푸드테크학 석사 학위논문

Necessity of Neo-Symbolic Artificial Intelligence in food and agricultural sector for increased efficiency, accuracy and reliability

2023년 8월

서울대학교 대학원

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이정환

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이 논문을 농학 석사학위논문으로 제출함

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이정환의 석사 학위논문을 인준함

2023년 6월

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Abstract

This explorative study delves into the dynamic and rapidly evolving market of AI driven Business Process Automation (AI -BPA) and Expert Advisory Systems (EAS) in food and agricultural sector through implementation of technology and software solutions to streamline and automate various repetitive and time-consuming tasks within an organization using a new approach known as the Neo-Symbolic AI. With the relentless pursuit of efficiency, cost reduction, and improved productivity, businesses across industries are increasingly turning to AI driven BPA solutions (AI -BPA) and Expert Advisory Systems (EAS).

Keywords: *AI, Canonical, Machine Learning, Foodtech, Transparency, Accuracy*.
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1. Introduction

1.1 Overview of the current AI landscape

Over the decades, combinations of various programming techniques have enabled slow spotty progress in AI—punctuated by occasional breakthroughs such as certain expert, decision and planning systems, and mastering Chess and Jeopardy! These approaches, and in particular those focused on symbolic representations, are generally referred to as GOFAI (Good Old-Fashioned AI). Importantly, a key characteristic that they share is that applications are hand-crafted and custom engineered: Programmers figure out how to solve a particular problem, then turning their insights into code. This essentially represents the 'First Wave'.

Starting in the early 2010's, huge amounts of training data together with massive computational power prompted a reevaluation of some particular 30-year-old neural network algorithms. To the surprise of many researchers this combination, aided by new innovations, managed to rapidly catapult these 'Deep Learning' systems way past the performance of traditional approaches in several domains—particularly in speech and image recognition, as well as most categorization tasks.

Deep Learning (DL) is a statistical, machine learning (ML) approach, and as such is very different from GOFAI. In DL/ML the idea is to provide the system with training data to enable it to 'program' itself—no human programming required!

In practice a ton of human intelligence is required to make DL systems function in the real world. In fact, top experts in this field are paid several times that of top programmers: Firstly, training data has to be carefully selected, tagged, and formatted; secondly, one has to select the type and configuration of DL network to use; and thirdly, myriad system parameters need to be tuned to get the whole thing to work effectively. All of these steps require tremendous skill, experience, and experimentation.

In spite of these difficulties, DL has been a roaring success in several areas: For example, the progress we see in self-driving cars and voice assistants such as Alexa would not have been possible without it. It is no exaggeration to say that Deep Learning has been a revolution in AI, with literally tens of billions of dollars being invested to further develop and exploit this technology. It is worthy of the title 'The Second Wave'.

1.2 Dawn of Neo-Symbolic AI

In spite of this recent progress, AI has a long way to go to approach human-level learning, thinking, and problem solving ability—a goal known as AGI (Artificial General Intelligence). Today's AIs are quite narrow and rigid.

The vast majority of researchers agree that current technology is nowhere near human (or even animal) intelligence in terms of general cognitive ability. In particular, today's AI is very poor at learning interactively (on-the-fly), adapting to changing circumstances, abstraction and reuse of knowledge and skills (transfer learning), reasoning and language understanding. As it turns out, Deep Learning is actually less capable than some First Wave approaches when it comes to certain language tasks, reasoning, planning and explaining its actions. There is widespread consensus that current DL/ML approaches will not get us to AGI.

Here's a small sample of it's shortcomings:

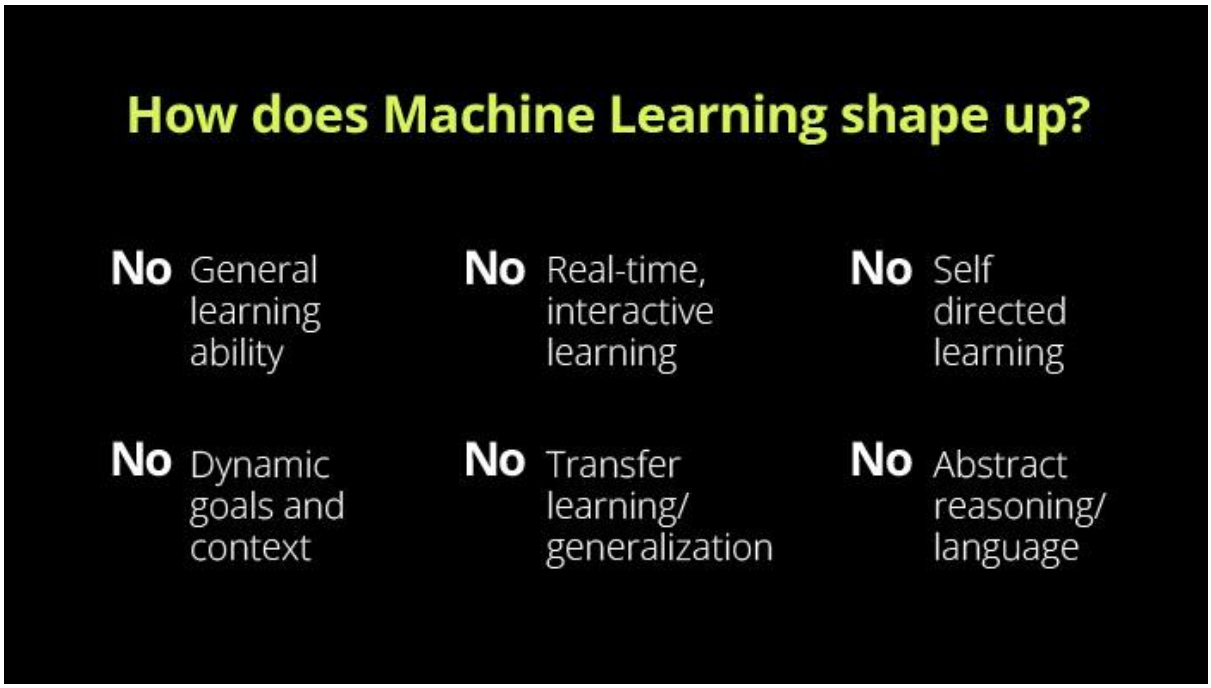


Figure 1 Machine Learning limitations

As limitations mentioned above (Figure 1) have become increasingly apparent, several AI luminaries have expressed the need for a new paradigm—some referring to it as The Third Wave. Some quotes:

- DL pioneer, Geoffrey Hinton: "My view is throw it all away and start again"

- A DARPA presentation: “In the third wave, the AI systems themselves will construct models that will explain how the world works.”
- Demis Hassabis, founder of Google’s DeepMind: “[in short,] contemporary AI programs are… not that intelligent”
- Another AI scientists goes as far as to say: “In the first wave of AI you had to be a programmer. In the second wave of AI you have to be a data scientist. The third wave of AI—the more moral you are the better.”

While there is some divergence as to what exactly this new approach should entail, there is good consensus on the ability to learn autonomously in real time, to generalize, and to be able to reason abstractly and use natural language. There is also strong sentiment that we need more complex, more comprehensive architectures.

1.3 Necessity for Neo-Symbolic AI in food and agricultural industry

In the realm of BPA, traditional solutions often present challenges related to resources, cost, infrastructure, and implementation time. It is imperative for businesses to carefully evaluate and address these obstacles in order to fully leverage the potential of AI-BPA and seamlessly integrate it into their operations. Moreover, modifying existing code to accommodate new changes can be a cumbersome process.

Recognizing these concerns, Mind AI has developed an advanced hyper-automation AI called Human Logic Intelligence (HLI). This cutting-edge technology empowers businesses to incorporate human logic into the decision-making process without any approximations. With its inherent transparency, HLI enables instant additions, deletions, and modifications of workflows and logic, providing clear visibility on where adjustments are needed. Through integration with Mind AI’s Conversational AI (CAI), Human Logic Intelligence goes beyond Machine-to-Machine connectivity by facilitating human involvement in interactions. This means that users can engage in natural language conversations, just as they would seek assistance from a human expert, without the need to trigger specific machine codes. Human Logic Intelligence revolutionizes the BPA landscape by bridging the gap between Machine-to-Human and Human-to-Machine interactions, enhancing operational efficiency and user experience.

These case studies examine commercial use cases, highlighting the challenges faced by two Thailand organizations in the food and agriculture sector, Villa Market and T-Ecosys, the adoption of HLI plus CAI, and the subsequent benefits realized. By exploring these cases, we can gain valuable insights into the transformative power of AI- BPA and EAS and their potential impact on organizational growth and success especially in the food and agricultural industry.

2. Deep technology review: Neo-Symbolic AI

2.1 Technology of Mind AI

Artificial intelligence systems are currently a set of specific solutions to certain problems to try and match the capability of human beings in a restricted subject, and is characterized as being one of the types of connectionist AI [1]. These systems demonstrate great capability for specific domains [2], outdoing world-class human experts in such areas as game playing [3] and visual recognition [4]. Two common factors in developing such "intelligences" are the deep neural networks and the massive amounts of data to train those networks. What forms when these technologies are implemented are black boxes, where anything resembling reasoning is represented only by matrices of numbers, and the resulting "knowledge" is generally inapplicable to any other domain but that of the specific one it targeted [5]. In contrast, we define a new paradigm that invokes the precision of symbolic AI along with methods to overcome the symbolic systems' weaknesses. Definitions and functions, when implemented in our system, are perfectly transparent, so to see at every step why the reasoning process took the steps that it did to reach its conclusion.

Trying to correct a faulty, many-dimensional problem solved by a neural network is a challenge, as it is impossible to find exactly where the error lies [6]. In this novel approach that we propose, however, it would be perfectly reasonable to discover and surgically modify the source of the mistake. The transparency of operation is important for domains in which verifiability is critical, and with this transparency, we are able to apply the same methods in other domains with ease. In addition, we can also observe whether the problem it solves is the actual problem we were looking to solve, rather than some coincidental solution. Biases could also be traced through the logic in our system. We would like to know the reason why, whenever the reasons may be relevant.

Here a new method of machine comprehension is described, using the principal "unit of reasoning" which we define as a canonical. This method of machine comprehension is fully transparent in its operation and capable of modeling anything which can theoretically be understood by human beings, in terms of natural language. We lay out how it is so fundamental: why it can be called a "unit of reasoning" and why logical reasoning naturally follows from the traversal of the structure when this organization principle is applied to any given data.

Theory of Information

From the ground up and the top down we introduce a new paradigm, a functional theory of information, what it is by what happens:

$$\text{Information} := \Delta\text{Potential}$$

Or, information is defined to be a change in potential. We then take this definition one step further:

$$\text{Measurement} := \Delta\text{Information}$$

Measurement is defined as a change in information. Diving further into a functional description of information, we describe "meaning" as a "change in state." By doing so, measurement is a change in one state which then changes another state. Or, finding meaning by putting one thing in terms of another thing. Described this way, we can understand that measurement has the same essential characteristics as causation. For instance, if someone is opening a door, then the person is making a specific kind of measurement in this action. We can even think of gravity as a measurement of two objects' masses, and in that measurement, the action of attraction between those two things.

Canonical Model

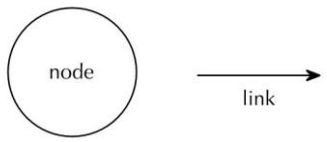


Figure 2.1 Node and Link

Like graph models, our network, at its base, is made of nodes and links. Together, these can form a connection:

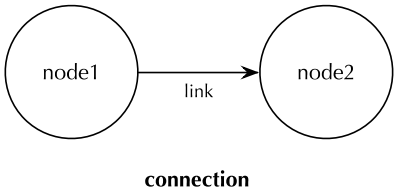


Figure 2.2 Connection

So, utilizing the above theory of information, the meaning is the change of state, which is the layout which is the reading of this connection: “Socrates is mortal”:

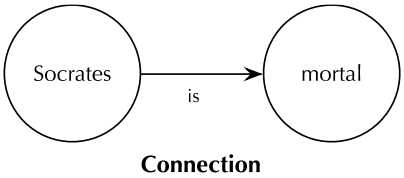


Figure 2.3 Socrates is mortal example

If we treat this like a finite automaton, we can imagine being in the state, “Socrates”. Then we traverse the link “is”, and we end in the state “mortal”. Clearly, what is possible from the state “mortal” is different from what is possible from the state “Socrates”, and so the change in state = meaning = Δpotential. The exact meaning is how “Socrates” is related to “mortal” by way of the transition of “is”. Note it is the exact change that occurred which defines the meaning: “Socrates” going through “is” to enter “mortal”, not any one of these, but the entire occurrence of the difference.

Another way of looking at a connection is that, in the above example, “Socrates” is put into the state of “mortal”. In this way is it the normal understanding of how information is defined within a canonical.

Three connections can come together as a unit in what we call a canonical, of which we have two types:

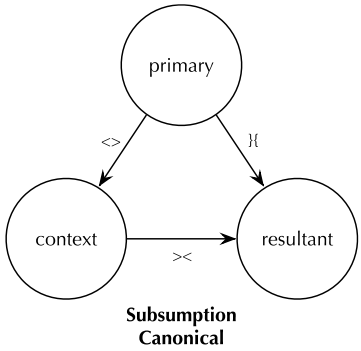


Figure 2.4 Subsumption canonical

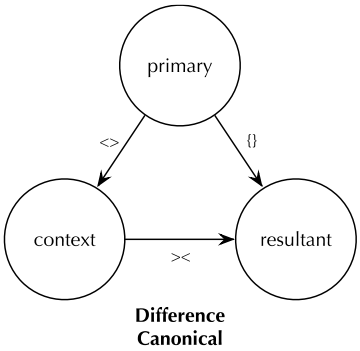


Figure 2.5 Difference canonical

The only difference being the last link, on the right, having }{ or {} as its designator. The Subsumption Canonical can be thought of as a definition, like (in a simple case), “a child is a young person”. This would fit with Aristotle’s definition of definition, “A is a C with B”: here, the primary would be “child”, context “young”, and resultant “person”. The subsumption is how the concept of “child” can be subsumed by the concept of “person”. A child is most definitely a person; and this is a one-way relationship (not all persons are children).

A Difference Canonical is the idea of a change that occurs, which means that the primary is not the same as the resultant, and the resultant does not subsume the primary, per se. The primary could be, “John is in New York”, the function of which could be “moved to Seoul”, and the resultant, then, “John is in Seoul”. Note how the state change is characterized.

The primitive symbols are outlined as follows:

? query, potential, “some”: not pictured above, like a wild card

{} none, nil, “becomes”

}{ all, any, “is”

<> bind, “has”

>< open, “does”

The definitions in quotes above are one way to understand how the symbols operate in our system. Essentially, they represent one level of semantics that are induced when elements are placed somewhere in this model. These primitives provide some basic semantics in which words, as nodes, can be placed in the positions in the model above. Even though we do not need all three nodes and all three links to be anything other than the “default” or unfilled values, it is fundamentally important where we place information when it is in structural form (a node/link or canonical). We call this an “augmented” network because a node can be a link, a link can be a node, and a canonical can be a link or a node.

The “has” side is information that sets up a position (in a matrix). When we describe information as a change in potential, we can actually think of a potential as a position. The “does” side, a measurement, takes the state of that potential, and either reflects or subsumes it between the resultant and primary (in a subsumption canonical) or changes it to a new state, thus putting the resultant into a new state. The meaning of this measurement, the “is” side, is exactly the reflection/subsumption or change of state that was performed.

Note that these designations are flexible. For instance, “the car is red” will not result in “car” in primary and “red” in the resultant. It is clear that “red” is a feature of “car”, so it would be placed in the context, instead.

Canonical Reasoning

We call a canonical a “unit of reasoning” because within this simple structure are represented the capability to model the three types of reasoning models that comprise human-level logical reasoning. The following shows what has been identified as the three embodiments of logical reasoning, as it pertains to the canonical model:

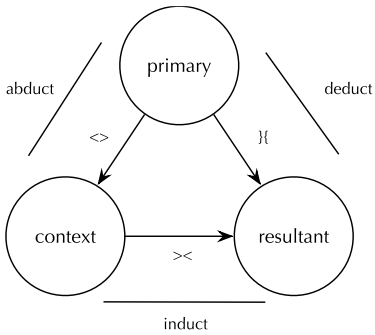


Figure 2.6 Canonical Reasoning

This, as far as taking one of these three paths at a time, is actually a well-known structure. However, we interpret those three types of reasoning in a novel manner. In the traditional interpretation, basically to obtain one inference (of the three), we fill in the other two sides of the triangle. For instance, }{ "deduction" would happen if we filled in the <> "abduction" connection as well as the >< "induction" connection. We do it a little differently. Let us take a simple example:

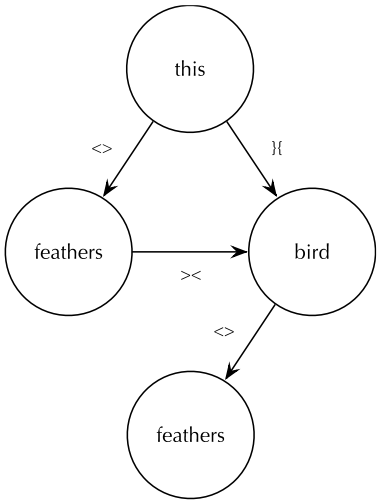


Figure 2.7 Canonical Reasoning example 1

Let us say that this structure is defined by three logical statements:

1. This has feathers (normally a case: the "<>" connection)
2. This is a bird (normally a fact: the "){" connection)
3. All birds [do] have feathers (normally a rule: the "><" connection, which maps to the bottom "<>" connection)

From the traditional way of looking at this structure, we are tempted to say that there are three relations:

a. 1 & 3 → 2 (deduction to infer fact, something held to be true)
b. 2 & 3 → 1 (abduction to infer case, a specific occurrence)
c. 1 & 2 → 3 (induction to infer rule, a general concept)

The difference, our unique way, when we lay it out in natural language form, more closely resembles how these three reasoning logics are understood to hold:

a. If this is a bird (2), and all birds have feathers (3), then this must have feathers (1). In other words, since you connect "this" to the rule, what is declared in the rule must also apply to "this". Another example: If Socrates is a man, and all men are mortal, then Socrates must be mortal.
    i. Deduction: the actual facts would be "this [does] have feathers" and "Socrates is mortal"
    ii. This is deduction through }{ (2)
b. If all birds have feathers (3), and this also has feathers (1), then this is inferred to be a bird (2). Or, if all men are mortal, and Socrates is mortal, then Socrates can be inferred to be a man.
    i. Abduction: the actual cases would be "this is a bird" and "Socrates is a man"
    ii. This is abduction through <> (1)
c. If this has feathers (1), and this is also a bird (2), then all birds can be inferred to have feathers (3). And so if Socrates is mortal, and Socrates is a man, then it can be inferred that all men are mortal.
    i. Induction: the actual rule would be "all birds [do] have feathers" and "all men are mortal"
    ii. This is induction through >< (3)

What is so paradigm shifting in our method of modeling comes from the fact that as we lay out our ontology in canonical form, it is also modeling the exact inferences that can be performed. That are, in fact, being performed. The information is coupled with the logic, because the information is the logic. Knowledge is the reasoning.

Understanding this principle, we can clearly ascertain that transparency is available from every level. The statements of fact that are entered, the questions that are asked: they are all canonicals. And then the process of reasoning that is done to answer questions, solve problems: since these are in fact, also canonicals, they are all readily comprehended by human as well as machine.

It is also worth noting that two of these types of inference are known to be not sound. Only the

deductive is considered sound. But if you really think about it, there can be cases where the deductions can also fail to be absolutely true. Below would be how exceptions could be modeled, what it means if the inferences above are false:

a. If "this" is an exception, then it can be a bird which does not have feathers. (contra/deduction)
b. "This" could be something else that has feathers, and not a bird. (contra/abduction)
c. Of course, not all birds necessarily have feathers as a contra/induction, but interestingly, what this logically conjectures that "at least one bird has feathers" if "this" is a bird and "this" has feathers.

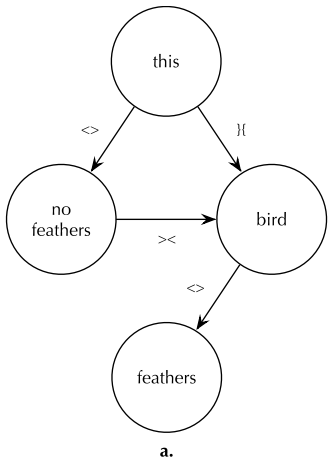


Figure 2.8 Canonical Reasoning example 2

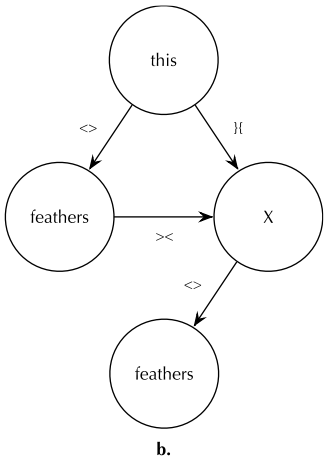


Figure 2.9 Canonical Reasoning example 3

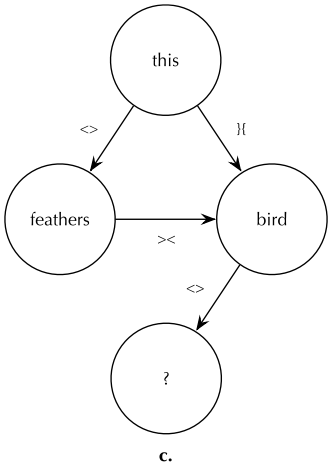


Figure 2.10 Canonical Reasoning example 4

Canonical Theory

We list here the theory which goes with the canonical model to perform certain tasks. Though the structure of the canonical is very simple, this does not mean that there are not many different, manifold reasoning processes that can be done with it. What they all have in common are the semantics of the positions within the canonical model.

Cause and Effect Theory

Below we define a predicate ontology, where we will demonstrate how we deal with causation:

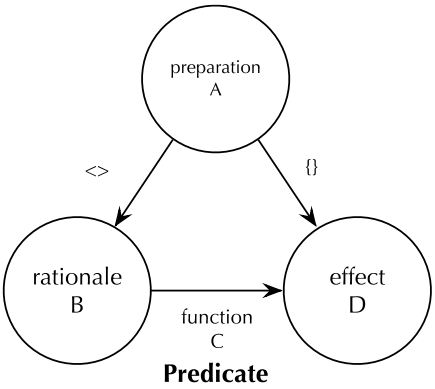
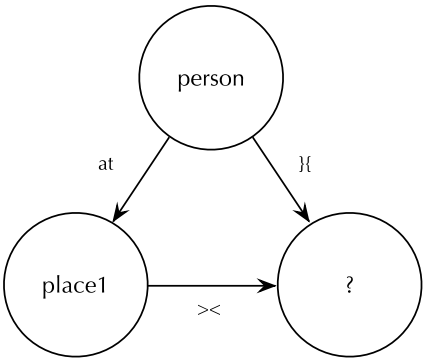


Figure 2.11 Causation

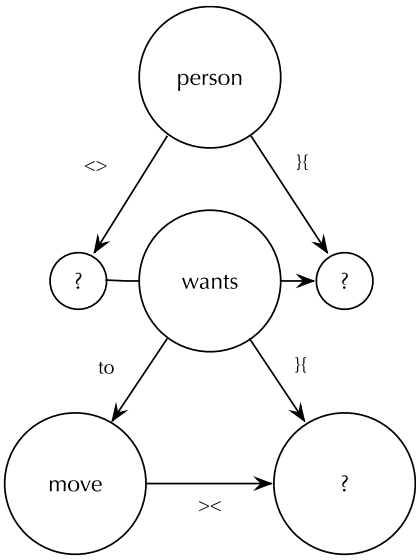
To define a change in terms of some function, we start with a preparation, which is a thing within some state, then the rationale being the context, where it outlines the purpose of why this change happens, then the function which is the modeling of the exact change itself, and the effect which

is the new state of what came into this canonical in the preparation. See how it may be modeled with a more specific event:



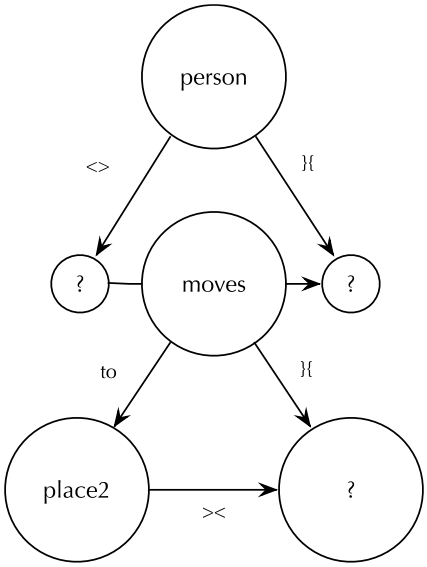
Preparation A

Figure 2.12 Preparation A



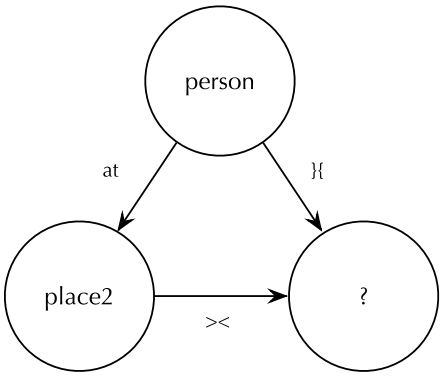
Rationale B

Figure 2.13 Rationale B



Function C

Figure 2.14 Function C



Effect D

Figure 2.15 Effect B

So a person is at place1 (preparation), and that person wants to move (rationale), so the person does so in moving to place2. We are then left with the person being at place2, which is the result of this causation.

Lateral Resolution Theory

The theory behind Lateral Resolution comes from the discovery that if two canonicals share a common inductive condition (the bottom connection), they are functionally identical. If we put that in terms of words, these words are said to be synonymous. However, they can be arbitrarily complex forms, canonicals augmenting nodes.

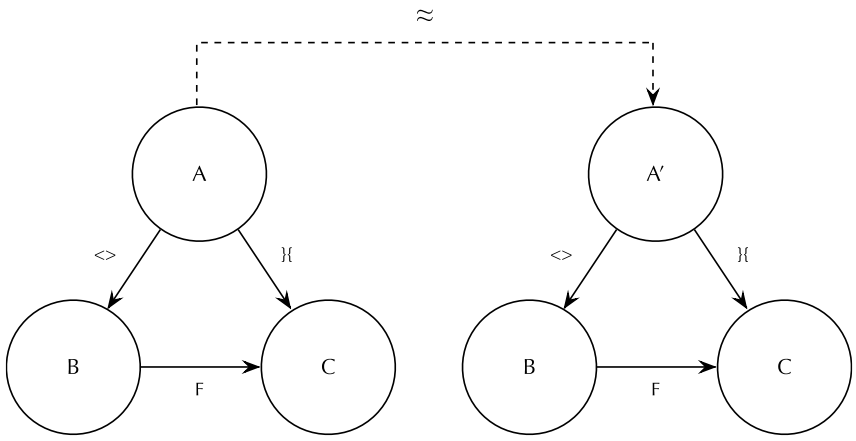


Figure 2.16 Lateral Resolution Theory 1

Here, whatever form goes into the positions of A and A', since they share the same functioning connection (the bottom connection), they are said to be functionally equivalent. As you can see, it is called "lateral" for a reason. Instead of defining A and A' to be in a subsumption relationship, they are at the same level. For example:

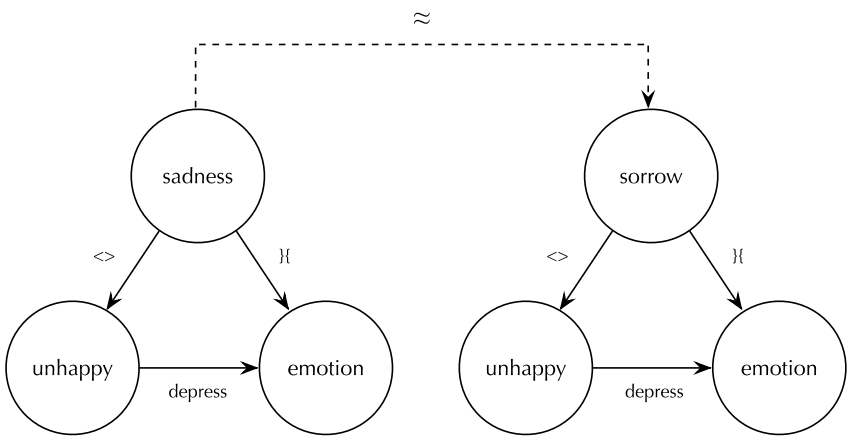


Figure 2.17 Lateral Resolution Theory 2

This captures the idea of synonymy in a clearer, more accurate way. When utilized in conjunction with activation logic, below, lateral resolution goes a long way in solving the brittleness problem that was inherent in old symbolic models.

Activation Theory

This goes hand-in-hand with the subject/point model. In the ontology of definitions and logical forms, when given a certain phrase, after putting the phrase into canonical form, the machine

needs to see what that phrase could possibly mean. When ontology is set up correctly, there will be relationships that can be traversed in order to see if something in a subject/point (the focus) can be triggered.

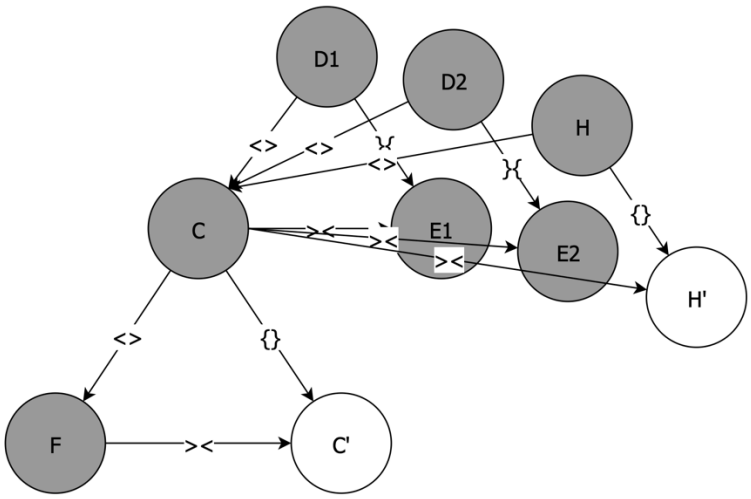


Figure 2.18 Activation Theory 1

One side effect to this is that when the ontology can be developed to handle that which possibly can be meant by something which the machine understands, in conjunction with lateral resolution, we then solve the brittleness problem of symbolic models. This occurred in previous models as perhaps a phrase needed to be formed only in the exact way the machine was programmed to understand it. Instead, with logical forms within an activation network, we can peruse the different tendrils of ontology to see in whatever way a person can put it into words, what they meant by it.

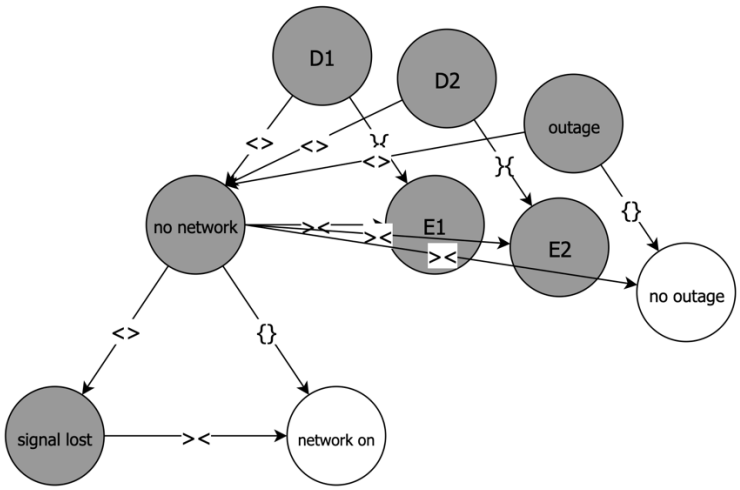


Figure 2.19 Activation Theory 2

The example here is that “no network” does not activate D1 & E1, D2 & E2, because of the rules of activation (so we don’t even have to know what they are), but “outage” and “signal lost” are activated. So therefore, what “no network” could possibly mean include “outage” or “signal lost”.

Conversation Theory

The first concept to understand the subject/point model is the idea of logical forms. Below, there is an example of a subject or point (the only difference being that the point is not a top level object, and a subject is). It is laid out as a difference canonical. The logical form is made up of the primary being defined as one condition [1], and which is entailed by another condition [3]. In a troubleshooting model, if one considers it, the notion of entailment comes naturally, and also fits ideally in canonical form. For some device there are parts of that device which, if any of these parts are necessary for functioning, if one or more are non-functional, the root device will also not work.

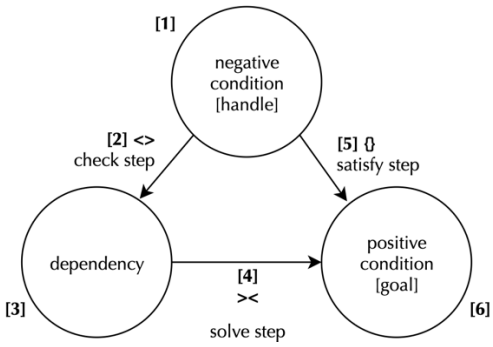


Figure 2.20 Conversation Theory 1

In general, a negative condition as a handle of a subject or point, goes through a “check step” to see if a dependency applies or not. The dependency could be a point or just a handle with a goal. This is what is at the end, the goal being the negative state having become a positive state. When the solve step is applied, we go to the satisfy step to see if we are now going into the goal of the model.

So being more specific, going into the negative condition of a router not working: if the power is not on, then necessarily, the router is not working. In this entailment, we know these things to be true, and when this is modeled here, so does the machine:

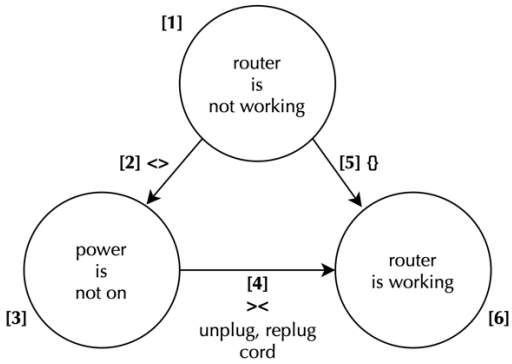


Figure 2.21 Conversation Theory 2

For a machine to help troubleshoot a router, let us say a user complains that their router is not working. This resolves to the primary state [1]. What follows is a guideline in customer support: let us try and diagnose why. In [2], which leads to [3], the machine can ask, "Is your power on?" And then, if the answer is "no" which resolves to "the power is not on", we continue to [4], which gives advice on how to change the state of that last logical form. After completion of that task, the machine, at [5], can ask, "Is your router working now?" and upon a "yes" (which resolves to "the router is working" [6]), we conclude the subject/point canonical for a troubleshooting procedure.

The subject/point model is to be able to define a focus for the collected ontologies. It is to take all the accumulated knowledge and apply it to a certain purpose. It is one example of how the canonical model can be repurposed between different domains of functioning, being a wholly universal model of logic, as it pertains to what logic can be possibly interpreted to operate.

Compartmentalization

There are four levels where information can be stored: global, local, user, and session.

- Global: holds the upper ontology, which are predicates that are globally relevant, unchanging knowledge which is at the root of the understanding of everything else
- Local (or domain information): can exist in a subhierarchy which holds the knowledge applied to a specific domain of interest, and further, to be germane only to a specific organization
- User: holds the profile and history of the user's specifics, and is used to help contextualize information as it pertains to that user. There also might be a subhierarchy of different classes of users

- Session: is transient information that is in effect between the time the user logs in to when that user logs out

Natural Language Generation

As more and more inputs are arranged into canonical form, we will keep track of the transformations that occur from the unstructured to the structured forms. In so doing, we can reverse the process, so as to create grammatically correct sentential representations with which to answer the user or to request more information. This is yet another example of its ability to learn by observation of the dialog that transpires between the system and its users. Whatever goes in can then come out. Idiomatic structures, once understood, can be formed as a response back to the user, where it might be relevant to do so.

Problem Solving

In claiming to be a universal model of reasoning, we must be able to cover all functions of cognition that are understood to be in the premises of intelligence. One such topic is that reasoning should have the capacity to be applied to solve problems. The most well-known type of problem solving would be the ability to solve word problems, as students of mathematics (along with other fields, like physics) need to learn to master.

One of our main goals in creating the reasoning engine, focused on natural language reasoning, is to be able to read a set of instructions which is written for a human agent and to be able to follow the instructions with as much capability as that human agent. The idea of problem solving, especially word problems, is a well known phenomenon written about through history, as far back as the concepts that problem solving could be aided by specific techniques. Comprehending instructions not only as entity models, but procedural models (generally, subsumption and difference canonicals, respectively), the reasoning engine can understand what techniques to apply for whatever problem can be recognized by the engine.

Generalization

When we are able to put new logical forms in relationships to the logical forms that are known, there is an immediate implicit effect. This enlarges the understanding of what something could possibly mean. When correctly put into a canonical network, this expands the means by which an event can cause another event to be triggered. It is highly useful for problem solving, especially if we take into account how the new information is put in logical relationship with what is known. We can build up a technique ontology in this way, and apply analogical reasoning to translate

from one kind of ontology, one domain, into another. Another term for this type of generalization is theoretics.

What theories are useful for are to be able to predict the future from what we have observed in the past. This means that a model of causation needs to be laid out which, when triggered by operating conditions, produces an accurate portrayal of the consequences when the theory is applied. Difference canonicals, in themselves, provide a simple idea of an event that occurs, which could be one step of some algorithm for performing some task.

The theoretics is reliant on the ontology, the relevant ontology, being in place. To make a logical conclusion, inductively, the process is to make observations, and then we need to know how these observations could possibly fit into one or more generalizations about how things must happen in the world. Usually this is done by setting up an experiment by which, if the experiment is successful, it is a deductive logical condition that will confirm if the hypothesis holds.

Critical Mass

In atomic theory, when the correct radioactive matter reaches a certain mass, an autocatalytic process is initiated [18]. Similarly, we describe ontological critical mass (and its trappings, namely, the reasoning facilities) as the containment/comprehension of enough information and functionality for Mind to learn on its own. If something is beyond the capability of the current state of the system to understand, it must, on its own, figure out just what that thing is in relation to what is known. For this to happen, as it relies on ontology, the knowledge basis must be in at least one sense "complete." There must be a way to be able to open up all possibilities. This is not an intractable problem.

What things can exist, what are they made of, and what can those things do? Note that these questions are mapped to the three sides of a canonical. These questions cover what can be understood. The only qualifier to understanding is what we can break down the understanding of something into. Nothing is magic. Either we have all the principles by which new information can be fathomed, or we need to invent new principles (The latter case is described in more detail below, in Metatheoretics).

On the practical side, if we can create an interface to the outside world (in cyberspace) for it to search the web and scrape the contents of the websites it finds, then in theory it should be able to do its own research on topics it knows very little about to solve some problem or query.

In preparation for the "critical mass" phenomenon, we need to include within Mind's functionality a means by which it can discern good information from bad. This can be seen as another aspect of it having "learned how to learn." The Mind needs to be able to understand and automatically weed out false information, and in situations in which a piece of information is beyond Minds ability to reasonably check its verity, it needs to turn to the community for assistance. Through assistance, Mind learns how to perform certain verity checks on its own, or which techniques it can apply at a future time when faced with similar challenges. These are the techniques of understanding and solving it accumulates.

Metatheoretics

The ultimate goal of this approach is to be able to create an artificial scientist that is able to create its own hypotheses and theories, and to perform experiments that reach new conclusions about the world. These functionalities can be founded upon simple statements, comprehensions of basic principles, and/or scientific theories. At the base of its functionality, we will set up rules for generalization, as stated above, the theoretics, which allow specific events to trigger the formation of broader predicates. We will focus on observing why events happen as they do. For example, when a pencil falls to the floor, the phenomenon can be explained by gravity, as all objects with mass are affected by gravity and all physical objects have mass. Therefore, at the most basic level of theorization, we can hypothesize that anything we drop that falls to the ground is a physical object with mass.

As Mind learns more about the world, it is able to understand the relationships between new information and its prior knowledge, and understand what can be measured, how things are connected, and how things make sense. As a result, Mind can then formulate its own hypotheses.

The art of crafting theories depends primarily upon finding a relationship between disparate phenomena. If Mind does not understand why something happens, it will try to obtain the information elsewhere to see if it can make sense of it. In addition to this capacity, it knows what to do if something is not resolved or if a resolution cannot be achieved with the scholarship that already exists. In the first iterations of the development of Metatheoretics, we will feed it situations so it can attempt to discover existing theories. We input past insights that humans used to create those theories into Mind, but we limit its reach of knowledge. Therefore, though it can see the observations that led to those theories, the conclusions of said evidence are not given. This "training" would be equivalent to an AI's university education. After it graduates, and understands how the great theories of the past came to be, it will be able to do some real world work. By allowing Mind to draw its own connections with limited knowledge, it will also have

theories about how such theories are made. This is the essence of Metatheoretics.

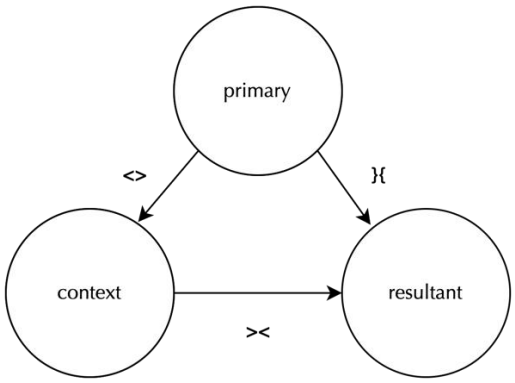
When Mind can come up with its own scholarship and reaches that height of artificial scientific method, we can truly say that we have created an intelligence. It will be able to do research on a level unprecedented by human reasoning. Experts in domains such as drug discovery or materials engineering have the entirety of all the existing scholarship in their fields including all the papers from the beginnings of their field's establishment. Yet, Mind will have all of that same information "in its head," properly annotated, and checked for logical missteps based on the understanding it has from the entirety of its knowledge. Mind will then be in a position to discover something truly new by formulating novel hypotheses and devising experiments to bear them out. Ultimately, because we all can see how insights are reached by Mind, we are in a position to advance our own intelligence. This is the essence of Mind.

2.2 First and higher order logic *vs* Mind AI

Theoretical comparison

The root of almost any assertion in natural language falls into objects, properties or relations (Russell and Norvig , p. 272). We take it as the theoretical benchmark to compare how canonicals, first-order logic, and higher-order logic differ.

Canonical model embodies the 3 types of logical reasoning as a structure of knowledge. We treat it as the "unit of reasoning".



Canonical

Figure 2.22 Canonical Theory

The three sides of a canonical triangle can be interpreted in different ways, but the symbols used to define their links give an intuition of what fits within it:

(1) The <> (bind) roughly translates to the properties (in the context) that some form (primary) is associated with
(2) The }{ (satisfy) is one way to define a relation between the primary and the resultant
(3) These together is very similar to Aristotle's definition of definition: A is a C with B, primary is a resultant with context
(4) Then there is the >< (open) link which is usually defined with some sort of action, representing the function of the primary, bound to the context, resulting in the resultant

There is one more thing about the }{ connection, being that its opposite (which would be {}) can be thought of as a potential value where:

(1) The canonicals with }{ are usually differentiated to be utilized as definitional canonicals, or a classification relation (here aligned with Aristotle, above)
(2) Canonicals specifically using {} are called difference canonicals, and usually define some sort of process (A becomes C when >< occurs with B: primary becomes resultant when >< occurs with the context)

How does canonical express objects, properties, and relations?

- Relations are in the context of <>, ><, and }{, since every node and link may be a canonical unto itself
- Properties are the relation of <>
- Object definition is similar to the definition of definition by Aristotle, properties with a ground to what the resultant is

What is first-order logic and higher-order logic

First-order logic is an extension of proposition logic, which can express the relations between entities. The lexicon of a first-order language contains the following (Fern, 2010):

- Logical connectives: (⇒, ∧, ∨, and ⇐⇒), negation (¬), and parentheses: ¬, →, ↔, ∧, ∨, ( ).
- Variables: x,y,z,... ranging over particulars (individual objects).
- Constants: a,b,c,... representing a specific element.
- Predicate: f,g,h,..., with arguments listed as f(x1,...xn).
- Function: R,S,... with an associated arity.
- Quantifiers: ∀ (universal) and ∃ (existential).

The symbols, therefore, come in three kinds: constant symbols, which stand for objects; predicate symbols, which stand for relations; and function symbols, which stand for functions (properties).

Higher order logic: The "order" of a logical system refers to the level of abstraction of the entities that can be quantified over. In first-order logic, we can quantify over individuals. In second-order logic, we can quantify over sets of individuals. In third-order logic one can quantify over sets of sets of individuals. In terms of objects, properties or relations, first-order logic allows quantification only over objects, second-order logic extends this to properties and relations, and higher-order logic allows quantification over entities of any type. Theoretically, you cannot obtain a complete, recursively enumerable deductive system in second and higher-order logics (Shapiro 1998). In contrast, this is possible with canonicals because each resultant in a canonical can be another canonical. As a resultant can be used for deductive reasoning, it is possible to recursively deduct in canonicals.

How is canonical model different

Table 2.1 Canonical model comparison with first and higher order logic

	Canonical	First-order logic	Higher-order logic
Scope of quantification	Allows quantification over objects, properties, and relations	Only allows quantification over objects	Allows quantification over objects, properties, and relations
Logical relations	Logical relations are built in	Need to use Logical connectives to express	Need to use Logical connectives to express

		logical relations	logical relations
Completeness	Yes	Yes	No

Practical comparison

While first-order logic can formalize many propositions with quantifiers in natural language, it only allows quantifiers over individual entities, but not over predicates. Inevitably, there are some limitations in what first-order logic can express (Gamut 1991, pp. 75 - 79). We can broadly summarize the expressive limitations of first-order logic into two categories: quantification over predicates and compound predicates. We will compare how first-order logic and canonical form deal with these difficulties with specific examples.

Quantification over predicate

In first order logic, we can only talk about properties that are bound to entities and not able to express properties in general.

(1) First order logic

Santa Claus has all the attributes of a sadist (example in Gamut (1991, p.76)). This breaks down to $\forall X(\forall x(Sx \rightarrow Xx) \rightarrow Xs)$ where we are ranging over the predicate to model this precisely, which is not allowed in first-order logic. However, this is achievable using second-order logic. If we lose some precision, it is also possible using many-sorted first-order logic. But there are problems if we believe the many-sorted variety can overcome all of first order logic's limitations (see below).

(2) Canonical form

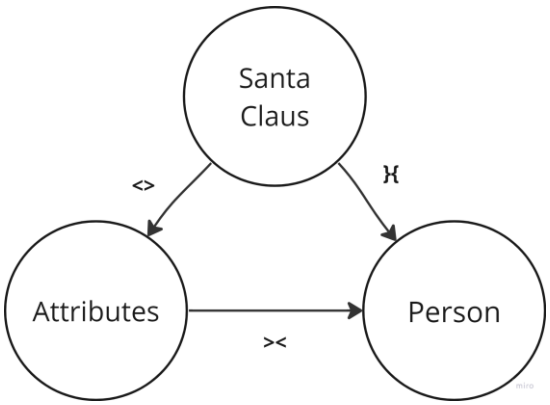


Figure 2.22 Canonical Theory 1a

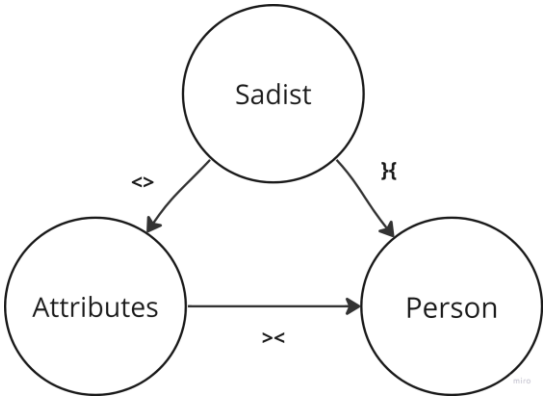


Figure 2.23 Canonical Theory 1b

The canonical form, on the other hand, allows quantification over predicates. As seen in (1a) and (1b), we can range over the attributes that are placed in the context. At the same time, canonicals can bind those predicates to the objects, making predicates more contextually interpretable. When we are ranging over the attributes, we know these are the attributes of Santa Claus and Sadist. And because they share the same resultant (i.e. Person), we know these attributes can be compared in a more general category of Person.

Compound predicate

First order logic cannot express propositions that contain compound predicates and therefore lead to logical contradiction.

(1) First-order logic

Sentence (2.1): Jumbo is a small elephant (example in Gamut (1991, p.77)).

Semantically, Sentence (2.1) cannot mean Jumbo is small and Jumbo is elephant. Even a small elephant can be big, because elephants are the largest land mammals on earth.

Sentence (2.1): Jumbo is a small elephant => *Small(Jumbo) ∧ Elephant(Jumbo)
Sentence (2.2): Jumbo is a big mammal => *Big(Jumbo) ∧ Mammal(Jumbo)

Formally, we cannot express Sentence (2.1) as: Small(Jumbo) ∧ Elephant (Jumbo). Because if we allow this expression, we will arrive at a logical contradiction that Jumbo is both big and small.

(2) Canonical form

The above issue can be solved using canonical form, because canonical form can split the compound predicate into different parts (i.e. context and resultant). The scope of the context is constrained simultaneously by primary and resultant. See the following examples.

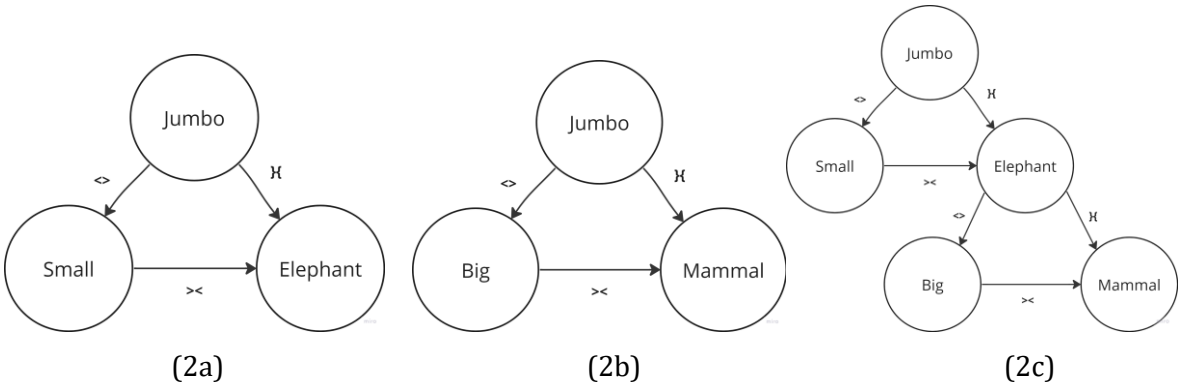


Figure 2.24 Canonical form

In Canonical (2a): Primary = Jumbo, Context = Small, Resultant = Elephant. In scope of the context (i.e. Small) is constrained by both the Primary and Resultant. Therefore, the meaning of canonical (2a) is: Jumbo is an elephant that has the attribute of smallness. Same applies to Canonical (2b), the meaning is: Jumbo is a mammal that has the attribute of bigness. In addition, Canonical (2a) and Canonical (2b) can be merged compactly into Canonical (2c), which is also correct and has no logical contradiction. Here we see two advantages of canonical form over first-order logic in this example. First, canonicals can precisely express the meaning of the proposition, as seen in Canonical (2a) and Canonical (2b) respectively. Second, canonical form does not introduce logical contradiction when new facts are added. Canonical (2a) and Canonical (2b) are correct when they stand alone, and they are also correct when they are combined, as in Canonical (2c).

What higher order logic cannot do, but canonical can do

Firstly, one thing to note is that researchers tend to prefer being able to model using first order logic and not a higher order. Practically, it is more computationally expensive to train things like deep learning models based on higher than first order systems, though there have been some advances in this (Shen et al. 2020). In canonical form, it is often computationally efficient because we can reduce the search space with the help of Primary and Resultant. As (1a) and (1b) show,

when we are doing any computational tasks about the attributes, we first narrow down the scope of attributes by Primary and Resultant. Higher-order logic can be vague and may have grounding problems. While higher-order logic has the ability to quantify over higher-order entities, this often makes the entities vague or undefined. It is not a problem in mathematics and philosophy, but it may not be suitable for natural language work because the symbols in natural language usually need to be grounded somehow in the real world. In comparison, canonicals define everything in the same way as the Genus–differentia definition proposed by Aristotle. Therefore, grounding will not be a problem. There are some methods that try to reduce second or higher-order logic to first-order logic, but the translation cannot be exact, and strictly, at least some second-order theories cannot be expressed as first-order ones. Notably, many-sorted first-order systems (using Henkin semantics) are sometimes taken to be able to model things usually requiring second or higher-order logics. This has been proven wrong numerous times (Jerzak 2009).

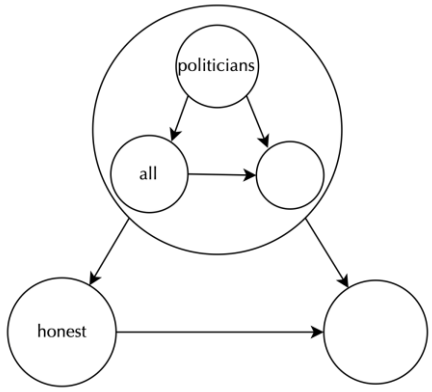
Limitations of Formal Logic (Canonical model and other logical representations)

From the above mentioned sections, we see how the canonical model can overcome the weaknesses of first-order logic and higher-order logic. However, the canonical model has some limitations and these limitations are actually shared across all other representations of formal logic. The limitation of formal logic lies in its inability to account for many aspects of human reasoning, such as ambiguity, vagueness, and context-dependence. It also has difficulty capturing non-logical aspects of language such as irony, sarcasm, and metaphor. Additionally, formal logic is limited in its ability to deal with incomplete or inconsistent information. Moreover, formal logic has a limited applicability to certain fields, such as ethical issues, moral, or aesthetics, where reasoning may not be as clear-cut or formalized. Formal logic also requires a clear and well-defined set of premises, which may not always be the case in real-world arguments.

Sarcasm, irony, insinuation, and emphasis

One of the notable limitations is sarcasm. Logic translation, or the process of representing a text from natural language to the formal language of a logical system, potentially will not completely represent every detail and all the aspects and nuances of the original text.

Table 2.2 Sample of natural language that conveys sarcasm

Natural language	All politicians are honest
First-order logic	$\forall x(P(x) \rightarrow H(x))$
Canonical shorthand	(politicians <> all) <> honest
Canonical diagram	

The sarcasm does not align with the truth value, i.e. the actual meaning is that NOT all politicians are honest. However, it is possible that the canonical form could be able to address this issue, through the contextualization available in the model. More studies and research is needed.

Vagueness and Ambiguity of Natural Language

The vagueness and ambiguity of natural language, in contrast to the precise nature of logic, often poses problems.

"Roses are red"

- First-order logic requires a quantifier (e.g., all or some).
- The canonical model allows this expression by leaving the quantifier empty. The vagueness is still present though it can be implied that some roses are red.

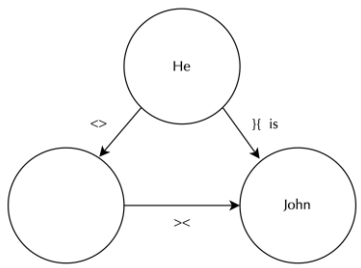
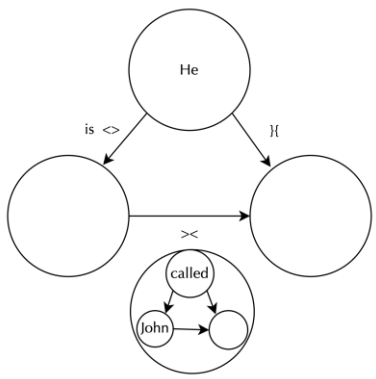
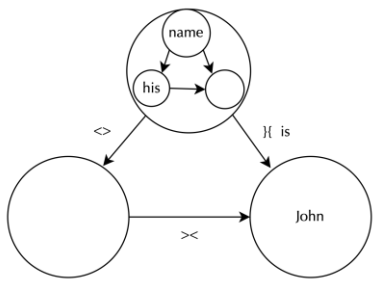
"I want fish and chips"

- There are two interpretations here:
    - I want two things. One is fish and the other is chips.
    - I want a menu item called "fish and chips".

Lack of explanation of how to use them for ordinary arguments

Natural language can have variations and synonymous expressions. Different structures can lead to different logical expressions.

Table 2.3 Sample of synonymous sentences

		
"He is John"	"He is called John"	"His name is John"

These sentences have a different canonical form though they are synonymous. Each natural language sentence can only have one canonical form and vice versa. However, the different canonical structure can lead to different logical reasoning. Canonical model still needs more research on how we should apply the model to natural language in all cases. On the other hand, one natural language sentence can have more than one possible FOL expression.

"Every person has a mother"

This statement could be expressed in first order logic in several ways, depending on how we define the domain and the predicates. Some possible ways to express this statement in first order logic are:

$\forall x \exists y(\text{MotherOf}(y, x))$

$\forall x(\text{Person}(x) \rightarrow \exists y(\text{MotherOf}(y, x)))$

$\forall x(\exists y(\text{Person}(y) \wedge \text{MotherOf}(y, x)))$

Each of these expressions represents the same meaning in natural language, but they differ in how they capture the meaning using first-order logic predicates and quantifiers. Here is an example of a first-order logic expression that can have various ordinary language expressions using a real-world object:

$\exists x \forall y\ (x > y)$

This expression can be interpreted in various ways depending on how we translate it into the context of real-world objects. For instance, we can say:

- There is a tallest building in the world that is taller than all other buildings.
- There is a building that is higher than any other building in the world.

Each of these expressions conveys the same meaning as the first order logic expression, but the translation can be various.

Discussion

We have discussed the differences between canonical form and first and higher-order logics. While we acknowledge that there are limitations to what can be represented in such logical structures, we believe that there are important benefits to utilizing canonical models to represent logical states and functions. Canonical forms were from their outset designed as a structure for use by computational machines, and therefore serious consideration should be given to using this model in the exploration of computational logic and its utility over more traditional structures.

Overall, we believe that canonical models offer a promising approach for representing logical states and functions in computational logic, and we continue further research and the development of the model. The logic that is encoded in canonical form will add great value to the field of AI, especially in the era of the large language model.

2.3 Generative AI *vs* Mind AI

Generative AI has amazed the AI world and exhibited marvelous performance in language understanding and content generation. Here we present Mind AI, which takes a different and novel route in AI with an emphasis on transparency, logic, and reasoning. We believe Mind AI will form a complementary pair with ChatGPT and the like.

Overview of Mind AI and Generative AI (ChatGPT)

Table 2.4 Comparison of Mind AI and Generative AI

	Mind AI	ChatGPT
Brief Description	A Natural Language Reasoning AI based on a new neuro-symbolic model centered around a patented data structure called a Canonical.	A Large Language Model-based generative system which can produce natural language and programming language output based on prompts.
Approach	New Neuro-Symbolic Paradigm	Machine Learning/Deep Learning
Core Technology	Relies on Canonicals, which are units of reasoning and provides real meanings and logical resolutions for reasoning problems	Relies on a Large Language Model, GPT-3.5, which is a minor upgrade from GPT-3 (which upon this release of their technology, caught up in a large hype cycle)
Data and Data Collection	Driven by Ontology. Ontology is data structured in Canonical form. Ontology is created, reviewed, and curated by trained linguists.	Driven by Large Language Model or text automatically collected from web scraping with crowdsourcing reviewers Takes less human effort, less expertise, and less time
Transparency	More than Explainable AI; Full transparency at every level (to know at any point what is going on) White box	Being a neural network based system, little to no information on how it processes Black box
Data Computing	Does not require machine training and therefore, costs less money	Requires a number of powerful machines to train a very large dataset and therefore costs more money not only during the training but also the call request
Understanding	Directly encode logic which is understandable by both human and machine (in Canonical form) Thus, it can learn something once and understand it forever It also connects with incoming information to make true, logical associations	All machine learning approaches only ever deal with approximations of human logic (like with adding together vectors of numbers) In terms of logic, it does not understand things semantically, only relying on the examples it's seen It will never actually be 100% logical
Use Case(s)	Problem solving through reasoning	Content creation (e.g. writing emails and

	Mind AI	ChatGPT
	Question answering with the ability to verify	letters, generating codes, etc.) Information retrieval (e.g. asking for suggestions or information)
Achievement if Given the Same Resources	An "open" AI Contrary to ChatGPT, Mind AI's prebuilt ontology can be open to clients. Clients can also contribute back to the community by adding, updating, and sharing ontology.	Less open AI ChatGPT is becoming less open. The language model is not released to the clients. Even if it is released, few clients, especially personal users, will have the required hardware to run it.
	Controllable With the transparency of the data structure or the ontology, users are able to control the results made by AI or able to adjust according to needs.	Uncontrollable Without transparency, the results can be unpredictable.
	An affordable AI Since Mind AI does not need to constantly train a big language model, the cost of data creation and maintenance will be much lower than ChatGPT. The users, in turn, can pay less for the service.	Costly AI Requires to train a big language model. There will be a cost of training each time. Users cannot extract a specific domain/topic of interest, instead of getting the whole thing (like downloading a big language model).
Pitfalls	New technology not easily understood by ML type researchers & clients Requires time, manual effort, and linguistic/domain expertise to review the ontology	Hallucination – it will often output grammatically correct, seemingly relevant information, but which is factually and/or logically incorrect This is because it has no sense of ontology, meaning it has literally no idea what it is talking about Further, this is inherent in any ML or statistical approach, as they only deal with approximations of meaning

The differences between Mind AI's theory and ChatGPT's

Mind AI is a new paradigm, based on a new symbolic idea of representing logic and reasoning in a way that humans and machines both can understand. We do not train, we educate when we give new information to the ontology. The way the model ends up is entirely based on the premise that we give it true, unbiased information. Thus at all times, we verify that what is being understood is also real and genuine. And at all times you can see how the logic is applied, and if something can go wrong, you can surgically correct it.

ChatGPT is state of the art deep learning, with billions of parameters, a Large Language Model
It does not actually "learn"—rather, it is "trained": the distinction is that "learning" implies actual cognitive capabilities, and ChatGPT does not pretend to have them. Although they have tried to follow in the steps according to what is now understood as "ethical AI", without bias, the amount of data it crunches through makes it difficult to strain such data out. Any logic it contains is not actual logic. Any meaning it seems to know is not actual meaning. They are all associations and it also doesn't know the difference when the data is being fed into it is false. As with all such models, it is a black box, non-transparent in operation.

Mind AI can mitigate hallucinations in ChatGPT. ChatGPT will spout out something that seems to make sense, but in reality it is making something up that is not logical, not factual, or both. If we develop the ontology, because we always deal with known facts and known truths, even on novel usage of our model, we can see or oversee what ChatGPT outputs. What happens when someone attempts to input ontology that is not true: we can detect that, then ask if we want to delete it or save it marked as invalid. We should be able to tell if something that is proclaimed by the Large Language Model also has a basis in reality or not. Also, such things as knowing when we don't know should improve on the current performance of ChatGPT's continuing to hallucinate in such topics, logic be damned (we know when to stop, ChatGPT doesn't).

One secret of ChatGPT's success is the high-quality data provided by experts. The canonical model, which integrates data and their logical relations at the same time, can be a useful way to fact-check and validate the data. Mind AI has a team of linguists and ontologists, curated linguistic data, and synergy from a crowd-sourcing platform. With these resources and tools, the data fed to ChatGPT can be further improved by human revision and verification. We will be able to provide an API to call for automatic quality control.

ChatGPT as fallback for Mind AI. When we have decided that we do not know what a customer is talking about, and we are sure that we don't know, then we can use a call to ChatGPT as a quick solution to deliver its take on that subject matter.Therefore, customers should have a "seamless experience" as there will be fewer or no fallback when the response seems to make sense syntactically. They should feel like they are really talking to a human.

When there is a question about some subject matter that we have capability to understand, but have no resource as to a request a fuller explanation about it, we can then also go to ChatGPT as a source for that general information. Then we can redirect back to where we have familiarity with the subject matter. Note that we can do "customized" ChatGPT (fine tune, not full-on training) and so make it better capable of answering relevant questions and not hallucinate.

2.4 Human logic intelligence and Conversational AI Infrastructure as a service

Mind Expression is a Human Logic Intelligence and Conversational AI Infrastructure as a Service (IaaS) for the development of Conversational AIs (also known as "chatbots") and Intelligence Process Automation (IPA), respectively. With a context-aware development interface, a developer can easily create complex conversation flows and test them immediately in the Sandbox. With a single, simple public API access, integration with any front end is easily interfaced. Developers can easily add specific knowledge from their own organizations and use it immediately. Mind Expression can naturally support human-like decision processes based on actual logic. Dead simple to set up, for any process that can be conceived, enter into the flow, and trace your way through simple questions & answers to follow through on the actions that need to be taken.

Unlike every other chatbot platform, our Conversational AI Builder does not rely on a machine learning (ML) framework to properly match a chatbot user's "intent". Mind uses a new Symbolic Paradigm, which overcomes the problems of the older, first-generation symbolic models, solving the problems of brittleness and adaptive learning. Mind doesn't rely on Big Data; we do not train our model, we educate it. Neural network (NN) and Machine learning (ML) models are not made to reason: they only spot patterns, and they don't know why something made "sense" to them or not, whereas Mind understands what's going on and why.

Since we are not dependent on training phrases, the ease of setup is unparalleled, and the development time is only a fraction of the ML models used by everyone else. Other systems use

training phrases (one after another after another) to train their "intents", whereas Mind just requires one logical statement to teach the meaning of what the developer wants to handle. As the components and actions that make up the flows are available in a context-aware development environment, the developer can easily add what is logical at every step of the building process. Interfaces to enterprise back-ends & fulfillment are easily configured without the need for any programming skills to develop them.

It is well known that ML/statistical/NN implementations are "black box" technologies. In contrast, the primary model we utilize, the Canonical, is modeled to be understood by both a human being as well as a machine, so transparency is available at every level. Our model is a Cognitive model: the phrases are understood logically and are logically related to other parts of the ontology by their meaning. In other words, the other systems only approximate meaning, whereas we deal with actual meaning, that makes sense to everyone. No other platform gives the capability of Context Hopping, which is available by default in any conversation flow created by the developer: no extra setup is required.

What is available in other platforms is a set of very rudimentary connections that are arbitrarily connected, and whose context is lost unless specifically programmed into the chatbot model that is being developed. Hopping means jumping from point to point in a subject and between subjects, where no context is lost in between the "hops. Where there is more context needed to properly enter a new state, we automatically go to where the required information is collected. Another related feature is "arbitrary entry points", which are like hopping into a flow from nowhere; these are also provided without additional setup.

Since everything is logically understood, transfer of knowledge is built in. Between domains, ontology that is understood by a certain context can be translated into other contexts for different domains (analogical reasoning, based on the cognitive model of abductive, deductive, and inductive reasoning). Between languages, as we work with meanings, what works in one language will work the same way in another language.

Along with the ease of setup, what is built is more accurate, too, than the ML/NN models available. Developers can easily insert new states where they logically fit (guided by our context-aware UI), and you don't have to worry if you've done something wrong in the setup.

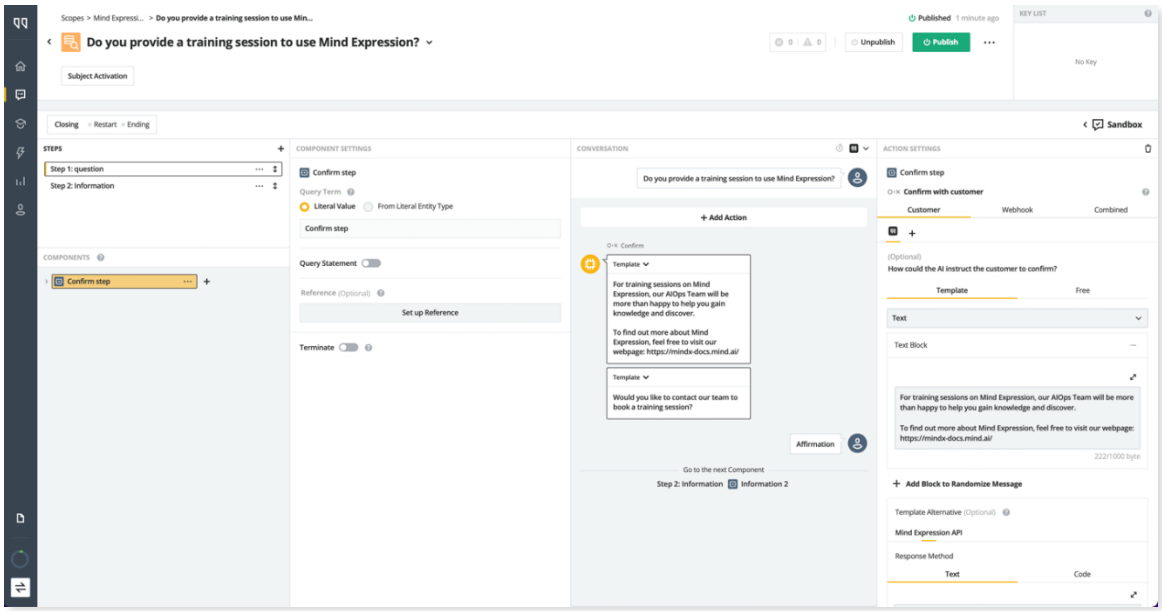


Figure 2.25 Comparison of Mind AI and Generative AI in setup

All changes cascade so the new flow is assimilated without any hand-rewiring. Completely automated, available day or night, any day of the week. Mind Expression maps the logic taken by human agents in the workflow, eliminating the middleman, making everything flow faster and more precisely. Context hopping is automatic, and it does not need to be configured, because everything has a specific purpose, and the context is kept throughout the conversation.

3. Experimental Study and Explorative Analysis: Commercial use cases

3.1 Retail and E-commerce: Villa Market's Inventory Management

Initiation and background

Villa Market, a prominent supermarket chain in Thailand, boasts an extensive network of 34 supermarkets throughout the country. Villa Market attempted to utilize Google Dialogflow for developing a customer service chatbot. However, they encountered challenges related to the extensive resources required for hard coding and the difficulties in identifying and rectifying errors within a Machine Learning black box model. Consequently, Villa Market faced a protracted timeline of over 6 months to develop just 10 intents (referred to as "Subjects" in Mind Expression). Ultimately, the project had to be halted due to ongoing struggles in adding and modifying intents.

Recognizing the need for a more effective solution, both parties initiated a Proof of Concept (PoC) involving 10 Subjects, and to Villa Market's amazement, Mind AI was able to successfully implement the desired functionalities within just 10 working days. Impressed by the significantly reduced deployment time, Villa Market proceeded with the project, extending its scope to include Consumer Conversational AI (CAI). Furthermore, the collaboration now encompasses the development of a CAI for Villa Market's suppliers and even connects and advises internal employees through a Call Flow CAI. This partnership with Mind AI has allowed Villa Market to overcome their previous obstacles and embark on an efficient and comprehensive conversational AI solution.

Inventory Management

Recently, Villa Market has encountered significant challenges with its inventory management system, specifically in effectively handling out-of-stock products. As a company operating on a large scale, Villa Market manages an extensive inventory consisting of over 40,000 stock keeping units (SKU). However, within this vast assortment, approximately 15% of these SKUs, accounting for approximately 6,000 units, present various challenges such as out-of-stock occurrences, overstocking, slow-moving products, and similar issues. Addressing these complexities necessitates the expertise of seasoned managers capable of diagnosing the situation and

formulating appropriate solutions for each individual SKU. Effective resolution demands a comprehensive understanding of the field, real-time information, sales analysis, and thorough examination of order history, enabling the manager to make informed decisions and implement suitable measures accordingly.

Presently, the out-of-stock and inventory management system is overseen by a solitary human expert. Consequently, this arrangement limits the expert's capacity to address only the most critical issues, leaving other aspects of the process to be handled by additional purchasing officers. As a consequence, all inspections and evaluations must be carried out manually, relying solely on human labor. This reliance on manual processes introduces potential inefficiencies and limitations in the overall management of out-of-stock and inventory, warranting a closer examination of the current system.

List of example questions the store manager has to consider before making a decision:

- Is the supplier delivery on time?
- Is the supplier delivery complete?
- Is the supplier delivery in full order?
- Is PAR enough?
- Is the sale normal?

Experimental Study and Integration

In order to integrate the decision-making logic of human experts into the HLI, it is imperative to visually represent this logic through a decision tree, process flow, or any other form of natural language that accurately depicts how a human expert would navigate and make decisions. With this in mind, Varakorn Klaiklang, the Chief Technology Officer (CTO) of Villa Market, collaborated with his team to develop a comprehensive flowchart that encompasses the entire decision-making process employed by the current sales manager (Figure 1).

By implementing this flowchart on the Mind Expression platform, which serves as the foundation for HLI solutions, our internal team successfully completed the integration in less than half an hour. The Villa Market team was enthralled to witness the real-time automation of a process that previously required over 34 store managers and 15 buyers to manually inspect all system inventories.

Furthermore, following the completion of the first field test, Klaiklang and his team further refined the initial flowchart, resulting in a more concise version (Figure 2). While Figure 1 served as a visual representation of the entire process, mirroring the decision-making process of human experts, Villa Market realized through the field test that the journey could be streamlined by eliminating redundant and unnecessary check steps. This discovery presented an opportunity for significant improvements in their current system, with the integration of HLI serving as a catalyst for this positive transformation. The design of HLI empowered the Villa Market team to critically examine their existing processes and make substantial enhancements.

The ability of the HLI plus CAI enables store managers and staff to no longer need to recall and input the specific issues that may have caused discrepancies. Instead, they can effortlessly follow the directions provided by HLI+CAI, which interacts with them in natural language as if they were consulting with a dedicated inventory expert.

Klaiklang stated, 'Users can significantly reduce the time required to access information and follow suggested actions. Store managers are no longer solely responsible for decision-making; they now rely on HLI's recommendations.'

Moreover, as a company operating in the Retail and Supermarket industry, Villa Market continually encounters dynamic out-of-stock situations and various issues that require attention. Modifying the BPA system to address these changes would typically demand substantial resources and costs due to its rigid, hard-coded nature. However, the inherent design of Mind AI's transparent ‘canonical’ engine, empowers developers to easily identify areas where logic can be added, deleted, or modified with different approaches.

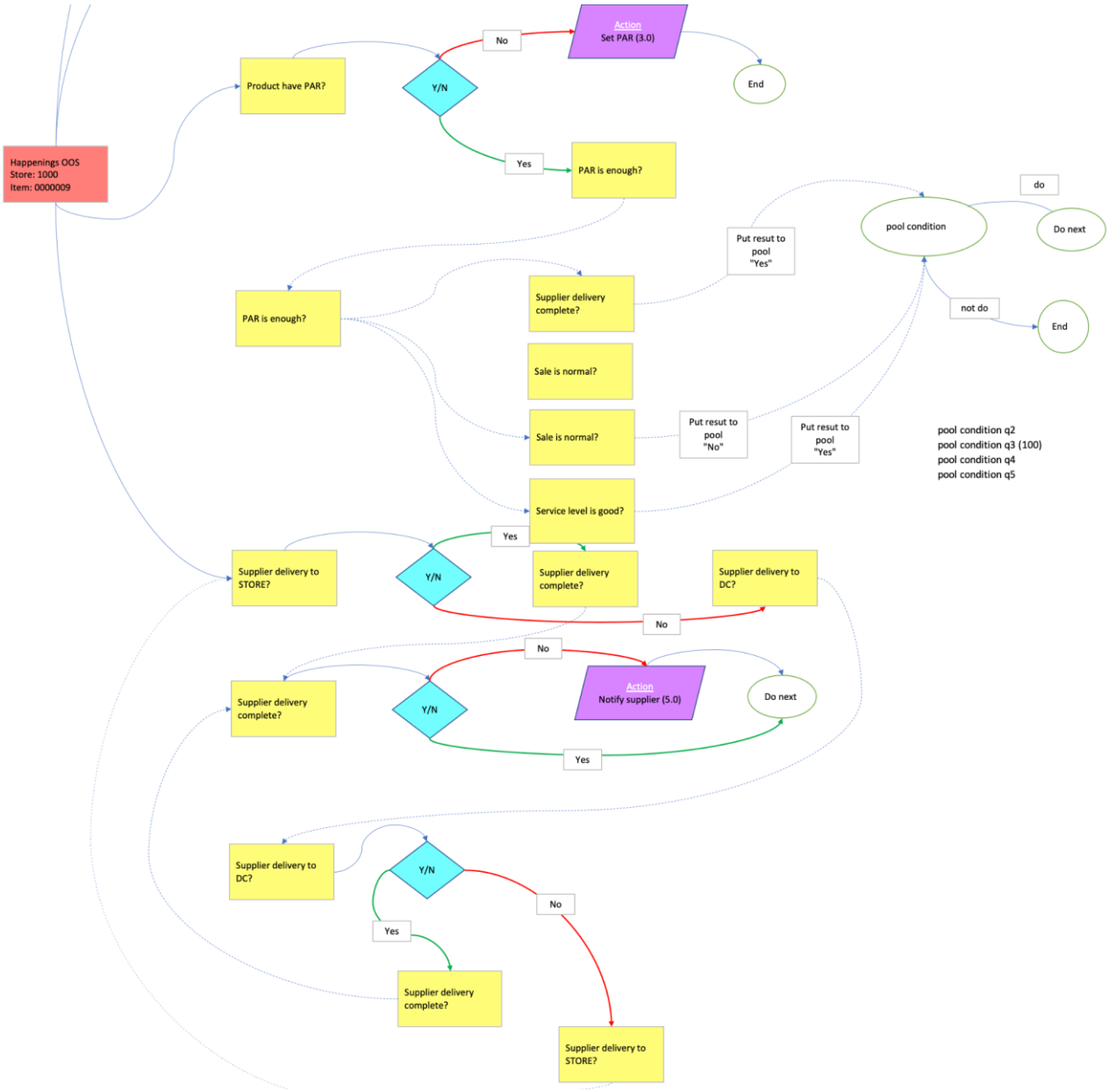


Figure 3.1 Out of Stock flowchart designed by the Villa Market team

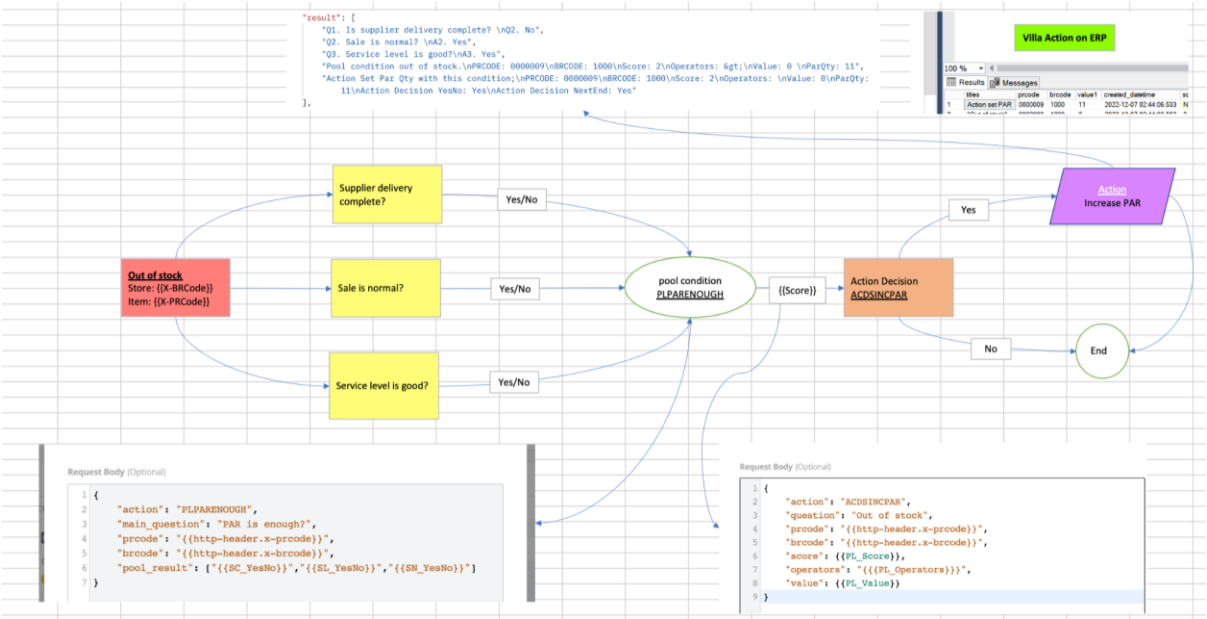


Figure 3.2 Enhanced Out of Stock flowchart modified into a much simpler version after the first field test

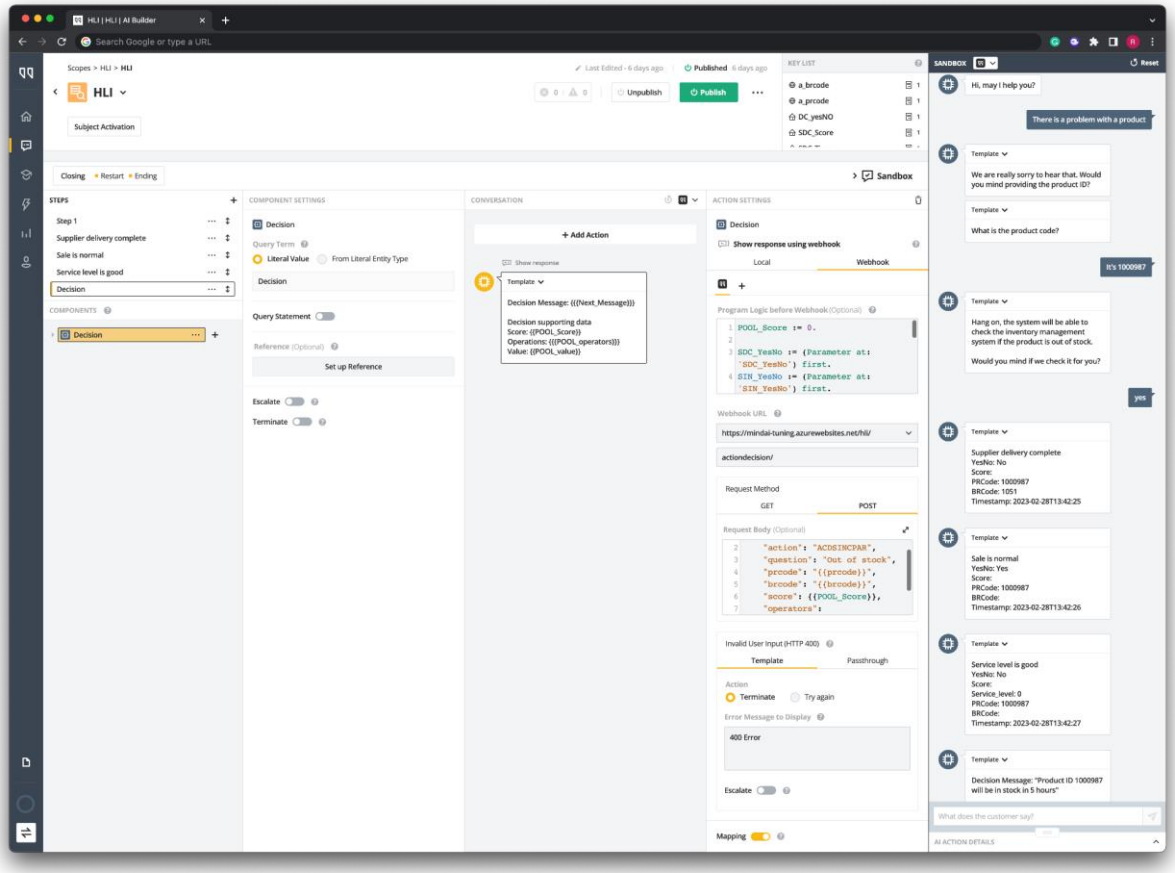


Figure 3.3 Mind Expression configuration on Villa Market Out of Stock and example conversation flow tested on Sandbox

Explorative Analysis

The Villa Market Inventory Management project is currently in its final testing stages, having undergone a series of three comprehensive field tests. Through effective measures, Villa Market has successfully minimized the occurrence of out-of-stock items, reducing the number of SKUs from 204,000 to less than 500. This remarkable achievement has yielded a noteworthy decrease of over 99% in the time expended by store managers and buyers when addressing out-of-stock situations. Consequently, Villa Market has experienced substantial cost savings, enabling the company to allocate resources more efficiently and optimize its operations.

In regards to operational efficiency, store managers and buyers previously faced limitations in their ability to investigate a large number of SKUs. However, with the implementation of HLI, Villa Market anticipates that every single SKU can now be thoroughly examined, thanks to the hyper-automation capabilities provided by the system. This advanced automation is expected to lead to a significant reduction in overall out-of-stock occurrences and greatly enhance operational efficiency throughout the organization.

During the course of the multiple field tests, the internal Villa Market team examined a total of 127 instances to assess the accuracy of HLI. The evaluation process entailed comparing the responses generated by HLI with the judgments made by human experts. The results of these tests revealed an outstanding outcome, with HLI achieving a flawless accuracy rate of 100%. This exceptional accuracy rate serves as a testament to the efficacy and reliability of HLI in comprehending and responding to a diverse range of queries and tasks. The outcomes of these successful field tests, along with the 100% accuracy rate obtained, further validate the potential of HLI to revolutionize decision-making processes and enhance operational efficiency within Villa Market.

Following the completion of three field tests, an internal post-implementation survey was conducted at Villa Market, involving a total of 49 employees, comprising 34 store managers and 15 buyers who play a key role in the inventory management system. The survey aimed to assess employee satisfaction regarding the effectiveness of HLI in addressing out-of-stock issues, the ease of use of the system, and the overall impact on their job performance. Quantitative measures were employed using rating scales ranging from 1 (lowest) to 5 (highest) to gather feedback on these aspects and provide a comprehensive understanding of employee satisfaction levels. The results are indicated on Figure 4 below.

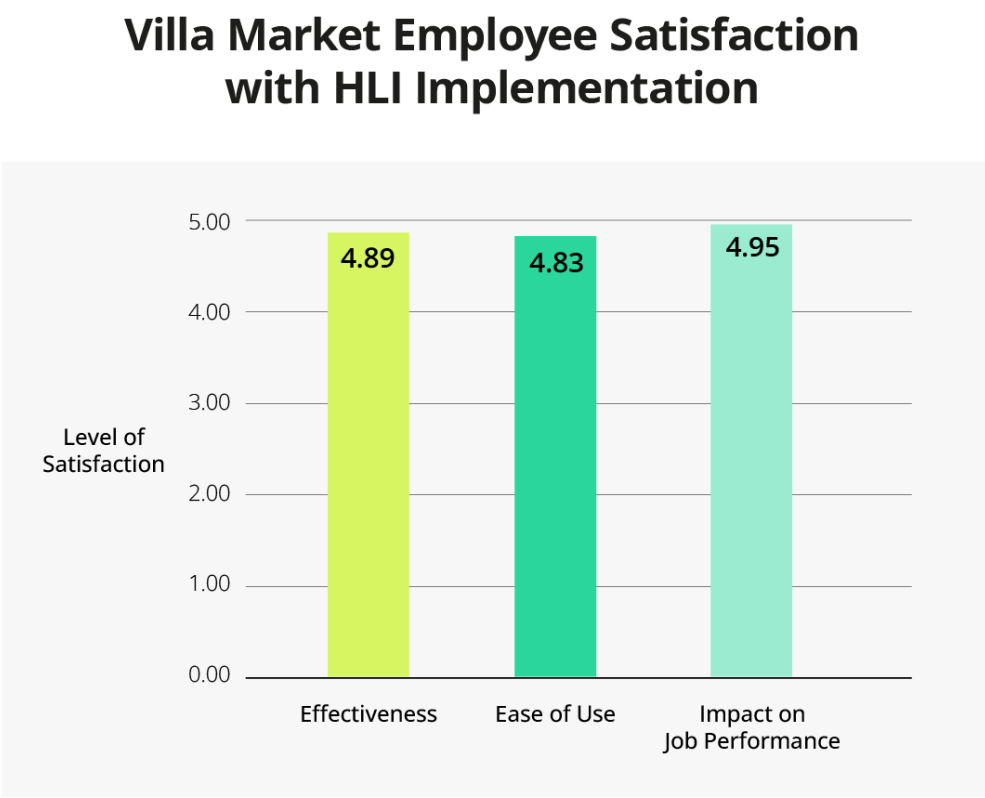


Figure 3.4 Employee Satisfaction with HLI Implementation: Effectiveness, Ease of Use, and Impact on Job Performance.

Furthermore, the advanced knowledge transfer capabilities of the Mind AI engine facilitate the seamless implementation of out-of-stock and inventory management solutions across various industries. With this technology, there is no need to start the solution development process from scratch. Instead, the process involves a straightforward cut and paste of relevant Subjects, with the option to modify the corresponding answers as needed. This streamlined approach significantly reduces the time and effort required to deploy effective solutions tailored to specific business contexts, enabling organizations to swiftly address out-of-stock and inventory management challenges without unnecessary duplication of work.

Villa Market is a bustling supermarket that serves a large number of customers, both in-store and through online platforms. However, the persistent challenge of out-of-stock items has resulted in missed sales opportunities and a decline in customer satisfaction. When customers visit the store or place orders online but are unable to find the products they intend to purchase, it creates a negative experience that may deter them from returning.

In order to effectively address the issue of out-of-stock items and maintain a strong customer relationship, Villa Market recognizes the importance of implementing HLI as a fundamental tool in their operations. By harnessing the combined power of HLI and CAI, Villa Market aims to not only resolve out-of-stock issues but also enhance overall customer service and satisfaction. Ensuring that customers consistently find the products they are looking for will help minimize customer churn and provide an exceptional shopping experience. The three field tests conducted have yielded several significant benefits, including a substantial reduction in SKUs, cost savings, a 100% accuracy rate, and high levels of employee satisfaction among the Villa Market team. Through the utilization of HLI and CAI, Villa Market is committed to overcoming out-of-stock challenges and delivering a flawless shopping experience to every customer, thereby ensuring their continued satisfaction and loyalty.

3.2 Smart Farming: T- Ecosys' Expert Advisory

Initiation and background

T-ECOSYS is an industrial digital platform business under the cooperation between PTT and the Ministry of Industry, together with the Industrial Estate Authority of Thailand, the Board of Investment (BOI), and financial institutions. It is an ecosystem for service providers and customers who want access to robotics, automation systems, and digital technologies through the Industrial Digital Platform (IDP) developed by PTT, a Thailand state-owned SET (Stock Exchange)-listed oil and gas company.

The company's mission is to drive Thailand's industries with a technology-integrated ecosystem in order to achieve sustainable excellence. Core to the company are 4 major visions:

- Develop a platform to support the creation of the industrial ecosystem by linking the needs of digital service providers to the industrial sector, government entrepreneurs, and financial institutions
- Be a center for analyzing and synthesizing insights, consulting, thus providing industry expertise across Thailand
- Raise the potential of digital service providers to the industrial sector through the use of automation and digital technology

- Create service standards in the industrial sector and through transparency, include raised service standards in other sectors

In Thailand, small and medium enterprises (SMEs) play a very important role in the country's economic direction. Data in 2021 from the Office of Small and Medium Enterprises Promotion (OSMEP) indicated that Gross Domestic Product (GDP) of SMEs is worth 161M USD or 34.6% of the country's GDP.[3] Developing and supporting SMEs has therefore been taken as an issue by T-ECOSYS, as SMEs' contribution to the economic development of Thailand affects the quality of life of the Thai people.

Agriculture accounts for 30% (13 million) of Thailand's labor force and is the country's main industry. Rice is the country's most important crop – employing 60% of its 13 million (7.8M) farmers – and is the chief agricultural export with a share at about 17.5% of a 34.9B USD total. However, most Thai farmers and farm operators are elderly and lack the knowledge in accessing information and benefits available to them, causing low productivity and high cost of production.

The above data gave birth to the project, "Development of Innovation in Small and Medium Business Organization – Diagnosis System on Digital Platform: Agriculture and Food Industry." It is a business enterprise diagnostic system that assists farm operators evaluate their own businesses.

Advisory services equip farmers and farm operators with adequate knowledge to prepare for challenges and with critical information to ensure they can make effective decisions in implementing the most tailored changes. For T-ECOSYS, if major issues for rice production can be solved by an Advisory AI, the same approach can be applied to other sectors of Thailand's other industries, such as the sugar sector, which is the next scope of the project.

AI technology was introduced as part of the development of digital tools to help assess the needs and problems of rice farmers by analyzing the root cause of business problems and extending to consulting so they can consider appropriate and sustainable solutions. Mind AI was selected for its reasoning engine, its solutions developed specifically for the Thai language, and its ability to verify the correctness and origin of various logics used to achieve accuracy and reliability.

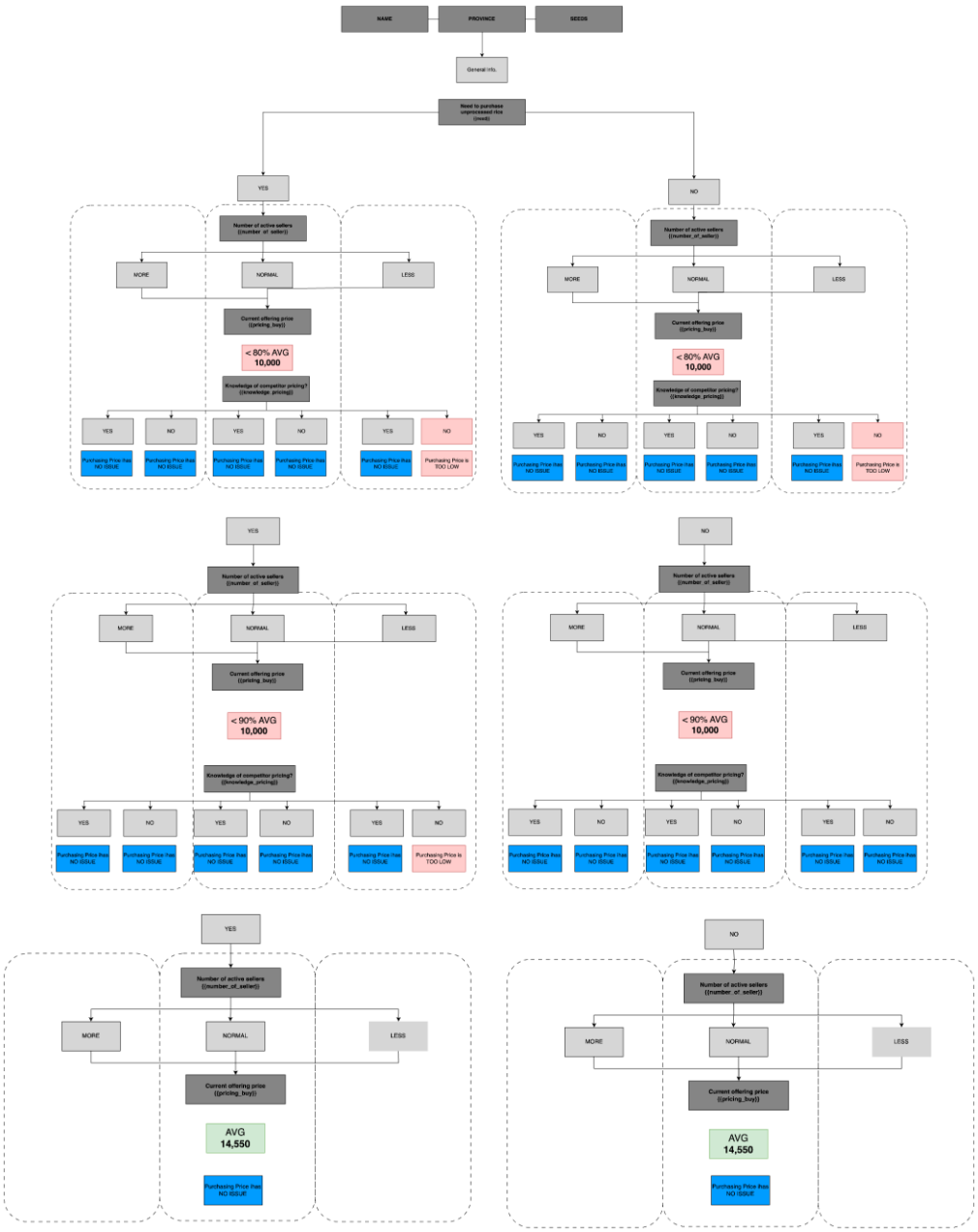
Experimental Study and Integration

Partnering with the Chulalongkorn University, Mind AI began collecting the Subjects and Conversation Flow designs. These consisted of problem statements, user details and inputs needed, and desired responses for every query. Unique contexts were created by the Linguists to allow Mind AI's reasoning engine to recognize every component of the problem in Thai. AI Operations configured these on Mind Expression to simulate the natural exchange of information between end-users and the AI Advisor, a process that took 6 business days to complete.

Solutions to the 8 most common issues of rice farmers were shared by T-ECOSYS in the form of tables and flowcharts. Some example issues are:

- Am I buying unmilled rice for too low?
- Is my electricity cost too high?
- Why is my company not earning?

AI Operations designed IF-ELSE relationships for every situation while creating representative structural outlines of every logic needed, including required mathematical formulas to achieve the exact advice for every unique scenario of end-users as shown on Images 1 to 3:


NAME
PROVINCE
SEEDS
General info.
Need to purchase unprocessed rice ({need})
YES
NO
Number of active sellers ({number_of_seller})
MORE
NORMAL
LESS
Current offering price ({pricing_buy})
< 80% AVG
10,000
< 90% AVG
10,000
AVG
14,550
Knowledge of competitor pricing? ({knowledge_pricing})
Purchasing Price Has NO ISSUE
Purchasing Price is TOO LOW

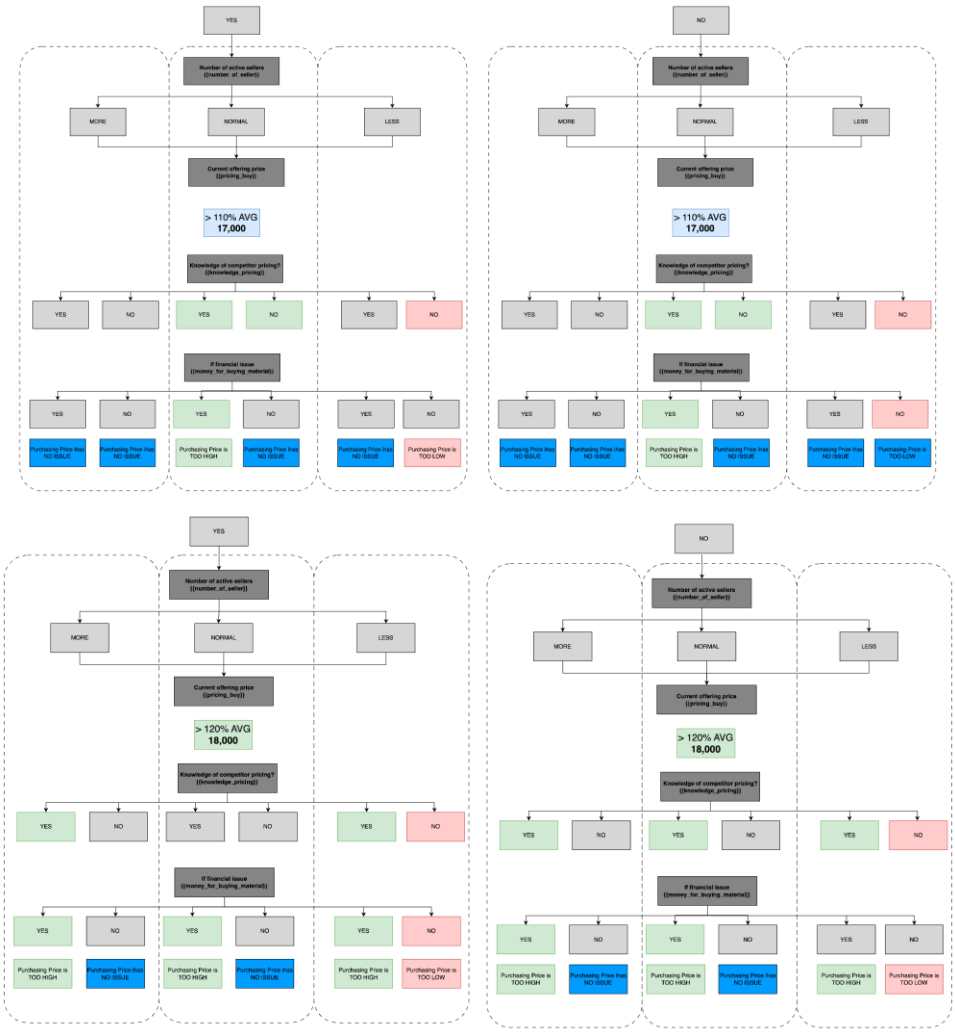


Figure 3.5 Diagnosis of "*Am I buying unmilled rice for too low?*" showing the 5 scenarios used. It starts by gathering general information (i.e., Name of the rice mill, Province, Seed type) and proceeds by asking if purchasing unmilled rice is needed. The average provincial price for the unmilled rice is provided as guidance and the end-user is asked of their offer price. Depending on the answer, HLI advises if the intended offer price is low, good, or high.

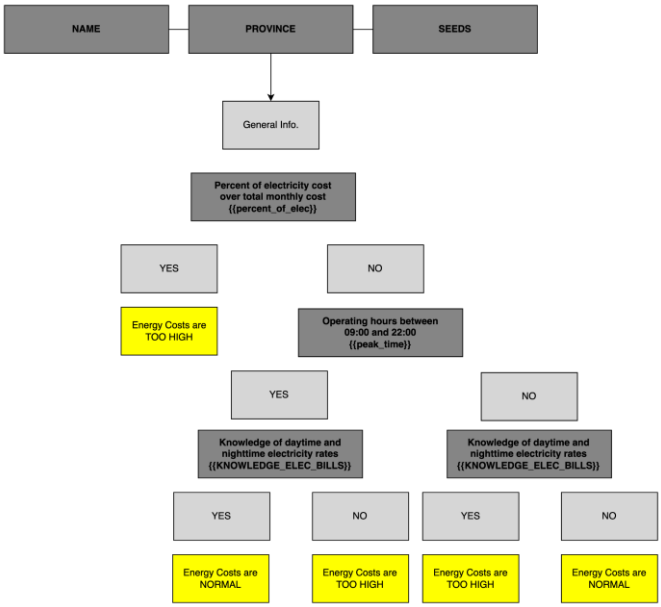


Figure 3.6 Diagnosis of "*Is my electricity cost too high?*" starts by gathering general information and proceeds by asking if electricity expenses accounts for more than 20% of the farm's total expenses (electricity cost + employee salaries). It continues by asking for the operating hours and if the end-user is aware that electricity costs are lower at night time and weekends. Depending on the answer, HLI suggests 4 methods to reduce electricity costs.

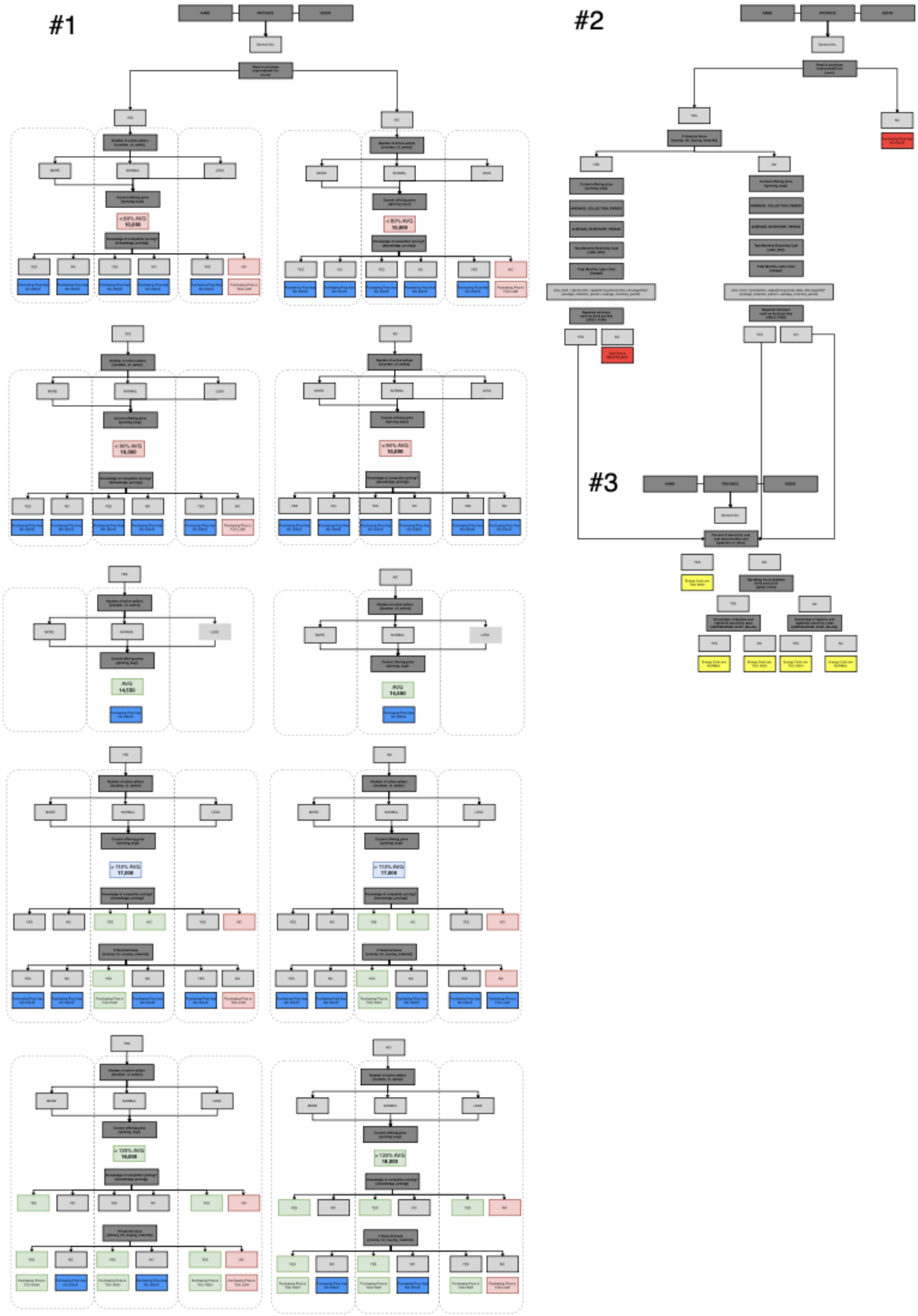


Figure 3.7 Diagnosis of "*Why is my company not earning?*" shows the dependency of the issue with multiple information gathered from 2 previous diagnoses (Images 1 and 3). Here, the sequence of diagnosis begins with the price for unmilled rice and ends with the electricity and labor costs.

However, because these details have already been gathered, the diagnosis no longer needs to ask the same questions and instead, proceeds to ask for the collection period and inventory period before proceeding to calculate the necessary operating expense (Cash on Hand). Depending on the end-user's response, HLI suggests 5 methods to solve cash flow problems.

By being able to iteratively test simple, nested, and complex logic relationships through Mind Expression's Sandbox real time (Image 4), 'wastes' in the processes were revealed and eliminated, resulting in a lean logical representation of all 3 issues and solutions (Image 5). This took 3 business days to complete.

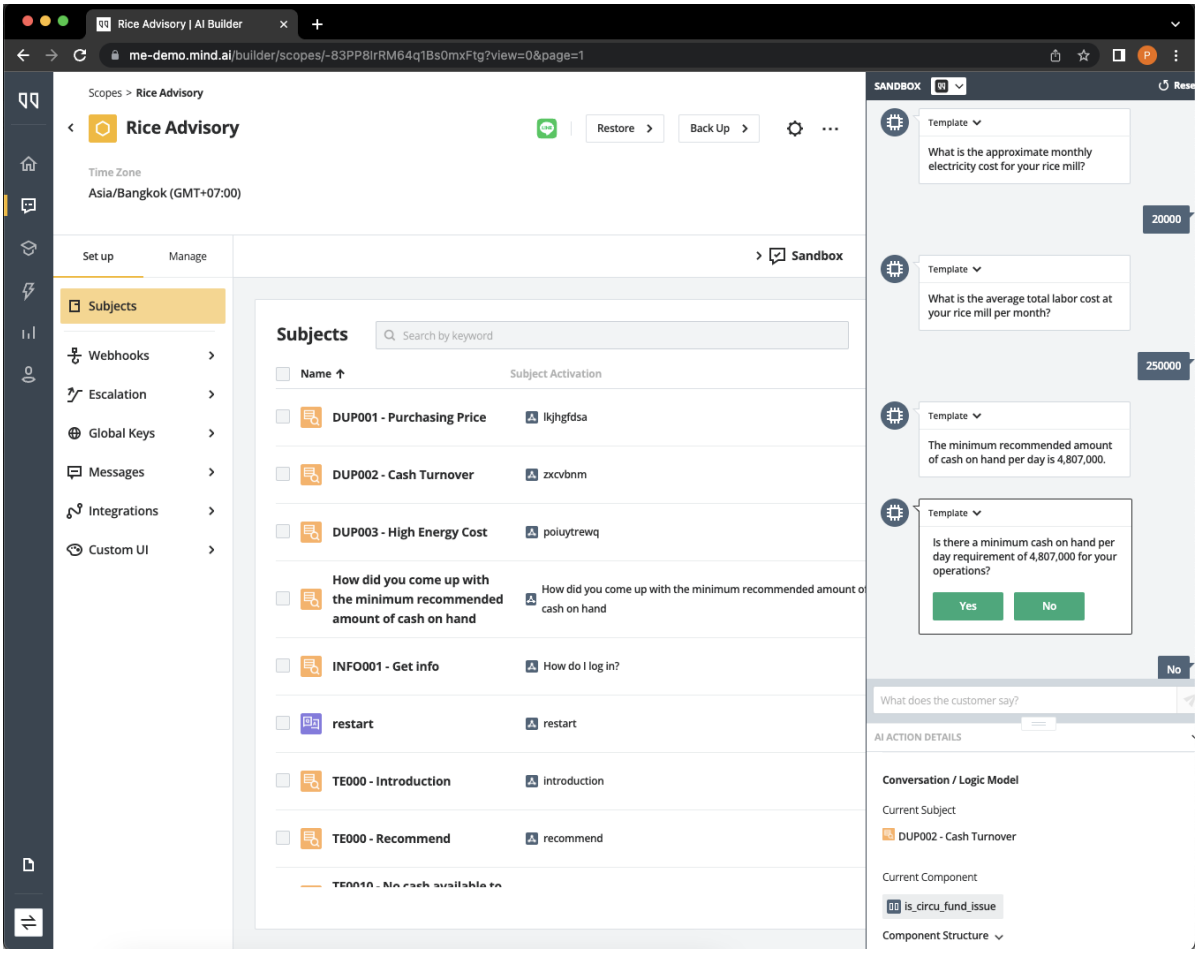


Figure 3.8 Mind Expression's Sandbox allows designers to see how conversations are carried out and logic statements, including mathematical formulas, are executed. Here, to arrive at the required Cash on Hand amount, the formula provided for "circu_fund" = ((production_capacity*avg price)+((elec_bill+wage)/30))* (average_collection_period + average_inventory_period) was executed accurately

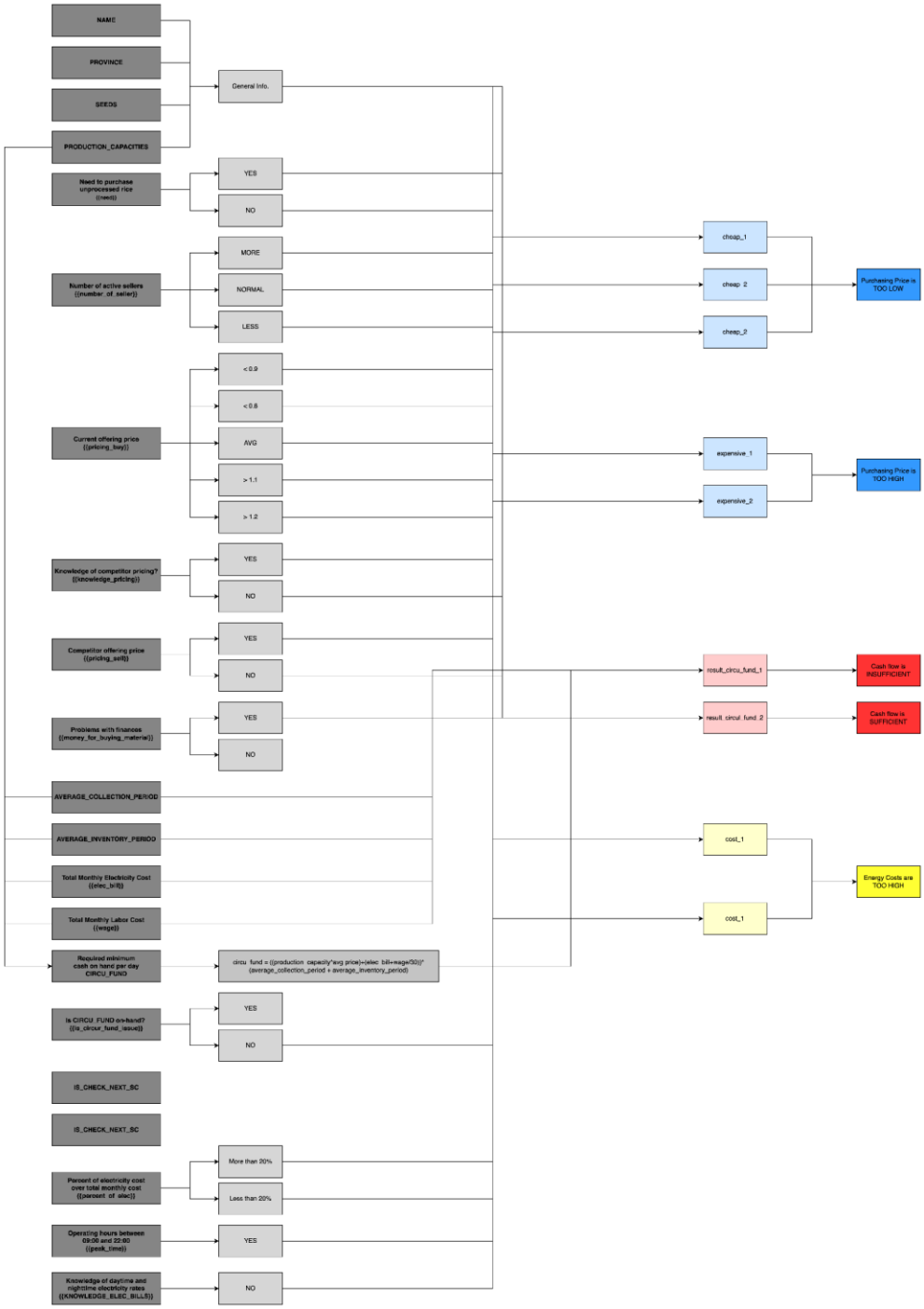


Figure 3.9 Lean decision tree for Issues 1 to 3 designed by Mind AI, with repetitive processes eliminated.

Mind Expression's ability to process complex logic is both convenient and superior. Implementing the exact processes of human logic in the same platform used to create a human-like conversation with end-users eliminates the need for third party applications to make a CAI powerfully functional (Image 6).

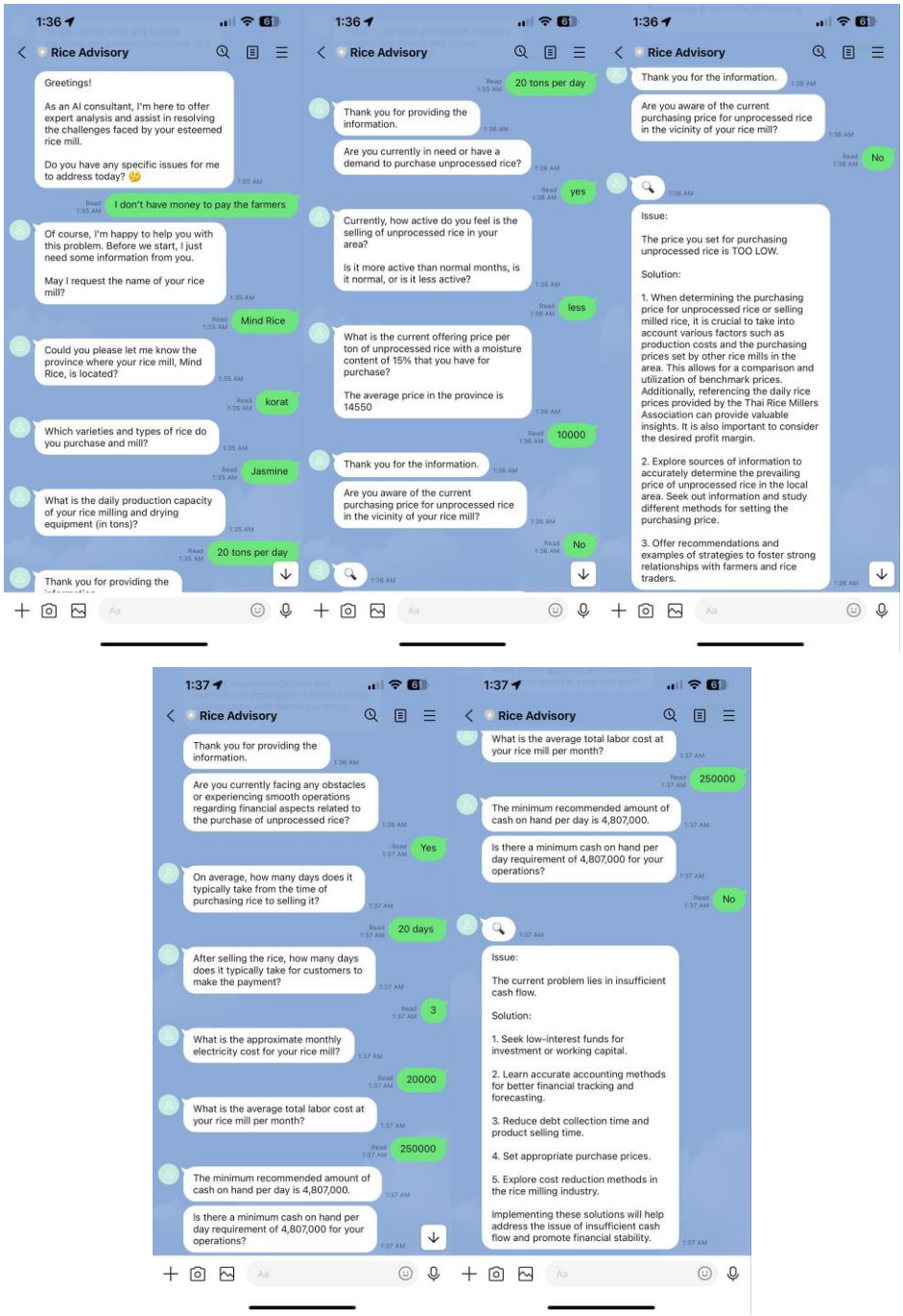


Figure 3.10 Mind AI's Expert Advisory in action: how troubleshooting a complex issue ("*I don't have money to pay the farmers*") is done on a Line-integrated T-ECOSYS Smart Advisor. Mind AI can also integrate with other front-end messaging systems.

Explorative Analysis

In test meetings with T-ECOSYS executive leadership (3 members) and Chulalongkorn University, the Expert Advisor was individually tested to a unanimous approval on the following areas:

- ability to make a successful diagnosis, including users not being stuck in the diagnosis
- accuracy of diagnosis and problem summary
- ease of use
- usefulness of the recommendations or of alternative solutions

Using a 5-point scale (1 - lowest, 5 - highest), the ratings were as follows:

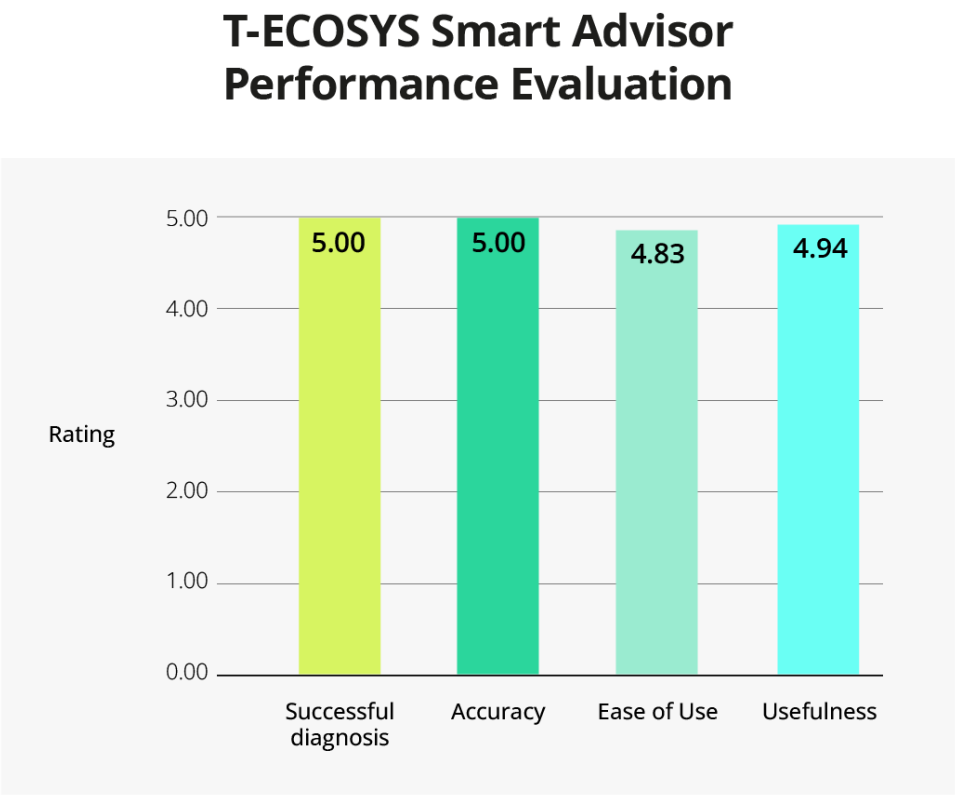


Figure 3.11 Employee Satisfaction with HLI Implementation

This will be followed by a series of field tests with rice mill operators and diagnostic experts to collect feedback, suggestions, satisfaction, and issues encountered. The results of such field tests will help improve the Expert Advisor prior to actual implementation.

T-ECOSYS is currently working on an implementation timeline to roll out the project initially to Northeastern Thailand. However, because the project is only on its first version, a Future Plan has been created to address its current limitations including:

- Adding 4 more types of questions in the diagnostic system, including (1) questions asking about symptoms to find potential problems, (2) questions to find out the root cause of the problem, (3) questions to collect new knowledge from users, and (4) questions to get feedback and user reviews
- Improving and adjust the flow of diagnostic questions for returning users
- Completing the database structure required in the system as T-ECOSYS gains domain expertise
- Adding more suggestions and referral sources
- Developing an identity verification system

Using the right AI for the Expert Advisor project is key, as it not only furthers T-ECOSYS' mission and vision, but it also provides Thailand a superior model that can be replicated and applied to other industries. An all-human Advisory group solution would have taken 123 full-time equivalent (FTEs) at a cost of USD 234,930/month (USD 2.819M/year) to be able to answer just 1% of the 7.8M farmers' monthly queries. This is based on the 2021 average monthly salary of a Thai business process outsourcing (BPO) employee at USD 1,910.

% Queries	Monthly Volume	Staff Needed	Monthly Cost	Annual Cost	Queries not answered in 20 seconds
1%	78,000	123	USD 234,930	USD 2.819M	15,600
5%	390,000	591	USD 1.129 M	USD 13.546M	78,000
10%	780,000	1,235	USD 1.452M	USD 17.428M	156,000

Table 3.1 Cost projection of a similar Advisor solution done through a BPO showing exponential staff and investment required to address increases in monthly inquiries. Standard assumptions used: 10-minute handling time, service level of 80% answered in 20 seconds, and occupancy of 85%.

Table 3.1's projected costs come with several issues which Mind AI's Expert Advisor easily solves:

- Scalability - the time to hire, train, and seat new employees is tedious and costly; the Expert Advisor is a one-time setup
- Availability - the model accounts for a standard staff shrinkage of 12%; the Expert Advisor is available 24-7
- Quality of service - human advisors take 6-12 months to achieve mastery; the Expert Advisor provides consistent recommendations immediately upon launch

T-ECOSYS' commitment to drive Thailand's industries with a sustainable technology-integrated ecosystem is fully supported by Mind AI's CAI + HLI solution. Implementing the Expert Advisor that demonstrates Mind AI's ability to completely replace humans-in-the-loop is a cost-effective and scalable solution. Its design and implementation can seamlessly be transferred to other industries, thanks to its inherent knowledge transfer capability. It has a proprietary Thai language pack to support any form of conversation with the intended Thai audience, and most importantly, it is able to perform complex diagnosis and recommend the most updated solutions, thus ensuring consistent and reliable advice is provided to its users. As the Expert Advisor continues to evolve, Thailand's farmers and farm operators' productivity is expected to improve, extending its impact to the country's share in the global rice export market, where at 21%, is currently only second to India's 25.2%.

4. Conclusion

The experimental studies of Villa Market and T-ECOSYS highlight the significant impacts of implementing HLI+CAI in their operations. These companies successfully replaced humans-in-the-loop with HLI+CAI, resulting in enhanced operational efficiency and achieving a remarkable 100% accuracy level. Both companies perceived the system as highly effective and easy to use.

However, the case studies also revealed certain limitations and challenges. T-ECOSYS faced difficulties in creating standard processes and recommendations due to the extensive data gathering required from farm operators who were not always knowledgeable and available. Similarly, Villa Market encountered the initial challenge of manually mapping out the decision-making process for their flowchart, which was time-consuming for their experts.

To overcome these obstacles, Mind AI's Science department is actively developing Literate Intelligence (LI). The beta version of LI is projected to be deployed by the fourth quarter of 2023. LI is a natural language reasoning system that reads, understands, and comprehends texts to perform correlation and causation. With LI, businesses can input their manuals and related documents, and LI will generate and recommend flowcharts based on the provided content. The crucial aspect of LI is its ability to disclose and explain the reasoning behind its conclusions, allowing experts and developers to identify false relations and make real-time logic adjustments.

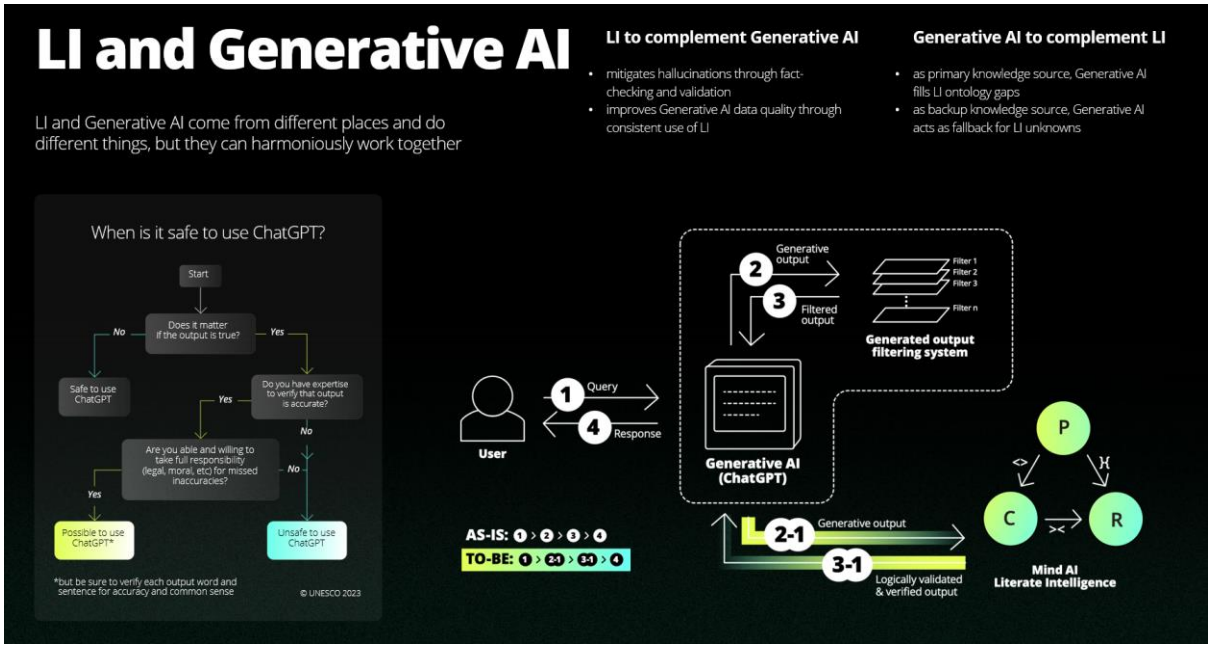


Figure 4.1 LI and Generative AI

The application of these case studies can be extended to virtually any industry that requires hyper-automation of complex processes through an Advisory and Recommendation platform. In the Food and Agriculture sector, Mind AI's solutions can be immediately implemented in areas such as Raw Material Management, Supply Chain Optimization, Food Processing and Packaging, and Smart Farming.

With Mind AI's neo-symbolic, natural language reasoning model, businesses and services in the Food and Agriculture sector can transition their decision-making processes to AI, enabling hyper-automated and human-like conversations through the combination of Human Logic Intelligence and Conversational AI.

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Abstract

This explorative study delves into the dynamic and rapidly evolving market of AI driven Business Process Automation (AI -BPA) and Expert Advisory Systems (EAS) in food and agricultural sector through implementation of technology and software solutions to streamline and automate various repetitive and time-consuming tasks within an organization using a new approach known as the Neo-Symbolic AI. With the relentless pursuit of efficiency, cost reduction, and improved productivity, businesses across industries are increasingly turning to AI driven BPA solutions (AI -BPA) and Expert Advisory Systems (EAS).

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