Human Cognition and Hyper Intelligence

D. Frank Hsu
Department of Computer and Informational Science
Fordham University
New York, NY 10023
U.S.A.

Mohammad Shehata, Shao-Min Hung & Shinsuke Shimojo
Division of Biology & Biological Engineering/Computation & Neural Systems, California Institute of Technology, Pasadena, U.S.A.

Ryota Kanai
Araya Inc.
ARK Mori Building
Akasaka, Minato-ku
Tokyo 107-6024
Japan

Christina Schweikert
Division of Computer Science, Mathematics and Science
St. John's University
Queens, New York 11439
U.S.A.

Michael W. David
School of Science & Technology Intelligence
National Intelligence University
Bethesda, MD
U.S.A.

Vincenzo Piuri
Department of Computer Science
Università degli Studi di Milano
via Celoria 18
20133 Milano
Italy

Jianhua Ma
Faculty of Computer and Information Sciences
Hosei University
Tokyo 184-8584, Japan

***Abstract*—Human cognition is a complex neural process ranging from sensor-motor tasks to decision making. Hyper intelligence strives to accomplish complex tasks through creation or combination of diverse intelligent systems used by humans or machines based on a variety of methodologies, algorithms, and models in statistics, computation, and mathematics. In this paper, we give perspectives on various aspects of human cognition and hyper intelligence, as well as their relations, interactions, and causal effects. In particular, we focus on a diverse set of topics: cognitive process, functions of consciousness, model fusion, supply chain development, and convergence of technologies. Opportunities and challenges of this emerging field are also discussed. In addition, several issues for further investigation are suggested.**

Keywords—ambient intelligence, hyper intelligence, human cognition, consciousness, model fusion, supply chain.

I. Introduction

Human cognition is a complex neural process ranging from simple sensor-motor tasks to a higher level of cognition such as judgement and decision making [1]. Hyper intelligence aims to accomplish complex tasks and reach higher level of intelligence through the creation and/or combination of multiple diverse intelligent systems designed and used by humans or machines based on various methodologies, algorithms, and models in statistics, computation, and mathematics.

Using bivariate analysis, it was shown that intelligence can change with age with a genetic correlation of 0.62 between intelligence at age 11 years and in old age [2, 3]. However, with the influence and support of computing, information, and communication science and technology, human cognition and intelligence have been enhanced. More recently, machine and artificial intelligence (ML/AI) have improved our ability to perform complex tasks such as prediction, estimation, association, clustering, and classification as well as data and information fusion [4, 40].

Hyper intelligence also refers to higher, super-intelligent abilities to accomplish complex tasks. Hyper intelligence is an inter-disciplinary field that studies hyper-connections, hyper-compositions, hyper-collaborations, and hyper-cognition of intelligent entities in various forms and functions that can be physical or digital, local or remote. Hyper-intelligent systems will usher in a new age of cyber-physical-social-human interactions, revolutionizing and reshaping the world as we know it.

This paper covers diverse aspects of human cognition and hyper intelligence. It also covers relation, interaction, and possible causal efforts between cognition and intelligence. By offering diverse perspectives and frameworks, we aim to combine multiple cognitive processes and multiple forms of intelligence to achieve a higher level of human cognition and hyper intelligence.

The rest of this paper is organized as follows. The next section (Sec. II) is focused on basic questions about upper limits and how to break them in relation to somatic and social characteristics of implicit cognitive processes. Section III discusses possible AI implementations of consciousness functions. Section IV presents a novel approach of model fusion by combining multiple ML/AI models with cognitive diversity. Hyper-intelligent supply chain developments and risks are explained in Section V, and ambient intelligence as convergence of technologies for smart environments is described in Section VI. Concluding remarks about possible future research directions and challenges are addressed in the last section.

II. "Upper Limits" and How to Break Them

Everything has its "upper limit," and physical/cognitive performances in individual humans are not exceptions. Note, however, that such a human performance limit is often a psychological construct (by the performers themselves, and by scientists measuring it). The subjectively-felt limit is typically way lower than physical or physiological limits, as well proven in the history of various sports (*e.g.:* 100 m dash, marathon, etc.). The outcome knowledge will no doubt provide a critical basis to explore "hyper intelligence," yet ironically, it is *everywhere* (in any human activity) but *nowhere* (as a theoretical research focus in cognitive or neuroscientific fields).

We first need to acknowledge that (a) the "upper limit" has reasons, *i.e.* biological benefits such as self-protection, and (b) the upper limit of performance is determined through "personal history" ("Raireki" in Japanese, "Laili" in Chinese).

978-1-6654-2174-4/21/$31.00 ©2021 IEEE
DOI 10.1109/DASC-PICom-CBDCom-CyberSciTech52372.2021.00127

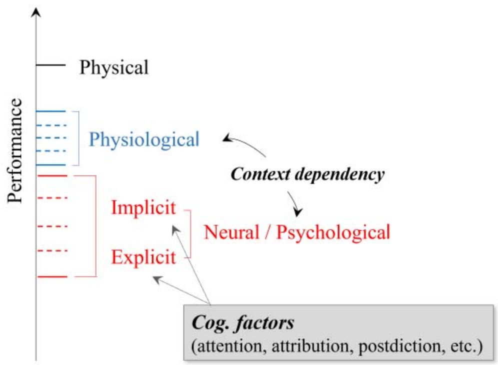

Fig. 1. Multiple layers of limit.

The limit has multiple layers/thresholds even within the same task, as illustrated in Fig. 1. Physiological limits are typically below the physical. For example, muscles have constraints such that physically impossible movements (in terms of power, speed, torque, etc.) cannot be accomplished. Yet physiological constraints such as fatigue/recovery of muscles/ion channels, and neural conductance delay may impose more strict limits. The psychological limits (implicit/explicit) are further below. Neural/psychological, as well as physiological limits are highly context-dependent, on top of which various cognitive factors such as motivation, attention, and *postdictive* causal attribution would affect (Shimojo, 2014) [17]. Such multiple limits as well as complex modulations provide plenty room for improvement, thus to break the limit.

Along the line, human performance is often *paradoxical*. For example, there are cases where an ***indirect*** task does it better (*e.g.*. Subliminal Mere Exposure Effect; Monahan, *et. al.*, 2000) [14]. Likewise, feature discrimination performance can go beyond the chance, while a mere detection is only at the chance level (Marcel, 1983) [11]. Also, a ***complex*** task or stimulus sometimes does it better than a simpler task in performance (*e.g.*. Watanabe, 2008) [19]. As a third example of human performance being paradoxical, the effects of ***reward*** are not always facilitatory. In special situations, it could have an aversive effect on learning (*e.g.*. *Undermining effect*; Lepper, Green & Nisbett, 1973) [10]. Likewise, a huge expected reward such as a gold medal may bring the player into choke (Chib, *et. al*., 2012; 2014) [5, 6].

Based on these observations, several intriguing perspectives as for "how to break it" may be offered:

1) **Placebo is *real*** (in the sense that it can affect even lower-level neural mechanisms). Indeed, neuronal activity triggered by placebo turned out to be very similar to the drug-induced neuro-pharmacological/physiological effects in Parkinson's, analgesia, antidepressant, etc. (*e.g*.. Sauro & Greenberg, 2005) [15]. When the upper limit is mainly imposed by a psychological constraint (such as Nocebo=negative Placebo, or a choke) [5, 6], then a placebo manipulation may work marvelously to break such a limit.

2) **Motivation matters, with the extreme cases of "flow" or "zone."** Personal limit is also a function of motivation, although it could have a negative effect as in the case of choke or yips as mentioned above. The flow (or zone) is the opposite extreme case where the personal limit can easily be broken.

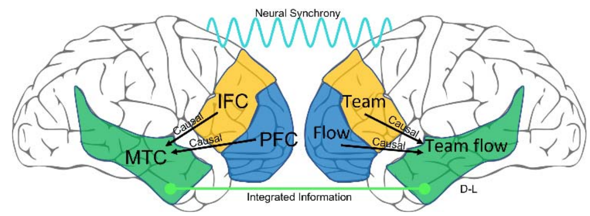

Fig. 2. Neural correlates of team flow.

The flow was originally a psychological concept obtained from interviews of top-level experts in various fields, such as sports, music, dance, chess, medical surgery, etc. (Csikszentmihalyi, 1990) [7]. It is highly challenging to duplicate this state in the laboratory to investigate neural correlates, yet we managed to make it happen to find that neural correlates of the "Team flow" are uniquely different from those of "Solo flow" or "social interaction without flow." Especially, the left middle temporal cortex was identified as the key node to integrate the flow and the social networks (See Fig. 2; Shehata, et al., 2021) [16].

3) **Implicit/explicit interactions both define, and break the limit**. Conscious (explicit) information processing is only "a tip of the iceberg" and overwhelming amount of processing is hidden in the unconscious (implicit) mind, as everybody intuitively knows. Fig. 3 summarizes what implicit cognitive process can do functionally (Hung & Shimojo, *unp.*). Against conventional belief that implicit processes are limited to simple sensory/motor functions, surprisingly-higher-level cognitive functions can be implicit, including emotional perception and even semantics. Our own studies indicate that implicit processing is even susceptible to task load, attention and/or top-down executive control (Hung, *et al*., 2020) [8], although it could still be felt *effortless*. Obviously, approaching to the implicit cognition which has enormous computation power would be one key to break the limit in almost any tasks.

Empirical evidence of visual/cognitive *unconscious* processing

* Orientation (Blake & Fox, 1974; Kanai, et al., 2006; Bahrami et al., 2008)
* Object (Berti & Rizzolatti, 1992; Almeida et al., 2008)
* **Emotion** (Öhman & Soares, 1994; Yang et al., 2007)
* **Face** (Murphy & Zajonc, 1993; Hung et al., 2017)
* Phonology (Lamy et al., 2008; Hung et al., 2017)
* Orthography (Costello et al., 2009)
* **Semantics** (Marcel, 1983; Dehaene et al., 1998; Hung et al., 2020)
* **Syntax** (Ansorge, et al., 2012; Hung et al., 2015/2021)

Fig. 3. A selected list of implicit cognitive functions.

As for future directions, we would like to emphasize two big perspectives:

(3-1) **Whose limit is it?** Technological extensions of brain-mind-body immediately lead to a question as to whose limit it is, especially when the hybrid system (*e.g.*. a handicapped athlete in Paralympic game with orthosis after enormous training) is compared with the same individual without it. This raises intriguing possibilities of switching among hybrid systems depending on the task context, and by the same token raises obvious ethical issues. Interdisciplinary efforts should be gathered to sort out techno-scientific goals as well as ethical issues. The examples such as team flow and other social contextual effects (*e.g.*. contagion from the audience) should be further examined.

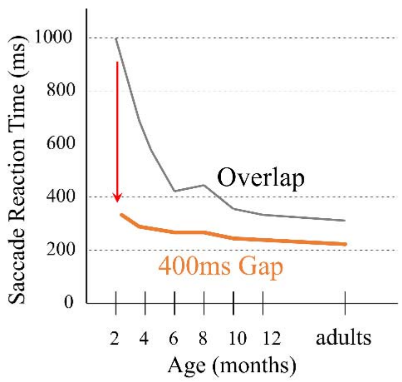

Fig. 4. Developmental changes in saccade reaction time (Matsuzawa & Shimojo, Infant Behav. & Develop., 1997 [13]).

(3-2) **Neural model?** It is way too premature to offer a united neural model for it. But having a simplest possible working hypothesis on the neural correlates may facilitate more empirical research, thus here it is: As for psychological limits, *sticky* engagement of attention is often the primary cause of limit at various level. Therefore, facilitating ***disengagement*** is helpful to break it. As for neural counterpart of this psychological hypothesis could be the following: Inhibition is the common mechanism which defines the upper limit. ***Disinhibition*** is the way to break it. Young infants' (2-3 months of age) express saccade would be a great example (see Fig. 4; Matsuzawa & Shimojo, 1997) [13] where what had been believed to be the motor limitation was easily and grossly broken by facilitating attention disengagement. Obviously, however, there should be lots of exceptions to this simple set of hypotheses. One obvious example would be Yips where more intricated interactions of facilitation and inhibitions at various scales/levels are responsible for the feedback in the negative direction at a functional level. Even these exceptions can be notable owing to the explicitly stated simplest hypotheses.

Our discussion here already challenges some main-stream psychological/philosophical frameworks, such as the limited capacity model of attention (Kahneman, 1973) [9], and the limit being defined *within* individual brain-body.

III. Implementing Functions of Consciousness

This section will introduce artificial consciousness research as an approach to expand existing theories of consciousness by considering possible AI implementations of the ideas expressed by those theories. This approach forces researchers to translate sometimes philosophical notions into mathematical and computational terms, and thereby clarify the fundamental relationships between consciousness and intelligence.

Building upon this approach, we propose the hypothesis that consciousness has evolved as a platform for general-purpose intelligence. General-purpose intelligence can be defined as the ability to generate solutions to new problems by applying knowledge and models learned from past experiences. Three possible methods are proposed to achieve such intelligent systems: 1) model-based internal simulation, 2) construction of new functions by combining specialized modules, and 3) generation of new modules based on meta-representation of models. We will discuss the relationship between intelligence and consciousness by comparing these proposed implementations of general-purpose intelligence with theoretical and empirical insights gained from consciousness research.

The first method, i.e., the acquisition of generality through internal simulation, corresponds to the information generation hypothesis of consciousness (Kanai et al., 2019) [20]. This hypothesis, based on empirical findings about biological benefits of having consciousness, argues that the core function of consciousness is the ability to internally generate counterfactual representations that are decoupled from current sensory inputs. The internally generated representations are shaped by models of sensory-motor contingency learned through interactions with the environment, and are the basis for functions such as intention, imagination, planning, short-term memory, attention, curiosity, and creativity. These functions contribute to the realization of non-reflexive behaviors that are characteristic of consciousness. In the context of artificial intelligence research, this corresponds to the acquisition and use of "world models".

The second method, i.e., the realization of general intelligence through the combination of function-specific modules, corresponds to the idea expressed by global workspace theory (VanRullen & Kanai, 2021) [21]. Global workspace theory posits that the function of consciousness is to integrates information and combines specialized modules across a large-scale system to achieve a higher level of cognition and awareness. Our ongoing efforts are shared to implement global workspace with deep learning and clarify the practical significance of the consciousness architecture proposed by this theory. Furthermore, we propose to create a global latent workspace (GLW) by unsupervised translation of representations between multiple latent spaces (neural networks trained on different tasks, different sensory inputs, and/or modalities), and discuss the functional benefits and neuroscientific significance of GLWs.

The third method, i.e., the generation of novel functions based on meta-representations, corresponds to the higher-order theory of consciousness, which states that sensory first-order information processing is insufficient for the generation of consciousness, and meta-representation of the first-order processing is needed. While this theory makes intuitive sense, the mathematical definition of meta-representation has been vague and computational implementation of meta-representation has been elusive. Here, we offer a possible definition of meta-representation as the embedding space of task-specific functions (e.g. neural networks). This hypothesis predicts that there are embedded meta- representations of the input-output relationships of neural networks exist also in the brain and proposes that this embedded space may be the basis of a sensory quality called qualia.

In summary, these three methods to implement general-purpose intelligence have corresponding theories of consciousness, and serve as possible methods to implement those machineries linked with consciousness in the context of modern consciousness research.

IV. Model Fusion: Combining Multiple ML/AI Models with Cognitive Diversity

Complex problems in machine learning and artificial intelligence can be examined with multiple models. These models may implement different algorithmic and statistical approaches and demonstrate varied performance. Ensemble methods are commonly used in ML/AI applications; however, it is not known whether the combination of models is likely to improve performance before testing the ensemble. The concept of diversity may refer to the difference in type of algorithm or data sources used. Here, we are specifically referring to quantitative measures of diversity. The combinatorial fusion algorithm (CFA) framework [24, 27] provides methods for model fusion and defines a rank-score function that can be used to measure the cognitive diversity between scoring systems.

Consider an ML/AI application in which we have multiple models that analyze or classify items in a dataset. In the combinatorial fusion algorithm (CFA) [24, 27], each model, X, is represented as a scoring system. Each scoring system has a score function s_X that maps each of the n data items in the dataset $D = \{d_1, d_2, \ldots, d_n\}$ to a real number in R, along with a corresponding rank function r_X that maps each data item to $N = \{1, 2, \ldots, n\}$ according to its ranking. If this is a classification problem, the scores are the probabilities that a data item belongs to a particular class. The rank-score characteristic function (RSC) [24, 27] is the composition of the score function and the inverse of the rank function, defined as: $f_X(i) = (s_X \circ r_X^{-1})(i)$ for $1 \leq i \leq n$. The RSC function is a mapping from a rank to a score, from $N \rightarrow R$, which captures the scoring behavior of the model. A sample RSC function graph is shown in Fig. 5. The relationships between the score, rank, and RSC functions of two systems is shown in Fig. 6. The notion of an RSC function was proposed by Hsu, Shapiro, and Taksa [26]. It has been used before in totally different contexts such as rank-size distribution [22] in a population study of urban city development and as rank-frequency distribution [23] in computational linguistics. An ensemble (fusion), of m multiple scoring systems is efficiently achieved by score combination (SC) or rank combination (RC), which are computed as the average, or weighted average, of scores (or ranks). The fused model is represented by the score functions of the score, or rank, combinations. It has been demonstrated that under certain conditions of larger diversity, rank combination outperforms score combination [27].

Diversity plays a critical role in the performance of a combined model that is the result of fusing multiple component models. Despite its importance, there is no standard diversity measurement for ML/AI models, though several have been proposed. From the statistical perspective, correlation is commonly used to measure the relationships between features; however, since correlation is applied directly to score functions, it is data-dependent. The concept of cognitive diversity as defined in CFA is data-independent since it uses the RSC function of the systems. The "cognitive diversity" (CD) between two models, A and B, is computed as the distance between the RSC functions [24, 25, 27, 29]:

$d(A,B) = d(f_A, f_B) = \sqrt{\sum_{i=1}^{n}((f_A(i) - f_B(i))^2/n}$. When considering more than 2 models, the CD between all system pairs is computed and for each system, X, the average CD for all pairs that include X is considered its "diversity strength". This can be used as a weight when computing a weighted score or rank combination.

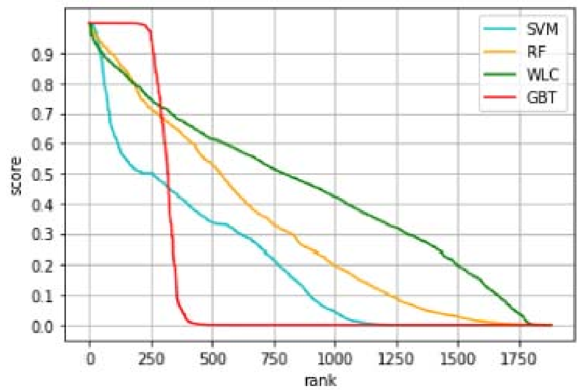

Fig. 5. Sample Rank-Score Characteristic (RSC) function graph for a chemoinformatics application in which the four models represent the ML algorithms: SVM (support vector machines), RF (random forests), WLC (weighted logistic classifier), and GBT (gradient boosted trees) [29].

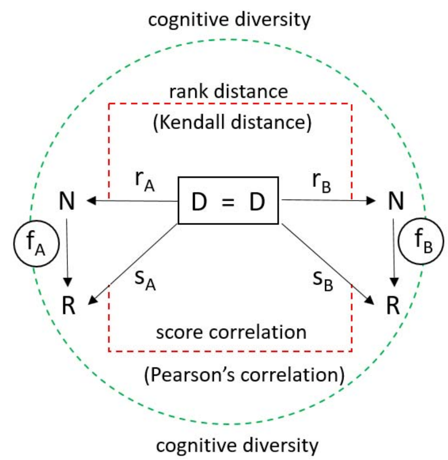

Fig. 6. The relationships between the score, rank, and RSC functions of two scoring systems, A and B [25].

The combinatorial fusion algorithm, along with cognitive diversity, is applicable to a variety of domains [28, 30]. Further, a multi-layer combinatorial fusion approach on the Kemeny rank space provides a comprehensive approach for preference prediction and reinforcement learning [28]. An evolutionary process involving a series of expansion (generating combinations) and reduction (selecting the top combinations using performance and diversity) phases can increase the overall performance of model fusion [28]. Model fusion was shown to improve not only prediction quality but also data quality (e.g.: [29]). Since each model is an intelligent system, the combined model can achieve hyper intelligence.

V. Hyper-Intelligent Supply Chain Developments and Risks

Hyper-intelligent systems are the foundational technology for developing hyperautomated supply chains. This began with the combination of traditional corporate information technology systems that were tied into robotic process

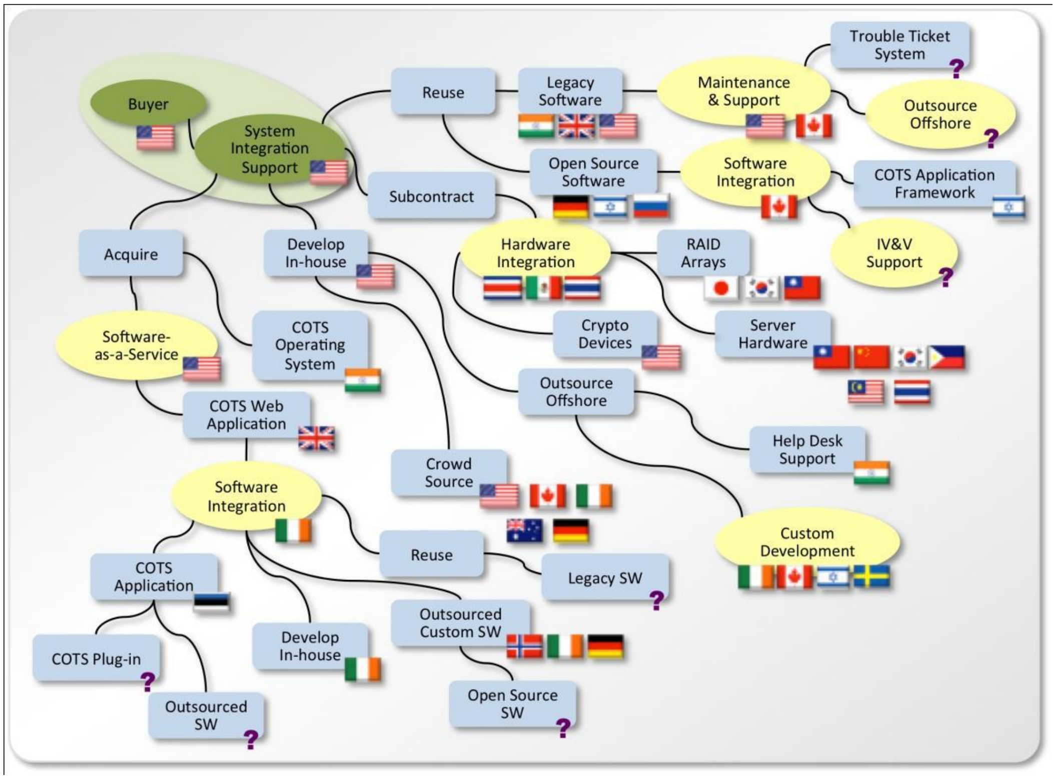

Fig. 7. Source: RSA Conference2015, SF, USA, April 20-24, Session ID: STR-F03, "Supply Chain as an Attack Chain: Key Lessons to Secure Your Business," 29 Oct 2018 [31].

automation (RPA). These are now being further integrated by artificial intelligence (AI), machine learning (ML), process mining, Internet of Things (IoT) sensor networks, and natural language processing to create end-to-end automated solutions. The end result is hyperautomation. It will be hyper-connected to include customers, vendors, manufacturing, logistics, transportation, accounting, risk management and all related systems.

Governments and other entities need several contracts to make information and communications technology (ICT) networks realities: one to design the networks; a second to procure the hardware; a third to acquire the software to run on the network so it can perform its required functions; and another to integrate all of them into one unified system of systems for operation. Finally, another contract is required to maintain them. This creates the multiple attack vectors in depicted in Fig. 7.

Ideally, Human Cognition and Hyper Intelligence (HCHI) will lead to hyperautomation that will enhance the development of more efficient, accurate, secure, resilient and cost-effective processes within global supply chains. Business intelligence analysts will integrate information from monitoring robotic process automation, intelligent delivery systems and intelligent document process, and shift to working with or applying intelligence based on analytics and insights to make more accurate predictions and decisions. The 2020 event involving the Solar Winds compromise served as a clear example of the impact of a hostile operation via the cyber software supply chain [32]. This event stirred the release of an Executive Order designed to ameliorate future imacts [33].

The hyperautomated supply chain should offer opportunities to create a more secure and resilient environment and help to improve the accuracy and efficiency of forecasts and predictions to deal with cyber supply chain incidents.

This leads to the more difficult question of how to hyperautomate a supply chain. This paper does not seek to find a solution in the brief period allowed, but does hope to motivate and stimulate more research and implementation of potential solutions.

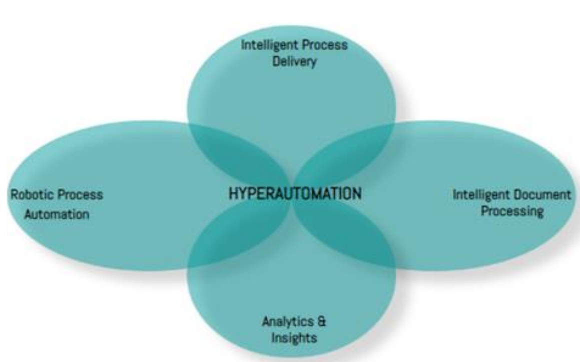

Fig. 8. From https://www.alphalake.ai/blog/what-is-hyper-automation [34].

Based on the depiction in Fig. 8, the hyperautomated supply chain would be a mix of various technologies and capabilities. Some of the most relevant technologies are IoT sensor networks and AI/ML-based data analytics to provide end-to-end supply chain monitoring and management [35]. The simplest example to understand would be warehouse automation where the integration of robots, conveyors and inventory control and management can be most easily seen. However, this is much more complex in the context of global supply chains in multiple geographic and political environments. These are subject to natural disasters, air, land and sea transport situations, local laws and regulations, as well as political stability, or the lack thereof [36]. These things are all easily said, but present great challenges to those charged with implementing effective hyper-intelligent supply chain management.

VI. Ambient Intelligence: Convergence of Technologies for Smart Environments

Adaptability and advanced services for ambient intelligence require an intelligent technological support for understanding the current needs and the desires of users in the interactions with the environment for their daily use, as well as for understanding the current status of the environment also in complex situations. This infrastructure constitutes an essential base for smart living. Various technologies are nowadays converging to support the creation of efficient and effective infrastructures for ambient intelligence.

Artificial intelligence can provide flexible techniques for designing and implementing monitoring and control systems, which can be configured from behavioral examples or by mimicking approximate reasoning processes to achieve adaptable systems. Machine learning can be effective in extracting knowledge form data and learn the actual and desired behaviors and needs of individuals as well as the environment to support informed decisions in managing the environment itself and its adaptation to the people's needs.

Biometrics can help in identifying individuals or groups: their profiles can be used for adjusting the behavior of the environment. Machine learning can be exploited for dynamically learning the preferences and needs of individuals and enrich/update the profile associated either to such individual or to the group. Biometrics can also be used to create advanced human-computer interaction frameworks.

Cloud/Fog/Edge computing and internet-of-things environments will be instrumental in allowing for world-wide availability of knowledge about the preferences and needs of individuals as well as services for ambient intelligence to build applications easily.

The opportunities offered by these technologies to support the realization of adaptable operations and intelligent services are very promising for smart living in an ambient intelligent infrastructures.

VII. Concluding Remarks

In this paper, we have provided five diverse perspectives on and several framework for enhancing human cognition and hyper intelligence. These perspectives cover a variety of features and components in the human cognition process and hyper intelligence space. These include "How to break the upper limit" in the human cognition process (Sec. II) and how to achieve higher general-purpose intelligence through simulation, combination, and generation in artificial consciousness research (Sec. III). Section IV provided a brief review of a new informatics and ML/AI paradigm: combinatorial fusion algorithm (CFA) with the rank-score characteristic (RSC) function and cognitive diversity (CD). Section V covered a hyper-intelligent supply chain development and its associated risks. In Section VI, we discussed how to achieve ambient intelligence through convergence of technologies in a smart monitoring and control environment.

These results in the paper have opened up an array of new dimensions for achieving higher human cognition and hyper intelligence. This paper has also inspired several fundamental issues worthy of further investigation. Three of them are listed here: (1) Explore causal effect in more details between cognition and intelligence [37]; (2) What other knowledge can hyper intelligence learn from the study of human cognition? and (3) Explore the structure and function of the information geometry: Kemeny rank space [38, 39].

It is believed that hyper-intelligence (HI) must be a next evolutionary phase of AI interwoven with IoT, big data, cognition science, brain informatics, nano technology, etc. Currently, hyper-intelligent systems are rapidly emerging and cover a multitude of application domains such as artificial intelligent chess engines, self-driving vehicles, autonomous weapons, automated drug discoveries, smart cities, etc. Due to its importance and revolutionary impact, a large group of colleagues in multi-disciplinary profession and practice from diverse geographical areas (different regions of the IEEE) have established the hyper-intelligence technical committee (HITC) under the IEEE Systems Council. HITC is aimed to promote global research and practice of hyper-intelligent systems for a smarter world and society. It peruses an open platform for people sharing the same interest to jointly explore hyper-intelligence theories, technologies, standards and applications. More information about the IEEE HITC is given at https://ieee-hyperintelligence.org/.

Acknowledgment

This article is co-authored by all members of the panel on Human Cognition and Hyper Intelligence. We appreciate the organizers of the sixth IEEE Cyber Science and Technology Congress (CyberSciTech 2021), especially its general chair, professor Oscar Lin, for strong support to the panel. We also thank Ms. Karen Stauff for her extraordinary assistance in designing the panel and setting up a nice online environment for conducting the panel.

References

[1] J. I. Gold and M. N. Shadlen; The neural basis of decision making, Annu. Rev. Neurosci. 2007.30:535-74.

[2] I. J. Deary et al; Genetic contributions to stability and change in intelligence from childhood to old age, Nature, Vol.482, Feb. 2012, p.212-215.

[3] R. Plomin; How intelligence changes with age, Nature, Vol.482, Feb. 2012, p.165-166.

[4] T. Storer and D. Winter (edited); Former Aspects of Cognitive Processes, Lecture Notes in Computer Science(LNCS #22), Springer-Verlag, 1972.

[5] Chib, V., De Martino, B., Shimojo, S. & O'Doherty, J. Neural Mechanisms Underlying, Paradoxical Performance for Monetary Incentives are Driven by Loss Aversion. Neuron, 74, 582-594, 2012. DOI 10.1016/j.neuron.2012.02.038, 2012.

[6] Chib, V.S., Shimojo, S. and O'Doherty, J.P. The effects of incentive framing on performance decrements for large monetary outcomes:

behavioral and neural mechanisms. J. Neurosci., 34-45:14833–14844, 2014.

[7] Csikszentmihalyi, M. Flow: The Psychology of Optimal Experience. New York: Harper and Row, 1990. ISBN 0060920432.

[8] Hung, S. -M., Wu, D. -A., & Shimojo, S. Task-induced attention guides and gates unconscious semantic interference. Nature Communications, 11, 2088, 2020. https://doi.org/10.1038/s41467-020-15439-x. 2020.

[9] Kahneman, D. Attention and Effort. Prentice-Hall, Englewood Cliffs, New Jersey, 1973.

[10] Lepper, M.R., Greene, D. and Nisbett, R.E. Undermining children's intrinsic interest with extrinsic reward: A test of the "overjustification" hypothesis. Journal of Personality and Social Psychology, 28-1, 129–137. https://doi.org/10.1037/h003551

[11] Marcel, A.J. Conscious and unconscious perception: An approach to the relations between phenomenal experience and perceptual processes. Cognitive Psychology, 15-2, 238-300, 1983.

[12] Marchant, J. A journey into the science of mind over body. Crown, 2016.

[13] Matsuzawa, M. and Shimojo, S. Infants' fast saccades under the gap paradigm and development of visual attention. Infant Behavior and Development, 20, 449-455, 1997.

[14] Monahan, J., Murphy, S.T. and Zajonc, R.B. Subliminal mere exposure: specific, general, and diffuse effects. Psychol. Science, 11-6, 462-466, 2000.

[15] Sauro, M.D. and Greenberg, R.P. Endogenous opiates and the placebo effect: A meta-analytic Review. Journal of Psychosomatic Research, 58-2, 115-120, 2005.

[16] Shehata, M., Cheng, M., Leung, A., Tsuchiya, N., Wu, D-A. Tseng, C., Nakauchi, S. and Shimojo, S. Team flow is a unique brain state associated with enhanced information integration and neural synchrony, eNeuro, in press. BioRxiv. doi: 10.1101/2020.06.17.157990, 2020.

[17] Shimojo, S. Postdiction: its implications on visual awareness, hindsight, and sense of agency. Frontiers in Psychology, 196, 1-19, 2014. doi: 10.3389/fpsyg.2014.00196, 2014.

[18] Shimojo, S. The implicit process of the mind and the "Personal History": perception, evolution, and social brain. In A Multidisciplinary Approach to Mind: A Japanese "Kokoro" Perspective. Toshio Kawai & Kyoto Univ. KOKORO center (eds.), Routledge, in press.

[19] Watanabe, K. Behavioral speed contagion: Automatic modulation of movement timing by observation of body movements. Cognition, 106-3, 1514-1524, 2008.

[20] Kanai, R., Chang, A., Yu, Y., Magrans de Abril, I., Biehl, M., & Guttenberg, N. (2019) Information generation as a functional basis of consciousness, Neuroscience of Consciousness, Volume 2019, Issue 1, niz016, https://doi.org/10.1093/nc/niz016

[21] VanRullen, R., & Kanai, R. (2021). Deep learning and the Global Workspace Theory. Trends in Neurosciences, 44, 9, 692-704. https://doi.org/10.1016/j.tins.2021.04.005

[22] Brakman S, Garretsen H, van Marrewijk C, & van den Berg MM (1999) The Return of Zipf: Towards a Further Understanding of the Rank-Size Distribution. Journal of Regional Science, 39(1), 183-213.

[23] Cocho G, Rodríguez RF, Sánchez S, Flores J, Pineda C, & Gershenson C (2019) Rank-difference of probabilities approach, Physica A: Statistical Mechanics and its Applications, Volume 532, 121795.

[24] Hsu DF, Chung YS, & Kristal BS (2006) Combinatorial fusion analysis: methods and practice of combining multiple scoring systems. In: Hsu HH (ed) Advanced data mining technologies in bioinformatics. Idea Group Inc., Calgary, pp 1157–1181.

[25] Hsu DF, Kristal B, Hao Y, Schweikert C. Cognitive Diversity: A Measurement of Dissimilarity Between Multiple Scoring Systems. J. Interconnect. Netw. 2019, 19, 1940001.

[26] Hsu DF, Shapiro J, & Taksa I (2002) "Methods of data fusion in information retrieval: Rank vs. Score combination," DIMACS, Rutgers Univ., Piscataway, NJ, USA, Tech. Rep. DIMACS TR 2002-58.

[27] Hsu DF & Taksa I (2005) Comparing rank and score combination methods for data fusion in information retrieval. Inform Retr 8(3):449–480.

[28] Hurley L, Kristal BS, Sirimulla S, Schweikert C & Hsu DF (2020) "Multi-Layer Combinatorial Fusion Using Cognitive Diversity," in IEEE Access, vol. 9, pp. 3919-3935, 2021, doi: 10.1109/ACCESS.2020.3047057.

[29] Tang Y, Li Z, Nellikkal M, Eramian H, Chan EM, Norquist AJ, Hsu DF, & Schrier J (2021) Improving Data and Prediction Quality of High-Throughput Perovskite Synthesis with Model Fusion. Journal of Chemical Information and Modeling 61 (4), 1593-1602.

[30] Yang JM et al (2005) Consensus scoring for improving enrichment in virtual screening. J Chem Inform Model, 45:1134–1146.

[31] https://docs.huihoo.com/rsaconference/usa-2015/str-f03-supply-chain-as-an-attack-chain-key-lessons-to-secure-your-business.pdf

[32] https://www.ic3.gov/Media/News/2020/201229.pdf

[33] https://www.whitehouse.gov/briefing-room/statements-releases/2021/06/08/fact-sheet-biden-harris-administration-announces-supply-chain-disruptions-task-force-to-address-short-term-supply-chain-discontinuities/

[34] https://www.alphalake.ai/blog/what-is-hyper-automation

[35] https://blogs.oracle.com/japac/revealing-tomorrows-supply-chain

[36] https://doi.org/10.1287/LYTX.2020.04.04

[37] E. Bareinboim and J. Pearl, Causal inference and the data-fusion problem, PNAS, July 5, 2016, Vol. 113, No. 27, pp. 7345-7352.

[38] W. J. Heiser and A. D'Ambrosio, Clustering and prediction of rankings within a Kemeny distance framework, in Algorithms from and for Nature and Life, Studies in Classification,Data Analysis, and Knowledge Organization, Springer International Publishing Switzerland, 2013, pp. 19-31.

[39] X. Zhong et al, Combining multiple ranking systems on the generalized permutation rank space, Proc. of IEEE 5th Int. Conf. Big Data Intell. Comput. (DATACOM), Nov. 2019, pp. 123-129.

[40] T. Meng et al; A survey on machine learning for data fusion, Information Fusion 57, 2020, pp. 115-129.