# Simulating Shopper Behavior using Fuzzy Logic in Shopping Center Simulation

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**Abstract.** To simulate real-world phenomena, a computer tool can be used to run a simulation and provide a detailed report. By using a computer-aided simulation tool, we can retrieve information relevant to the simulated subject in a relatively short time. This study is an extended and complete version of an initial research done by Christian and Hansun and presents a prototype of a multi-agent shopping center simulation tool along with a fuzzy logic algorithm implemented in the system. Shopping centers and all their components are represented in a simulated 3D environment. The simulation tool was created using the Unity3D engine to build the 3D environment and to run the simulation. To model and simulate the behavior of agents inside the simulation, a fuzzy logic algorithm that uses the agents' basic knowledge as input was built to determine the agents' behavior inside the system and to simulate human behaviors as realistically as possible.

## 1      Introduction

In a world where technology progresses rapidly, computer simulation is considered an important tool for modeling and simulating real-world phenomena. With a simulation tool one can achieve similar results as with real-world observation and analysis but much faster. For the purpose of developing a simulation tool, the paradigm of the multi-agent system can be used to build and model the simulation design.

The authors picked shopping centers as the subject of the simulation. Shopping centers have become an important part of society. The definition of a shopping center is a group of retail stores that are managed as a single property. Mall managers and developers currently lack automated tools that can be used to model, predict and see the outcome of a shopping center. The proposed simulation tool was built not only to serve the purpose of the development of

shopping centers themselves but also as a tool for simulating human-like decision making.

To make the simulated agents able to imitate real-world phenomena as realistically as possible, the system was provided with an artificial intelligence (AI) algorithm that simulates human behaviors. The simulation tool utilizes fuzzy logic to simulate the human activities and decision-making processes in a shopping center. Fuzzy logic was chosen due to its flexible approach and human-like interaction, which is crucial for imitating the real-world behavior. In the game domain, fuzzy logic not only acts as an AI method but also as a quality behavior generator, which is able to provide complex behavior and increase the quality of interaction between agents [1]. The knowledge base and rules were taken from various publications on consumer behavior and analysis [2-10]. The design of the agent itself contains its knowledge base and decision rules crafted in fuzzy logic, but the agents have very little knowledge of the virtual environment and the other agents. This will be discussed in detail in Section 4.

## 2        Related Works and Research Methodology

There are a number of works related to this research's topic. As stated in [11], experiments with computer-simulated shopping have opened up new opportunities for marketing research. Some of them were done in conventional ways by collaborating with traditional or modern shopping centers and incorporating the simulation program in them, while others have been done by incorporating the program into an online or a virtual supermarket environment [12,13].

In this study, we built SimMal, a mall simulation program that simulates shopping behavior, which was then incorporated in a number of modern shopping centers. As suggested by Schenk, *et al.* [14], it implements an agent-based approach in a multi-agent system. To model and simulate the shopper's behavior as realistically as possible, an artificial intelligence (AI) method was implemented. Çağil and Erdem [12] used the Naïve Bayes Classifier and artificial neural networks as AI methods in their simulation system, while in this study we used fuzzy logic as the AI method, which is able to provide complex behavior and increase the quality of interaction between the agents [1]. Drennan, *et al.* [15] have also done similar research, however, their goal was to conduct and evaluate consumer misbehavior using a game simulation approach.

The research methodology incorporated in this study can be described as follows:

1. Literature study
   We used a large number of books, journals, reports, and websites relating to the research topic, especially about the multi-agent system, artificial intelligence and shopping center simulation. References [2-10] were used to provide the basis and rules in building the simulation tool, while other references were used to assume and extract the attributes that the agents can possess.
2. Data gathering
   Data collection was conducted through direct observation in several shopping centers in Tangerang. Direct observation included the analysis of mall layouts, entry doors and estimation of shop's properties.
3. System design and building
   Based on the data collected from various resources, the simulation was designed according to the principles of the multi-agent system. Designing the simulation tool involved building the 3D environment, designing the agents' set of actions and behavior by using fuzzy logic, and testing it.
4. System implementation
   The simulation tool was built using Unity3D. It doesn't use any 3rd party plug-ins or APIs. The tool starts the simulation based on the layout of the shopping center that is built. The result of the simulation is shown directly from the simulation tool's graphical user interface (GUI).
5. System validation and analysis
   The validation of the simulation tool involved experts on shopping centers. By using the face validation technique, the tool was tested directly by the experts, in this case mall managers of shopping malls in the Tangerang area. A questionnaire was also given to the experts to measure the accuracy of the simulation and for feedback.
6. Research report and documentation
   The results, references, and all other findings related to this research were documented in a research report. Publication of the research results was also done in the research phase.

## 3       Multi-Agent System

A multi-agent system is a system that consists of several software units or entities, which are called agents, scattered across a virtual environment [16]. What makes it different from common software systems is that the entities are autonomous, capable of thinking and are able to communicate with other entities. The multi-agent-oriented approach in building complex systems is based on object-oriented principles. Agents in a multi-agent environment are defined as objects with additional features, such as the state and behavior of the objects [17]. The agent-based approach has been incorporated in many projects,

especially in projects that use AI algorithms to a high degree, such as digital games and simulations.

The difference between agents and objects lies in their autonomous behavior. Agents have a certain degree of freedom in changing their actions and behavior patterns, which make them active in the simulated environment, whereas objects are passive. Most intelligent agents are modeled and built on top of different layers, such as a knowledge base, an AI algorithm and a decision-making system.

In social science, multi-agent systems have been used for describing and exploring social behaviors between agents, environments and the interactions between them [18]. Application in social science requires categorization into a complex social simulation because even the simplest form of virtual agent could give an unpredictable simulation result due to its high level of interaction. This is why simulations in social science have certain weaknesses. One of them is that the simulation of a complex social system is only an approximation of the real-world phenomena [19].

## 4        Fuzzy Logic and Decision Making

Fuzzy logic is an AI algorithm based on the uncertainty of a given situation. In classic logic, an assertion is either true or false, zero or one. Fuzzy logic extends the logical values by allowing a certain value range between true and false [20]. Referring to Lotfi A. Zadeh, the inventor of fuzzy logic, the concept that plays the central role in the application of fuzzy logic is that of linguistic variables [21,22].

Fuzzy logic is also an AI algorithm that can be used to incorporate and imitate human-like behavior and is very useful for environments with vague, uncertain information and a need for human reasoning [23]. In the present research, fuzzy logic was used as the AI algorithm to model and imitate the behavior of the shopper agents. The agent's basic knowledge is transformed into a fuzzy set, containing a value between 0 and 1. This fuzzy set is then evaluated with a set of pre-defined fuzzy rules. The steps are:

1. Fuzzification. The transformation of the agent's basic knowledge into a fuzzy value.
2. Rule evaluation. The fuzzy value is evaluated against the fuzzy rules.
3. Defuzzification. Turning back the evaluated value into a crisp value, in this case using the centroid method.

The fuzzy rules were built and referenced from literature taken from social science [2-10] and from experts' recommendations. As for attributes such as income or age, they are fairly easy to model by referencing official documentation in each country. Other, more abstract attributes, such as effort, are quite hard to model and in this case the fuzzy rules were based on the approximation and analysis of real-world examples, for example, through interviews.
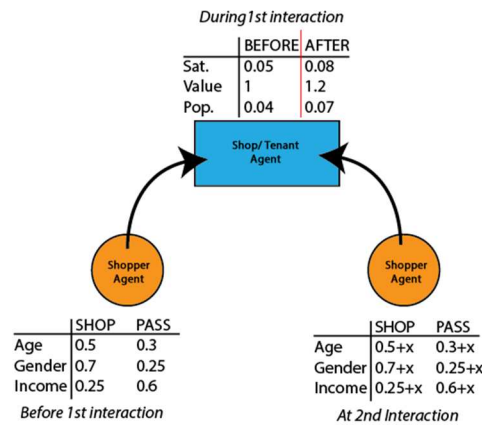
In the developed prototype, the fuzzy-logic calculation is done twice. The agent's basic knowledge is evaluated against the fuzzy rules, whose crisp value is then evaluated again a number of additional COST-STAMINA fuzzy rules. In the case of the shopper agents, human behavior is simulated on the basis of at least two aspects, i.e. desire and resources. The first fuzzy rule determines the desire of the agent and the second one refers to the resources the agent disposes of, which are money and effort in this case. This was done to add more complexity to the shopper agents' behavior and to make it more human-like. The steps taken in the double-step fuzzy logic calculation are shown on the figure in Section 5.

In terms of the decision-making process, it has been stated above that the system only has the knowledge base of the simulated agents and the fuzzy rules to simulate their behavior. The agents have only little knowledge of the simulated environment and their access to the environment is limited. Imperfection of the perceived information is what makes the agents new to the environment and renders them unable to make decisions in the early stages. The simulation offers WALKING behavior, which can be perceived as the basic action of the agents. It is essential for them to gather more knowledge about the perceived environment and based on game theory, the agents have perfect recall. Thus things can be added to their knowledge base.

The decision-making mechanism was developed by utilizing the utility value gained from the fuzzy logic calculation. As in epistemic game theory, a decision choice rule provides recommendations for how the agents should behave. In this case it is related to the fuzzy sets and processing of the utility value. It also uses a number of mathematical and probability values [24]. The utility value as the output of the fuzzy logic calculation serves as the input for the choice rule, which is used to determine the behavior of the agents.

The lack of interaction between shopper agents, which will be discussed in Section 7, also affects the decision-making process of the agents. Each shopper agent is unaware of what activities will be done by the other agents and the decision-making process can only be done within interactions between shopper agents and tenant agents. Each interaction builds up a utility value and modifies

the knowledge base of the agents. Other agents will indirectly evaluate their own decisions and utility values based on their modified knowledge base as a result of previous interactions with agents. For example, a shop agent may update its attributes based on the satisfaction rate and popularity of the incoming shopper agents. Other shopper agents may subsequently also take these attributes into consideration, aside from their own attributes, and re-evaluate their decision-making process. These additional attributes are represented in the Figure 1 below as the variable x, which is added to the utility value.



**During 1st interaction**

|        | BEFORE | AFTER |
|--------|--------|-------|
| Sat.   | 0.05   | 0.08  |
| Value  | 1      | 1.2   |
| Pop.   | 0.04   | 0.07  |

Shop/ Tenant Agent

Shopper Agent

|        | SHOP | PASS |
|--------|------|------|
| Age    | 0.5  | 0.3  |
| Gender | 0.7  | 0.25 |
| Income | 0.25 | 0.6  |

*Before 1st interaction*

Shopper Agent

|        | SHOP    | PASS    |
|--------|---------|---------|
| Age    | 0.5+x   | 0.3+x   |
| Gender | 0.7+x   | 0.25+x  |
| Income | 0.25+x  | 0.6+x   |

*At 2nd Interaction*

**Figure 1**  Indirect interaction between agents.

This creates uncertainty about how the agents may behave and unpredictable behavior may arise from it. The original strategy of an agent may also be updated due to changes in one of the other agents.

## 5      The Simulation

A simulation, in this case using a shopping center as the real-world example, means putting real-world activities in a shopping center into a virtual one. Consumers and tenants are treated as individual agents with their own thinking capabilities and preferences [9]. Environments such as roads, floors, and walls are treated as passive objects, which are mainly used as pathfinding variables.

Agents in a simulated environment follow simplified real-world rules. Social norms are implemented in various ways, depending on the algorithm used. The rules are mainly used for the agents' decision-making ability. One of the models for the agents' decision-making strategy is to choose their actions based on a

maximum utility value [25]. The utility value can be mathematically calculated using Eq. (1) [25].

$$a = argmax_{a_i} \left( utility_{role}(a_i) \right) \qquad (1)$$

where $a$ refers to the action the agent chooses from a set of possible actions that can be done based on its role, which is defined by its knowledge base and is represented by the $utility_{role}(a_i)$ function. The total utility value is a combination of all values that are obtained from the activities done by the shopping center agent (for example, eating, window shopping and others yield a certain value pertaining to the agent's knowledge base). The utility value can be calculated based on:

1. Interaction between agents
2. The agent's knowledge base, which is transformed into a fuzzy value that can be calculated
3. Optional random number generation to provide a bit of randomness

In the simulation, utility values are retrieved, calculated and scattered among all possible actions the agent can do using the fuzzy logic algorithm. From the actions and the values attached to it, the agent will be able to select the action with the highest utility value and execute it. The sequence of getting the utility value is shown on Figure 2 below.
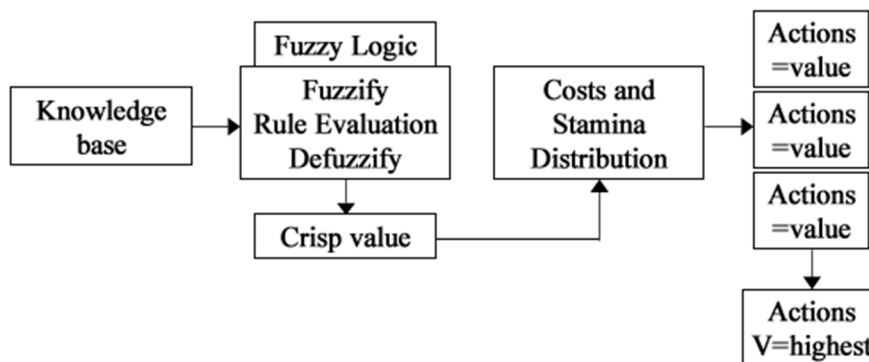


**Figure 2**  Utility value flow.

Beside the logic behind the simulation, a visual representation for and interaction with the user are important factors to support the simulation's usability [10]. A visual representation of the simulation can be shown in a 2D or 3D environment, using simple graphical representations to represent the virtual environment. It can also include a representation of the data in the form of

tables or graphics. The simulation environment in this tool is presented in a 3D environment using primitive 3D shapes, such as cubes, cylinders, and other primitive shapes to represent the agents in the system.

## 6        The System

The proposed simulation tool is called Simulate Mall (SimMal). It was built using the Unity3D engine and the C# programming language for the 3D visualization, data representation and the agents' logic calculation. The simulation system is divided into four parts, i.e. environment, agents, artificial intelligence, and fuzzy logic implementation.

### 6.1      Environment

This part handles the shopping center design module, which is used to design and populate the shopping center with tenants. Using the environment building mechanism, the simulation itself will be able to simulate and design different mall layouts and scenarios. SimMal utilizes a grid-based multi-level layout. Each cell represents a spot to place a shop or to use as a node for the pathfinding algorithm. Figure 3 shows virtual representations of some virtual agents in the simulation environment.



**Figure 3**  Virtual representations of virtual agents.

### 6.2      The Agents

As stated in Section 5, there are two types of agents, i.e. active and passive agents. Consumers (shoppers) and tenants (shops) are active agents, while environments such as roads, floors and walls are treated as passive objects.

Active agents, such as shopper agents, are able to create passive agents that perform calculations (mainly the decision-making calculation) to determine the behavior of the active agents themselves.

Agents in SimMal are represented by several primitive shapes used in a 3D world. The agents are made from classes and each class has its own update method, which makes them autonomous. Their attributes are implemented in the form of a hash table.

All agents in SimMal have a similar interaction method. Message-passing is used with certain formal message parameters using key-value pairings. An example of the message structure can be seen in Table 1.

**Table 1**     Example of message structure.

|         | Key         | Value       |
|---------|-------------|-------------|
| Header  | Sender      | "shopper-23" |
|         | Receiver    | "shop-45"   |
|         | messageType | "purchase"  |
| Content | value       | "3"         |
|         | other       | "0.7"       |

Each agent can send or receive messages. Every successfully received message is accepted and stripped of its headers. The content will then be used to update the knowledge base of the agent.

The pathfinding feature and thinking ability are handled by the passive agents. Active agents, such as shopper agents, are able to create passive agents that can perform calculations (mainly the decision-making calculation) to determine the behavior of the active agents. For instance, a shopper agent could ask the pathfinder agent department to find the way to a designated shop.

The pathfinder agent then creates a small agent that performs the pathfinding algorithm. Then it will send the message containing the path back to the shopper agent. This makes it easy to separate different functionalities of the agents and allows the active agents to utilize more than one passive agent simultaneously.

## 6.3     Artificial Intelligence

The most essential part of the simulation is embedding the AI algorithm in the active agents. Two AI algorithms are used. The first algorithm is a fuzzy logic algorithm and the second algorithm is the A-star pathfinding algorithm which is used to navigate the virtual environment [20-23]. The input data for the fuzzy

logic algorithm are taken from the shopper agents' attributes, such as age, gender and income, each with their own fuzzy membership functions. Beside the attributes, each agent has a historical database that is used for data gathering and data visualization.

On top of the usual shopping behavior, shopper agents are also able to simulate impulse-buying behavior. This behavior is especially triggered when a certain shop enables a promotion agent. The promotion agent is able to send messages to nearby shopper agents about an upcoming promotion.

Each shopper agent has an impulse-buying tendency, which is implemented in a membership function, and is affected by its attributes. If this tendency is high, there is a probability to ignore the current goal and to execute the impulse-buying behavior. This type of interaction basically increases the probability of a shopper agent doing activities that are outside of its original strategy.

## 6.4    Fuzzy Logic

The system utilizes fuzzy logic in the agents' thinking capability and decision-making process. It allows the shopper agents to execute behaviors based on their attributes, choosing from a range of shops that can satisfy their needs and updating their knowledge base. The structure of fuzzy logic calculation implemented on the system can be illustrated as can be seen on Figure 4.
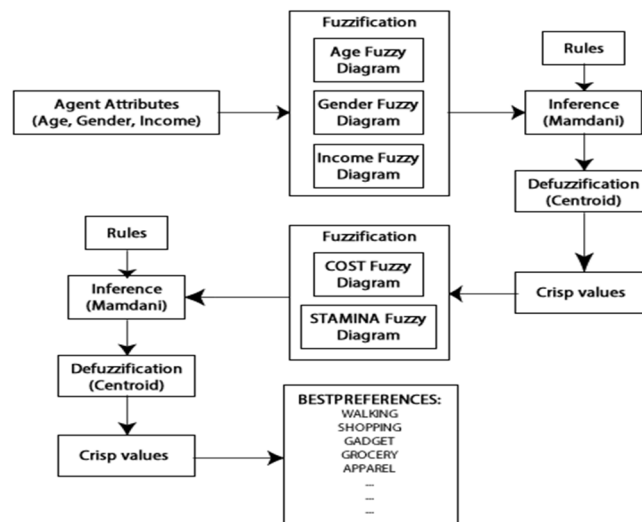


**Figure 4**  Structure of the fuzzy logic calculation.

There are three attributes that serve as the basic knowledge of the system. They are age, income, and gender. These demographic attributes were selected because they are fairly easy to incorporate into the fuzzy engine and they are the attributes that influence decisions the most, especially related to shopping behavior. In this research, we used the Mamdani fuzzy inference engine to evaluate the agents' attributes with the rules in the system. Figures 5-7 show the fuzzy values used to describe the attributes [26].
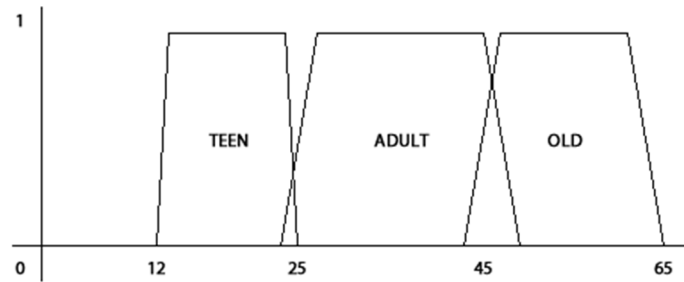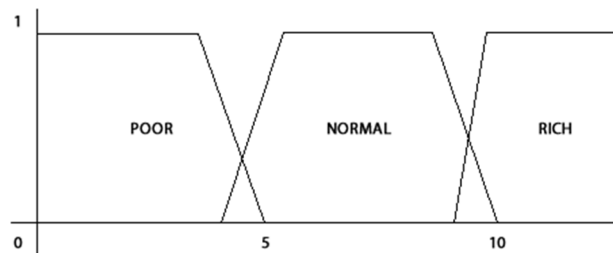


**Figure 5**  Age fuzzy sets.



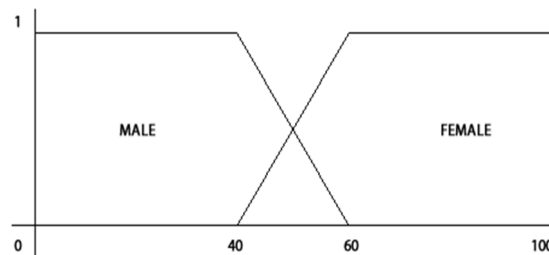**Figure 6**  Income fuzzy sets.



**Figure 7**  Gender fuzzy sets.

The Gender attribute was given a cross-section to provide a bit of randomness and to model human-like behavior for some types of action. For example, not

all male agents like shopping for gadgets, or not all female agents like to go window-shopping.

Based on the attributes, the outcome (the crisp value) is determined by using the fuzzy membership functions. The centroid (center of gravity) method is used as the defuzzification method. The center of gravity is obtained from the accumulation of fuzzy values and can be expressed as [27],

$$z^* = \frac{\int \mu_C(z).z\, dz}{\int \mu_C(z)\, dz} \qquad (2)$$

```
set fuzzyResultAgentAttribute(COST, STAMINA) as defuzzification value
    of (age, income, gender)
set fuzzyResultFinal(COST, STAMINA) as fuzzification value of (COST,
    STAMINA)
set actionValues(agentActions.Length) as 0
set chosenAction as null
set highestValue as lowest Integer value

for(agentActions → action)
        if(action matches (COST, STAMINA))
                increment value(action) by 1

for(actionValues → value)
        if(value > highestValue)
                highestValue = value
                chosenAction = action

process the chosenAction
```

**Figure 8**  Pseudo-code to find the best action.

The crisp value itself is distributed to two more membership functions, i.e. COST and STAMINA. The COST and STAMINA membership functions act as barriers that re-evaluate an agent's desire from the previous calculation against the agent's resources. The agent will then choose the action with the highest value. Pseudo-code of this process can be seen in Figure 8.

The second fuzzy rule evaluates the given crisp value from the agent's knowledge base into crisp values related to COST (the resources at its disposal) and STAMINA (the effort to carry out the activities). These fuzzy rules determine whether the desire based on the agent's knowledge is doable or takes minimal effort to do. For example, an 'old', 'poor', 'male' agent, despite its desire to buy a gadget, is limited due to the COST-STAMINA fuzzy rules, which may be very low in this case. Thus, the agent may forget its desire or find another activity to do.

Another, smaller fuzzy logic implementation is the impulse-buying behavior. The fuzzy logic calculation pertaining to impulse-buying behavior is activated when a shopper agent is inside the field of a 'promotion' area. This is used to model the behavior of shop agents that are giving promotion or discounts. It basically lowers the constraint of the fuzzy rules and gives shopper agents an unpredictable and more complex behavior towards their preferred activities, as shown in Figure 9.
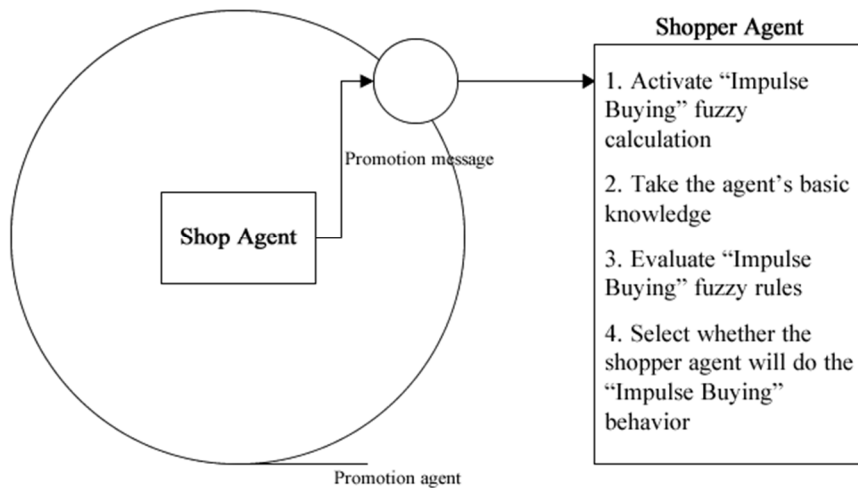


**Figure 9** Promotion agent.

The fuzzy rules and membership functions were constructed and obtained from various publications on social multi-agent systems [2-10]. The rules are string-based and are parsed within the application. Some examples of the rules are:

*IF Age is Teen AND Gender is Female, Cost is Normal AND Stamina is Low*

*IF Age is Old AND Gender is Male, Cost is High AND Stamina is Low*

*IF Age is Adult, Income is Poor, AND Gender is Female,*

*Cost is Low AND Stamina is Low*

From the rules, we extract two crisp values, which will then be calculated into two membership functions (i.e. COST and STAMINA). Another crisp value is obtained from the fuzzy rules between the agent's attributes and its choice of action. These crisp values are calculated to produce the utility value, which is used to select the best course of action.

# 7      Results and Discussion

The validation of the simulation involved expert analysis and direct observation in a number of shopping centers around Tangerang city. For the purpose of validation, three shopping centers were selected, i.e. Summarecon Mall Serpong, Giant Serpong and Supermall Karawaci. The layout of the shopping centers and the tenants' placements were reproduced as similar as possible in the simulation environment using the environment building tool.

The validation of the simulation tool used the face validation method as proposed by Mitre [28]. This involved experts in consumer behavior and their analysis to validate the reliability and accuracy of the simulation. It also verifies whether the logic implemented and input-output relationships are correct and acceptable [28]. Although it was limited by the subjectivity of the experts and it lacks statistical analysis, this technique provides a very descriptive analysis of the model [29].

The respective mall managers of the selected shopping centers were chosen as the experts since they have practical experience and knowledge related to real mall shopper behavior. They were given a questionnaire regarding the features of the simulation. Below is the activity indexes table (Table 2), which will be referred to in Table 3.

**Table 2**    Activity indexes.

| Index | Activity |
|-------|----------|
| 1 | WALKING |
| 2 | WINDOW SHOPPING |
| 3 | EATING |
| 4 | ENTERTAINMENT |
| 5 | APPAREL |
| 6 | GADGET |
| 7 | GROCERY |
| 8 | SOUVENIR |

Figure 10 shows the summary window that was brought up at the end of each simulation day. It compiles and shows the gathered data from each agent in the simulation, such as the most visited shops, the shopper agents' treatment of a certain shop category, and other information.

The system's simulation result was then compared with the experts' analysis to determine the correctness and reliability of the AI algorithm in simulating the consumer behavior in the shopping centers. Each agent with different attributes has two sets of three activities from the system-generated values and experts'

recommendation. If more similarities were detected, it was assumed that the accuracy of the system was getting better.



**Figure 10**  Summary window.

**Table 3**  Comparison of Expert Evaluation and System-generated Values

| Age | Gdr | Inc | Exp | Sys | Sim. |
|---|---|---|---|---|---|
| Teen | Male | P | 4-1-3 | 3-4-7 | 2 |
| | | N | 4-3-8 | 3-5-4 | 2 |
| | | R | 4-3-6 | 8-1-6 | 1 |
| | Female | P | 3-1-4 | 1-2-3 | 2 |
| | | N | 3-4-7 | 7-6-2 | 1 |
| | | R | 4-2-3 | 3-5-4 | 2 |
| Adult | Male | P | 1-2-4 | 3-1-7 | 1 |
| | | N | 3-4-8 | 3-5-6 | 1 |
| | | R | 5-6-7 | 4-6-1 | 1 |
| | Female | P | 1-3-4 | 5-4-1 | 2 |
| | | N | 2-3-7 | 4-2-1 | 1 |
| | | R | 5-6-7 | 3-6-2 | 1 |
| Old | Male | P | 1-2-7 | 5-6-7 | 1 |
| | | N | 1-3-7 | 7-1-2 | 2 |
| | | R | 3-7-8 | 4-7-8 | 2 |
| | Female | P | 1-2-7 | 3-4-2 | 1 |
| | | N | 1-3-7 | 3-8-4 | 1 |
| | | R | 3-7-8 | 4-8-3 | 2 |
| No. of similarities | | | | | 26 |
| Average percentage | | | | | 48.15% |

The first three headers in Table 3 indicate the agents' knowledge bases, i.e. Age, Gender (Gdr), and Income (Inc). The headings Expert (Exp) and System (Sys) represent the experts' evaluation and the values generated by the system.

Similarity (Sim) represents the similarity between both results. P, N, and R are abbreviations for 'Poor', 'Normal', and 'Rich'.

The similarity between the experts' and the system's results was counted for each agent with different basic attributes. The result was then divided by 54, the target value of the system's similarity. Overall, the result of the simulation yielded only 48.15% accuracy. We may conclude that the performance of the simulation is not yet suitable to model real-world behavior due to its low accuracy. However, based on the simulation's results, some similarity between human behavior and real world phenomena was shown. There are many causes for the lack of accuracy the simulation introduces:

1. The lack of interaction between agents in the system. So far, the only interaction designed in the simulation is between the shopper agents and the tenant agents because of the difficult challenges of designing model interactions between shopper agents. The interaction between shopper agents is produced indirectly via the tenant agents. The messages passing between shopper agents and tenant agents also change the knowledge base of the tenant agents, which in turn affects other shopper agents' decision making. In the future, this problem may be addressed by adding a suitable design for interaction between shopper agents.
2. The relatively small amount of data gathered. The results of this research were obtained by running the simulation for only 30 days of virtual time.
3. The utility value alone is not enough to determine the behavior of the agents. Although its outcome is unpredictable, its accuracy reviews did not improve, based on the experts' evaluation. There should be more real-world factors that can affect the utility value to provide a better simulation.
4. In the future, there should be a better validation method to verify the results of the simulation. The experts' opinions tended to be more subjective than objective.

We also noticed several interesting patterns in the simulation. Even with a small number of simple attributes and a message-based interaction setup, the results of the simulation may become very unpredictable. For example, an 'old' shopper agent would prefer to shop at nearby tenant agents. The result of the simulation from the tenants' point of view shows that those agents tend to shop more based on their Income attribute than on distance. Even though each attribute has the same weight in the fuzzy logic calculation, unpredictable behavior still occurs more than every so often. This may become an interesting topic for future research. Another finding concerns the usage of the message-based interaction between agents. It was found that using messages with predefined key-value pairs enables the autonomous agents to easily filter and react based on the

messages' header and contents. This has also proven to be scalable, especially when adding new types of agents or derived agents.

## 8        Conclusion

A social-science simulation is a very complex simulation with many ranges of data and unpredictable results. Even a simple attribute calculation can result in a non-linear result of the simulation. This may lead to numerous research opportunities, especially with a multi-agent system as the system model.

A simulation tool called SimMal was built successfully to simulate the shopping behavior of customers in a shopping center. A double-step fuzzy logic algorithm was implemented for the artificial intelligence of the agents in a multi-agent system together with the A-star pathfinding algorithm. Based on the face validation technique with input from three different experts, it was concluded that the simulation result reached only 48.15% accuracy.

There is plenty of room for improvement of the system: the foundation of the system, the knowledge base and the rules are some of them. Experts are not only required to validate the outcome of the simulation but also the rules and knowledge base used in the simulation software. The data visualization needs to be improved. Business intelligence plays an important role in turning the data into a nice visualization that is appealing for the user. Other improvements that can be made are the interaction among shopper agents to create a more dynamic and realistic simulation and a more proper utility-value-based calculation.

Mall simulations have been proven to be a useful tool for mall managers and developers when developing their shopping centers. A unified tool means an easy way for mall managers and developers to manage, predict and see the approximate outcome of their mall, which can be a factor in their decision-making process.

## Acknowledgements

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