BRAIN-INSPIRED MODEL FOR DECISION-MAKING IN THE SELECTION OF BENEFICIAL INFORMATION PATTERNS AMONG SIGNALS RECEIVED BY AN UNPREDICTABLE INFORMATION-DEVELOPMENT ENVIRONMENT

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ABSTRACT

With its diversification in products and services, today's marketplace makes competition wildly dynamic and unpredictable for industries. In such an environment, daily operational decision-making has a vital role in producing value for products and services while avoiding the risk of loss and hazard to human health and safety. However, it makes a large portion of operational costs for industries. The main reason is that decision-making belongs to the operational tasks dominated by humans. The less involvement of humans, as a less controllable entity, in industrial operation could also favorable for improving workplace health and safety. To this end, artificial intelligence is proposed as an alternative to doing human decision-making tasks. Still, some of the functional characteristics of the brain that allow humans to make decisions in unpredictable environments like the current industry, especially knowledge generalization, are challenging for artificial intelligence. To find an applicable solution, we study the principles that underlie the human brain functions in decision-making. The relative base functions are realized to develop a model in a simulated unpredictable environment for a decision-making system that could decide which information is beneficial to choose. The method executed to build our model's neuronal interactions is unique that aims to mimic some simple functions of the brain in decision-making. It has the potential to develop for systems acting in the higher abstraction levels and complexities in real-world environments. This system and our study will help to integrate more artificial intelligence in industrial operations and settings. The more successful implementation of artificial intelligence will be the steeper decreasing operational costs and risks.

KEYWORDS: Artificial intelligence, Decision-making, Brain-inspired systems, Unpredictable environments, Dynamic tasks, Knowledge generalization

1. INTRODUCTION

Today's marketplace is seeing more and more diversification in products and services, a situation that has generated unpredictable and dynamic competition for industries, which forced industries to challenge the emerged complex operational environments. One of the main challenges in such environments is managing tasks like decision-making, which, despite growing industrial automation, require more human involvement in the process. So, these tasks cause higher operating costs and a less controllable environment. To some extent, the occurred problem has been mitigated by executing artificial intelligence (AI) in industrial operations [1]. However, current AI systems are flawed by algorithm-complexity, unpredictable behaviors, and difficulty working at abstract levels [2, 3]. They lack the ability to adapt to changing environments, generalize knowledge, and do causal reasoning [2, 4]. They cannot generalize acquired knowledge for any further changes in the environment that transcend their limitations [5].

An AI system could function in an unpredictable environment if it learns from experience and generalizes knowledge to choose an alternative and take action [6]. These functions are what the brain does in the decision-making tasks. The brain could separately abstract a state's features or its interrelation with the other states of an environment. The brain does not make complex decisions by calculation but through cooperation between the neurobiological, neuro-structural, neurochemical, and psychological mechanisms [7]. It adequately not perfectly makes decisions based on imperfect information received [8]. It realizes data rapidly most of the time [8, 9] in an episode of sequential actions [10] within a vast decentralized network of neurons [11, 12] through unconscious layers [13]. Here, the success key is knowledge generalization and learning through the abstraction of similarities between experienced states' features and their interrelations. The brain receives information from its sensory system. If it discovers similarity in some aspects between the detected information and any experiences records, it generalizes that for the realization of the new state [13, 14]. Hence, to overcome our problem, we build a model for decision-making inspired by the brain function in generalizing knowledge, learning from experiences, and improving knowledge on imperfect information in unpredictable environments. The system seeks benefits in the unpredictable states of a simulated information development environment. However, there are some key questions before building this system that we should answer: How does the brain find similarities between experienced states and generalize their values for new states? What is the method it uses to judge values and make decisions? Finally, what is its fundamental function to learn from experiencing new state and value similar experienced states?

To this end, we plan our study into six sections. The first section introduces the problem with a brief background and outline of the study. Section two investigates the principles underlying the brain functions on generalizing knowledge for decision-making and learning through experiences. The derived principles are the basis for developing an intelligent decision-making model, which we realize in the third section. Then, section four describes an experiment, which we do to evaluate our system in finding similarities between experienced states and generalizing knowledge for decision-making, judging alternatives, and learning through new experiences. The results of our experiments are presented in the fifth section, and we conclude with our analysis of our results and suggestions for future work in section six.

2. BRAIN FUNCTION PRINCIPLES FOR DECISION-MAKING

Studies show that the brain uses simple principles to interpret information signals received on its sensory systems [15, 16]. Helmholtz (1867) discussed that the brain interprets the sensory data in the convergence of information flow from the brain's accumulated knowledge [17]. For example, the brain interpolates knowledge from the visual cortex into the data stream coming through the retina to determine the final visual information [18]; then, through the realized visual information, an action could be initiated [19]. The familiarity between the received information (current state) and knowledge (those experienced) is extracted for selecting a proper alternative [8, 18]. The brain regulates the motivation values applied to alternatives by setting the loss and likelihood of achievement [15, 20]. In this way, different neurotransmitters (chemical messengers in the brain) associating with the motivation and nurturing of excitatory and inhibitory neuronal circuits to locate beneficial information, support alternatives for action, and develop knowledge [21]. In a neuronal circuit, a neuron reaches its action threshold and then activates the next neurons in the path. The excitatory and inhibitory connections to a neuron determine when it does action and activates the next neurons in a neuronal circuit [22]. Excitatory and inhibitory neuronal circuits are cultivated between neuronal clusters (grouped same-characteristic neurons) in the brain [23]. Every neuron here would link into several neurons [24] (an average of 255 ± 13 connections [25]). In the decision-making process, each circuit normally supports one definite choice [23]. The winner circuit induces turning off the other active circuits [26]. The reward of the made decision modifies and strengthens the winner neuronal circuit [27]. To this end, neuronal circuits recall information patterns experienced with relative alternatives and achieved values [28] and the brain establishes Knowledge over time [5, 29].

We have found two studies, which explicitly described the brain's process of valuing the states of an environment, judging choices, choosing an alternative for decision-making, and revaluate values. Both are the main body parts of our decision-making model. In the first, Groman (2019) shows the brain's performance when taking or avoiding choices in the information received from a state. They show that the brain activates the neuronal circuits with similar experiences to the detected state for finding the most and less rewarded alternatives. The best and the worst ones then go to the last match of decision-making to choose or avoid a choice [30]. In the second study, Liu (2019) reveals the modification of alternative-values through the achieved reward after the made decision on information received. A set of sequential experiments was built to study the brain's function during action selection and alternative revaluation. They found that the brain continuously revaluates and reorganizes its alternatives through experiencing new states [14].

This work relies on the studies discussed above and does not aim to structure the brain's exact functions. We seek to examine if our model could make decisions through realizing common patterns between experienced states. The modeled system aims to generalize knowledge for decision-making through the worst and best values achieved by common patterns of states experienced. Then, this study verifies if the model learns and updates knowledge through reevaluating the best and worst achieved values.

3. DEVELOPMENT OF A BRAIN-INSPIRED MODEL FOR DECISION-MAKING

Following the investigation of the brain's decision-making functions, we developed a system to mimic brain functions during the decision-making process. The system should provide adequate decisions in response to unpredictable states. The states were in a simulated information development environment. Such an environment experiences unpredictable information flow from the resource provider's (newly available, effective, and ineffective resource information) and the customer's sides (the data flow about satisfied or failed information) [31, 32]. Specifically, the system makes decisions to proceed with or avoid the development ("develop information" or "skip information") of new information received from the resource provider side. Table 1 presents our model realization steps with the relative principles inspired by brain function.

Table 1. The steps to develop a brain-inspired intelligent decision-making system

Brain functions	Aspects realized in the decision-making system
Chaining the evaluation and revision episodes of neuronal circuits to develop alternatives→	1. Build an episodic process of realizing patterns, choosing between alternatives, decision-making, and altering the alternative by achieved values.
Triggering current in a neuronal circuit by detecting sensory data and ending by selecting a choice→	2. Structure a decision-making process, which begins from the information sensory gate, continues in the information pattern realization stage, and ends with the alternative realization stage before decision-making.
The same characteristic neurons contribute to the same neuronal cluster→	3. Place the same characteristic neurons in the same matrix at each stage of the decision-making process. Each matrix realizes a certain level of information commonality between states .
Generalizing information patterns similarities for any new state and discriminating them to find the most similar one→	4. Arrange neuronal matrices in three levels: vague, approximate, and explicit, to generalize knowledge for detected patterns and discriminate the most similar ones for decision-making.
Each neuron is interconnected with 255 ± 13 of neurons in other neuronal clusters→	5. A neuron in each matrix is connectable with all neurons of the other levels to realize a larger number of patterns and alternatives.
Motivating and demotivating neuronal circuits to contrast the benefits and disadvantages of choices.	6. Build neuronal circuits between matrices through their values' similarities and differences to find alternatives and discriminate them.
A neuron in a neuronal circuit activated by its upstream neurons and reaches the action threshold then activates its downstream neurons→	7. Define a process of activation and action initiation for neurons during the information transportation.
Gleaning information from data received "the environment's states"→	8. Define information features of the environment's states on the information-sensory gate.
Accumulating knowledge over time through the similarities between information patterns and achieved rewards→	9. Record and classify received signals according to their frequencies' common patterns and corresponding values achieved on the value-adding sensory gate.
Interconnecting the sensory information with achieved knowledge to realize choices Generalizing experienced alternatives for new data→	10. Compare the detected signal patterns with the common patterns of experienced states on the pattern realization stage to find similar ones and determine a proper alternative.
Controlling neuronal communication by the motivation values of excitatory and inhibitory circuits to determine which neurons communicate when and with whom→	11. Consolidate the neuronal circuits at the pattern realization stage with higher motivated alternatives.
Realizing alternatives by acquired knowledge	12. Realize alternatives through the experienced states.
Making the same reference for reward and loss. Attaching the best and the worst rewarded alternatives for similar states	13. Put for each pattern matrix's neuron at the same level the best and worst alternatives.
Comparing the best and the worst rewarded alternatives from similar states for decision-making→	14. Decide on "do" or "skip" the "development of information" according to the best and the worst alternatives.
Learning through updating the motivation level of the involved neuronal circuits→	15. Give a value to each alternative based on the relative achieved value and modify it by new experiences and value-added achievement.

Neurons involved in our system are clustered in four classes of matrices (information signal representation, pattern label realization, alternative realization, and value-add realization matrices) aside from decision-maker neurons (**Figure 1**). These matrices realize and classify information into three levels of similarities (vague, approximate, and explicit). At each level, every experienced pattern links up to two alternatives with the best and worst achievements, which motivate the decision-makers to do or avoid information received. The value-adding sensory gate receives valuing signals from the customer side for made decisions. The system then records values with the new information's pattern and modifies one of the experienced pattern's linked alternatives if it got a higher score. The following discussions introduce the stages of the system.

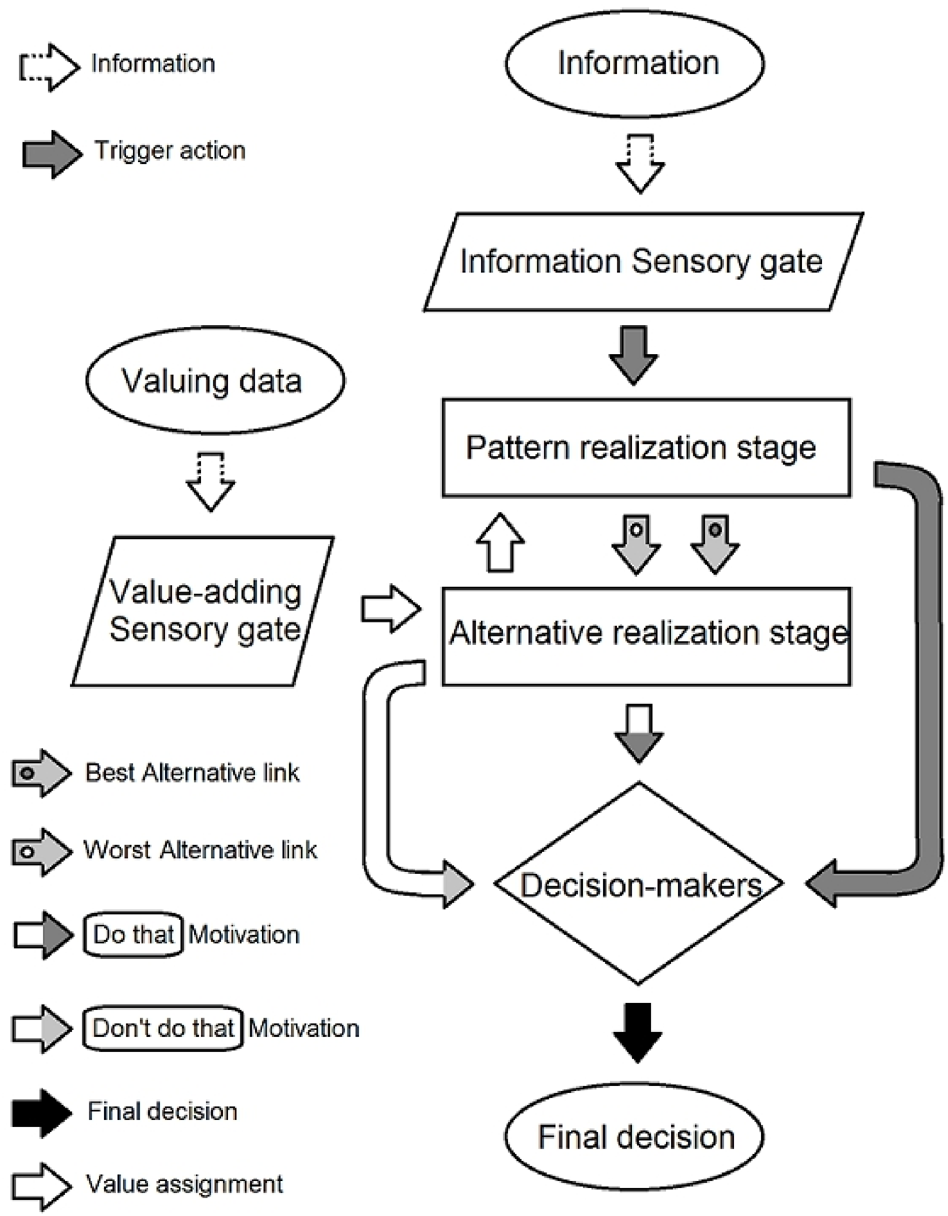

Figure 1. The diagram of our decision-making system. The information-sensory gate receives a new information signal of a resource, derives the common patterns of information features, and sends them to the pattern realization stage. The pattern-realization stage labels those patterns. If a label has had the experience, it activates the attached alternatives at the alternative realization stage. Those alternatives determine the motivation values for the relative decision-making neurons. After making the decision, the value-adding sensory gate gets the resulted value-adding data and recorded it for the label. If this new value proposes to the label a new option on top of one of the best or worst alternatives, the option replaces that best (or best) alternative.

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3.1. The information sensory gate

The information-sensory gate detects signals whose represent the patterns of information features of the resource-provider. Here, eight frequencies represent eight features of information. The literature presents eight features for information such as source, accuracy, validity, completeness, consistency, accessibility, uniqueness, and timeliness [33]. Each frequency and the relative intensity respectively represent a feature of information and the feature value (Figure 2). The system projects the signal patterns to three levels, the patterns with vague commonalities (in the low and high values), approximate commonalities (in the lowest, low, high, and highest values). In the last level, explicit-common patterns have all eight intensity levels. Therefore, the information sensory gate is a matrix of 64 neurons based on the frequencies' possible variations. From the received information, the turned-on information sensory neurons turn on the counterpart neurons at all pattern representative levels of the pattern realization stage (the vague level (level-I), approximate level (level-II), and explicit level (level-III)) (the left side of Figure 3) and trigger the neurons in the pattern-realization matrix-I. The triggered neurons begin a countdown process at a certain time. The most motivated neuron in the matrix is the one that finishes the process first and does the action and respectively triggers or turns on its connected neurons.

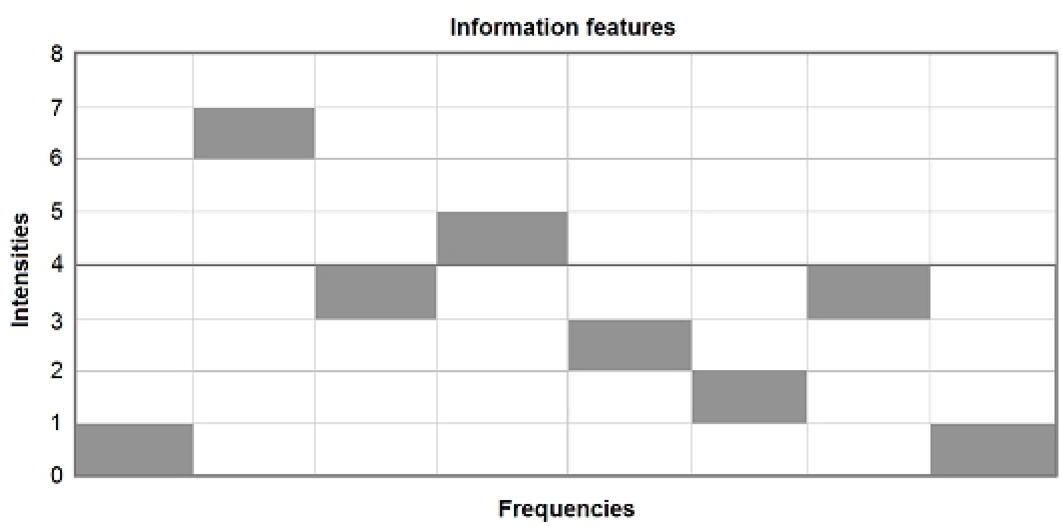

Figure 2. An example of the information pattern on the information sensory gate. A signal on the information-sensory

gate makes a pattern of eight different frequencies representing the embedded information features. The intensities in the vertical axis show the value of each feature.

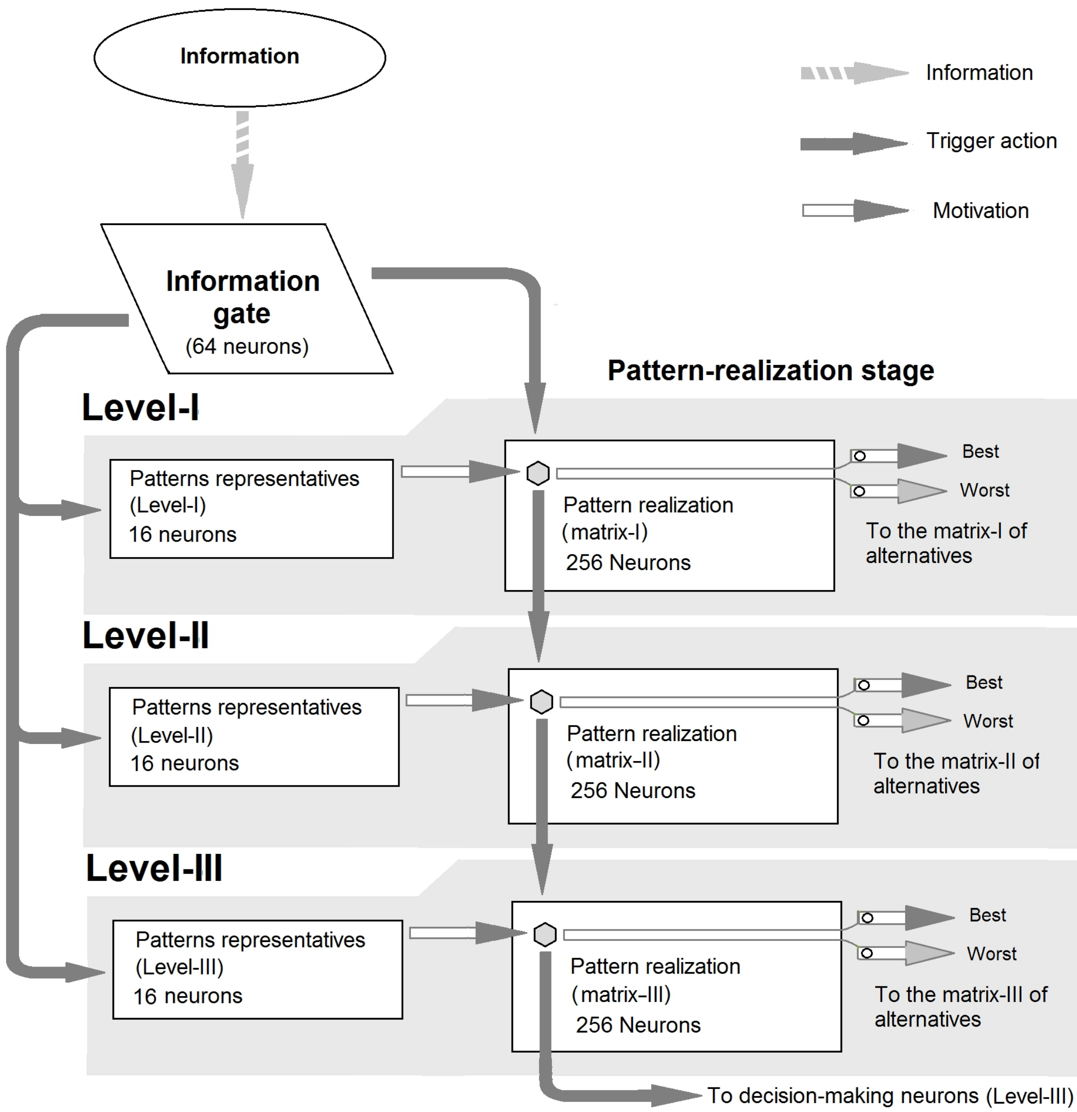

Figure 3. The schematic of the pattern realization stage. The pattern realization stage is in two parts, pattern representative matrices (left) and pattern-labels' matrices (right).

3.2. Pattern realization stage

The pattern realization stage compares states represented by the information sensory gate with patterns experienced. It abstracts similar patterns at three realization levels (from vague to exact commonalities) to value states (Figure 3). Matrix-I recognizes a detected signal through similar patterns with vague feature-commonalities. Matrix-II finds ones with approximate feature-commonalities. Matrix-III then discriminates the signal pattern from the most-similar one. A realized pattern (a pattern labeled before for a state at least) has at least a linkage to a neuron at the alternative stage and one at the value-adding sensory gate.

Each matrix comprises 256 neurons (the maximum number of labels for the common patterns possible at each level). The realization process begins from the vague-commonalities at level-I and ends up with the most-commonalities at level-III. From level-I, on-neurons at the signal-representative matrix motivate the connected neurons at the pattern-realization matrix-I for the identical pattern and most-similar ones with linked alternatives (the best or worst link). All features of an identical pattern are rival to their corresponding representative ones. The most motivated neuron (that with the identical pattern label) does the action and triggers neurons in matrix-II to do the same. The most motivated one with alternative-linkage does action and turns on the linked neurons in matrix-I at the alternative stage. This process continues till level-III the last matrix). At matrix-III, the most motivated neuron triggers the decision-making neurons at level-III to do the action. By determining all three levels' interrelations, the pattern-realization stage could realize up to 16,777,216 different patterns. Level-I could find a maximum of 65536 similar patterns for each detected signal. Level-II could catch up to 256 similar patterns. Then, level-III could discriminate maximum between the 256 most similar patterns. Adding another level augments this ability up to the realization of 4,294,967,296 different patterns.

3.3. Alternative realization stage

Each labeled neuron in a pattern-realization matrix could link at the same level to two same-level alternatives (the best and the worst) at the alternative realization stage. Each alternative realization matrix is divided into two areas Figure 4. The area above with gray color displays the best possible alternatives and the one below represents the worst possible alternatives. The best and the worst alternatives motivate the decision-making neurons sat at the same level for "develop" and "skip" decisions. The most motivated one between the two is the first one that does the action and triggers the same-objective neuron at the next level (the left side of Figure 4). At the final level, the first one who does the action nails the final decision. Then, the system brings out its output result.

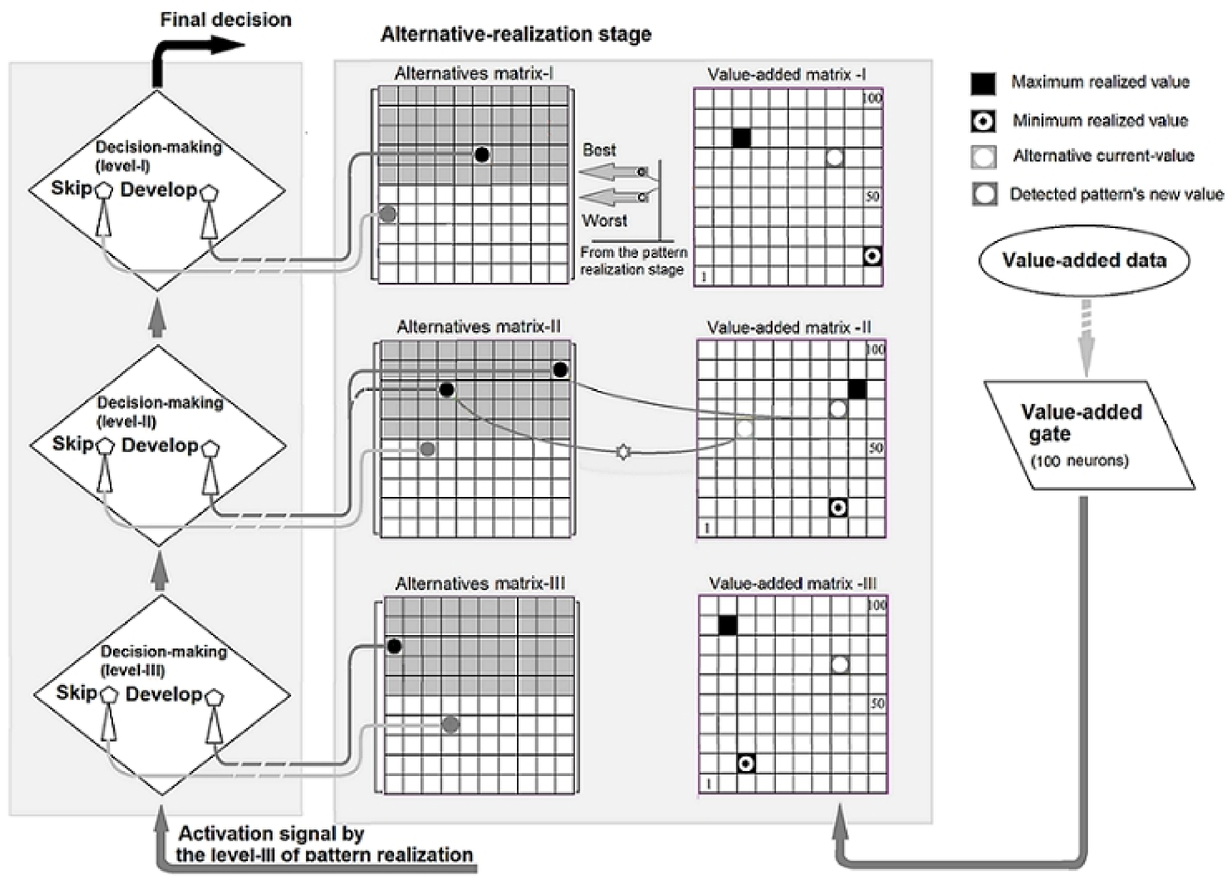

Figure 4. The schematic of the alternative realization stage. The left side shows the decision-making neurons motivated by the same-level best and worst alternatives in the middle (the gray area represents the best alternatives). Those alternatives are linked to the same level realized pattern-labels. They could be replaced by received value achievements. The right side depicts the matrices that record receiving signals on the value-adding sensory gate for the realized pattern-labels.

3.4. Value-adding sensory gate

For each made "Develop" decision, the system receives value data by the value-adding sensory gate. That gate transfers the value to the three corresponding value-added matrices (right side of **Figure 4**). The neuron with received data connects to the on-neuron in the pattern realization matrix. The on-neuron temporarily assigns an alternative to the new value. If this alternative pins a new record more significant than the old one (the best or the worst alternative), it replaces that alternative.

4. EXPERIMENT TO TEST THE SYSTEM'S PERFORMANCE

We structured an experimental setup to test if the system learns through experiences and generalizes knowledge for decision-making. The first step to evaluate the system on knowledge generalization and decision-making method was to verify if the system could do decision-making by itself (non-default decisions) through its realization process. Second, we aimed to justify if the system achieves knowledge to make decisions with more than 50% correct results through experiences. Moreover, we measured the effect of each realization level on making successful decisions. To verify the system on learning and updating knowledge, we evaluated if the system learns information features through experiencing different states.

The information-sensory gate was receiving signals with random features between 1 and 8. Those signals did not represent any real resource provider's information. They were only generated to evaluate the system. Likewise, the made decisions achieved values were not from the real customer side. We estimated each value according to the ranks of features and the intensities of frequencies before applying it. We had ranked each feature as listed in Table 3. We should say that the ranks of information features are combinatory in real environments. However, we ignored that to allow a simple configuration of input data. Here, a signal value was the sum of the ranks multiplied in the intensities of the frequencies.

The values achieved for each pattern determined the relative alternatives motivation for "Develop" and "Skip" decisions. If there were no notable alternatives for a detected pattern, the system made a default decision, which was delivering a "Develop" decision. The decisions made were evaluated by comparing them to the expected results (estimated information values for the non-default "develop" decisions). Here, a non-default decision (certain-decision) was made based on acquired knowledge. The experiment was designed to prove or disprove if our built system performs as the principles derived from brain function. In each experiment's state, a random signal was applied to the information-sensory gate. The system then realized the information pattern to address the best and the worst alternatives in each realization level. Then, those alternatives motivated the decision-makers from level three to level one. The last one decided to develop or skip the information signal. Finally, an estimated value for the non-default "develop" decision, if made, was applied to the value-adding sensory gate to evaluate the decision and modify the alternatives.

Table 3. Defined information features' ranks for our experiments

Frequencies	ranks
Accuracy (f1)	5
Completeness (f2)	1
Consistency (f3)	3
Uniqueness (f4)	4
Validity (f5)	6
Accessibility (f6)	4
Timeliness (f7)	1
Source (f8)	2

To analyze the experiment's results, we first measured the number of non-default decisions made. We then compared the values of the non-default "develop" decisions made at all realization levels with the estimated values to define how many of made decisions were successful. To complete the verification of knowledge generalization and decision-making, we looked for if the system could make successful decisions with a rate of more than 50%. Moreover, we evaluated the effect of each realization level on the success of decisions. Then, we examined the distribution of the successful decisions based on the information features to compare with the ranks considered for the information features to verify the system learning process.

5. RESULTS

From the first state of the experiment to state number 1000, the tendency of the system to make "certain decisions" (non-default decisions) increased continuously to 94%. The system kept that percentage of certainty roughly the same until the experiment's last state (Figure. 6, the red curve). Nonetheless, at that point, only 4 of 10 non-default "develop" decisions were successful at the state 1000 (Figure. 6, the purple curve). We continued the experiment to determine that if the number of successful decisions increases or not, if yes, where is the point that the system passes 50% success. After state 1000, the percentage of success was growing with a smooth slope to the last state. Around state 37000, the system passed the threshold of 50% of successful decisions. At this point, the system had experienced 0.2% of the total possible states. The failed "Develop" decisions decreased from 60% after state number 1000 to 40% at the end of the experiment (Figure. 6, the purple curve).

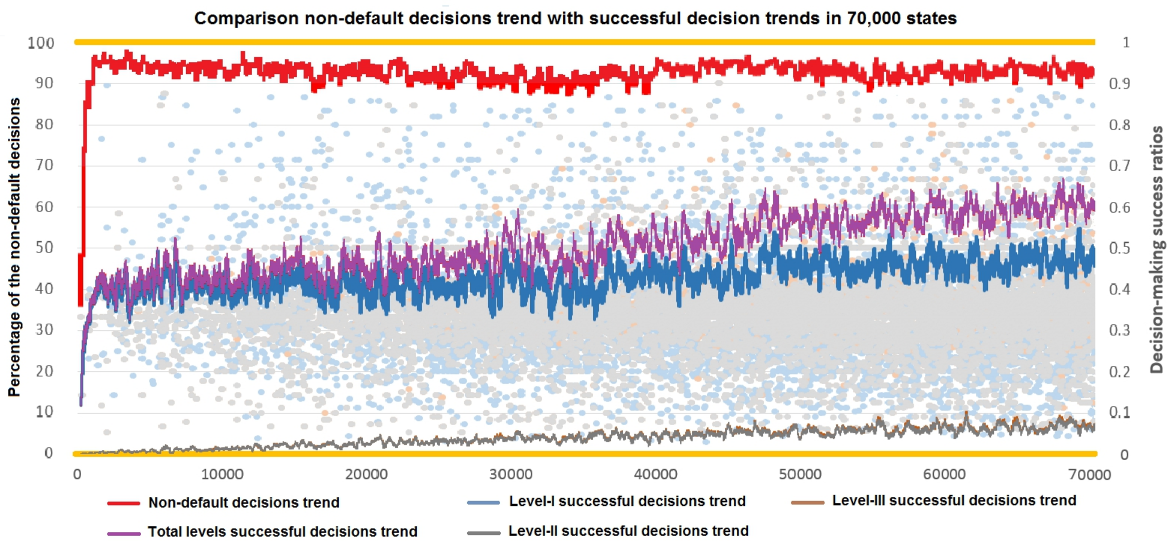

Figure. 6. The system trend in non-default decision-making and successful made-decisions. For the red curve: The horizontal axis represents the number of states, the vertical axis shows non-default decisions percentages ("0" and "1" are respectively for “default decisions” and “certain decisions”). For the other curves: The vertical axis depicts successful-decisions ratios. The tendency of the total successful decisions (purple line) is compared with levels I, II, and III (the blue, brown, and gray lines, respectively). Level-I (vague similarity level) shows a quick adaptation to the environment. The impacting percentages of the level-II and level-III on the successful decisions continuously increased at a constant rate.

The three realization levels processed the detected information signals step by step, from roughly similar to most familiar ones, to have enough alternatives for the fulfillment of any new states. Level three was for discriminating between patterns to recognize the most similar patterns between more similar ones, which actually this level was not tested in this experiment. We evaluated the effect of the first and second levels on the success of each state’s final non-default “develop” decision. In this regard, Figure. 6 shows that 46% of successful decisions in the threshold of 50% success were relative to the level-I functioning. And, 4% of successful decisions were relative to level-II. The effects of level-II and level-III had the same value because of the low rate of pattern repetitions at level two. We continued the experiment to test the trend consistency of the successful decision. The results show that the system continued the same trend for making successful decisions until the end. Figure. 6 compares the tendency of the total successful decisions with levels I, II, and III. Level-I shows a quick adaptation to the environment. Before state 69000, the system made 60% successful decisions, 49% relative to level-I. Eleven percent of successful decisions were relative to the other levels. Here, the second level found on average two similar patterns for each new state.

Level-I was responsible for 100% of the successful decisions made, at state numbers 1000, declining to about 82% at state number 69,000, the other levels up to a total maximum of about 18%.

Figure. 7-a shows that the level-I reaches an average of 4 repetitions on each pattern before state 1000, which, by the way, was responsible for all 40% of the made-decision success. Increasing the average repetition then slowly affected the success of decisions. Accordingly, in the point of 50% successful decisions, level-I with an average of 147 repetitions on each pattern lead to only 46% success. At the end of the experiment, level-I with 271 repetitions of each pattern accompanied 49% of the successful decisions. Figure. 7-b shows that the number of repetitions of each pattern after state 100 had a direct relation to the percentage of made-decision success.

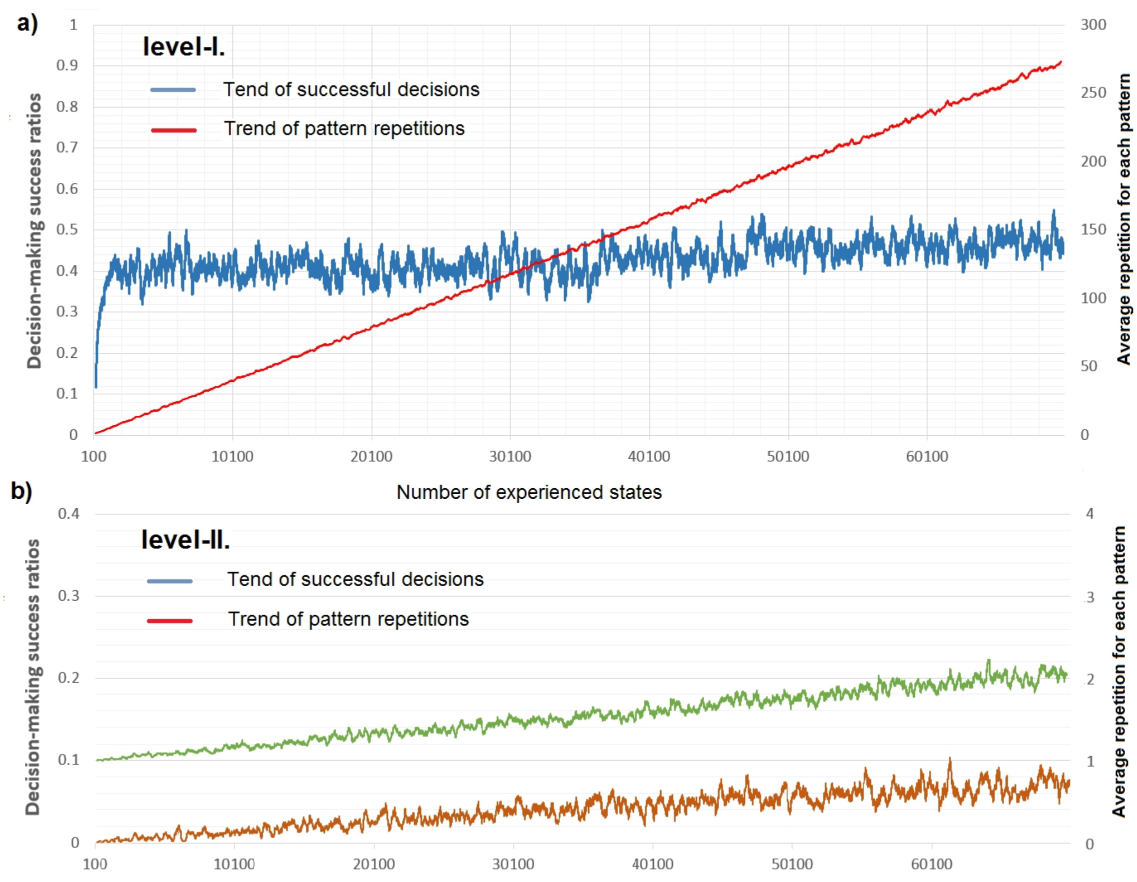

Figure. 7. The effects of all levels on successful "develop" decisions for experiments on 70,000 states. a- The trend of pattern repetitions, blue line, is compared with the trend of successful decisions, red line, for level-I. b- The trend of pattern repetitions, green line, is compared with the trend of successful decisions, red line, for level-II.

To evaluate the system's learning from its experiences, we measured the accumulation of successful "Develop" decisions on each frequency throughout all states. We verified the system on recognizing the difference between the values of information features. Figure 8 compares those values with the ranks applied to information features. Value one in the graph left of Figure 8 represents the frequency with the maximum accumulation of successful "Develop" decisions. The other frequencies in this graph are compared with this frequency. The highest accumulation was for f5, which shows a correlation with the highest rank of information features. The lowest accumulation value was for f2 and f7, likewise, correlated with the minimum information rank.

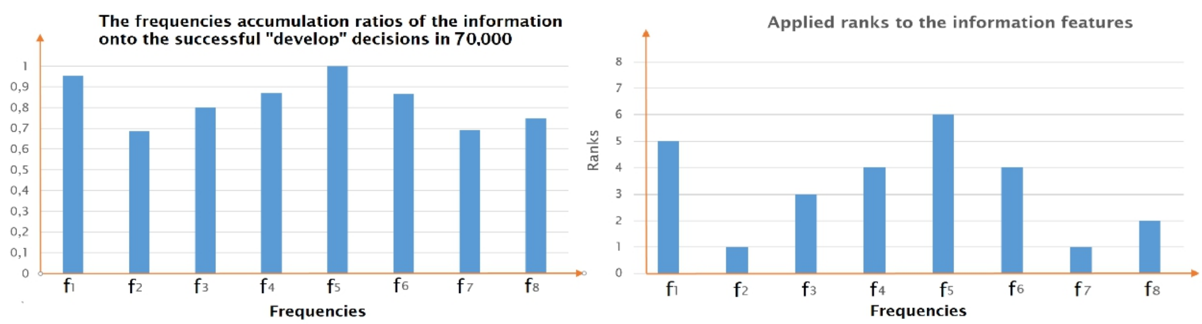

Figure 8. Left side, the accumulation of successful "Develop" decisions on the frequencies in 70,000 states, compared to the features' given ranks on the right side. The ratios of the accumulated successful decisions are on the vertical axis in the left-side graph, and the ranks of information features are on the vertical axis (between 1, 2.., and 8). In the right-side graph. These graphs show the system's ability to differentiate between beneficial and non-beneficial features.

6. DISCUSSION

We then developed a decision-making system based on brain functions in finding similar similar patterns between experienced states, generalizing knowledge, action selection, and learning from experiencing new states. The evaluation of our model was figured through progressing the states of the experiment. In each state, the system received information with a random pattern. Then, it decided if to develop or skip that. For each "Develop" decision, we calculated a value and applied it to the value-adding sensory gate. The system performance was measured using the results from the realization of each state, determining relative alternatives, decision-making, and value-added achievements. The results allowed us to reach the following conclusions

For the generalization of knowledge and decision-making:

We evaluated the effect of level-I and level-II on decision-making. However, we didn't examine the system's ability to discriminate most similar states in level-III, which could be important for complex environments. It needs to be investigated in the future. In Figure. 6, the blue line shows that level-I by abstracting higher numbers of states in common patterns could help the system to adapt faster to unpredictable environments. Level-I provided through previous experiences further alternatives possible for responding to new states. Level-I provided on average 147 values comparing to level-II with an average of 1.5 values for each common pattern at the brink of 50% success. Level-II and level-III made more qualified decisions with higher achievement rates, however, scarce alternatives for decision-making. Both levels showed a slow inclination, which suggests a large number of states required to be experienced to make high-value decisions.

For the ability of learning and modifying alternatives:

The system showed that be able to improve the decision-making process. It improved the process of realizing alternatives through the abstraction of different patterns of the information features of experienced states. A common pattern's value was generalized for all relevant new states. We evaluated the ability of level-I and level-II for generalizing knowledge on decision-making. However, we didn't examine the ability to discriminate most similar states. Level-III was for realizing this characteristic, which could be important for complex environments and needs to be investigated in the future. The decision-making behavior of level-I is represented in Figure. 6, the blue line. It shows that level-I by abstracting more similar features from experiences could help the system to adapt faster to unpredictable environments. At the brink of 50% success, level-I was responsible for 92% of successful decisions. This level provided through previous experiences further alternatives possible for responding to new states. Level-I provided for each common pattern on average 147 values comparing to level-II with an average of 1.5 values. The other two levels increased the precision of decision-making and the rate of higher achievements, however, for a shorter scope of similarities. According to Figure. 7, the successful decision inclination for more than 50% success correlated with the level-II and level-III participation in decision-making. The effects of both levels were the same because of the low possible repetitions for level-II during our experiment. Nevertheless, both levels showed a slow inclination, which suggests a large number of experiences required for making more precise decisions.

We verified the ability of the system to learn information features and differentiate them by evaluating the accumulation of successful decisions on detected signal frequencies (Figure 8). The system developed the learning process through the modification of the alternative motivation-scores. It could recognize the feature values in detected frequencies through learning from experiences and generalize knowledge for new unpredictable states.

In this study, the pattern and alternatives realization stages mimicked the brain principles in decision-making. The similarities between valued states were derived from the built neuronal circuits between the realization matrices. The system generalized knowledge for decision-making through experiences. The alternative realization stage modified alternatives based on the value-added achievements of made decisions. This study could be developed for implementation in real-world environments with real unpredictable information signals and real value-added achievements considering unknown interrelations between information aspects. Our next study will be developing a decision-making system on dynamic tasks considering hazardous materials in an unpredictable environment. We should note that the system could be used as a basis for developing artificial general intelligence (AGI) to configuring complex tasks derived from a combination of different data as what is realized by the brain.

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