

## Modeling Habit Patterns Using Conditional Reflexes in Agency

Qura-Tul-Ain Khan<sup>1</sup>, Taher M. Ghazal<sup>2,3</sup>, Sagheer Abbas<sup>1</sup>, Wasim Ahmad Khan<sup>1</sup>, Muhammad Adnan Khan<sup>5,6</sup>, Raed A. Said<sup>4</sup>, Munir Ahmad<sup>1</sup> and Muhammad Asif<sup>1,\*</sup>

<sup>1</sup>School of Computer Science, National College of Business administration and Economics, Lahore, 54000, Pakistan

<sup>2</sup>Center for Cyber Security, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), 43600, Bangi, Malaysia

<sup>3</sup>School of Information Technology, Skyline University College, University City Sharjah, 1797, Sharjah, UAE

<sup>4</sup>Canadian University Dubai, Dubai, UAE

<sup>5</sup>Faculty of Computing, Riphah International University Lahore Campus, Lahore, 54000, Pakistan

<sup>6</sup>Pattern Recognition and Machine Learning Lab, Department of Software Engineering, Gachon University, Seongnam, 13120, Korea

\*Corresponding Author: Muhammad Asif. Email: muhammadasif@ncbae.edu.pk

Received: 24 March 2021; Accepted: 25 April 2021

**Abstract:** For decision-making and behavior dynamics in humans, the principal focus is on cognition. Cognition can be described using cognitive behavior, which has multiple states. This cognitive behavior can be incorporated with one of the internal mental states' help, which includes desires, beliefs, emotions, intentions, different levels of knowledge, goals, skills, etc. That leads to habit development. Habits are highly refined patterns formed in the unconscious that evolve from conscious skill patterns in the human, and the same process can be implemented in the agency. These habit patterns are the outcomes of many internal values that may vary due to variations in parameter values forming these patterns. Fluctuations in the individual agent's conditional reflexes may subject to strong habit patterns and leads to rationality. This paper presents the modeling of habit patterns in agency using conditional reflexes. Learning patterns, limited reflex patterns, skill patterns are working as main parameters for generating habit patterns. These input and output parameters will be validated using a scenario by applying fuzzy logic cascade techniques in which validation occurs at two levels. At the first level, conditional reflexes and initial patterns are applied, which form the output's skill patterns. Then these skill patterns are interconnected with each other to form habit patterns.

**Keywords:** Human psychology; decision making; habit; rationality; agent's behavior

### 1 Introduction

AGI is a growing field focusing on developing general-purpose systems with human-like properties. All human-like properties are multi-dimensional and complex that is dynamic nature of these characteristics making it more inspiring in designing intelligent agents. An important feature is a rational behavior that is interlaced with many different practices and functions. The limitation of wisdom is not limited to reasoning and logic, but it also incorporates motivations, intents, and emotions.



This work is licensed under a Creative Commons Attribution 4.0 International License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Furthermore, AGI classified the process into unconscious and conscious structures. For achieving complete rationality, habit plays a vital role in human behavior. Based on expert knowledge, highly refined data patterns are habits, and the formations of these patterns become part of the unconscious. Habit growth and its effect on independent behavior development, decision-making, and the relation with inspirations need to be assessed to establish rationality.

The primary goal of AGI is to explain the mechanism of the learning process, cognition, and human mind, including its implementation in agents. AGI can be achieved by duplicating the human brain at a fundamental level and understanding the complete mechanism of AGI. It is imperative to understand the human mind at functional, capability, and behavioral levels.

The main hurdles in achieving AGI are the lack of dynamic and rational behavior. Due to this hurdle, the agent is not adapted to make its own decisions in multiple situations, whereas human phenomenon is much different from a typical robot. A human's ability is that he works differently in various conditions and if the environment is different, but the situation may be the same; in both cases, a human has very different behavior.

Different AGI theories are still beginning, but it is promising to spot the increasing attention that it has established in past years. The traditional AI plays a critical role and offers convenient examples and AGI outcomes [1].

Many theories are proposed on human behavior. One of the approaches is the Social Cognitive Theory offers that only external forces are there to change the human response. For decision-making, internal effects have no impact on human behavior. Many environmental factors are included in external forces that depict situational influence, and the internal troops include individual motivational effects, instincts, traits and drives, and. As the environment changes, the behavior also changes, and it may also include providing the chances for behavior change [2].

Another theory is the Theory of Planned Behavior. It proposes human behavior is dependent on the individual's intention, and intention itself is determined by an individual's attitude and an individual's observation of the ability. This theory said that intention is an utmost important parameter in predicting behavioral change, and it is often linked to an individual's emotions and motivations [3].

## 2 Literature

Cognitive architecture plays a vital role in constructing intelligent systems. These systems support a full range of capabilities that are human-like [4]. In cognitive agents for acquiring knowledge and learning new skills, new developmental techniques have been used. This is ambiguity among researchers between learning and development. One of the specific forms of education is development, according to some researchers. In contrast, knowledge is the leading behavior of the active model. According to other researchers, the active model's leading behavior and the active model's leading behavior are the new models [5].

In achieving rationality, some AGI approaches are helpful because AGI is inspired by the human mind's behavior and structure, knowledge processing, and decision-making. It is motivated by practical methods and its implementation of problem-solving and rational principles.

Term 'rationality' is used in variation in different disciplines. Cognitive science is associated with cognitive processes in an agent intelligence's explicit environment and to incorporate them. It is vital to study the phenomenon of human intelligence for modeling agents' intelligence and incorporating them. This study also helps in finding deficiencies [6].

Learning and knowledge are the primary cognitive skills to perform a goal, and it is also required to evaluate the reliability and condition of the task. Changes in the system can be denoted by learning. The system is permissible to accomplish the same task more proficiently in the future. Learning could be supervised, semi-supervised, unsupervised, or reinforcement learning. For -time learning supervised learning model is used. After a numeral of iterations-time learning, supervised learning models are used.

After a numeral of iterations, this supervised mode transfers to semi-supervised and then unsupervised learning mode [7].

Emotions are also the core part of developing habit patterns. For researchers, emotion modeling is the critical area, and there is a need to incorporate a multifaceted emotional approach for manipulating decision-making and rationality in the agency [8]. Primary emotions are activated in response to an event that occurs. Secondary emotions arise in the reaction of other emotions. For example, if a person feels fear, then the secondary emotion may be threatened or anger [9]. Sensory memory sends the emotions to working memory then the working memory transfer these emotion patterns for intensity check [10].

Motivation is also considered to be a vital parameter of cognition. To achieve any goal, motivation helps in boosting the level up. The goal is the scheme characterized by action or event and is based on behavior [11].

Learning, knowledge, emotions, motivations, and goal are the habit development procedure's active participants. Similarly, intentions and desires play an essential role. Intentions are a set of representations that structure, stimulate and control the flow of execution of actions. Intentions hierarchy is required to reach the goal [11].

The agent must set any goal by sensing the external environment to work in a complex environment. The agent also responds to the situation when the skill is developed and performs a relevant action after developing the habit to achieve the goal [12].

The agent must set a goal to work in a complex environment autonomously by sensing the external environment and then reply to the environment after attaining skills and then executing actions to accomplish the goal.

Many theories are present in AGI that emphasizes on the achievement of cognition and rationality. Many models are developed like CLARION, IDA, and LIDA. LIDA model is called as "Theory of Everything". LIDA architecture is grounded on the LIDA cognitive cycle, and it provides the platform for comparing and designing the AGI system.

To attain skills, human behavior is mostly a matter of learning, then getting experience, and then applying learning experience to develop a habit. The actions taken by humans are automatic, and goal-directed actions contain a part of human behavior. Even a very complicated operation is rehearsed up to some maximum level; that action becomes a portion of the unconscious and is developed into a habit. There is a minor boundary line between skills and habit. Intentional goal-directed activities are rehearsed to become skills. Habits are part of unconsciousness [13].

### 3 Proposed Model

From rhythmic patterns, automatic control can be made, and these patterns have many counterparts throughout the learning period. Migration of behavior to non-goal directed from goal-directed patterns takes place [14]. Many steps are involved in this transfer process that leads to ultimate habit development. With the help of conditions, goal-directed actions are formed and are believed to be achieved. Habits are actions that are independent and are not affected by the changes.

Making an agent wholly autonomous and adaptive, all intelligent processing properties that start from defining the goal-to-goal achievement and transforming skills into habits should be assimilated [15].

This paper focuses on the development of habit patterns in agency using conditional reflexes. This research also focuses on the impact of conscious parameters such as goals, learning, intentions, satisfaction, behavior, explicit knowledge, experience, skills, and unconscious parameters like desires, emotions, motivations, and implicit knowledge and memory management involvement. Habit

development is as important as developing motivations, emotions, and other unconscious factors to attain more rationality in the agent's behavior and decision-making.

Intelligence is the multilayered phenomenon and is the core part of rationality in the agency. Researchers have presented a combination of implicit and explicit knowledge, a hybrid approach that leads to positive behavior [16].

The proposed model consists of three layers based on the primary two classifications of unconscious and conscious, the same as in the human mind. The first layer includes a conditional reflex module [17], a memory module, and a habit loop. The second layer is the operational layer, which comprises goal, learner, intentions, and control modules. The third layer comprises knowledge, satisfaction, emotions, motivations, and skills.

Knowledge plays an essential role in the learning process, generation of desires, intentions, motivations, skills, emotions, and ultimately habit. In this modeling, knowledge is divided into implicit and explicit knowledge according to conscious and unconscious layers. A learning mechanism is essential to produce the knowledge patterns that help form habit patterns and make an agent rational in behavior. For intentional situations, explicit knowledge is activated backed by precise learning patterns. In contrast, implicit learning takes place where the actions are sudden; they may change at any time and in any situation.

Concerning literature, habits reside in the unconscious part, but it integrates various inputs from different components working in a conscious part of the mind. Learning is the key function to start refining and developing the knowledge explicitly at a conscious level.

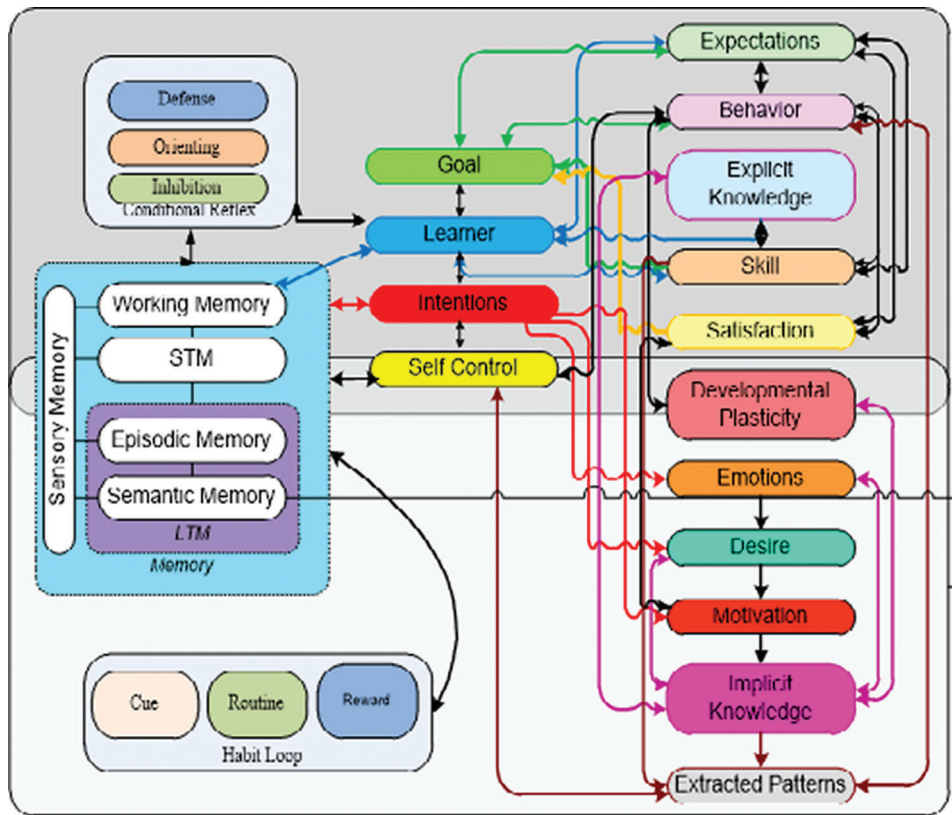
#### **4 Working on Proposed Model**

The first point of contact is a sensory memory when a peripheral stimulus starts a goal-oriented process shown in Fig. 1. Sensory memory is associated with long-term memory, short-term memory, and working memory. Sensory memory transfers the input to working memory for further processing. It goes to -term memory and then to long-term memory in episodic or semantic memory, depending upon the input patterns.

Many iterations of learning generate specific skills set at a conscious level. These iterations are dependent upon conditional reflexes modules. This module is having defense and orienting conditional reflex and inhibition. Defense conditional reflex handles the immediate response or unexpected stimuli patterns like in the reaction to pain. Orienting conditional reflex feels the immediate response that arises due to change in its environment. To manage the behavior, inhibition controls the conditional reflexes during the habit development process.

In case of similar activity patterns, these patterns start populating and enhancing and developing a particular experience or multiple episodes of the same goal. A skilled pattern will be established by performing the same purpose with minor variations. At some threshold levels, the same patterns cannot affect goal achievement performance. In real life, humans can't stop the generations of these patterns, e.g., while driving a car. At this level, these patterns will start shifting to the unconscious part of memory through developmental plasticity. This could only be possible if an agent could attain a certain satisfaction level. Once the models start moving to the unconscious, these patterns are known as habit patterns and help inhabit.

Multiple parameters are contributing to habit development at an unconscious and conscious level. Desires, motivations, implicit knowledge, and emotions are participating at an unconscious level. These unconscious components accept basic patterns and process them after processing generates some new refine patterns. Implicit knowledge and intentions create emotion patterns that work as input for producing desires with tacit knowledge.



**Figure 1:** Habit development model using conditional reflexes

When conscious modules are activated, it produces a certain level of satisfaction due to unconscious modules and operational modules. It also impacts expectations and behavior as in human comfort, and behavior change is directly proportional. Similarly, skills, expectations, and behavior are dependent on the learner and goal.

When extracted patterns are populated after the number of iterations, habit is developed. According to the human phenomenon, similar goal completion once occurs. New patterns could not be formed because skill is already generated, and further generation of patterns could not affect the skill. These patterns move to the unconscious, where they are termed habit patterns. These are the patterns dependent on conditional reflexes because the conditional reflex module formulates them in the beginning during sensory input.

The habit loop is part of the unconscious because it handles the habit patterns. Cue tells the extracted pattern module to go into automatic mode and also triggers the agent's behavior. Normal controls the behavior, and reward are used to process the habit patterns and habit loop in the future.

Developmental plasticity is occupied as an intermediary and is dynamic for both the unconscious and conscious at the same time. It helps shift patterns from habit, learner, skills, and overlearned patterns from conscious to unconscious and vice versa. Self-control is working as an internal mechanism both at the unconscious and conscious level. It is responsible for monitoring the threshold level of skill patterns. As the overlearned patterns start to formulate, it transfers these overlearned patterns to the unconscious as extracted patterns. The stronger the extracted patterns are stronger the habit is.

## 5 Analysis of Proposed Model

The proposed habit development model using conditional reflexes is analyzed with the help of a case study.

### 5.1 Proposed Case study

As discussed in the previous section of methodology, habits required highly refined learning patterns, conditional reflexes, and skills. O, habits required the highly refined patterns of learning, conditional reflexes, and skills. Once these patterns are formed, the agent's task is automatic because the habit patterns are unconscious. A case study is discussed in this section to implement this model, which shows the extraction of highly refined driving habit patterns.

Driving is considered to be the most active task which involves conscious and unconscious at the same time because it needs continuous learning, skill, and then the conversion of skill into a habit that is unconscious. In this case study, the agent is a driver and has to drive a car from home to its workplace.

In the first iteration, when the agent drives a car for the first time, specific learning patterns are generated. At that time agent is in supervised learning mode. Still, as some iterations increase, these learning patterns reach a certain threshold level where the agent does not need any supervision and skill patterns to start to generate. As agents continue to drive, these skill patterns will reach a certain threshold level, and after this threshold, no further learning occurs. Development of similar skills is not possible, so these patterns transform into habit patterns that result are not possible, so these patterns transform into habit patterns that result in unconscious or automatic behavior. After habit formation, the agent can drive a car with less processing cost and more efficiently. If any sudden change may occur due to the environment or any other factor, control shifted to learning and skill development modules to update learning and skill patterns.

### 5.2 Assumptions

- Time is dependent on the external environment.
- It is assumed that there is only one agent.
- It is also assumed that much iteration occurs and skill is developed up to a certain threshold level.

### 5.3 Constraints

There are some constraints on which this model is implemented, and then it is evaluated.

#### 5.3.1 External Changes

- Weather condition
- Route
- Speed

#### 5.3.2 Cognitive Dynamics

- Emotional changes
- Motivational changes
- Behavioral changes
- Skill generation
- Satisfaction level
- Intention generation
- Conditional Reflexes
- Experience
- Desires

#### 5.4 Fuzzy Logic Analysis

Implementation of fuzzy logic is divided into two phases. In the first phase, external factors are taken as input, and internal factors are considered as the output. It means firstly, the impact of external factors is calculated on internal conscious and unconscious elements. In the second phase, dominant internal factors learning, conditional reflexes, and skill are analyzed to show the impact on habit patterns.

#### 5.5 Parameters of the First Phase

The first phase contains certain inputs and outputs for the development of a habit pattern.

##### 5.5.1 Inputs

Input variables are taken from external sources or the environment and are divided into subcategories, ranges from minimum to maximum processing. The route includes the route which the agent uses from its source to destination. Similarly, weather conditions may vary, sometimes it is worst due to heavy rain, fog, or some other factor, and sometimes the weather is very pleasant means it is clear. The speed of the car may also vary from slow to fast. Following is the list of input variables that are used in the fuzzy logic implementation.

- Route (Short (S), Average (A), Long (L))
- Weather condition (Good (G), Bad (B), Worst (W))
- The speed of the car (Slow (S), Average (A), Fast (F))

##### 5.5.2 Outputs

As there are three inputs, there are multiple outputs whose intensity is identified concerning these inputs. As more intense the inputs are, they affect output parameters more adversely.

- Learning (Slow (S), Mediocre (M), Fast (F))
- Intentions (Wishing (Wis), Wanting (Wan), Intention (I), Passion (P))
- Motivations (motivation of Communion (Com), Subconscious motivation (Sub), Conscious motivation (Cons))
- Emotions (Low (L), Medium (M), High (H))
- Desires (Need (N), Wants (W), Urges (U))
- Conditional reflexes (Idle (I), Average (A), Quick (Q))
- Implicit Knowledge (Less (L), Average (A), High (H))
- Explicit Knowledge (Less (A), Average (A), High (H))
- Satisfaction (Less (L), Moderate (Mod), More (Mr))
- Experience (Less (L), Medium (Med), More (Mr))
- Skill (Weak (W), Moderate (M), Strong (S))

Weather conditions, the routing which agents adapt to reach a destination, and the car's speed greatly impact developing strong skill. The learning mechanism is more adverse; the input conditions are fast, and strong and stronger skill patterns are generated.

##### 5.5.3 The range of Input Variables

The route, weather condition, and speed of a car fall in certain ranges, ranged from minimum to maximum.

- Weather Condition
- worst (0 0 0.5)
- bad (0 0.5 1)
- good (0.5 1 1)

- Route
- Short (0 0 0.5)
- Average (0 0.5 1)
- Long (0.5 1 1)
- Speed
- Slow (0 0 0.5)
- Average (0 0.5 1)
- Fast (0.5 1 1)

Fig. 2 shows the multiple input and output variables of proposed model.

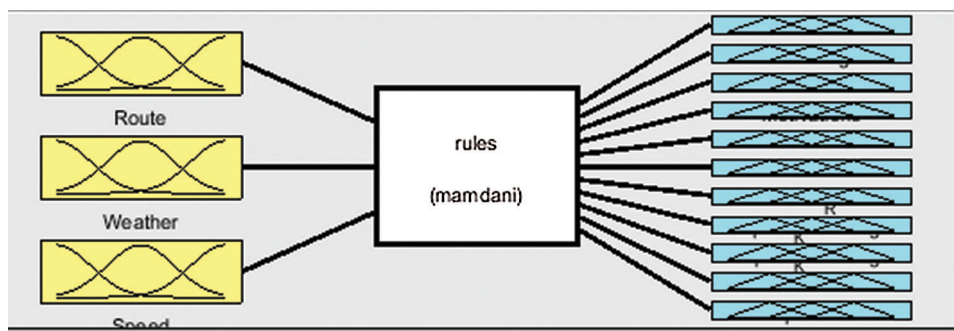


Figure 2: Input and output variables

#### 5.5.4 Membership Functions

Membership functions of all inputs and outputs are shown in Tab. 1. Input includes weather conditions, the route from source to destination, and the speed of the car. Output includes learning, intentions, motivations, emotions, desires, conditional reflexes, implicit knowledge, explicit knowledge, satisfaction, experience, and skill.

Table 1: Inputs/outputs with membership functions and graphical representations

Input/output	Membership Function	Graphical Representation of MF
$Route = \mu_R(r)$	$\mu_P^R(r) = \left\{ \max \left( \min \left( 1, \frac{45-r}{20} \right), 0 \right) \right\}$ $\mu_R(r) = \left\{ \max \left( \min \left( \frac{r-25}{20}, 1, \frac{75-r}{20} \right), 0 \right) \right\}$ $\mu_R(r) = \left\{ \max \left( \min \left( \frac{r-55}{20}, 1 \right), 0 \right) \right\}$	
$W = \mu_W(w)$	$\mu_W(w) = \left\{ \max \left( \min \left( 1, \frac{35-w}{5} \right), 0 \right) \right\}$ $\mu_W(w) = \left\{ \max \left( \min \left( \frac{w-30}{5}, 1, \frac{50-w}{5} \right), 0 \right) \right\}$ $\mu_W(w) = \left\{ \max \left( \min \left( \frac{w-45}{5}, 1 \right), 0 \right) \right\}$	



**Table 1 (continued).**

Input/output	Membership Function	Graphical Representation of MF
$S = \mu_S(s)$	$\mu_S(s) = \left\{ \max \left( \min \left( 1, \frac{25-s}{10} \right), 0 \right) \right\}$ $\mu_S(s) = \left\{ \max \left( \min \left( \frac{s-15}{10}, 1, \frac{45-s}{10} \right), 0 \right) \right\}$ $\mu_S(s) = \left\{ \max \left( \min \left( \frac{s-35}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows three membership functions for the input variable "Speed" on a scale from 0 to 100. The "Slow" function (red line) starts at 1.0 for s=0 and decreases linearly to 0 at s=25. The "Average" function (black line) starts at 0 at s=25, reaches 1.0 at s=45, and then decreases to 0 at s=65. The "Fast" function (black line) starts at 0 at s=45 and reaches 1.0 at s=65, remaining at 1.0 until s=100.</p>
$L = \mu_L(l)$	$\mu_L(l) = \left\{ \max \left( \min \left( 1, \frac{30-l}{10} \right), 0 \right) \right\}$ $\mu_L(l) = \left\{ \max \left( \min \left( \frac{l-20}{10}, 1, \frac{70-l}{10} \right), 0 \right) \right\}$ $\mu_L(l) = \left\{ \max \left( \min \left( \frac{l-60}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows three membership functions for the output variable "Learning" on a scale from 0 to 100. The "Slow" function (red line) starts at 1.0 for l=0 and decreases linearly to 0 at l=30. The "Average" function (black line) starts at 0 at l=30, reaches 1.0 at l=60, and then decreases to 0 at l=70. The "Fast" function (black line) starts at 0 at l=60 and reaches 1.0 at l=70, remaining at 1.0 until l=100.</p>
$I = \mu_I(i)$	$\mu_I(i) = \left\{ \max \left( \min \left( 1, \frac{25-i}{10} \right), 0 \right) \right\}$ $\mu_I(i) = \left\{ \max \left( \min \left( \frac{i-15}{10}, 1, \frac{55-i}{10} \right), 0 \right) \right\}$ $\mu_I(i) = \left\{ \max \left( \min \left( \frac{i-45}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows three membership functions for the output variable "Intentions" on a scale from 0 to 100. The "Wishing" function (red line) starts at 1.0 for i=0 and decreases linearly to 0 at i=25. The "Wanting" function (black line) starts at 0 at i=25, reaches 1.0 at i=45, and then decreases to 0 at i=65. The "Passion" function (black line) starts at 0 at i=45 and reaches 1.0 at i=65, remaining at 1.0 until i=100.</p>
$M = \mu_M(m)$	$\mu_M(m) = \left\{ \max \left( \min \left( 1, \frac{65-m}{20} \right), 0 \right) \right\}$ $\mu_M(m) = \left\{ \max \left( \min \left( \frac{m-45}{20}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions for the output variable "Motivations" on a scale from 0 to 100. The "Subconscious" function (red line) starts at 1.0 for m=0 and remains at 1.0 until m=45, then decreases linearly to 0 at m=65. The "Conscious" function (black line) starts at 0 at m=45 and increases linearly to 1.0 at m=65, remaining at 1.0 until m=100.</p>
$E = \mu_E(e)$	$\mu_E(e) = \left\{ \max \left( \min \left( 1, \frac{50-e}{20} \right), 0 \right) \right\}$ $\mu_E(e) = \left\{ \max \left( \min \left( \frac{e-30}{20}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions for the output variable "Emotions" on a scale from 0 to 100. The "No" function (red line) starts at 1.0 for e=0 and remains at 1.0 until e=30, then decreases linearly to 0 at e=50. The "Yes" function (black line) starts at 0 at e=30 and increases linearly to 1.0 at e=50, remaining at 1.0 until e=100.</p>

(Continued)

**Table 1 (continued).**

Input/output	Membership Function	Graphical Representation of MF
$D = \mu_D(d)$	$\mu_D(d) = \left\{ \max \left( \min \left( 1, \frac{35-d}{5} \right), 0 \right) \right\}$ $\mu_D(d) = \left\{ \max \left( \min \left( \frac{d-30}{5}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions on a scale from 0 to 100. The first function, labeled 'Needs', is a red line that is 1 from 0 to 30, then decreases linearly to 0 at 35. The second function, labeled 'Wants', is a black line that is 0 until 30, then increases linearly to 1 at 35, and remains at 1 until 100.</p>
$CR = \mu_{CR}(cr)$	$\mu_{CR}(cr) = \left\{ \max \left( \min \left( 1, \frac{45-cr}{5} \right), 0 \right) \right\}$ $\mu_{CR}(cr) = \left\{ \max \left( \min \left( \frac{cr-40}{5}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions on a scale from 0 to 100. The first function, labeled 'No', is a red line that is 1 from 0 to 40, then decreases linearly to 0 at 45. The second function, labeled 'Yes', is a black line that is 0 until 40, then increases linearly to 1 at 45, and remains at 1 until 100.</p>
$K = \mu_K(k)$	$\mu_K(k) = \left\{ \max \left( \min \left( 1, \frac{45-k}{10} \right), 0 \right) \right\}$ $\mu_K(k) = \left\{ \max \left( \min \left( \frac{k-35}{10}, 1, \frac{75-k}{10} \right), 0 \right) \right\}$ $\mu_K(k) = \left\{ \max \left( \min \left( \frac{k-65}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows three membership functions on a scale from 0 to 100. The first function, labeled 'Less', is a red line that is 1 from 0 to 35, then decreases linearly to 0 at 45. The second function, labeled 'Average', is a black trapezoidal function that starts at 0 at 35, reaches 1 at 45, stays at 1 until 65, and then decreases to 0 at 75. The third function, labeled 'High', is a black trapezoidal function that starts at 0 at 65, reaches 1 at 75, and stays at 1 until 100.</p>
$J = \mu_J(j)$	$\mu_J(j) = \left\{ \max \left( \min \left( 1, \frac{35-j}{10} \right), 0 \right) \right\}$ $\mu_J(j) = \left\{ \max \left( \min \left( \frac{j-25}{10}, 1, \frac{75-j}{10} \right), 0 \right) \right\}$ $\mu_J(j) = \left\{ \max \left( \min \left( \frac{j-65}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows three membership functions on a scale from 0 to 100. The first function, labeled 'Less', is a red line that is 1 from 0 to 25, then decreases linearly to 0 at 35. The second function, labeled 'Average', is a black trapezoidal function that starts at 0 at 25, reaches 1 at 35, stays at 1 until 65, and then decreases to 0 at 75. The third function, labeled 'High', is a black trapezoidal function that starts at 0 at 65, reaches 1 at 75, and stays at 1 until 100.</p>
$F = \mu_F(f)$	$\mu_F(f) = \left\{ \max \left( \min \left( 1, \frac{60-f}{10} \right), 0 \right) \right\}$ $\mu_F(f) = \left\{ \max \left( \min \left( \frac{f-50}{10}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions on a scale from 0 to 100. The first function, labeled 'No', is a red line that is 1 from 0 to 50, then decreases linearly to 0 at 60. The second function, labeled 'Yes', is a black line that is 0 until 50, then increases linearly to 1 at 60, and remains at 1 until 100.</p>

**Table 1 (continued).**

Input/output	Membership Function	Graphical Representation of MF
$E = \mu_G(g)$	$\mu_G(g) = \left\{ \max \left( \min \left( 1, \frac{45 - g}{15} \right), 0 \right) \right\}$ $\mu_G(g) = \left\{ \max \left( \min \left( \frac{g - 30}{15}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions for the output variable 'Experience' on a scale from 0 to 100. The 'No' function (red line) starts at 1.0 for x=0, remains constant until x=30, then decreases linearly to 0.0 at x=45, and remains at 0.0 for x &gt; 45. The 'Yes' function (black line) starts at 0.0 for x &lt; 30, increases linearly from 0.0 at x=30 to 1.0 at x=45, and remains constant at 1.0 for x &gt; 45.</p>
$H = \mu_H(h)$	$\mu_H(h) = \left\{ \max \left( \min \left( 1, \frac{45 - h}{20} \right), 0 \right) \right\}$ $\mu_H(h) = \left\{ \max \left( \min \left( \frac{h - 25}{20}, 1 \right), 0 \right) \right\}$	<p>The graph shows two membership functions for the output variable 'Skill' on a scale from 0 to 100. The 'No' function (red line) starts at 1.0 for x=0, remains constant until x=25, then decreases linearly to 0.0 at x=45, and remains at 0.0 for x &gt; 45. The 'Yes' function (black line) starts at 0.0 for x &lt; 25, increases linearly from 0.0 at x=25 to 1.0 at x=45, and remains constant at 1.0 for x &gt; 45.</p>

### 5.5.5 Fuzzy Interface Engine

Combining the fuzzy IF-THEN rules from the fuzzy rule base into a mapping from a fuzzy input set to a fuzzy output-based fuzzy logic principle is called a fuzzy inference engine. The fundamental part of Fuzzy Inference is membership functions, fuzzy logic operators, and if-then rules. All guidelines in the fuzzy rule base are consolidated into a single fuzzy relation that lies under an internal item on info universes of discourse, which is then seen as a single fuzzy IF-THEN rule. A reasonable operator for joining the rules is a union.

IF-THEN fuzzy represent as:

$$R_{\mathcal{Q}^n} = R^n \times W^n \times S^n \tag{1}$$

$$\mu_{R \cap W \cap S}(r, w, s) = \mu_R(r) \cap \mu_W(w) \cap \mu_S(s) \tag{2}$$

Interpreted as a single fuzzy relation defined by

$$R_{105} = \bigcup_{n=1}^{105} R_{\mathcal{Q}^n}$$

Suppose  $\varphi$ ,  $\lambda$  and  $\psi$  be any three arbitrary fuzzy sets and are also input and output to the fuzzy inference engine, respectively. To view  $R_{27}$  as a single fuzzy IF-THEN rule and using the generalized modus ponens

$$\mu_{root \cap weather \cap speed}(\varphi) = Sup_{\lambda \in (R, W, S)} t [\mu_{\lambda}(R, W, S), \mu_{R_{105}}(R, W, S)] \tag{3}$$

Product Inference Engine format

$$\mu_{\varphi}(T) = \max_{0 \leq x \leq 105} \left[ \sup_{(r,w,s) \in U} (\mu_{R,W,S}(r, w, s)) \left( \prod_{k=1}^{105} (\mu_{r_k, w_k, s_k}(r_k, w_k, s_k), \mu_{\varphi}x(T)) \right) \right] \quad (4)$$

5.5.6 Fuzzy Rule Viewer

The fuzzy rule viewer of MATLAB shows different values of inputs and their impact on outputs. As input values are increased or decreased, output values and graphs also vary, respectively.

Fig. 3 shows that If (Route is Short) and (Weather is Worst) and (Speed is Slow) then (Learning is Slow) (Intensions is Wishing) (Motivations is Subconscious) (Emotions is No) (Desires is Needs) (CR is No) (IK is Less) (EK is Less) (Satisfaction is No) (Experience is No) (Skill is No). Fig. 4 shows that If (Route is Average) and (Weather is Worst) and (Speed is Slow) then (Learning is Slow) (Intensions wishes) (Motivations is Conscious) (Emotions is No) (Desires is Needs) (CR is No) (IK is Less) (EK is Less) (Satisfaction is No) (Experience is No) (Skill is No). Fig. 5 shows that If (Route is Long) and (Weather is Good) and (Speed is Fast) then (Learning is Fast) (Intensions is Passion) (Motivations is Conscious) (Emotions is Yes) (Desires is Wants) (CR is Yes) (IK is High) (EK is High) (Satisfaction is Yes) (Experience is Yes) (Skill is Yes).

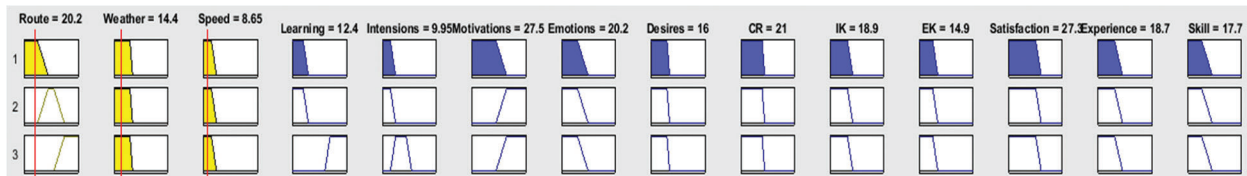


Figure 3: Fuzzy rule viewer



Figure 4: Fuzzy rule viewer

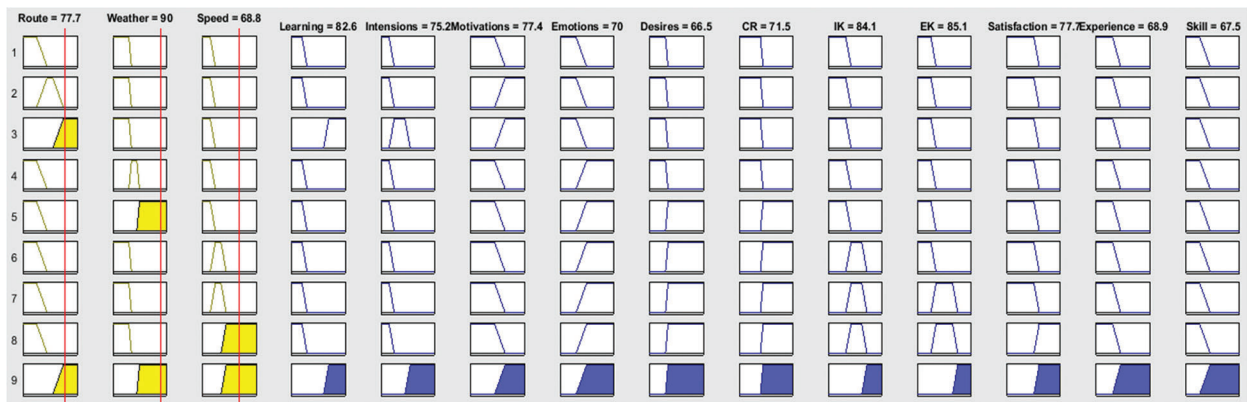
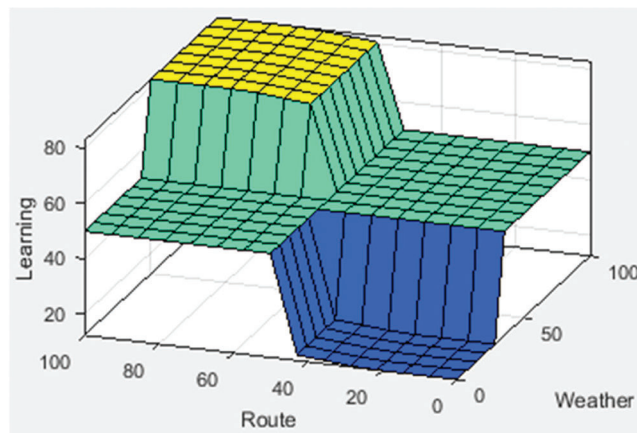


Figure 5: Fuzzy rule viewer

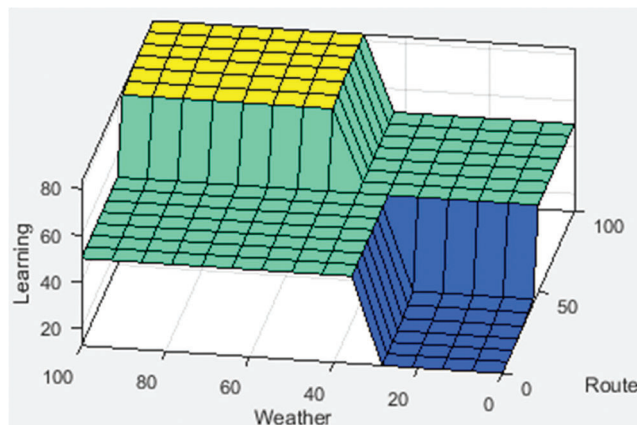
### 5.5.7 Surface Graph

Concerning the above rules following surface, graphs are formed showing two inputs on the x-axis and y-axis, and the outcome of these inputs is shown in the graph. Different combinations are made to show the exact impact of inputs.

Fig. 6 represents the 3D view of a proposed system's ruled surface based on Route and Weather. It observed that the Proposed system simulation results are Good (Yellow shade) and Satisfied (Greenish Shade), and Weak or Poor (Bluish Shade), respectively. Fig. 7 represents the 3D view of a proposed system's ruled surface based on Weather and Route. It observed that the Proposed system simulation results are Good (Yellow shade) and Satisfied (Greenish Shade), and Weak or Poor (Bluish Shade), respectively.



**Figure 6:** Surface Graph based on Route and Weather



**Figure 7:** Surface Graph based on Weather and Route

## 5.6 Conclusion

In AGI, the basic purpose is to achieve rationality, and researchers are trying their best. Work is in progress in various domains like emotions, motivations, desires, intentions, knowledge, drives, etc. This paper's primary focus is to develop habit patterns from different internal state parameters and how these habits transferred to the conscious level from the unconscious for rational decision-making and behavior change.

This research also defines the boundary line between skills and habit in agency and how skill would be transformed in patterns from conscious to unconscious in habit patterns. These habit patterns are refined.

In this paper, the impact of habit on an agent's behavior when conditional reflexes are a core part of habit development is also presented. Learning, conditional reflex, and skill patterns reside in a conscious part of memory. Once the skill patterns reach a threshold level, they start transferring to the unconscious part of memory, where these overlearned skill patterns start to form habit patterns. A scenario is developed to analyze habit development in which habit patterns generate using two phases "Cascade Approach" of fuzzy logic. Fuzzy logic implementation is done using MATLAB.

**Acknowledgement:** Thanks to our families & colleagues who supported us morally.

**Funding Statement:** The authors received no specific funding for this study.

**Conflict of Interest:** The authors declare that they have no conflicts of interest to report regarding the present study.

## References

- [1] A. Fattah, M. Ahmed, R. Besold, H. Gust, U. Krumnack *et al.*, "Rationality-guided AGI as cognitive systems," *Proceedings of the Annual Meeting of the Cognitive Science Society*, vol. 34, no. 34, pp. 258–297, 2012.
- [2] A. Atifa, K. Ahmed, S. Abbas and Y. Saeed, "Modeling cooperative and competitive emotions using parallel SOM for artificially intelligent agents," *International Journal of Computer Science and Network Security*, vol. 17, no. 2, pp. 48–58, 2017.
- [3] B. Albert, "Social cognitive theory of self-regulation," *Organizational Behavior and Human Decision Processes*, vol. 50, no. 2, pp. 248–287, 2015.
- [4] D. Peter, "Goal-directed control and its antipodes," *Neural Networks*, vol. 22, no. 3, pp. 213–219, 2019.
- [5] D. Wlodzislaw, R. J. Oentaryo and M. Pasquier, "Cognitive architectures where do we go from here," *In Agi*, vol. 171, no. 2, pp. 122–136, 2018.
- [6] S. B. Ho and F. Liausvia, "Knowledge representation, learning and problem solving for general intelligence," in *Int. Conf. on Artificial General Intelligence*, Berlin, Heidelberg: Springer, pp. 60–69, 2013.
- [7] K. Y. Hsiao and D. Roy, "A habit system for an interactive robot," in *AAAI Fall Sym. from Reactive to Anticipatory Cognitive Embodied Systems*, pp. 99–106, 2015.
- [8] M. Pothitou, A. J. Kolios and L. Varga, "A framework for targeting household energy savings through habitual behavioral change," *International Journal of Sustainable Energy*, vol. 35, no. 7, pp. 686–700, 2014.
- [9] M. D. Egbert and X. E. Barandiaran, "Modeling habits as self-sustaining patterns of sensorimotor behavior," *Frontiers in Human Neuroscience*, vol. 8, no. 522, pp. 243, 2014.
- [10] Q. Khan and T. Alyas, "Modeling emotional mutation and evolvment using genetic algorithm in the agency," *Lahore Garrison University Research Journal of Computer Science and Information Technology*, vol. 1, pp. 52–61, 2017.
- [11] A. Chohra and K. Madani, "Affect in complex decision-making systems: From psychology to computer science perspectives," in *IFIP Int. Conf. on Artificial Intelligence Applications and Innovations*, Springer, pp. 174–183, 2014.
- [12] B. Goertzel, "Artificial general intelligence: Concept, state of the art, and future prospects," *Journal of Artificial General Intelligence*, vol. 5, no. 1, pp. 1–48, 2014.
- [13] I. Kotseruba, O. J. A. Gonzalez and J. K. Tsotsos, "A review of 40 years of cognitive architecture research, focus on perception, attention, learning and applications," Arxiv Preprint Arxiv, pp. 1–74, 2016.
- [14] C. Ullrich and A. Chen, "An easily implementable method to support goal-directed learning," in *Proc. of the World Conf. on Educational Multimedia, Hypermedia & Telecommunications*, pp. 5–16, 2016.
- [15] K. Merrick, "Value systems for developmental cognitive robotics: A survey," *Cognitive Systems Research*, vol. 41, no. 1, pp. 38–55, 2017.
- [16] H. Li, X. Wang and S. Ding, "Research and development of neural network ensembles: A survey," *Artificial Intelligence Review*, vol. 49, no. 4, pp. 455–479, 2018.
- [17] Y. Cao, "The application of conditioned reflex mechanism in cybernetics is studied based on computer-aided technology," *Journal of Physics: Conference Series*, vol. 1574, pp. 012063, 2020.