly shifts its preference toward the average value such that agents' preferences in a particular node will converge. Considering the fact that the agent does not socially interact at every mealtime, we added a 10% probability of interaction to slow down the rate of convergence in a realistic way.

Parameters, Variables, and Simulation. We simulated a population of 500 agents distributed on a random social network [14]. Small initial values of μ and ϵ are assigned to each agent. The simulation ran for 300 steps, similar to the duration of 100 days, assuming three mealtimes a day. A `python` code equipped with `agentpy` package [4] was used for the ABM simulation [9].

To assess the behaviour of the model, we ran the simulation using several scenarios, from the simplest one to the more complex one. Table 1 summarizes the parameters used in the scenarios. The output variable is the time-weighted population's average preference for rice at the end of the simulation.

In the **base scenario**, all cues were considered in both decision models. The structure of the FFTree follows the empirical model depicted in the left panel of Figure 1. All thresholds for single-cue decisions were set to 0.7.

In **scenario A**, the familiarity thresholds were gradually changed from 0.7 to 0.3 such that a decrease in preference was expected to change. This change at the population level mimics a systematic change in society, either promoted by the government or driven by the socioeconomic situation. This change at the population level mimics a systematic change in society, either promoted by the government or driven by the socioeconomic situation.

Table 1. Summary of the simulation parameters for five different scenarios.

	Scenario				
Parameter	Base	A	B	C	D
Attitude threshold	0.7	0.7	0.7	0.7	0.52
Ease threshold	0.7	0.7	0.7	0.7	0.69
Familiarity threshold	0.7	variable[a]	0.7	variable[b]	variable[b]
Situation threshold	0.7	0.7	0.7	0.7	0.61
Taste threshold	0.7	0.7	0.7	0.7	0.51
Time threshold	0.7	0.7	0.7	0.7	0.40
# cues	6	6	random	6	random
FFTree	fixed	fixed	random	fixed	random
Influencers	0%	0%	0%	10%	10%

[a]gradual change from 0.7 to 0.3
[b]change by social influence

In **scenario B**, randomization was included in the decision models. Explicitly, the number of cues for tallying was randomly selected from $[1, 2, \ldots, 6]$ while the tree structure was also randomized. **Scenario C** departed from the base scenario where we considered the role of social influence, and one-tenth (10%) of the population was converted into influencers (i.e. agents with high persuasiveness and low preference for rice). At last, **Scenario D** adopted thresholds derived from our empirical data, but the familiarity was influenced by social interaction. These adopted thresholds were associated with an average preference for rice of 60%. As in scenario C, scenario D started with 10% influencers with a low preference for rice.

3 Results and Discussion

Figure 2 showcases the average preference for rice over time, simulated under different scenarios in a single run with a constant random seed. The result from the base scenario run shows flat lines at different values. Even though the single-cue decision thresholds were set to 0.7, the average preferences for rice were higher than 0.7. Multi-run experiment (50 repetitions) with this scenario yields the average preferences of 0.93 ± 0.01 and 0.84 ± 0.01 for tallying and FFTree models, respectively.

A simple linear model of a multi-cue decision may lead to an average preference that is close to or even equal to the single-cue preference, while non-linear models like tallying and FFTree may behave slightly differently. For each agent, the single-cue preferences were drawn from random numbers with uniform distribution and then translated into single-cue choices by thresholding rule: choose rice if preference $<$ threshold parameter (population-level) or choose non-rice. The rule produces around 70% positive decisions (choosing rice) and 30% negative (choosing non-rice). Draw in the tallying with an even number of cues resulted in a higher tendency toward default choice (rice). This explains a significant deviation of the average preference from the expected value of 0.7.

On the other hand, FFTree yields a more moderate deviation from the single-cue preference, mainly because of its unique decision tree structure. Instead of evaluating the entire FFTree, an agent can rely on some parts of the tree to make a decision. Referring to the example in subsection Agent Attributes and the FFTree in figure 1(a) agent i only considers the two uppermost decision nodes (non-rice for both ease and attitude) before the final choice of non-rice.

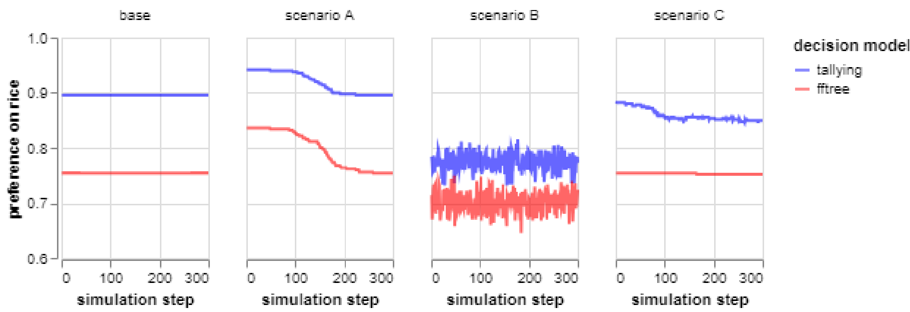

Fig. 2. The average preference for rice over time, faceted over different scenarios.

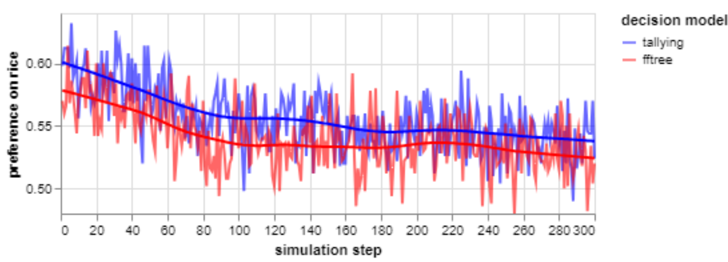

Fig. 3. The average preference for rice from scenario D. Tick curves are the locally smoothed profiles.

Scenario A defines a systemic change in the familiarity threshold. The systematic change of the familiarity threshold (from 0.7 to 0.3) in tallying model transformed the average preference from 0.94 to 0.90. This reduced effect is due to the fact that familiarity is just one out of six cues considered in the simulation. Meanwhile, the model with FFtree shows an even more suppressed change of approximately 0.01. The reason is that familiarity is located at the bottom of the decision tree (Figure 1).

In this scenario, an ideal intervention would be the involvement of the central government in promoting non-rice consumption. A massive introduction to alternative staples is expected to increase the preference. Referring to the cues, ease and attitude played an important role in scenario A. Alternative staples can be upgraded by being processed for consumers' convenience. For instance, cassava can be sold in a washed, peeled, and grained form, while yam can be distributed in a ready-to-cook noodle, and potato can be cut in frozen packaging.

Scenario B illustrates the uncertain nature of food choice. Due to the variability of the number of cues taken into consideration, the tallying model produced an average preference that fluctuates around 0.84. The same fluctuation is also observed in the result from FFTree, while the average preference is around 0.73. These observed fluctuations of preference at the population level are coming from the same fluctuations at the agent level.

Scenario C induces social influence on the staple food choice. Familiarity with alternative staples may change over time due to the interaction with other agents, especially the influencers who promote non-rice consumption. The decreases in the average preference for rice are observed, though the effect for the model with FFTree is suppressed. The same explanation as in scenario A is applicable to this suppressed change. To increase familiarity towards alternative staples, some possible interventions are intensifying the recruitment of influencers and boosting social media publications as non-rice consumption normalisation.

Figure 3 displays the simulation result for scenario D, where the thresholds were drawn from empirical while the tree was randomized. The tallying started from the average preference of 0.60, while the second model started from 0.58. From our empirical data, a naive rice preference estimate is 0.60. At a glance, the tallying model sufficiently provides a good estimate of the average preference though its dynamics over time require further examination.

In summary, the presented results demonstrate explainable behaviours of aggregated preferences for rice, which are based on tallying and FFTree decision models. The key feature of the models is the time-variant characteristics affected by systematic intervention, social influence, and random processes.

4 Limitation and Future Work

Understanding individual staple food choice behaviour is paramount to achieving climate-friendly food system goals. ABM is powerful in capturing the tacit staple food choice mechanism and articulating the emerging properties of social interaction.

We introduce simple heuristics as a mental model for staple food choices in the agents. Explainable properties and behaviours of the model are presented. Thus, including such decision models for more practical cases becomes possible. How the staple food choice affects the demand for rice and other commodities can be of interest in the near future. As an archipelagic country with a diverse pattern of staple food production and consumption, Indonesia can be the test bed for the model.

Even though the simulation result with empirical data is presented, it can only be validated with single-time data. The dynamics of staple food choice under social influence is a fascinating aspect to simulate, but the model validation needs time-series data which is harder to get. The national economic survey by the Indonesian Bureau of Statistics (BPS) can be the source of such data. However, harmonisation and homogenisation of the data are challenging to accomplish before utilising the data.

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