On Autonomous Systems:
From Reflexive, Imperative and Adaptive Intelligence to Autonomous and Cognitive Intelligence

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Abstract — Autonomous systems underpinned by cognitive intelligence represent advanced forms of artificial intelligence studied in intelligence science, systems science, and computational intelligence. Traditional theories and technologies of autonomous systems put emphases on human-system interactions and humans in-the-loop. This paper explores the intelligence and system foundations of autonomous systems. It focuses on what structural and behavioral properties constitute the intelligence power of autonomous systems. It explains how system intelligence aggregates from reflexive, imperative, adaptive intelligence to autonomous and cognitive intelligence. A Hierarchical Intelligence Model (HIM) is introduced to elaborate the evolution of human and system intelligence as an inductive process. A set of properties of system autonomy is formally analyzed towards a wide range of autonomous system applications in computational intelligence and systems engineering.

Keywords — Autonomous systems, intelligence science, system science, framework of intelligence, cognitive systems, adaptive systems, unmanned systems, human-in-the-loop, human-robot taskforce

I. INTRODUCTION

Autonomous systems (AS) used to be perceived as an Internet protocol in industry. Machine learning and control theories focus on human-system interactions in AS' where humans are in-the-loop cooperating with the machine [9]. NATO refers AS to a system that "exhibits goal-oriented and potentially unpredictable and non-fully deterministic behaviors [6]." In basic studies of intelligence science and systems science, the field of AS investigates intelligent systems for implementing advanced human intelligence by computational systems and neural networks [1, 2, 5, 6, 8, 12, 13, 16, 18, 20, 23], which embodies the high-level machine intelligence built on those of imperative and adaptive systems.

The natural and machine intelligence underpinning autonomous systems may be inductively generated through data, information, and knowledge as illustrated in Figure 1 from the bottom up. Figure 1 indicates that intelligence may not be directly aggregated from data as some neural network technologies inferred, because there are multiple inductive layers from data to intelligence. Therefore, a matured AS would be expected to be able to independently discover a law in sciences (inductive intelligence) or autonomously comprehend the semantics of a joke in natural languages (inference intelligence). None of them is trivial in order to extend the AS' intelligence power beyond data aggregation abilities.

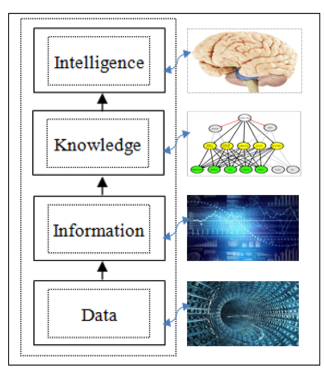

Fig. 1 The cognitive entities in the brain of natural intelligence

In the past 60 years of AI and systems engineering, few fully autonomous systems have been developed, because the theoretical foundations for autonomous intelligence and systems were not sufficiently mature [1, 2, 4, 7, 11, 14, 16, 19, 20, 22]. Many AI systems are still bounded by the intelligence bottleneck of adaptive systems where machine intelligence is constrained by the lower-level reflexive, imperative, and deterministic adaptive intelligent abilities [18, 23].

This paper explores the nature and the theoretical framework of autonomous systems beyond traditional reflexive, imperative, and adaptive systems. The framework of intelligence science underpinning autonomous systems is formally introduced in Section II with a set of mathematical models. Theories of autonomous systems are developed in Section III in order to elaborate the generation of systems autonomy and the role of human factors in hybrid AS.

II. THE FRAMEWORK OF INTELLIGENCE SCIENCE UNDERPINNING AUTONOMOUS SYSTEMS

Intelligence is the paramount cognitive ability of humans that may be mimicked by computational intelligence and cognitive systems. Intelligence science studies the general form of intelligence, formal principles and properties, as well as engineering applications [17, 21, 24]. This section explores the cognitive and intelligent foundations of AS underpinned by intelligence science.

2.1 The Cognitive Foundations of Intelligence Science

The intension and extension of the concept of intelligence, C_1(*intelligence*), may be formally described by a set of attributes (A_1) and of objects (O_1) according to concept algebra:

$$C_1(intelligence: A_1, O_1, R_1^c, R_1^i, R_1^o)$$
$$= \begin{cases} A_1 = \{cognitive\_object^*, mental\_power, aware\_to\_be, \\ \quad able\_to\_do, process, execution, transfer\_information\_ \\ \quad to\_knowledge, transfer\_information\_to\_behaviour\} \\ O_1 = \{brain, robots, natural_i, AI, animal_i, reflexive_i, \\ \quad imperative_i, adaptive_i, autonomous_i, cognitive_i\} \\ R_1^c = O_1 \times A_1 \\ R_1^i \subseteq \mathfrak{K} \times C_1 \\ R_1^o \subseteq C_1 \times \mathfrak{K} \end{cases} \quad (1)$$

where R_1^c, R_1^i, and R_1^o represent the sets of internal and input/output relations of C_1 among the objects and attributes or from/to existing knowledge $\mathfrak{K}$ as the external context.

Definition 1. *Intelligence* $\dot{\mathbb{I}}$ is a human, animal, or system ability that autonomously transfers a piece of information I into a behavior B or an item of knowledge K, particularly the former, i.e.:

$$\dot{\mathbb{I}} = f_{to-do}: I \to B \;|\; f_{to-be}: I \to K \quad (2)$$

Intelligence science is a contemporary discipline that studies the mechanisms and properties of intelligence, and the theories of intelligence across the neural, cognitive, functional, and mathematical levels from the bottom up.

A classification of intelligent systems may be derived based on the forms of inputs and outputs dealt with by the system as shown in Table 1. The reflexive and imperative systems may be implemented by deterministic algorithms or processes. The adaptive systems can be realized by deterministic behaviors constrained by the predefined context. However, AS is characterized as having both varied inputs and outputs where its inputs must be adaptive, and its outputs have to be rationally fine-tuned to problem-specific or goal-oriented behaviors.

Table 1. Classification of autonomous and nonautonomous systems

		Behavior (O)	
		Constant	Varied
Stimulus (I)	Constant	*Reflexive*	*Adaptive*
	Varied	*Imperative*	*Autonomous*

According to Definition 1 and Table 1, AS is a highly intelligent system for dealing with variable events by flexible and fine-tuned behaviors without the intervention of humans.

2.2 The Hierarchical Model of Intelligence

A *hierarchical intelligence model* (HIM) is created for identifying the levels of intelligence and their difficulty for implementation in computational intelligence as shown in Figure 2 based on the *abstract intelligence* (αI) theory [17]. In HIM, the levels of intelligence are aggregated from reflexive, imperative, adaptive, autonomous, and cognitive intelligence with 16 categories of intelligent behaviors. Types of system intelligence across the HIM layers are formally described in the following subsections using the stimulus/event-driven formula as defined in Eq. 2.

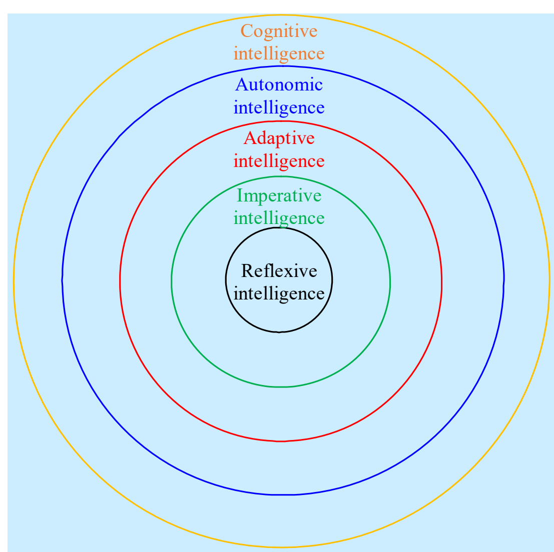

Fig. 2 The hierarchical intelligence model (HIM)

2.2.1 Reflexive Intelligence

Reflexive intelligence $\dot{I}_{ref}$ is the bottom-layer intelligence coupled by a stimulus and a reaction. $\dot{I}_{ref}$ is shared among humans, animals, and machines, which forms the foundation of higher layer intelligence.

Definition 2. The *reflexive intelligence* $\dot{I}_{ref}$ is a set of wired behaviors B_{ref} directly driven by specifically coupled external stimuli or trigger events @e_i|REF, i.e.:

$$\dot{I}_{ref} \triangleq \mathop{R}_{i=1}^{n_{ref}} @e_i|\text{REF} \hookrightarrow B_{ref}(i)|\text{PM} \tag{3}$$

where the *big-R notation* is a mathematical calculus that denotes a sequence of iterative behaviors or a set of recurring structures [19], $\hookrightarrow$ a dispatching operator between an event and a specified function, @ the event prefix of systems, |REF the string suffix of a reflexive event, and |PM the process model suffix.

2.2.2 Imperative Intelligence

Imperative intelligence $\dot{I}_{imp}$ is a form of instructive and reflective behaviors dispatched by a system based on the layer of reflexive intelligence. $\dot{I}_{imp}$ encompasses event-driven behaviors (B^{e}_{imp}), time-driven behaviors (B^{t}_{imp}), and interrupt-driven behaviors (B^{int}_{imp}).

Definition 3. The *event-driven intelligence* $\dot{I}^{e}_{imp}$ is a predefined imperative behavior B^{e}_{imp} driven by an event @e_i|E, i.e.:

$$\dot{I}^{e}_{imp} \triangleq \mathop{R}_{i=1}^{n_e} @e_i|\text{E} \hookrightarrow B^{e}_{imp}(i)|\text{PM} \tag{4}$$

Definition 4. The *time-driven intelligence* $\dot{I}^{t}_{imp}$ is a predefined imperative behavior B^{t}_{imp} driven by a point of time @e_i|TM, i.e.:

$$\dot{I}^{t}_{imp} \triangleq \mathop{R}_{i=1}^{n_t} @e_i|\text{TM} \hookrightarrow B^{t}_{imp}(i)|\text{PM} \tag{5}$$

where @e_i|TM may be a system or external timing event.

Definition 5. The *interrupt-driven intelligence* $\dot{I}^{int}_{imp}$ is a predefined imperative behavior B^{int}_{imp} driven by a system-triggered interrupt event @e_i|⦿, i.e.:

$$\dot{I}^{int}_{imp} \triangleq \mathop{R}_{i=1}^{n_{int}} @e_i|\odot \hookrightarrow B^{int}_{imp}(i)|\text{PM} \tag{6}$$

where the *interrupt*, @int_i|⦿, triggers an embedded process, $B_1|\text{PM} \lightning B_2|\text{PM} = B_1|\text{PM} \,||\, (e^{i}_{\text{int}}|\odot \nearrow B_2|\text{PM} \searrow \odot)$, where the current process B_1 is temporarily held by a higher priority process B_2 requested by the interrupt event at the interrupt point ⦿. The interrupted process will be resumed when the high priority process has been completed.

The imperative system powered by $\dot{I}_{imp}$ is not adaptive, and may merely implement deterministic, context-free, and stored-program controlled behaviors.

2.2.3 Adaptive Intelligence

Adaptive intelligence $\dot{I}_{adp}$ is a form of run-time determined behaviors where a set of predictable scenarios is determined for processing variable problems. $\dot{I}_{adp}$ encompasses analogy-based behaviors (B^{ab}_{adp}), feedback-modulated behaviors (B^{fm}_{adp}), and environment-awareness behaviors (B^{ea}_{adp}).

Definition 6. The *analogy-based intelligence* $\dot{I}^{ab}_{adp}$ is a set of adaptive behavior B^{ab}_{adp} that operate by seeking an equivalent solution for a given request @e_i|RQ, i.e.:

$$\dot{I}^{ab}_{adp} \triangleq \mathop{R}_{i=1}^{n_{ab}} @e_i|\text{RQ} \hookrightarrow B^{ab}_{adp}(i)|\text{PM} \tag{7}$$

Definition 7. The *feedback-modulated intelligence* $\dot{I}^{fm}_{adp}$ is a set of adaptive behaviors B^{fm}_{adp} rectified by the feedback of temporal system output @e_i|FM, i.e.:

$$\dot{I}^{fm}_{adp} \triangleq \mathop{R}_{i=1}^{n_{fm}} @e_i|\text{FM} \hookrightarrow B^{fm}_{adp}(i)|\text{PM} \tag{8}$$

Definition 8. The *environment-awareness intelligence* $\dot{I}^{ea}_{adp}$ is a set of adaptive behavior B^{ea}_{adp} where multiple prototype behaviors are modulated by the change of external environment @e_i|EA, i.e.:

$$\dot{I}^{ea}_{adp} \triangleq \mathop{R}_{i=1}^{n_{ea}} @e_i|\text{EA} \hookrightarrow B^{ea}_{adp}(i)|\text{PM} \tag{9}$$

$\dot{I}_{ada}$ is constrained by deterministic rules where the scenarios are prespecified. If a request is out of the defined domain of an adaptive system, its behaviors will no longer be adaptive or predictable.

2.2.4 Autonomous Intelligence

Autonomous intelligence $\dot{I}_{aut}$ is the fourth-layer intelligence powered by internally motivated and self-generated behaviors underpinned by senses of system consciousness and environment awareness. $\dot{I}_{aut}$ encompasses the perceptive behaviors (B^{pe}_{aut}), problem-driven behaviors (B^{pd}_{aut}), goal-oriented behaviors (B^{go}_{aut}), decision-driven behaviors (B^{dd}_{aut}), and deductive behaviors (B^{de}_{aut}) built on the Layers 1 through 3 intelligent behaviors.

Definition 9. The *perceptive intelligence* $\dot{\mathbb{I}}_{aut}^{pe}$ is a set of autonomous behaviors B_{aut}^{pe} based on the selection of a perceptive inference @e_i|PE, i.e.:

$$\dot{\mathbb{I}}_{aut}^{pe} \triangleq \mathop{R}_{i=1}^{n_{pe}} @e_i|\text{PE} \hookrightarrow B_{aut}^{pe}(i)|\text{PM} \tag{10}$$

Definition 10. The *problem-driven intelligence* $\dot{\mathbb{I}}_{aut}^{pd}$ is a set of autonomous behaviors B_{aut}^{pd} that seeks a rational solution for the given problem @e_i|PD, i.e.:

$$\dot{\mathbb{I}}_{aut}^{pd} \triangleq \mathop{R}_{i=1}^{n_{pd}} @e_i|\text{PD} \hookrightarrow B_{aut}^{pd}(i)|\text{PM} \tag{11}$$

Definition 11. The *goal-oriented intelligence* $\dot{\mathbb{I}}_{aut}^{go}$ is a set of autonomous behaviors B_{aut}^{go} seeking an optimal path towards the given goal @e_i|GO, i.e.:

$$\dot{\mathbb{I}}_{aut}^{go} \triangleq \mathop{R}_{i=1}^{n_{go}} @e_i|\text{GO} \hookrightarrow B_{aut}^{go}(i)|\text{PM} \tag{12}$$

where the goal, g|SM = (P, Ω, Θ), is a structure model (SM) in which P is a finite nonempty set of *purposes* or motivations, Ω a finite set of *constraints* to the goal, and Θ the environment of the goal.

Definition 12. A *decision-driven intelligence* $\dot{\mathbb{I}}_{aut}^{dd}$, is a set of autonomous behaviors B_{aut}^{dd} driven by the outcome of a decision process @e_i|DD, i.e.:

$$\dot{\mathbb{I}}_{aut}^{dd} \triangleq \mathop{R}_{i=1}^{n_{dd}} @e_i|\text{DD} \hookrightarrow B_{aut}^{dd}(i)|\text{PM} \tag{13}$$

where the decision, d|SM = (A, C), is a structure model in which A is a finite nonempty set of *alternatives*, and C a finite set of *criteria*.

Definition 13. The *deductive intelligence* $\dot{\mathbb{I}}_{aut}^{de}$ is a set of autonomous behaviors B_{aut}^{de} driven by a deductive process @e_i|DE based on known principles, i.e.:

$$\dot{\mathbb{I}}_{aut}^{de} \triangleq \mathop{R}_{i=1}^{n_{de}} @e_i|\text{DE} \hookrightarrow B_{aut}^{de}(i)|\text{PM} \tag{14}$$

$\dot{\mathbb{I}}_{aut}$ is self-driven by the system based on internal consciousness and environmental awareness beyond the deterministic behaviors of adaptive intelligence. $\dot{\mathbb{I}}_{aut}$ represents nondeterministic, context-dependent, run-time autonomic, and self-adaptive behaviors.

2.2.5 Cognitive Intelligence

Cognitive intelligence $\dot{\mathbb{I}}_{cog}$ is the fifth-layer of intelligence that generates inductive- and inference-based behaviors powered by autonomous reasoning. $\dot{\mathbb{I}}_{cog}$ encompasses the knowledge-based behaviors (B_{cog}^{kb}), learning-driven behaviors (B_{cog}^{ld}), inference-driven behaviors (B_{cog}^{if}), and inductive behaviors (B_{cog}^{id}) built on the intelligence powers of Layers 1 through 4.

Definition 14. The *knowledge-based intelligence* $\dot{\mathbb{I}}_{cog}^{kb}$ is a set of cognitive behaviors B_{cog}^{kb} generated by introspection of acquired knowledge @e_i|KB, i.e.:

$$\dot{\mathbb{I}}_{cog}^{kb} \triangleq \mathop{R}_{i=1}^{n_{kb}} @e_i|\text{KB} \hookrightarrow B_{cog}^{kb}(i)|\text{PM} \tag{15}$$

Definition 15. The *learning-driven intelligence* $\dot{\mathbb{I}}_{cog}^{ld}$ is a set of cognitive behaviors B_{cog}^{ld} generated by both internal introspection and external searching @e_i|LD, i.e.:

$$\dot{\mathbb{I}}_{cog}^{ld} \triangleq \mathop{R}_{i=1}^{n_{ld}} @e_i|\text{LD} \hookrightarrow B_{cog}^{ld}(i)|\text{PM} \tag{16}$$

Definition 16. The *inference-driven intelligence* $\dot{\mathbb{I}}_{cog}^{if}$ is a set of cognitive behaviors B_{cog}^{if} that creates a causal chain from a problem to a rational solution driven by @e_i|ID, i.e.:

$$\dot{\mathbb{I}}_{cog}^{if} \triangleq \mathop{R}_{i=1}^{n_{if}} @e_i|\text{ID} \hookrightarrow B_{cog}^{if}(i)|\text{PM} \tag{17}$$

Definition 17. The *inductive intelligence* $\dot{\mathbb{I}}_{cog}^{id}$ is a set of cognitive behaviors B_{cog}^{id} that draws a general rule based on multiple observations or common properties @e_i|ID, i.e.:

$$\dot{\mathbb{I}}_{cog}^{id} \triangleq \mathop{R}_{i=1}^{n_{id}} @e_i|\text{ID} \hookrightarrow B_{cog}^{id}(i)|\text{PM} \tag{18}$$

$\dot{\mathbb{I}}_{cog}$ is nonlinear, nondeterministic, context-dependent, knowledge-dependent, and self-constitute, which represents the highest level of system intelligence mimicking the brain. $\dot{\mathbb{I}}_{cog}$ indicates the ultimate goal of AI and machine intelligence.

The mathematical models of HIM indicate that the current level of machine intelligence has been stuck at the level of $\dot{\mathbb{I}}_{adp}$ in the past 60 years. One would rarely find any current AI system that is fully autonomous comparable to the level of human natural intelligence.

III. THE THEORY OF AUTONOMOUS SYSTEMS

On the basis of the HIM models of intelligence science as elaborated in the preceding section, autonomous systems will be derived as a computational implementation of autonomous intelligence aggregated from the lower layers.

3.1 Properties of System Autonomy and Autonomous Systems

According to the HIM model, *autonomy* is a property of intelligent systems that "can change their behavior in response to unanticipated events during operation [23]" "without human intervention [6]."

Definition 18. The *mathematical model of an AS* is a high-level intelligent system for implementing advanced and complex intelligent abilities compatible to human intelligence in systems, i.e.:

$$AS \triangleq \mathop{R}\limits_{i=1}^{n_{AS}} @e^{i}_{AS}|\mathrm{S} \hookrightarrow [B_{AS}(i)|\mathrm{PM} \mid B_{AS}(i)|\mathrm{PM} \geq 4] \qquad (19)$$

which extends system intelligent power from reflexive, imperative, and adaptive to autonomous and cognitive intelligence.

AS implements nondeterministic, context-dependent, and adaptive behaviors. AS is a nonlinear system that depends not only on current stimuli or demands, but also on internal status and willingness formed by long-term historical events and current rational or emotional goals (see Figure 3). The major capabilities of AS will need to be extended to the cognitive intelligence level towards highly intelligent systems beyond classic adaptive and imperative systems.

Lemma 1. The *behavioral model* of AS, AS|§, is inclusively aggregated from the bottom up, i.e.:

$$\begin{aligned}
AS|\S \triangleq\ & (B_{Ref}, B_{Imp}, B_{Adp}, B_{Aut}, B_{Cog}) \\
= \{\ & (B_{rf}) && // \ B_{Ref} \\
& || \ (B_e, B_t, B_{int}) \cup B_{Ref} && // \ B_{Imp} \\
& || \ (B_{ab}, B_{fm}, B_{ea}) \cup B_{Imp} \cup B_{Ref} && // \ B_{Ada} \\
& || \ (B_{pe}, B_{pd}, B_{go}, B_{dd}, B_{de}) \cup B_{Adp} \cup B_{Imp} \cup B_{Ref} && // \ B_{Aut} \\
& || \ (B_{kb}, B_{ld}, B_{if}, B_{id}) \cup B_{Aut} \cup B_{Adp} \cup B_{Imp} \cup B_{Ref} && // \ B_{Cog} \\
\}\ &
\end{aligned} \qquad (20)$$

where || denotes a parallel relation, |§ the system suffix, and each intelligent behavior has been formally defined in Section II.

Proof. Lemma 1 can be directly proven based on the definitions in the HIM model. ■

Theorem 1. The relationships among all levels of intelligent behaviors as formally modeled in HIM are hierarchical (a) and inclusive (b), i.e.:

$$HIM|\S \triangleq \begin{cases} a) \ \mathop{R}\limits_{k=1}^{4} B^k(B^{k-1}), B^0 = \mathop{R}\limits_{i=1}^{n_{ref}} @e_i|\mathrm{REF} \hookrightarrow B_{ref}(i)|\mathrm{PM} \\ b) \ B_{Cog} \supseteq B_{Aut} \supseteq B_{Ada} \supseteq B_{Imp} \supseteq B_{Ref} \end{cases} \qquad (21)$$

Proof. According to Lemma 1, a) Since $\mathop{R}\limits_{k=1}^{4} B^k(B^{k-1})$ in Eq.21(a) aggregates B^0 through B^4 hierarchically, the AS can be deductively reduced from the top down as well as inductively composed from the bottom up when B^0 is deterministic; b) Since Eq. 21(b) is a partial order, it is inclusive between adjacent layers of system intelligence from the bottom up. ■

Theorem 1 indicates that any lower layer behavior of an AS is a subset of those of a higher layer. In other words, any higher layer behavior of AS is a natural aggregation of those of lower layers as shown in Figure 2 and Eqs. 20/21. Therefore, Theorem 1 and Lemma 1 reveals the necessary and sufficient condition of AS.

3.2 The Effect of Human in Hybrid Autonomous Systems

Because the only matured paradigm of AS is the brain, advanced AS is naturally open to incorporate human intelligence as indicated by the HIM model. This notion leads to a broad form of hybrid AS with coherent human-system interactions. Therefore, human factors play an irreplaceable role in hybrid AS in intelligence and system theories.

Definition 19. *Human factors* are the roles and effects of humans in a hybrid AS that introduces special strengths, weaknesses, and/or uncertainty.

The properties of human *strengths* in AS are recognized such as highly matured autonomous behaviors, complex decision-making, skilled operations, comprehensive senses, flexible adaptivity, perceptive power, and complicated system cooperation. However, the properties of human *weaknesses* in AS are identified such as low efficiency, tiredness, slow reactions, error-proneness, and distraction. In addition, a set of human *uncertainty* in AS is revealed such as productivity, performance, accuracy, reaction time, persistency, reliability, attitude, motivation, and the tendency to try unknown things even if they are prohibited.

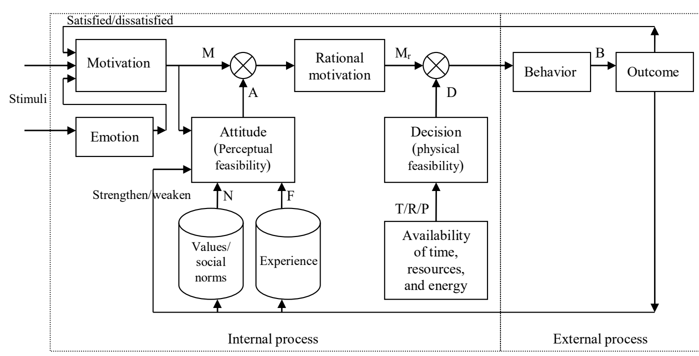

Fig. 3 The roles of human intelligence in autonomous systems

We found that human motivation, attitude, and social norms (rules) may affect human perceptive and decision-making behaviors as well as their trustworthiness as shown in Figure 3 by the Autonomous Human Behavior Model (AHBM). AHBM illustrates the interactions of human perceptive behaviors involving emotions, motivations, attitudes, and decisions [17]. In the AHBM model, a rational motivation, decision and behavior can be quantitatively derived before an observable action is executed. The AHBM model of humans in AS may be applied as a reference model for trustworthy decision-making by machines and cognitive systems.

According to Theorem 1 and Lemma 1, a hybrid AS with humans in the loop will gain strengths towards the implementation of cognitive intelligent systems. The cognitive AS will sufficiently enable a powerful intelligent system by the strengths of both human and machine intelligence. This is what intelligence and system sciences may inspire towards the development of fully autonomous systems in highly demanded engineering applications [3, 5, 6, 10, 15, 20, 25].

VI. CONCLUSION

It has been recognized that autonomous systems are characterized by the power of perceptive, problem-driven, goal-driven, decision-driven, and deductive intelligence, which are able to deal with unanticipated and indeterministic events in real-time. This work has explored the intelligence and system science foundations of autonomous systems. A Hierarchical Intelligence Model (HIM) has been developed for elaborating the properties of autonomous systems built upon reflexive, imperative, and adaptive systems. The nature of system autonomy and human factors in autonomous systems has been formally analyzed. This work has provided a theoretical framework for developing cognitive autonomous systems towards highly demanded engineering applications including brain-inspired cognitive systems, unmanned systems, self-driving vehicles, cognitive robots, and intelligent IoTs.

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