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Natural, Artificial & Synthetic Intelligence: A Conceptual Discourse

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Abstract: Why do biological systems appear to produce adaptive, intelligent decisions using vastly less energy and computation than modern AI systems? Neural network based Artificial Intelligence can be conceptually described as the interrogable compressed human knowledge that is implemented on vast amounts of computational capabilities. The goal of this paper is to propose a conceptual approach to low computational models for machine-based intelligence. Based on the review of Natural Intelligence and Artificial Intelligence, Mental Activity can be deconstructed into Physical Cognition, Emotional Cognition, Mental Cognition, and Intelligence. A syntax-free Semantic Information which requires a goal-relative semantic concept of information (not the powerful Shannon's Information for communication theory, compression, and uncertainty reduction) is used to construct knowledge structures that are related by their semantic information. Neither is it Transformers that are dependent on language syntax to *infer* semantic information. This paper proposes that one reason biological intelligence appears computationally efficient is that it operates through structured semantic knowledge domains rather than through brute-force syntactic or statistical search. Asymmetric Information Resolution (AIR) Models are presented as a candidate architecture for such semantic decision structures. This paper provides a simple Predator-Prey knowledge structure to illustrate the versality of AIR Models. The surprise is that modern AI is based on mathematical theory of networks and not on a theory of knowledge or decision theory, but it works.

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I. INTRODUCTION

How can one improve machine-based intelligence? For starters, by identifying conceptual weakness and when possible, propose conceivable solutions. This is attained by (i) That there are different types of Cognitions with a constrained definition of Intelligence. (ii) Proposing that a common communications protocol is necessarily required for these different brain functions to seamlessly and synergistically work together. (iii) Thus, requiring a careful redefinition of terms. It is about modeling mental activity as a whole rather than cognition or intelligence. (iv) Knowledge cannot be sufficiently defined by syntax.

This paper proposes alternative paradigms to modeling mental activity, usually referred to as intelligence, by deconstructing current theories, evolutionary findings, using knowledge relationships (Knowledge Constructs) and decision theory. The approach in this paper is to review Natural Intelligence (NI) and Artificial Intelligence (AI) and then propose a *new* definition for Synthetic Intelligence (SI) that is based on Knowledge Constructs, while the current definition of Synthetic Intelligence, Lark Editorial Team [1], still requires machine learning and deep learning techniques. This paper proposes that one reason biological intelligence appears computationally efficient is that it operates through structured semantic knowledge domains rather than through brute-force syntactic or statistical search. Asymmetric Information Resolution (AIR) Models are presented as a candidate architecture for such semantic decision structures.

It is necessary to model living organisms as *bio*logical automa*tons* (or biotons) in order to sidestep the issues of sentients, consciousness and awareness, for now, though this paper touches on the latter two, to provide a consistent conceptual basis. Even though mimicking biological structures can probably lead to more rapid advancement in the science of modeling mental activity, this paper presents an conceptual basis rather than a physical one, to model mental activity that is based on the structure of knowledge. The hope is that as observed in Nature, Newen & Montemayor [2], this will lead to many different types of physical models for intelligence.

The key concepts proposed are (i) Mental Activity can be deconstructed into Physical, Emotional & Mental Cognitions and Intelligence. (ii) This lends itself to a narrowed, manageable definition of Intelligence as the application of these three types of Cognitions to deliver sustainable decision-making while the decision context is valid, given a specific goal i.e. intention. (iii) Knowledge is a structure of information. (iv) There is, necessarily, a common communications protocol between the many different and distinct parts of the human brain for the human brain to function seamlessly. (v) Semantic Information is not the same

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as Shannon's Information. While both are correct, these operate in different domains.

This paper can be loosely categorized into 4 sections, A Structure of Knowledge, Natural Intelligence, Artificial Intelligence and Synthetic Intelligence. In 'A Knowledge Structure', this paper introduces cautions that are necessary to avoid pitfalls. For example, Semantic Information is not the same as Shannon's Information. In Natural Intelligence, this paper examines current brain research to infer additional properties required for the different human brain functions to operate seamlessly and synergistically with each other. Much of this research is bottom-up. In the Artificial Intelligence section, this paper examines how Artificial Intelligence developed over time (its history) to infer the nature of the AI, particularly neural nets, Deep Blue & Deep Mind. In Synthetic Intelligence, this paper proposes, a top-down approach for a *new* definition for Synthetic Intelligence (that is not related to neural networks) and how it can be constructed, and why, like the human brain, it is a low computation platform for decision-making.

II. A KNOWLEDGE STRUCTURE

These five cautions inform one that knowledge modeling requires a different approach.

➢ *Soundness:*

Bear in mind that mathematics, Klein [3], has become so sophisticated that it could be used to prove anything. That is, mathematical theorems are only as good as the validity of their *implicit and explicit* axioms they are based on. A change in any of these axioms can produce many more theorems (Riemann Geometry branching off from Euclidean Geometry, Mittelstaedt [4]) or a negation of all related theories (Rayleigh–Jeans law, Nave [5]).

➢ *Blind Spots:*

A blind spot is when mathematical formulae cannot be solved in a formulaic analytical manner. For example, non-integrable formulae. The work around requires numerical integration to determine a solution if one exits.

➢ *Syntax:*

Searle [6] proposed that a 'machine' that uses rules to provide answers to questions are inference engines. From this, one can infer that all mathematics and written languages are the two most important forms of syntax – very powerful but rule based. One could make the case that words are compound symbols aggregated from simple symbols. That there is generally (not always) a one-to-one relationship between English compound symbols or words, and for example, to individual Mandarin characters. Thus, English words are still symbols. Therefore, symbolic manipulation, whether written mathematics or written languages, require their own versions of syntaxes to produce a linear sequence of symbols that can be understood by an informed reader. Furthermore, mathematics and human languages are context sensitive. Mathematics is dependent on the context of it implicit and explicit axioms and its particular field of study, while languages are dependent on the context of life experiences.

➢ *Incompleteness:*

Gödel's Incompleteness Theorems, Wolchover [7], "…established that no formal system of mathematics — no finite set of rules, or axioms, from which everything is supposed to follow — can ever be complete. There will always be true mathematical statements that don't logically follow from those axioms." This theorem cautions against assuming that formal symbolic systems can be fully grounded in their own truth conditions. By analogy, a model for intelligence that relies only on syntactic manipulation may fail to account for semantic grounding, context, and goal-relative meaning. This paper therefore treats syntax as useful but insufficient. This is confirmed by the fact that many types of human language syntaxes refer to the same knowledge descriptions, a many-to-one relationships. That is, the key is to first construct a model for knowledge, and then translate syntactically into language and not the other way around.

➢ *Emergence:*

Emergence is how new properties emerge from older properties. Solomon [8] proposed 7 requirements for true Emergence, New, Stimulus, Resemblance, External Factor, Form, Inheritance & Reversion which is different from that found in survey of the literature on Emergence, Lichtenstein [9]. The aim is to design systems that can exhibit true Emergence.

Emergence and Synergy are different. The common parlance or classical definition of synergy is that the "whole that is greater than the sum of its parts", without clarifying how 'sum' is realized. However, 'aggregation' would be better description for 'sum'. This 'aggregation' is dictated by the stimulus. Given the Parts P_i, the Synergistic Whole W_S, a formalism (not a proof) to describe Synergy is,

$$W_S > \Sigma_i \mathrm{P}_i \qquad \text{Synergy} \qquad (1)$$

If (1) is not true, i.e. (2), then there is no synergy. For example, (2) is Group Activity not Teamwork.

$$W_S = \Sigma_i \mathrm{P}_i \qquad \text{No Synergy i.e. Group Activity} \qquad (2)$$

If neither (1) or (2) is not true, i.e. (3) is true, then a Burden is present,

$$W_S < \Sigma_i \mathrm{P}_i \qquad \text{No Synergy i.e. Burden} \qquad (3)$$

Emergence is evident when whole W_E is *different* from the sum of its parts, Ritchie & Tucker-Drob [10],

$$W_E \neq \Sigma_i \mathrm{P}_i \qquad \text{Emergence} \qquad (4)$$

And if (4) is not true, i.e. (5), then there is no emergence. It is a collective process,

$$W_E = \Sigma_i \mathrm{P}_i \qquad \text{No Emergence i.e. Summation} \qquad (5)$$

That the aggregation does not have to be better or worse than what was previously there, but it is noticed when the emergence is evident.

It is proposed that Synergy is a necessary condition for Emergence. For example, the wheels provide rolling motion, the transmission transfers the engine power to propel the wheels, the engine converts chemical energy into mechanical motion and the steering wheel provides directional change. All these different properties must work synergistically for Mobility to Emerge. In other words, the new property, Mobility, emerges from the specific aggregation of the existing properties by a stimulus, the specific manner by which all the electrical and mechanical parts are assembled to build a *working* car.

Solomon's proposed [8,11 & 12], that to build a model for knowledge necessarily requires a structure for data, information, knowledge, and wisdom,

- *Data:*

Data D_i are apparently random factual bits (such as measurements or statistics). A good example are Test yields in a semiconductor Assembly/Test operation producing thousands of lots, each with unique test yields.

- *Semantic Information [11]:*

As opposed to Communication Information of Shannon's Law [13]. Shannon information is powerful for communication theory, compression, and uncertainty reduction, but it is not sufficient by itself to model semantic decision-making. For example, Sarah sends Jane, the message that Betsy gave birth to six. The obvious semantic (1^{st} order) is that Betsy had six. The meaning behind the meaning (2^{nd} order) requires a shared context between Sarah and Jane, that (a) Betsy is Zoe's female dog that gave birth to six puppies, and (b) Zoe had taken good care of Betsy. Shannon's Communication Information does not provide for this, as there is hidden information, Zoe is Betsy's owner, and hidden variables, e.g. number of participants, in this message. This paper requires a goal-relative semantic concept of information. Semantic Information [11] R_j, given a set of data, D_i, transformation, Δ_k, and goal, G_l, is given by,

$$R_j = \Delta_k\{D_i\}|G_l \quad \text{Semantic Information Rule} \qquad (6)$$

The transformation, Δ_k, can be *any function* that operates on data and will change on case-by-case basis. For example, in an Assembly/Test operation it a descending order sort of the data D_i, by bonder with worst to best test yields. The intention is to solve the test quality problems. The goal, G_l, is to find the top few worst bonders that are producing low Test yields. The goal, G_l, is a critical requirement, as without a goal, any transformation of the data is purposeless. In this case R_j is an exception report with unwanted data removed, filtered out, by this analysis. Similarly, in animals, this is a possible conceptual approach to how the brain removes all distracting data to focus on only the important details. In this paper the term 'Information' shall represent Semantic Information and not Shannon's.

- *Knowledge:*

Knowledge Constructs[i], Solomon [11], use knowledge relationships to connect knowledge elements, to facilitate decision making. More in a later section. Knowledge elements are basic representations of knowledge which cannot or should not be reduced further, for example, knowledge elements can be categorized, Solomon [12], as states, factors, barriers, and migration strategies depending on how the knowledge model is constructed. They do have scalar-like and vector-like properties, however, more research is required. Knowledge relationships are concepts that are associated with knowledge elements and are related to, by meaning but not syntax. Fig. 1 depicts a Framework for Asymmetric Information Resolution (AIR) Models, Solomon [12]. Two AIR Models have been built. The Strategy AIR Model (Holistic Business Model) consists of 14 Frameworks while the Financial Risk AIR Model (not published) consists of 20 Frameworks. A complete AIR Model consists of Maps, and Maps consists of Frameworks. These are multi-player models. See Solomon [12] for a detailed explanation. Fig.1 demonstrates a knowledge structure that is bound by the semantic relationships of factors, co-factors, barriers, transitions and states. This is syntax-free as the relationship between symbolic representations of concepts are not bound by one dimensional symbolic dependent parsing but by two dimensional semantic relationships, i.e. can be immediately transliterated into any language words independently of their syntax.

- *Wisdom:*

This is the path [12] taken in the multi-step decision-making process to reach a best if not a consistently good outcome over many decision-making steps.

In summary, Emergence is not magic. All that is required is that at least some of the existing properties participate in the new property emerging given a stimulus that determines exactly how the aggregation is conducted. This provides the means to designing Emergent Systems supported by clear definitions of data, semantic information, knowledge & wisdom.

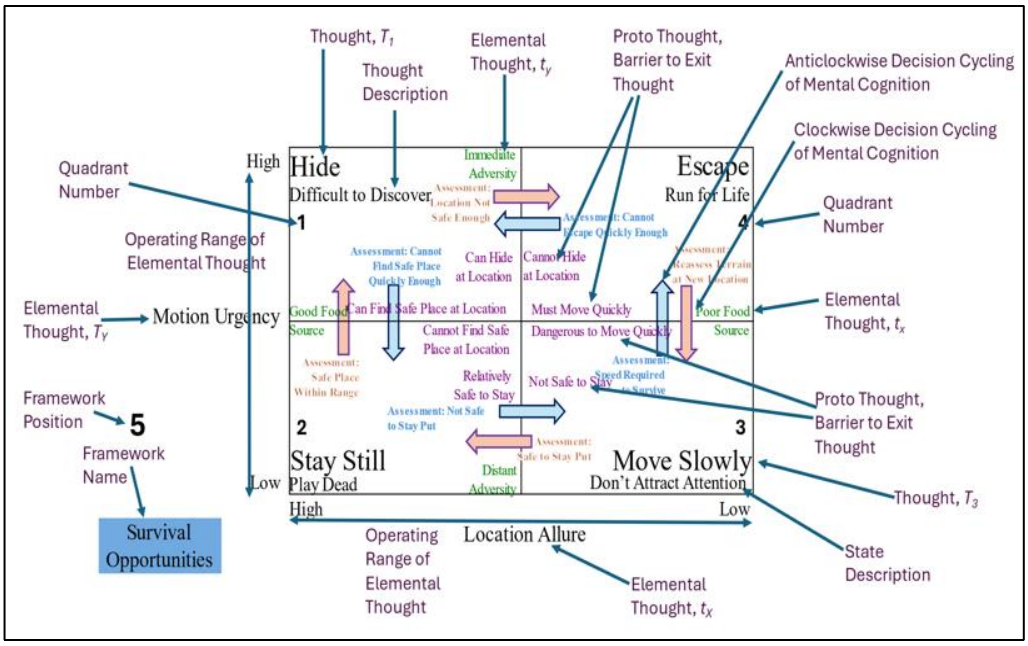

Fig 1 Basic Framework for Decision-Making.
Source: Solomon [12]

➢ *Evolution of Natural Intelligence:*

Natural Intelligence evolved over hundreds of millions of years consisting of 5 transitions as proposed by Ginsburg and Jablonka [14],

- Learning in non-neural animals to learning in the first neural animals.
- Animals showing limited, elemental associative learning, entailing neural centralization and primary brain differentiation.
- Animals capable of unlimited associative learning. . . constitutes sentience and entails hierarchical brain organization and dedicated memory and value networks.
- Imaginative animals that can plan and learn through selection among virtual events.
- Human symbol-based cognition and cultural learning.

Ginsburg and Jablonka [14] discovered that different types of brain structures are added to previous ancestral brain structures to enable progressively more sophisticated mental activity. Some of these brain structures are almost fully present in childhood, Hiershe *et al* [15]. That is, the more sophisticated the mental activity exhibited, the more sophisticated the brain structure evident.

Using humans and lions as an example to illustrate, ancestral human brain development accelerated with an increased meat diet, Bragazzi *et al* [16], but lions did not. That means other factors were required for the evolution of mental activity. A bioton's physical structure suggests one possible reason. The lion is limited by its physical structure to engage with its environment in a specific manner. Therefore, there is little reason for a lion to substantially evolve sophisticated mental activity comparable to that of a human. Humans, on the other hand, have "unlimited associative learning" with respect to its environment, to the point where humans can and have altered their environment.

The question that needs to be answered is, how does Awareness emerge from Natural Intelligence? Is it the brain structure that acts as the Stimulus for Emergence? Like the earlier Mobility example, Ginsburg and Jablonka [14] suggest that this maybe the case, that at least a minimum type of brain structure facilitates the Emergence of Awareness. The term Awareness is used instead of Consciousness, as it is easier to define. Meriam Webster defines Awareness as "the quality or state of being aware, knowledge and understanding that something is happening or exists", and Consciousness as "a: the quality or state of being aware especially of something within oneself & b: the state or fact of being conscious of an external object, state, or fact". That is, Awareness is a necessary condition for Consciousness.

Summarizing, Natural Intelligence evolved over millions of years by developing specialized brain parts in response to new and different needs of the evolving environment that included many other participants.

➢ *Cognition Versus Intelligence:*

Merriam-Webster defines cognition as conscious mental activities: the activities of thinking, understanding, learning, and remembering. Ginsburg and Jablonka [14] uses cognition interchangeably with intelligence, referencing Shettleworth [17] "'the mechanisms by which animals acquire, process, store, and act on information from the environment. These include perception, learning, memory, and decision making".

Unlike Ginsburg and Jablonka [14] or Shettleworth [17], this paper proposes an alternate hypothesis, that cognition and intelligence are different. This deconstruction, presented here, proposes that cognition is the mechanisms by which animals acquire, process, and store information from the environment while the mental activity of Natural

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Intelligence, of biological and evolutionary origins, is defined by 5 main characteristics,

- *Core Purpose:*
  The core purpose of Natural Intelligence is to make decisions.

- *Cognition i.e. Support Analyses:*
  The decision-making process is supported by the analyses of the environment. Cognition derives a set of inferences for Natural Intelligence's decision-making process to arrive at a conclusion, i.e. the Natural Intelligence selects an outcome from several possible inferences. Improvements in cognition, Ritchie & Tucker-Drob [10], does improve IQ test scores.

- *Learning Adaptation:*
  Learning is a necessary adaption to speed up subsequent decision-making processes for the specific environment. This is not Natural Intelligence in its raw form but an adaptation to suit the new environment of the specific endeavor. Thus, learning is the process of building biological information and knowledge (not data) structures that facilitate future decision-making.

- *Decision Promptness:*
  In a dynamic, conflicting, ambiguous environment, the speed of reaching the correct decision becomes critical to survival. In humans, to some degree, this is measured by Intelligence Quotient (IQ).

- *Intelligence Quotient:*
  IQ is a measure of raw Natural Intelligence as brain speed to make the correct decisions, given Physical, Emotional & Mental Cognitions while in the absence of modifying factors such as social, cultural, personality, emotional bias, study etc. with cognition impacting the IQ scores, Ritchie & Tucker-Drob [10].

As a starting point, from a systems design perspective, there are 5 good working definitions for intellectual mental activity,

- *Intelligence:*
  The ability to make sustainable decisions within a valid context, and pertinent goal in both familiar and unfamiliar environments. This definition avoids or side-steps the ethical questions of good versus bad.

- *Physical Cognition:*
  The ability to process and convert external stimuli, external to the brain, into information. Hyvärinen *et al* [18] have shown that babies are born with inherent vision capabilities (Nature) that after birth develop significantly (Nurture) over the next 12 months. That is, the human brain has specialized parts for handling different types of stimuli. Physical Cognition is equivalent to Newen & Montemayor "basic awareness" [19] or "basic arousal" [2]. Furthermore, Yang Chen *et al* [20] have proven the existence of different types of neurons in different locations of the brain.

- *Emotional Cognition:*
  The ability to process and convert emotional data into emotional information is an inference equivalent to Physical Cognition. The deconstruction of Emotional Cognition is beyond the scope of this paper.

- *Mental Cognition:*
  The ability to process and convert internal stimuli, internal to the brain, into information was demonstrated by Ilyka *et al* [21], that "in addition to being born with a set of predispositions to navigate the social world the vast repertoire of infant's social and communicative skills develops with experience within the context of interaction with other humans . . .". Mental Cognition is equivalent to Newen & Montemayor [2] "Reflexive self-consciousness".

- *Learning Adaptation:*
  The ability to build brain knowledge models from the cognitive information. It's not just about learning but about learning faster with more cognitive information and previous learning. Chevalier *et al* [22] established this, "Just like motor learning involves efficient activation of the right muscles rather than greater overall muscle activation, cognitive control development involves increasingly efficient and differentiated PFC recruitment". (PFC is the prefrontal cortex.).

- *Functioning Adaptation:*
  This inferred ability is the use of Intelligence and Cognitions to respond to both external and internal stimuli.

Physical Cognitional is a prerequisite but not the same as Awareness. To illustrate [23], the F-35s provide "situational awareness" but strictly speaking this is Physical Cognition (computers converting data into information) with *trained, informed* human pilots providing the Awareness. A better term for "situational awareness" would be "situational cognition". Therefore, returning to the question, how does awareness emerge from Natural Intelligence? One can now infer that Mental Cognition would be a necessary requirement for Awareness to Emerge.

➢ *The Necessity of a Common Communications Protocol:*

To understand Natural Intelligence, one needs to define thoughts. Watching one's thought process, one infers that word thoughts are reference concepts and ideas associated with the grammar and sound of the language one thinks in. Visual thoughts are associated with concepts. Music thoughts are associated with sound and emotions. Thoughts about smell are associated with emotions and substances (Brann *et al* [24]).

At this stage it is necessary to constrain this discussion to intellectual thoughts as Emotional Cognition is not supported by a non-trivial model for emotions. For example, Barrett [25] details how emotions transpire in the brain, but not how one would construct a definition of what an emotion is. For example, are emotions constructed from proto emotions? Thus, for starters, one possible definition for intellectual thoughts is that thoughts are ideas or concepts that engage the various part of the brain to store, recall and

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evaluate the information and knowledge within the brain. However, different parts of the brain that process different types of stimuli, but are still able communicate with each other, Hiersche *et al* [15], which necessarily implies a common communication protocol between different brain functions. Proto thoughts maybe such a mechanism.

In its very simplest form, a CPU's protocol is a 2-part mechanism that tells the CPU whether (i) to execute, for example, a 32-bit data or (ii) to get or put this 32-bit data from or to memory, respectively.

Summarizing, a sophisticated brain has many specialized centers for cognition that work with each other. This requires a common protocol between all these centers of cognition. This is an amazing achievement considering that the human brain runs at about 20 Watts, Balasubramanian [26]. In a later section, this paper proposes that memory consists of knowledge structures rather than data structures to achieve low-computational mental activity.

➢ *Key Design Concepts of Artificial Intelligence (AI) & Neural Networks (NN):*

This summary of the development of AI as NN is in part based on Singh's [27] summary so that key design concepts can be presented. This section is confined to neural networks. The history and development of networks as an approach to brain modeling is as follows,

- *1943:*

The ideal that the brain can be modeled as neural nets can be traced back to McCulloch & Pitts [28] 1943 paper, where "all-or-one" neural activity can be treated as propositional logic[ii], while providing equivalent electrical networks. However, a feedback mechanism such as feedback neurons is required.

- *1950:*

Turing [29], considers the question 'Can machines think?' and provides pro and cons to the question. In the author's opinion the most important statement is Lady Lovelace's Objection, "The Analytical Engine has no pretensions to originate anything. It can do *whatever we know how to order it* to perform". Modern neural networks break this by enabling the neural networks to learn on its own. One could say that Searle's work [6] (see section, A Knowledge Structure: Syntax, above) is an expansion of Turing [29].

- *1955:*

McCarthy *et al* [30] defined Artificial Intelligence as "…making a machine behave in ways that would be called intelligent if a human were so behaving." However, if clear definitions are required, the definition of 'Intelligence' is missing, but this is acceptable for its time, as these scientists were probing the dark to light a candle. Cumulatively, with many candles lighting up the room contributing to describing the field – a necessary requirement of science.

- *1957:*

Rosenblatt [31, 32] created the first trained network that could learn with weights, step activation. Somewhat by trial and error adding additional layers improved the results, proving the need for very large neural networks.

- *1963:*

Michie [33] demonstrated that a machine, using reinforced learning, could play Tic-Tac-Toe.

- *1969-1985:*

Hinton *et al* [34] "…backpropagation algorithm for learning multiple layers of features was invented several times in the 70's and 80's" by Bryson & Ho (1969), Werbos (1974), Rumelhart *et. al.* (1981), Parker (1985), LeCun (1985), Rumelhart *et. al.* (1985). Back propagation is an ingenious mechanism to fulfil the need for feedback but is computationally expensive.

- *1986:*

Jordan [35] presents "…a theory of serial order which describes how a sequence of actions maybe learned and performed." And recurrent and non-recurrent networks using a few neurons.

- *1990:*

Elman [36] considered time and important requirement for cognition and used a bigger network of 50 neurons.

- *2011:*

Sutskever *et al* [37] recognized that "text compression requires an understanding that is "equivalent to intelligence"" that led to MRRNs, Multiplicative Recurrent Neural Networks using thousands of neurons. Sutskever *et al* [37] concluded that "If we could train much bigger MRNNs with millions of units and billions of connections, it is possible that brute force alone would be sufficient to achieve an even higher standard of performance. But this will of course require considerably more computational power."

- *2015:*

Andrej Karpathy [38] presented the 'shocking' results that much bigger neural networks were not only easier to train but also provided much better results.

- *2017:*

Radford *et al* [39] built on Karpathy's work and discovered the sentiment neuron.

- *2017:*

Vaswani *et al* [40], proposed the first modern LLM core architecture that defines modern LLMs. Essentially, 'Attention', the Transformer approach to substantially speed up and to significantly improve the results of neural networks. Not to take away from the genius of this solution but Transformers are dependent on *non-local* associations language syntax. That is, syntax is an implicit axiom of language based neural networks. Syntax underpins knowledge, meaning, and human intelligence by the relationship between words. This hypothesis can be tested. If random words are the basis for developing Transformers, then would the Transformer technology still provide useful results? This is consistent with Poper's Falsifiability, Thorton

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[41]. If it does not, then it proves that the Transformer technology is a technique for compressing and extracting ‘intelligent’ responses to and from, respectively, the depository of compressed knowledge.

- *2019:*

Radford *et al* [42] demonstrated “that language models begin to learn these tasks without any explicit supervision”.

➢ *A Brief Introduction to Other Types of Systems*

- *Expert Systems:*

From Reddy & Fields [43] “An Expert System (ES) is defined as a subset of Artificial Intelligence (AI) with the aim to solve different difficult problems using factual expert knowledge and at times heuristics … This knowledge base is usually represented in an expert system either in the form of data or rules.” There is an overlap between data and knowledge which is different from that proposed in the section ‘A Knowledge Structure’, above. Aren’t finite Expert Systems inference engines?

- *Knowledge Representation:*

A method to represent knowledge structures using object orient programming, Kohen [44]. Fikes & Garvey [45] provide a good history of Knowledge Representation. However, even though knowledge can be classified into 6 categories, Kohen [44], (objects, events, procedures, relations, mental states, meta knowledge), there isn’t a clear definition for ‘knowledge’. This will be addressed in later section. Solomon [12] proposed a different approach to knowledge representation that is syntax-free.

One infers that the lack of progress in these types of systems (Expert Systems & Knowledge Representation) was the result of the lack of clear definitions and handling of data, semantic information, knowledge & wisdom.

Summarizing, the historical track record of neural-networks-based AI shows that neural networks are grounded on mathematical models of networks. As evident in the historical development, neural networks were developed by guided trial and error (a valid approach for fundamental research). These neural networks are neither based on a theory of knowledge nor any decision theory, but they work incredibly well. One could proffer that neural networks are a means to interrogate the compressed knowledge (as weights) to produce McCarthy’s [30] definition of ‘intelligent’ solutions.

➢ *What is a Board Game?:*

What is a game? Haller *et al* [46] provide “player studies” of broad categorization of games (educational, therapeutic and entertainment) and heuristic evaluation for the game design process. Neves & Zagalo [47] present “game studies” approach, that is “an attempt to fulfill the role of … a clear formulation of what constitutes quality in games”. With consideration to Deep Blue and Deep Mind, this paper defines a “game structure” approach to board games as a Confined Domain Space because a board constitutes a finite game playing space. Using chess as an example, a non-trivial Confined Domain Space, is proposed as having,

- *Token Rules:*

A finite set of known rules[iii] for each token (chess piece) and its transitions (chess moves). There are 6 types of tokens in chess, pawn, bishop, knight, rook, king, and queen. Each chess piece, or token, has 4 or 8 directions it can move, depending on the token (chess piece). In Go there 2 types of tokens or stones, black and white.

- *Operating Domain:*

Such that the tokens operate in a domain having a finite set of transition states. A chess board has only 64 squares or Domain Transition States.

- *Horizon:*

This is the maximum transitions states within an Operating Domain. In chess, of 8x8 squares, the horizontal, vertical, and diagonal, have a maximum of 7 transitions states or a Horizon of 7 transition States. In Go, the Horizon is 18 transitions states.

- *Domain Transition:*

The Domain Transitions express a very large number of transitions or moves. Domain Transition are many orders of magnitude (10^{120}) greater than the Operating Domain (64).

- *Goal:*

By seeking a specific desired outcome, i.e. to win, two types of goal are evident. (a) The primary goal is to end the game with a win, while the (b) the secondary goal is to stay in the game during beginning and mid play.

- *Stochastically Dominant:*

The desired outcome is facilitated by Stochastically Dominant sequence-of-transitions (e.g. chess openings or other execution rules) in a dynamic environment of more than one participant. That is, when execution (sequence-of-transitions) rules are stochastically dominant, these increase the probability of attaining the desired outcome of winning the game.

Both Deep Blue and Deep Mind required enormous computational power to be successful. Structuring as Confined Domain Space,

✓ *IBM’s Deep Blue:*

The development of what would eventually become Deep Blue can traced back to 1957, IBM Heritage [48], and culminating in the May 1997 win over Garry Kasparov, the world reigning chess champion. An amazing achievement. This was achieved with 32 processors, evaluating 200 million chess positions per second underpinned by 11.4 billion flops. The game of chess[iv] consisting of only 64 squares (Operating Domain) has 10^{120} possible moves or Domain Transition States.

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✓ *Google's Deep Mind:*

In 2015 and 2015 AlphaGo, Google DeepMind [49], beat the world champions in the Chinese game of Go. An amazing achievement. Go consists of only two types of tokens, the black & white pieces, an Operating Domain of 361 intersections and an Operating Domain of 10^{170} board configurations. AlphaGo used 180 TFLOPS, ARS Staff [50], tensor processor unit (TPU) module (no information on how many TPUs were used in AlphaGo). AlphaGo, invented by Silver *et al* [51], is "an AI system that combines deep neural networks with advanced search algorithms" using reinforcement learning, Murel & Kavlakoglu [52], – playing against itself after some initial set up – to determine Stochastically Dominant sequence-of-transitions.

Given that good chess players[v] consciously consider only 2 or 3 moves ahead. Constructing and evaluating shorter Horizon sub–Operating Domains, for example, 4x4, 5x5 or 6x6 squares or intersections does lead to Stochastic Dominance that is computationally significantly less intensive. This would more closely mimic human thought and should reduce the Operating Domain from pure permutations to some combination of permutations. This is the genius of AlphaGo, by using "... value networks, policy networks ... trained by a novel combination of supervised learning, and reinforcement learning..." Silver *et al* [51], AlphaGo reduced the computational permutation problem to computationally significantly less intensive to some combination of more valuable permutations.

➢ *Thus, there are Two Necessary Considerations*

- Does size indefinitely improve AI results? Table 1 presents some statistics about ChatGPT. If results improve linearly with size, then more is better, but there is only so much information to train with, from the internet and published works. So, the reality maybe that beyond a certain machine computational capacity, there may not be sufficient improvement in the results to warrant additional AI processing capabilities. Thus, one infers that since about 2015, the focus of neural network research has shifted to improving the quality of AI's output results.

Table 1 ChatGPT Size

Model	**Parameters**	**Layers**	**Attention Heads**
GPT-1	117M	12	12
GPT-2	1.5B	48	16
GPT-3	175B	96	96

Source: Christiano [53]

➢ *Important Considerations*

- *Pre-Determined (Hidden) Execution Rules:*

Michie [33], Deep Blue and Deep Mind, demonstrated that given a simple set of token-move rules for a specific Operating Domain (e.g. chess board) necessarily pre-determines a select finite set of stochastically dominant game-playing or execution rules (e.g. chess opening moves). That is, many 'new' concepts derived from AI are not new but inherent in the Operating Domain and waiting to be discovered.

- *Minimum Computational Requirements for Discovery:*

The brute force required is the same whether it is by many hundreds of Grand Masters over many thousands of years or huge computational machine over several hours. The inference here is that there is minimum computational power, whether human or machine, required to discover most if not all the stochastically dominant execution rules, for that specific Operating Domain & token-move rules.

- *Implementation Neutrality:*

Assume that (i) one has a gigantic computer, call it Deep-Tera, that is many orders more powerful than either Deep Blue or Deep Mind, and (ii) both the software and hardware of ChatGPT is coded entirely as software in Deep-Tera. Is the reasoning, derived by stochastically dominant execution rules, real or simulated? However, Pre-Determination suggests that stochastically dominant execution rules, whether hidden or known, is a function of the Operating Domain, and not how it is implemented.

- *Computational Capability:*

Deep Blue and Deep Mind have proven that computational capability or brute force, matters. The more powerful this capability, the more complex the problem that can be handled.

- *Viability:*

A quick and dirty approach to modeling the number of Domain Transitions T_D based on the Operating Domain's Horizon size H is,

$$T_D = 10^{k.(H+1).(H+1)} \quad \text{Quick \& Dirty} \quad (7)$$

Where k is some game constant. For chess, $k=1.875$, and for Go $k=0.525$. That is, when H is small, about 20, brute force is a viable approach to determining the many stochastically dominant game-playing or execution rules. However, as H increases substantially, say 99, the Domain Transitions range between $10^{5,250}$ and $10^{18,750}$ or clearly not within current computing technology capabilities. That is, even though brute force is a feasible computational approach, it is no longer a viable computational approach for large Operating Domains. That there is a tension between Viability and Computational Capability. This may have viability implications for World Models (Castelvecchi [54]). A better approach is required.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26may1775

- *Theory Versus Laws:*

Schurger & Graziano [55] make the clear distinction between theory and law. The former explains 'why', while the later explains 'how'. For example, Newton's Laws explains 'how' gravity works, but Einstein's General Relativity explains 'why'. Thus, since neural networks are based on mathematical (syntax) models of networks, they not based on a theory of knowledge (why knowledge produces answers) or any decision theory. As can be seen in the earlier historical development, neural networks developed by guided trial and error (a valid approach for fundamental research), each later discovery developed from earlier discoveries. This is equivalent to the evolution of the brain (Ginsburg and Jablonka [14]).

- *Discovery Versus Invention:*

There is a clear distinction between discovery and invention. Discovery is the finding of existing hidden properties (e.g. execution rules) while invention is the emergence of new properties using a specific stimulus from existing properties.

Jumper *et al* [56] used AlphaFold, a novel machine learning approach that incorporates physical and biological knowledge about protein structure, to determine 200 million protein folds. The inference is, using the known rules of protein structures with initial training, AlphaFold (like DeepBlue and AlphaGo) determined the Hidden Execution Rules to solve the protein folding problem. That is, there a specific class of problems that neural-network-based AI is very good at solving. Let's name this class of solutions 'Rule Exploration'. Given known Rules R_K and unknown Rules R_U, the total rules R_T in an Operating Domain can be represented as,

$$R_T = \{R_K\} + \{R_U\} \qquad \text{Known \& Hidden Rules} \qquad (8)$$

Which is different from Emergence (4).

An aside: Do DNA bases, A, T, G & C (tokens) built on a double-helix structure (Operating Domain) exhibiting a very large number of transitions (Domain Transition) demonstrate Stochastically Dominant execution rules?

- *Computational Domain Types:*

Many dominant AI architectures approximate intelligence through large-scale statistical transformation over comparatively uniform computational substrates. By contrast, biological intelligence appears to rely on functionally differentiated subsystems whose outputs are coordinated across perception, affect, memory, attention, prediction, and action. This paper calls the first tendency "relatively flat" i.e. Flat Computational Domain and the second "non-flat" i.e. Non-Flat Computational Domain. Thus,

- *Flat Computational Domain:*

One can make the case that neural networks consist of a flat computational domain space, in that, independently of how these neural network weights are derived, the weights have the same properties across the entire neural network (Computational Domain). This can also be considered true for chess and Go game boards, that they are Flat Computational Domains.

- *Non-Flat Computational Domain:*

The human brain is an example of a non-flat computational domain. This brain consists of different types of information processing (Physical, Emotional & Mental Cognition) that when integrated by a (to be proposed) protocol, leads to the emergence of intelligent mental activity.

This leads to the question how does one convert a Flat Computational Domain into a Non-Flat Computational Domain? A possible solution is the use multiple AI Agents, Google Staff [57], to construct a Non-Flat Computational Domain. Bausch *et al* [58] provide evidence of possible agents in the human brain. These agents need to be specialized in limited fields (see Mobility example above).

Current neural networks are compressed human knowledge of the combined intelligence, emotional and intellectual information. Therefore, possible examples of different AI-agents are, but not limited to, types of physical interactions inputs and outputs, types of emotional inputs and outputs, types of intellectual reasoning, many language interpretations, etc. Given the correct stimulus and a common protocol for communication between AI-agents, this could give rise to Non-Flat Computational Domain which enables Emergence, Solomon [8]. Turker *et al* [59] provide possible evidence of a common protocol communication (stimulus) between distinct brain functions (bio-Agents?). However, in neural networks, this may not be true Emergence as it is an extraction of existing properties.

Therefore, I acknowledge, by confessing that one may never truly be able to distinguish the results of Artificial Intelligence from Natural Intelligence because much of this is a structural rather than implementational.

- *Synthetic Intelligence:*

Haugeland [60] proposed the Natural Intelligence must meet 4 conditions,

- Intentional Holism: Observing empirically that the outputs make sense.
- Common-Sense Holism: How everything fits in with everything else.
- Situation Holism: Depends on the understanding of the specific situation(s)
- Existential Holism: Most ordinary conversations are fraught with life and all its meanings.

Neural Network based Artificial Intelligence probably partially complies with all 4 of these conditions because it is based on the compressed knowledge of human language that encodes these 4 conditions.

Therefore, from the previous discussions one can represent the human Natural Intelligence as a Non-Flat Computational Domain consisting of distinct brain structures for Physical, Emotional and Mental Cognitions. Of course, it

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goes without saying, that each of these Cognitions require use memory, computational capacity and algorithms that enable low energy use.

Thus, one can derive a definition for Synthetic Intelligence as opposed to Artificial Intelligence.

✓ Artificial Intelligence, in its current form, is the extraction of outputs from a Flat Computational Domain Space that is consistent with McCarthy's [30] definition of intelligence.

✓ Synthetic Intelligence, on the other hand, is the ability to produce sustainable decisions from a Non-Flat Computational Domain Space driven by a goal within a valid context, in a reasonable time and reasonable energy utilization. The human brain, Natural Intelligence, is an example, as it operates at about 20 Watts, Balasubramanian [26]. This Non-Flat Computational Domain Space integrates many computational structures that produce *information* (existing properties) from the environmental *data*, using a common communications protocol (stimulus) to cause the emergence of sustainable decisions (new Emergent properties).

➢ *What is the Protocol?:*

What protocol, does the brain use, in a consistent manner, to manage different types of thoughts across different brain function types? The human brain probably uses several types of protocols at different levels of Mental Activity. However, this paper proposes one possible hypothesis that answers this question at a higher level of Mental Activity. See Fig. 2 (Survival Opportunities) & 3 (Landscape Opportunities). Both are adapted from Fig. 1. They depict a possible 2 Framework decision structure in a Predator-Prey setting consisting of a 4-tiered thought structure, within a Knowledge Construct[vi] of AIR Models, Solomon [12],

- *Elemental Thought:*

Elemental thoughts are derived from Physical Cognition to form the Factors or the basis of thought Framework structure. For example, from Fig. 2, is the location good or alluring? Is there plenty of food in that location? Is there any urgency to move? Is adversity present? Elemental Thoughts have vector-like properties, in that they have a range of values.

- *Proto Thoughts:*

Proto thoughts are derived from Mental Cognition using information from the Physical Cognition to form the Barriers of thought Framework structure. For example, does a safe place exist? Is it dangerous to move quickly? Can hide? . . . Proto Thoughts have go-no-go like properties and trigger Transition Thoughts when required.

- *Static Thoughts:*

Static Thoughts are States formed by Mental Cognition by assembling elemental and proto thoughts into Quadrants of the Framework structure and identifies the current position. For example, Stay Still, Move Slowly, Hide or Escape. Static Thoughts have scalar-like properties in that they have a single value.

- *Transition Thoughts:*

Assessments Thoughts are Mental Cognition's Transition Thoughts which inform brain when to change Thought States, if necessary. Transition Thoughts trigger Action to transition to a neighboring Static Thought if and when Action can be taken.

Thus, Proto Thoughts emerge from Elemental Thoughts. Static Thoughts are derived from Elemental Thoughts and Proto Thoughts. Transition Thoughts emerge from Proto Thoughts and Elemental Thoughts.

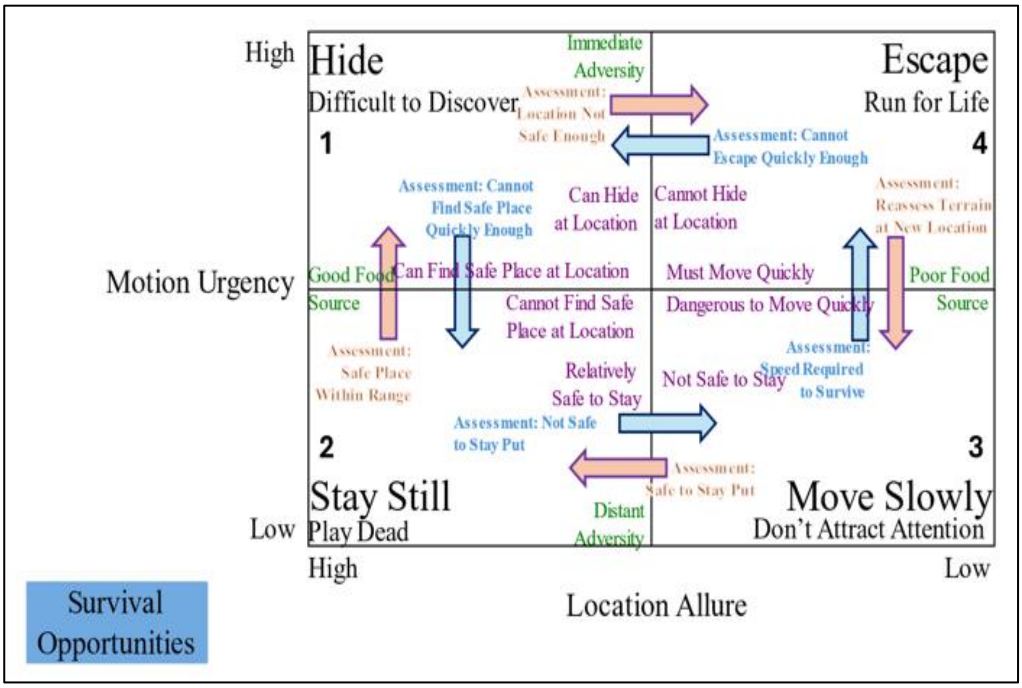

Fig 2 Framework for Prey's Survival Opportunities Decision-Making.

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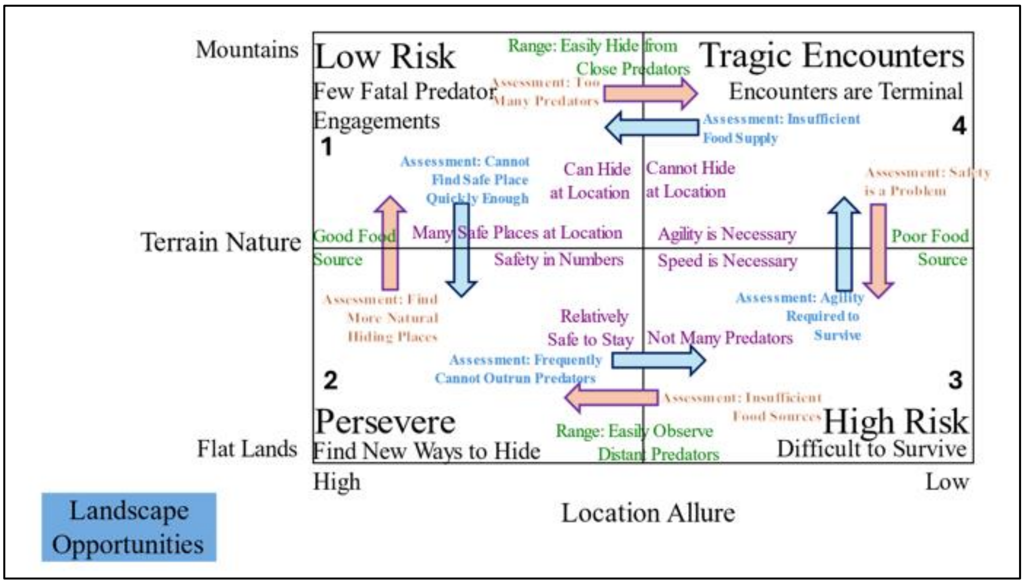

Fig 3 Framework for Prey's Landscape Opportunities Decision-Making.

This 4-tiered thought structure enables the construction of decision structure that facilitates quick, low energy computations as there are only 3 decision options at each Quadrant, stay put, move horizontally, and move vertically. Thus, the decision required is almost obvious. It also allows for dynamic thought management that generates different types of thoughts and even create new types of thoughts by creating new Frameworks. It is inferred that this type of thought management is built into the brain function, possibly in the Theory of Mind function (Newen & Montemayor [2]).

The Frameworks form Maps of Thoughts when neighboring Factors (Elemental Thoughts) are the same, thus joining neighboring Frameworks. See Fig. 4 (for a 2-Framework Map) & Solomon [12] (for a 5-Framework Map). Frameworks behave like a collection of neurons in that a transition to the neighboring State (Static Thought) occurs only when the Barriers (Proto Thoughts) are overcome by the necessary Assessment (Transition Thought) i.e. that specific neuron can fire. Given, 2 Frameworks joined by a common axis of Factor (Elemental Thought), the neighboring State (Static Thought), see Fig 4, must be vertically or horizontally constrained by the preceding Framework to the 2 States in that half of the subsequent Framework. The net result is that a Framework behaves like a Constrained-Conditional-Transition-States. That is, unlike transition state matrices where probabilities but not rules are imposed on transition states, Frameworks require knowledge relationships for state transitions. The Framework is a set of Constrained-Conditional-Transition-States. Constrained by the earlier Framework (Static Thought) States, and conditional upon the Barriers (Proto Thoughts) and Transition Thoughts (Assessments).

Fig. 2 (Survival Opportunities) & 3 (Landscape Opportunities) depict how Intentional, Common-Sense and Situation Holism could be implemented. Furthermore, the Barriers and Assessments are equivalent to 'the meaning behind the meaning'. One could propose that Common Sense are frequently used Maps whose Transition Thoughts are Stochastically Dominant, but more research is required.

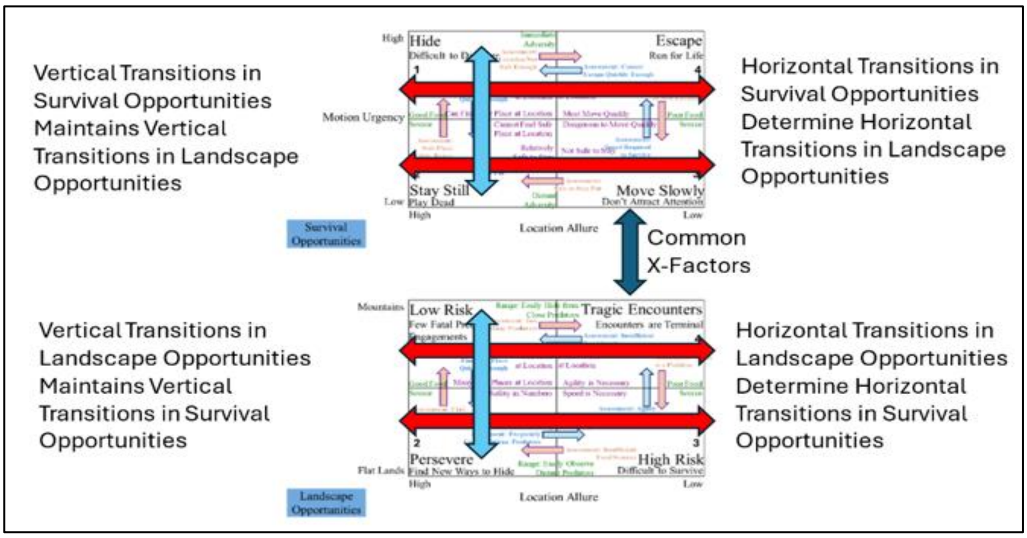

Fig 4 Illustrates How Horizontal Changes in One Framework Affects the other that is joined by a Common Factor

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Poupart [61] presents Partially Observable Markov Decision Processes (POMDP), as a "…class of sequential decision-making problems under uncertainty… indicating the probability of reaching" a state with an action as a single matrix. Frameworks can be used to depict the probability of the magnitude of a Factor or Elemental Thought, but that is not the point. There is no uncertainty in the selection of outcomes. The apparent uncertainty in outcomes originates from the uncertainty of the context i.e. external environment in which the Framework is applied. In a full Map of Frameworks, the possible decisions are clear. Any State or Static Thought has only 3 options for a decision, (i) stay put, (ii) move horizontally or (iii) move vertically and constrained by the preceding and subsequent Frameworks i.e. multiple Frameworks (matrices?) are involved. Furthermore, POMDP does not handle 'the meaning behind the meaning'.

Note, unlike Transformers, Vaswani *et al* [40], that are syntax-based word usages on their 'closeness', AIR Model's factors, states, barriers and transitions are based on the semantic relationships between concepts. A second consideration, from Solomon [12], is that (i) the X & Y Factors cannot be correlated else there is no new knowledge to be derived i.e. learned, and (ii) that the respective Factors and Co-Factors are related to strengthen the robustness of the overall decision process. See Fig. 2 & 3.

- *What is Knowledge?:*

That raises the question, what is knowledge? Knowledge is structured semantic information. These are structural effects not implementation effects, thus, like the earlier Mobility example, Emergence needs to be intentionally designed into the structure of knowledge. A structure effect allows for different types of implementations.

Of course, much more research is required to enable a programable approach to building AIR Model Frameworks. Frameworks are the basis of prediction of future outcomes, as it provides options for decision making within a clearly defined limited context. Combining different Frameworks by their common Factors (i.e. Maps) expands this ability to more sophisticated predictions of future outcomes.

- *Limits of the Present Paper: Awareness and Consciousness:*

This paper does not attempt to solve consciousness and neither does it address spiritual, religious, or metaphysical accounts of cognition. Fitch *et al* [62] and Maldarelli & Güntürkün [63] point to the growing body of evidence that consciousness may be present across species that are phylogenetically distant from each other with remarkably different brain structures. This paper's scope is limited to decision-oriented cognitive architecture, with the expectation that the discussion in this section would lead to research and development of algorithms and structures that cause consciousness to emerge.

The English philosopher John Locke (1632-1704) defined consciousness, Encyclopaedia Britannica Editors [64], as "the perception of what passes in a man's own mind." Subsequently, many researchers have proposed approaches to defining or at least hypothesizing consciousness.

- *The Global Neuronal Workspace Theory (GNWT):*

Mashour *et al* [65], requires "…that perceptual contents, which are acted upon by localized processors, only become conscious when they are widely broadcasted to other processors across the brain" and that "neural information becomes conscious when the neural activity carrying that information gains access, in a winner-take-all fashion, to the global neuronal workspace.", Schurger & Graziano [55]. This would necessarily imply that (i) there is a common communications protocol (ii) between the different processors in the brain.

- *The Integrated Information Theory (IIT):*

Balduzzi & Tononi [66] consider consciousness as a function of "how much information is generated … when a system enters a particular state through causal interactions among its elements, above and beyond the information generated independently by its parts". In other words, what is the impact of Synergy on the brains use of information? Schurger & Graziano [55] do not think that IIT is a theory of consciousness.

- *Attention Schema Theory (AST):*

Graziano & Kastner [67], "…awareness is a perceptual reconstruction of attentional state; and the machinery that computes information about other people's awareness is the same machinery that computes information about our own awareness". Schurger & Graziano [55] makes the case that consciousness is similar in many ways to attention.

Give the above discussion, some fundaments for cognition that can be inferred are,

- *Collage Focus:*

This Focus is on the big picture when details are not important. For example, a sunrise or listening to an orchestra. The brain is not particularly interested in every detail but in the overall effect of the collage of information provided by Physical Cognition from the data (individual pixels or individual notes, respectively). Physical Cognition communicates this information to the Mental Cognition that provides matching memories and emotions for Consciousness to appreciate the experience.

- *Confined Focus:*

This occurs when Physical Cognition focuses on a small part of the data received, to provide a narrow portion of information (from the Physical Cognition's processing of the data). For example, with sight, Physical Cognition provides clear information that is at the center of one's vision. This is similar to Semantic Information of (6) above. This Confined Focus is built into the brain's Physical Cognition function so that Mental Cognition can process this information further.

- *Attention:*

This is the attending to, i.e. the processing of, the information provided by either Collage Focus or Confined

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Focus. This is an automatic response of both Physical and Mental Cognitions. For example, the deer sees a lion. The deer does not have the luxury of, "let me think about that". It must make a decision and respond immediately.

So, what is Awareness? Merikle [68] debates whether Awareness is related to forced-choice, "...awareness was defined as the ability to make better than chance level, forced-choice decisions concerning either the identity or the presence of the primes, and, conversely, it was assumed that observers were unaware of the primes when these decisions were at a chance level of performance." However, the deer and lion scenario above, shows that the deer has to instantly or nearly instantly be aware of three questions. (i) Is the animal nearby a predator? In the case of the lion, the answer is, yes. (ii) Is the lion hunting for prey? (iii) If so, is the deer within the hunting range of this lion? For survival, one would presume that these are automatic and not forced inquiries. The first question would be derived from a learned experience of Physical Cognition, while the next two questions would be derived from a learned experience of Mental Cognition as it needs additional mental processing.

Schipper [69] provides two insights, (i) Awareness is derive from Old German "gewahr" to be "wary", and (ii) The modeling of Awareness needs to be syntax-free, however, stated in the opposite as "We have seen that awareness structures are not syntax-free since they involve a syntactic awareness correspondence."

A preliminary definition of Awareness is a syntax-free recognition of the consequences of both Physical and Mental Cognitions.

Given the above, this paper infers that consciousness is external to either cognition or knowledge. That, as knowledge cannot be sufficiently defined by syntax, consciousness cannot be defined by cognition, awareness, or attention, and this simplifies the design of modeling cognition. Thus, (i) Consciousness could be described as the free-will selection of a specific Awareness. (ii) Free will can be described as the ability to decide between present and perceived Awarenesses based on personal beliefs about what is important within a context at the time of the decision. However, these are open to debate.

III. CONCLUSION

This paper has proposed the deconstruction of Mental Activity into Physical Cognition, Emotional Cognition, Mental Cognition, and Intelligence. Thereby requiring a common communication protocol for these mental functions to work together synergistically. The aim is to design structures that enable Emergence. More research is required to develop the theory of Knowledge Constructs and to detail more relationships between concepts. This includes (i) an improved structure of knowledge based on semantic information and (ii) other models similar to AIR models. Much more research is required before one can build true Synthetic Intelligence.

REFERENCES

[1]. Lark Editorial Team, Synthetic Intelligence, Lark Technologies Pte. Ltd, 12/24/2023, https://www.larksuite.com/en_us/topics/ai-glossary/synthetic-intelligence

[2]. Newen A, Montemayor C. 2025, Three types of phenomenal consciousness and their functional roles: unfolding the ALARM theory of consciousness. Phil. Trans. R. Soc. B 380: 20240314. https://doi.org/10.1098/rstb.2024.0314

[3]. Kline M, 1982, Mathematics: The Loss of Certainty 1982, Oxford University Press https://global.oup.com/academic/product/mathematics-9780195030853?cc=us&lang=en&

[4]. Mittelstaedt, P. (1976). Euclidean and Riemannian Geometry. In: Philosophical Problems of Modern Physics. Boston Studies in the Philosophy of Science, vol 18. Springer, Dordrecht. https://doi.org/10.1007/978-94-010-9617-1_3 (https://link.springer.com/chapter/10.1007/978-94-010-9617-1_3)

[5]. R Nave, Comments on the Development of the Rayleigh-Jeans Law, Blackbody Radiation Notes, Georgia State University, HyperPhysics, undated. http://www.hyperphysics.phy-astr.gsu.edu/hbase/mod6.html#c6 (accessed March-May 2026)

[6]. John Searl, 1980, The Chinese Room, excerpted from: Minds, Brains, & Programs, https://rintintin.colorado.edu/~vancecd/phil201/Searle.pdf

[7]. Natalie Wolchover, What Do Gödel's Incompleteness Theorems Truly Mean?, Quanta Magazine, May 18 2026, https://www.quantamagazine.org/what-do-godels-incompleteness-theorems-truly-mean-20260518/

[8]. Benjamin T. Solomon. "A Proposal for the Definition of Emergence", Volume 11, Issue 3, March – 2026, International Journal of Innovative Science and Research Technology, https://doi.org/10.38124/ijisrt/26mar451, https://www.ijisrt.com/assets/upload/files/IJISRT26MAR451.pdf

[9]. Lichtenstein B (2025) Emergence as a science. Front. Complex Syst. 3:1667670. doi: 10.3389/fcpxs.2025.1667670

[10]. Ritchie SJ, Tucker-Drob EM. How Much Does Education Improve Intelligence? A Meta-Analysis. Psychol Sci. 2018 Aug;29(8):1358-1369. doi: 10.1177/0956797618774253. Epub 2018 Jun 18. PMID: 29911926; PMCID: PMC6088505.

[11]. Benjamin T. Solomon. "Structuring Knowledge Using an Example from Texas Instruments", Volume 11, Issue 2, February – 2026, International Journal of Innovative Science and Research Technology, https://doi.org/10.38124/ijisrt/26feb1421, https://www.ijisrt.com/assets/upload/files/IJISRT26FEB1421.pdf

[12]. Benjamin T. Solomon. "Asymmetric Information Resolution (AIR) Models." Volume. 11 Issue.1,

January 2026 International Journal of Innovative Science and Research Technology (IJISRT) 1412-1433, https://doi.org/10.38124/ijisrt/26jan404, https://www.ijisrt.com/assets/upload/files/IJISRT26JAN404.pdf

[13]. Shannon, Claude Elwood (July 1948). "A Mathematical Theory of Communication" (PDF). Bell System Technical Journal. 27 (3): 379–423. doi:10.1002/j.1538-7305.1948.tb01338.x. https://people.math.harvard.edu/~ctm/home/text/others/shannon/entropy/entropy.pdf

[14]. Ginsburg S, Jablonka E., 2021 Evolutionary transitions in learning and cognition. Phil. Trans. R. Soc. B 376: 20190766. https://doi.org/10.1098/rstb.2019.0766

[15]. Hiersche, K.J., Osher, D.E. & Saygin, Z.M. Functional dissociation of language and theory of mind in the developing superior temporal lobe. Commun Biol 9, 558 (2026). https://doi.org/10.1038/s42003-026-10040-2

[16]. Nicola Luigi Bragazzi, Daniele Del Rio, Emeran A Mayer, Pedro Mena, We Are What, When, And How We Eat: The Evolutionary Impact of Dietary Shifts on Physical and Cognitive Development, Health, and Disease, Advances in Nutrition, Volume 15, Issue 9, 2024, 100280, ISSN 2161-8313, https://doi.org/10.1016/j.advnut.2024.100280. (https://www.sciencedirect.com/science/article/pii/S2161831324001145)

[17]. Shettleworth SJ. 1998 Cognition, evolution, and behavior. New York, NY: Oxford University Press.

[18]. Hyvärinen L, Walthes R, Jacob N, Chaplin KN, Leonhardt M. Current Understanding of What Infants See. Curr Ophthalmol Rep. 2014;2(4):142-149. doi: 10.1007/s40135-014-0056-2. PMID: 25478306; PMCID: PMC4243010.

[19]. Albert Newen and Carlos Montemayor, The ALARM Theory of Consciousness, A Two-Level Theory of Phenomenal Consciousness, Journal of Consciousness Studies, 30, No. 3–4, 2023, pp. 84–105, DOI: 10.53765/20512201.30.3.084

[20]. Yang Chen, Marinus Kloos, Zsuzsanna Varga, Yonghai Zhang, Inken Piro, Tatsuo K. Sato, Bert Sakmann, Israel Nelken, and Arthur Konnerth, Thalamic activation of the visual cortex at the single-synapse level, Science, Vol 391, Issue 6792, pp. 1349-1354, 26 Mar 2026, DOI:10.1126/science.aec9923, https://www.science.org/doi/10.1126/science.aec9923

[21]. Dianna Ilyka, Mark H. Johnson, Sarah Lloyd-Fox, Infant social interactions and brain development: A systematic review, Neuroscience & Biobehavioral Reviews, Volume 130, 2021, Pages 448-469, ISSN 0149-7634, https://doi.org/10.1016/j.neubiorev.2021.09.001. (https://www.sciencedirect.com/science/article/pii/S0149763421003833)

[22]. Nicolas Chevalier, Judith Jackson, Alexia Revueltas Roux, Yusuke Moriguchi, Bonnie Auyeung, Differentiation in prefrontal cortex recruitment during childhood: Evidence from cognitive control demands and social contexts, Developmental Cognitive Neuroscience, Volume 36, 2019, 100629, ISSN 1878-9293, https://doi.org/10.1016/j.dcn.2019.100629. (https://www.sciencedirect.com/science/article/pii/S1878929318302226)

[23]. F-35A Lightning II, US Air Force Fact Sheets, accessed March-May 2026, https://www.af.mil/About-Us/Fact-Sheets/Display/Article/478441/f-35a-lightning-ii/

[24]. David H. Brann, Tatsuya Tsukahara, Cyrus Tau, Dennis Kalloor, Rylin Lubash, Lakshanyaa Thamarai Kannan, Nell Klimpert, Mihaly Kollo, Martín Escamilla-Del-Arenal, Bogdan Bintu, Andreas Schaefer, Alexander Fleischmann, Thomas Bozza, Sandeep Robert Datta, A spatial code governs olfactory receptor choice and aligns sensory maps in the nose and brain, Cell, 2026, ISSN 0092-8674, https://doi.org/10.1016/j.cell.2026.03.051. (https://www.sciencedirect.com/science/article/pii/S0092867426003879)

[25]. Barrett LF. The theory of constructed emotion: an active inference account of interoception and categorization. Soc Cogn Affect Neurosci. 2017 Jan 1;12(1):1-23. doi: 10.1093/scan/nsw154. Erratum in: Soc Cogn Affect Neurosci. 2017 Nov 1;12(11):1833. doi: 10.1093/scan/nsx060. PMID: 27798257; PMCID: PMC5390700.

[26]. Vijay Balasubramanian, Brain power, Biophysics and Computational Biology, August 2, 2021, https://doi.org/10.1073/pnas.2107022118 (https://www.pnas.org/doi/10.1073/pnas.2107022118)

[27]. Karan Singh, Exploring Artificial Intelligence: A Deep Review of Foundational Theories, Applications, and Future Trends, JOURNAL OF SCIENTIFIC INNOVATION AND ADVANCED RESEARCH (JSIAR), VOLUME 1, ISSUE 6, SEPTEMBER 2025, https://jsiar.com/2025-September/JSIAR-S-25-09238.pdf

[28]. McCulloch, W.S., Pitts, W. A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biophysics* **5**, 115–133 (1943). https://doi.org/10.1007/BF02478259

[29]. A. M. Turing, “Computing machinery and intelligence,” Mind, vol. LIX, no. 236, pp. 433–460, 1950. https://academic.oup.com/mind/article/LIX/236/433/986238

[30]. McCarthy, J., Minsky, M.L., Rochester, N., Shannon, C.E., “A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955,” AI Magazine, vol. 27, no. 4, pp. 12–14, 2006. https://onlinelibrary.wiley.com/doi/epdf/10.1609/aimag.v27i4.1904

[31]. Rosenblatt, F., The Perceptron — A Perceiving and Recognizing Automaton. Tech. Rep. 85-460-1 (Cornell Aeronautical Laboratory, 1957). https://bpb-us-e2.wpmucdn.com/websites.umass.edu/dist/a/27637/files/2016/03/rosenblatt-1957.pdf

[32]. Rosenblatt, F., The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain, Psychological Review, Vol. 65, No 6, 1958.

https://homepages.math.uic.edu/~lreyzin/papers/rosenblatt58.pdf

[33]. Donald Michie (1963), Experiments on the mechanization of game-learning: Part I. Characterization of the model and its parameters, Computer Journal, 6, 232-236, https://gwern.net/doc/reinforcement-learning/model-free/1963-michie.pdf

[34]. Geoffrey Hinton, Nitish Srivastava, Kevin Swersky, Tijmen Tieleman, Abdel-Rahman Mohamed, Lecture 13a, The ups and downs of backpropagation, Neural Networks for Machine Learning, Department of Computer Science, University of Toronto, undated, https://www.cs.toronto.edu/~hinton/coursera/lecture13/lec13.pdf

[35]. Michael Jordan, Serial Order: A Parallel Distributed Processing Approach, ICS Report 8604, May 1986, https://cseweb.ucsd.edu/~gary/258/jordan-tr.pdf

[36]. Jeffrey L. Elman, Finding Structure in Time, COGNITIVE SCIENCE 14, 179-21 1 (1 990), https://onlinelibrary.wiley.com/doi/pdf/10.1207/s15516709cog1402_1

[37]. Ilya Sutskever, James Martens, Geoffrey Hinton, Generating Text with Recurrent Neural Networks, Proceedings of the 28th International Conference on Machine Learning, Bellevue, WA, USA, 2011. https://icml.cc/2011/papers/524_icmlpaper.pdf

[38]. Andrej Karpathy, The Unreasonable Effectiveness of Recurrent Neural Networks, Andrej Karpathy blog, May 21, 2015, https://karpathy.github.io/2015/05/21/rnn-effectiveness/

[39]. Alec Radford, Rafal Jozefowicz, Ilya Sutskever, Learning to Generate Reviews and Discovering Sentiment, arXiv:1704.01444v2 [cs.LG] 6 Apr 2017, https://dn711107.ca.archive.org/0/items/arxiv-1704.01444/1704.01444.pdf

[40]. Vaswani, Ashish; Shazeer, Noam; Parmar, Niki; Uszkoreit, Jakob; Jones, Llion; Gomez, Aidan N Gomez; Łukasz Kaiser; Illia Polosukhin. "Attention is All you Need", 31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA. https://arxiv.org/abs/1706.03762, 2 Aug 2023.

[41]. Thornton, Stephen, "Karl Popper", The Stanford Encyclopedia of Philosophy (Winter 2023 Edition), Edward N. Zalta & Uri Nodelman (eds.), https://plato.stanford.edu/archives/win2023/entries/popper/.

[42]. Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, Language Models are Unsupervised Multitask Learners, 1OpenAI, San Francisco, California, United States, 2019, https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf

[43]. Bharath Reddy & Richard Fields, From Past to Present – A Comprehensive Technical Review ofRule-based Expert Systems from 1980 – 2021, ACM Southeast Conference – ACMSE 2022 – Session 1: Full Papers – ISBN: 978-1-4503-8697-5 Virtual Event, USA, April 18-20, 2022167. https://dl.acm.org/doi/epdf/10.1145/3476883.3520211

[44]. Philipp Koehn, Knowledge Representation, John Hopkins University lectures, 6 March 2025, https://www.cs.jhu.edu/~phi/ai/slides/lecture-knowledge-representation.pdf

[45]. Fikes, R. and Garvey, T. (2020), Knowledge Representation and Reasoning — A History of DARPA Leadership. AI Magazine, 41: 9-21. https://doi.org/10.1609/aimag.v41i2.5295, https://onlinelibrary.wiley.com/doi/epdf/10.1609/aimag.v41i2.5295?msockid=3992fb2527716b0b3a68ec75265a6a81

[46]. Michael Haller, Clifton Forlines, Christina Köffel, Jakob Leitner, Chia Shen, Tabletop Games: Platforms, Experimental Games and Design Recommendations, Art and Technology of Entertainment Computing and Communication (pp.271-296), January 2010, DOI:10.1007/978-1-84996-137-0_11, (https://www.researchgate.net/profile/Clifton-Forlines/publication/230739547_Tabletop_Games_Platforms_Experimental_Games_and_Design_Recommendations/links/02e7e5322f7014d947000000/Tabletop-Games-Platforms-Experimental-Games-and-Design-Recommendations.pdf?_tp=eyJjb250ZXh0Ijp7ImZpcnN0UGFnZSI6InB1YmxpY2F0aW9uIiwicGFnZSI6InB1YmxpY2F0aW9uIn19)

[47]. Pedro Pinto Neves, Nelson Zagalo, Game Design as an Autonomous Research Subject, Special Issue The Systems and Methods of Game Design, Information 2021, 12(9), 367; https://doi.org/10.3390/info12090367, (https://www.mdpi.com/2078-2489/12/9/367)

[48]. IBM Heritage, Deep Blue, Advancing Humanity, undated, accessed March-May 2026, https://www.ibm.com/history/deep-blue

[49]. Google DeepMind, AlphaGo, Google Research, undated, accessed March-May 2026, https://deepmind.google/research/alphago/

[50]. ARS Staff, Google brings 45 teraflops tensor flow processors to its compute cloud, ARS Technica, May 17, 2017, accessed March-May 2026, https://web.archive.org/web/20220306073142/https://arstechnica.com/information-technology/2017/05/google-brings-45-teraflops-tensor-flow-processors-to-its-compute-cloud/

[51]. David Silver, Aja Huang, Chris J. Maddison, Arthur Guez, Laurent Sifre, George van den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, Sander Dieleman, Dominik Grewe, John Nham, Nal Kalchbrenner, Ilya Sutskever, Timothy Lillicrap, Madeleine Leach, Koray Kavukcuoglu, Thore Graepel & Demis Hassabis. Mastering the game of Go with deep neural networks and tree search. Nature 529, 484–489 (2016). https://doi.org/10.1038/nature16961 (https://www.nature.com/articles/nature16961)

[52]. Jacob Murel, Eda Kavlakoglu, What is reinforcement learning?, IBM Research, undated, accessed March-May 2026,

https://www.ibm.com/think/topics/reinforcement-learning
[53]. Paul Christiano, ChatGPT and the Mystery of Its Hidden Layers, Expert Beacon, August 3, 2024, accessed March-May 2026, https://expertbeacon.com/chatgpt-and-the-mystery-of-its-hidden-layers/
[54]. Davide Castelvecchi, 'World models' are AI's latest sensation: what are they and what can they do?, Nature, April 28, 2026, doi: https://doi.org/10.1038/d41586-026-00820-5 (https://www.nature.com/articles/d41586-026-00820-5)
[55]. Schurger A, Graziano M. Consciousness explained or described? Neurosci Conscious. 2022 Jan 21;2022(2):niac001. doi: 10.1093/nc/niac001. PMID: 35145759; PMCID: PMC8824704. (https://pmc.ncbi.nlm.nih.gov/articles/PMC8824704/pdf/niac001.pdf)
[56]. John Jumper, Richard Evans, Alexander Pritzel1, Tim Green1, Michael Figurnov, Olaf Ronneberger, Kathryn Tunyasuvunakool, Russ Bates, Augustin Žídek, Anna Potapenko, Alex Bridgland, Clemens Meyer, Simon A. A. Kohl1, Andrew J. Ballard, Andrew Cowie1, Bernardino Romera-Paredes, Stanislav Nikolov, Rishub Jain, Jonas Adler, Trevor Back, Stig Petersen, David Reiman, Ellen Clancy1, Michal Zielinski, Martin Steinegger, Michalina Pacholska, Tamas Berghammer, Sebastian Bodenstein, David Silver, Oriol Vinyals, Andrew W. Senior, Koray Kavukcuoglu, Pushmeet Kohli1 & Demis Hassabis. Highly accurate protein structure prediction with AlphaFold, Nature, Vol 596, 26 August 2021, https://doi.org/10.1038/s41586-021-03819-2 (https://www.nature.com/articles/s41586-021-03819-2.pdf)
[57]. Google Staff, What is an AI agent?, Google Cloud, April 02, 2026, accessed March-May 2026, https://cloud.google.com/discover/what-are-ai-agents
[58]. Marcel Bausch, Johannes Niediek, Thomas P. Reber, Sina Mackay, Jan Boström, Christian E. Elger & Florian Mormann. Distinct neuronal populations in the human brain combine content and context. Nature 650, 690–700 (2026). https://doi.org/10.1038/s41586-025-09910-2 https://www.nature.com/articles/s41586-025-09910-2#citeas
[59]. Sabrina Turker, Beatrice Fumagalli, Philipp Kuhnke, Gesa Hartwigsen, The 'reading' brain: Meta-analytic insight into functional activation during reading in adults, Neuroscience & Biobehavioral Reviews, Volume 173, 2025, 106166, ISSN 0149-7634, https://doi.org/10.1016/j.neubiorev.2025.106166. (https://www.sciencedirect.com/science/article/pii/S0149763425001666)
[60]. John Haugeland, "Understanding Natural Language", Journal of Philosophy 76, 1979, 619–632. https://www.beisecker.faculty.unlv.edu/Courses/PHIL%20330/Haugeland,%20Understanding%20Natural%20Language.pdf
[61]. Poupart, P. (2011). Partially Observable Markov Decision Processes. In: Sammut, C., Webb, G.I. (eds) Encyclopedia of Machine Learning. Springer, Boston, MA. https://doi.org/10.1007/978-0-387-30164-8_629 (https://link.springer.com/rwe/10.1007/978-0-387-30164-8_629)
[62]. Fitch WT, Allen C, Roskies AL. Evolutionary functions of consciousness, Philosophical Transactions of the Royal Society B: Biological Sciences November 2025, Vol.380, 20240299. doi:https://doi.org/10.1098/rstb.2024.0299 (https://royalsocietypublishing.org/rstb/article/380/1939/20240299/235164/The-evolutionary-functions-of-consciousnessThe)
[63]. Maldarelli G, Güntürkün O. 2025 Conscious birds. Phil. Trans. R. Soc. B 380:20240308. https://doi.org/10.1098/rstb.2024.0308 (https://royalsocietypublishing.org/rstb/article/380/1939/20240308/235178/Conscious-birdsConscious-birds)
[64]. Encyclopaedia Britannica Editors, Consciousness, Encyclopaedia Britannica, April 04, 2026, Accessed March - May 2026, https://www.britannica.com/topic/consciousness
[65]. George A. Mashour, Pieter Roelfsema, Jean-Pierre Changeux, and Stanislas Dehaene, Conscious Processing and the Global Neuronal Workspace Hypothesis, Neuron, 105, 776-798, March 4, 2020, https://doi.org/10.1016/j.neuron.2020.01.026 (https://www.cell.com/action/showPdf?pii=S0896-6273%2820%2930052-0)
[66]. Balduzzi D, Tononi G (2008) Integrated Information in Discrete Dynamical Systems: Motivation and Theoretical Framework. PLOS Computational Biology 4(6): e1000091. https://doi.org/10.1371/journal.pcbi.1000091 (https://journals.plos.org/ploscompbiol/article?id=10.1371/journal.pcbi.1000091)
[67]. Graziano MS, Kastner S. Human consciousness and its relationship to social neuroscience: A novel hypothesis. Cogn Neurosci. 2011 Jan 1;2(2):98-113. doi: 10.1080/17588928.2011.565121. PMID: 22121395; PMCID: PMC3223025.
[68]. Merikle, P.M. Toward a definition of awareness. Bull. Psychon. Soc. 22, 449–450 (1984). https://doi.org/10.3758/BF03333874
[69]. Schipper, Burkhard C., Awareness (May 6, 2014). Available at SSRN: https://ssrn.com/abstract=2401352 or http://dx.doi.org/10.2139/ssrn.2401352

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[i] I started working on private information in 1985 while at Texas Instruments. I wondered whether it was possible to legally and ethically determine company private information. Private information is not encrypted data and in a corporate setting, is defined as the information that a small select group of managers have that the rest of the company and the public do not have access to. I have found that private information has not been rigorously researched but versions of this are

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related to data encryption, privacy protection or quantum information modeling, both of which are not about private information but about how to protect data. Over the next 3 decades (1995-2026), I developed several Asymmetric Information Resolution (AIR) Models. The two most important are the qualitative strategy AIR model, named the Holistic Business Model and the quantitative Financial / Credit Risk AIR Model (not published).

The original goal of AIR Models evolved to enable corporate managers formulate better decisions because they now have access to private information of multiple players in their industry by expanding the context of their knowledge base. The manuscript for Asymmetric Information Resolution (AIR) Models was finally published in 2026. This paper considers economic utility, decision theory and AIR Models.

My experience suggests that there are 3 types of decision models, (i) best outcome (given external states are not controllable), (ii) best path (given states are known and selectable) and (iii) decision assist (given that an optimal solution is difficult due to the problem being time variant, etc.).

[ii] https://en.wikipedia.org/wiki/Propositional_logic (accessed March-May 2026)
[iii] https://rcc.fide.com/fide-laws-of-chess_fulltexthtml/ (accessed March-May 2026)
[iv] https://www.chessjournal.com/how-many-possible-moves-are-there-in-chess/ (accessed March-May 2026)
[v] https://www.firstpost.com/sports/chess/magnus-carlsen-how-many-moves-ahead-chess-visualisation-13985603.html (accessed March-May 2026)
[vi] Knowledge Construct is a proposed new field for decision making of which AIR Models is one such model.