Review Article

Intelligence: The Quest for a Universal Assessment Framework

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Consciousness is a phenomenon which can be extensively discussed as subjective or objective, structural or holistic, hierarchical or modular, but cannot be imagined without intelligence. There might be an intellect without consciousness, and this is the opinion of many domain specialists about artificial intelligence. But there is hardly any question of the impossibility of any consciousness without at least basic intellectual functions. It makes intelligence an important, crucial subject for evaluation in assessing any consciousness. There are inseparable steps and related problems in intelligence investigations, like those in the assessment of consciousness. There are inescapable questions about modularity and hierarchy of intelligence levels, possible types of intelligence and its emerging nature. The last question is closely related to the more fundamental question: What is intelligence? This categorical question is inevitably followed by a more detailed inquiry. If we discuss different types of intelligence, what makes them different, except for ontological classes? Is there a hierarchy, scale of levels, or types of intelligence that can be seen as sibling sub-classes? If intelligence possesses a universal quality, can we create a universal measurement scale of any kind of intelligence, regardless of its source? The universal scale or framework could have a profound utilitarian function. On the other hand, this solution is only partially possible, especially in the case of less universal, highly modular multiaxial intelligence. If this is so, the situation will require a number of specific scales designed for different types of intelligence. The appropriate design of such a framework will allow us to be precise in the intelligence evaluation and comparison, regardless of the type of intelligent agent and be potentially applicable to new types of agents. In this case, a universal scale can be constructed from sub-scales.

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1. Introduction

Cognition is considered to be an essential part of consciousness. Intellectual functions are supposedly more approachable and measurable. However, there is an ongoing debate about the possibility of the general intelligence coefficient, the various types of intelligence, multiple intelligences, and ways to measure it. Models range from four to twelve main types, and Howard Gardner, in his seminal work, provided descriptions for eight types[1]. Guilford, an author of the "coefficient g" concept, or general intelligence, 1955 devised a triaxial model of Structured Intellect with scales for every axis[2]. In 1960th, Torrance developed a creativity test based on Guilford′s works and later made 22 years longitudinal study[3].

The multiple intelligence model was a partial answer to objections about the subjectivity of IQ tests and particular difficulties when applied cross-culturally, with the expectation of trans-cultural universality. This argument is even stronger when creating standard tests and scales for measuring non-human intellectual abilities. The promising movement is reflected in the usage of Piaget′s theory for tests of animal cognition[4]. A similar Piagetian approach is thought for the DevRobotics[5]. Generally, human-oriented tests are not easily applicable to the evaluation of animal cognition capabilities. This holds even more relevance for Artificial Intelligence[6].

Non-biological intelligence creation was initially inspired by biological, mostly human intelligence. Still, many expectations about rule-based or formal intelligence models from the earlier decades were not met. Today, a vast volume of research and practical applications is focused on neural network-based Artificial Intelligence, which has evolved from perceptrons. Hebb proposed another early development in the area of biological and non-biological neural networks, which today is the basis for the concept of Hebbian learning[7].

There is an inevitable necessity to compare Natural and Artificial Intelligence, and a number of frameworks were proposed besides measuring it by the chess or Go human-computer competitions[8][9]. The direct implication of these frameworks′ proposals for the measured comparison of natural and artificial intelligence is their extension into the presumed realm of non-terrestrial intelligence. The last option, naturally, remains quite speculative due to the purely theoretical nature of the subject[10][11]. Yet the discussion about modes of relationship between different types of intelligence and, possibly, consciousness is important for the scaffold of all kinds of inter-intelligence interactions, including extended human intelligence[12].

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It is considered commonplace to mention potential threats of Artificial Intelligence for humankind[13]. The possible widening of the argument to include any non-human intelligence, existing or potential, can provide the universal levelling field for intelligence assessment and focus attention on universal measuring tools and techniques. This certainly practical outcome is essential for the ongoing discussion about consciousness, our ability to create Artificial Consciousness and the estimation of the necessity to moderate these efforts. Figure 1 provides the roadmap of the following sections.

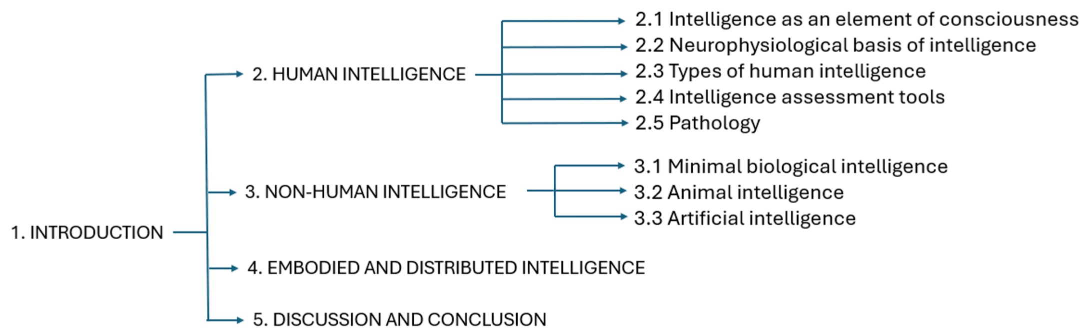

Figure 1. Structure of the article

2. Human intelligence

Intelligence is a many-sided phenomenon and has many descriptions and interpretations. It encompasses a broad range of mental capabilities, including reasoning, problem solving and planning. Intelligence includes abstract thinking, understanding complex ideas and learning from experience, among other attributes[14]. Intelligence is considered to be both multifaceted and generalized. General intelligence, often referred to as "g," is the ability to solve various tasks and adapt actively to changing environments. The "g" coefficient is thought to reflect the summation of an individual's abilities to perform different intellectual tasks[15].

Facets of intelligence represent several abilities: verbal, numerical, perceptual, memory, visuo-spatial and some others[16]. There is an opinion that intelligence is the result of loose interaction between multiple specific networks with their own tasks[17]. Each network is independent, and intelligence appears to be an emergent property of anatomically distinct cognitive systems. Intelligence can be viewed in biological terms as an advanced development of minimal cognitive functions[17] or in psychological terms, such as

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social and linguistic property development or a type of computational symbolic ability growth[18]. It is impossible to ignore non-biological cognition, so intelligence cannot be seen as only an anthropocentric or strictly biological phenomenon. Still, there is probably a possibility of dividing tasks between machine-performed and human-performed[19]. An interaction between human and artificial cognitive systems in task performance, learning, and decision-making reflects different faces of intelligence.

2.1. Intelligence as an element of consciousness

Intelligence is intimately connected to consciousness – or is it? Prescientific and proto-scientific metaphysical theories included the possibility of panpsychism and intelligence in the world itself and all its parts, animate or supposedly inanimate[20]. Human intelligence is observable and, to some extent, measurable, at least indirectly[21]. It is possible to create frameworks for intelligence detection and measurement, regardless of their nature, for example, on the basis of the ability to solve problems or to make predictions. However, human intelligence is the primary comparative example for any observations or measurements. It is possible to expand our understanding of intelligence to lesser life forms and even attribute to them proto-consciousness in the form of basic sentience[22].

However, there is no vision of consciousness without underlying intelligence[23], yet there is Artificial Intelligence without clearly recognized consciousness[24]. One of the arguments about the difference between human intelligence and AI is based on the singular abilities of machine intellectual power if compared to the generalized human cognitive abilities[25]. Human intelligence is generalized and inseparable from the conscious states. In early studies on patients with neurological lesions and healthy individuals, intelligence was described as an inherent ability to discriminate between fundamentals. Crystallized, or Intelligence A, is more represented by reasoning, while fluid, or Intelligence B, is closer to appropriate skills[26].

Gardner famously divided cognitive and mental abilities into eight types (discussed in section 2.3)[27]. After a long period of being “a Piagetian” believer in the generalized forms of intelligence development, he discovered that standards, especially culturally dependent tests, do not cover a long list of other abilities. Knowledge base, different from test one, such as local geography knowledge, musical skills, other types of reasoning, and memorization of non-western types of knowledge. If intelligence is a problem-solving or tool-devising capability, scientific theory starts from problem-finding, and it is not obvious that it can serve as a reliable tool. Gardner sees intelligence as preeminently culturally related and not an out-of-context basic ability.

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At the same time, there is evidence from tests on the positive correlative relationship of abilities for verbal comprehension, perceptual organization, working memory and processing speed[28]. There are several disputed points about human intelligence. Is it unitary or multidimensional, is it primarily inherited or acquired, mathematically and computationally based or has higher levels of realization[29]? Cognitive abilities might be supplemented with feelings and willingness, as well as emotional and volitional abilities. Factor "g" is seen as a basis for up to 50% of different cognitive abilities, and the genetic component for the factor is estimated at between 30% in childhood and over 50% in adulthood[30].

Debate exists about the relationship between spontaneous pre-conscious processing and controlled cognitive processes[31]. There is evidence about the role of unconscious processes in the domains of creative thinking and social interactions. Intuitive implicit cognition is probably based in significant part on precocious processes. Intelligent action control and fluidly automatic performance in the case of high expertise may demonstrate additional support for Unconscious Thinking Theory (UTT)[32].

It is possible to speak about a "conscious-centric mind" bias when unconscious is often equated with subliminal, not intelligent enough[33]. There is an old asymmetry between models of rational choice and observable data[34]. The decision-making process, which includes the transition from uncertainty to contextual certainty, is often executed pre-consciously, and quick thinking is prone to formal mistakes. However, it may give a natural advantage in uncertain situations[35].

2.2. Neurophysiological basis of intelligence

Genetics implies a clear biological substrate for intelligence. Brain structures predominantly responsible for it, or at least correlating with it, are parietal-frontal pathways[36]. Structural and functional differences in these pathways, seen in Magnetic Resonance Imaging (MRI), functional MRI (fMRI) and Positron Emission Tomography (PET), are likely to contribute to the diversity in the results of intelligence tests[37]. Neurons, the main functional basis of neural tissues, are recognized as relatively simple logical gates with the ability to fire after reaching a certain threshold with all incoming impulses. Brain regions are specialized, and cognitive functions are divided between particular sensorimotor, regulatory or analytical fields. However, neuronal plasticity makes it possible to compensate for lower functionality[38]. There is a hypothesis that neuronal plasticity is partially responsible for the "g" intelligence.

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A neural logic-gate mechanism is proposed, with the additional ability to fire after achieving a certain threshold from a number of inputs. There is also a strong hypothesis that three large-scale neural circuits control these gates: the cortex, basal ganglia, and thalamus[39]. Timing differences in correlated excitation–inhibition tonic stimulation activity and phasic transient activity can represent temporal gating[40]. As measured by structural MRI, total brain volume is moderately (0.3-0.4) correlated with intelligence[36]. Some specific regions of interest, such as the frontal, parietal, temporal, hippocampus and cerebellum, show higher correlation. There is also a basic generalized structural and functional element reflecting higher intelligence. Recent comparative studies on the grey and white matter correlation demonstrated higher correlative indexes for the last one, but usually close to 0.31[36]. Diffusion Tensor Imaging (DTI) is more suitable for white matter, and its generally higher volume's correlation with intelligence demonstrates connectivity's role[41].

Compared with other mammals, intelligence can depend on absolute and relative brain size, uncorrected or amended for body size[42]. Inconsistencies correlating to intelligence show that neither absolutely nor relatively large brains demonstrate it. The highest correlation is achieved with a combination of factors: the number of specifically cortical neurons, their packing density, average intraneuronal distance, and axonal conductive velocity. They determine the general Information Processing Capacity (IPC). Regions of the human brain responsible for intelligence have general purpose and content-specific adaptive specializations. Social and linguistic group connections allow for the distribution of tasks and higher efficiency in data processing[43].

2.3. Types of human intelligence

Intellectual Quotient, or IQ, is an integrative number supposedly reflecting a number of cognitive abilities inherited or acquired[44]. Normal IQ is presumed to be around 100 points, plus or minus 10, ranging from 90 to 110. Intelligence tests have different scales, and IQ results are corrected with age. In childhood, IQ is adjusted with age until 18, and the quotient is supposed to be stagnant afterwards. There are indications of generational change in the IQ level, the so-called Flynn effect, and the steady improvement of the general population's IQ in the last 100 years[45].

IQ comparison between generations has to take into account the adjustment made to comply with the standard measurement and equate it to 100 for a certain generation. The Flynn effect can be counterbalanced by the "Lynn effect" and the "negative Flynn effect"[46]. The normal intelligence of the adult person is the ability to analyze and memorize complex information and adapt to the behaviour. There is a question of how accurate various IQ tests are in assessing cognition[47]. Guilford famously proposed a 3D description of the intellectual functions, with axes representing the type of content, level of content organization and type of operation with it[48].

Howard Gardiner developed the theory of multiple intelligence when different fields of human life are attributed to different types of "intellectual" functioning: linguistic, logical-mathematical, musical, bodily-kinesthetic, spatial-visual, interpersonal, intrapersonal and naturalistic[49]. It is undoubtedly a question of how strong the relationship is between different types of intelligence with the "g" coefficient, IQ and between every type[50]. Based on information from Guilford, J.P. (1980), the intellect structure can be visualized in three dimensions (see Figure 2).

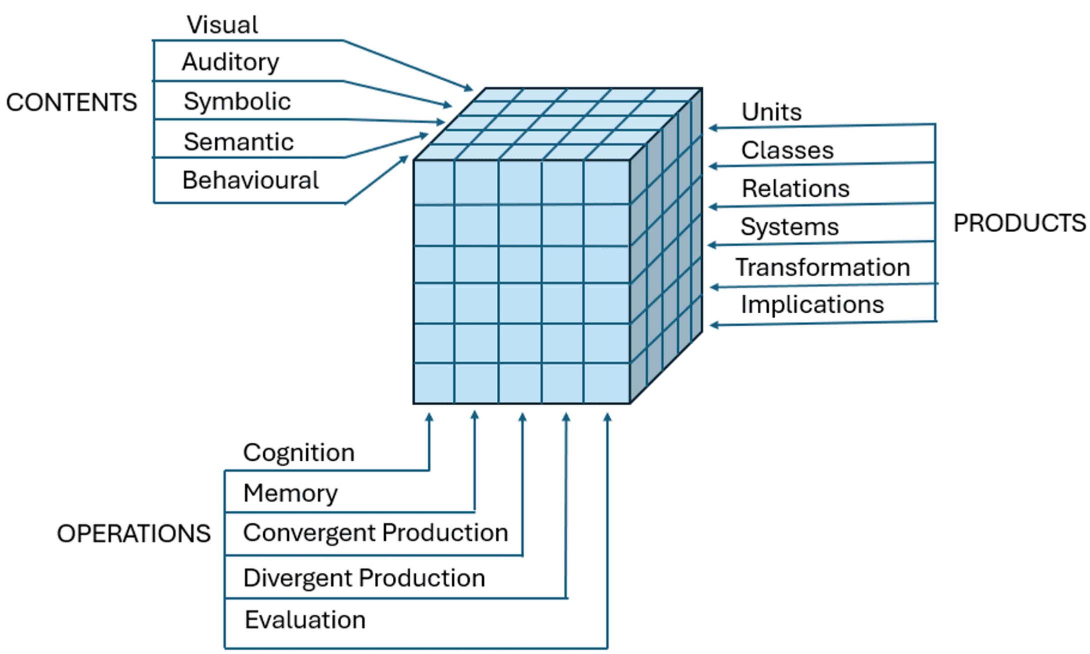

Figure 2. Guilford's structure of intellect

There are possible signs that multiple intelligence results do not converge to one generalized "g", and there are no indications that there are several "g" factors reflecting every Gardiner type and not less[51].

However, there are indications for specific neural correlates for every Gardiner type of intelligence[52]. At the same time, some structures, such as cortical spindle-form von Economo connectivity neurons, can be

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responsible for general intelligence factors[53]. Some Gardiner types of intelligence, such as linguistic, logical-mathematical, spatial, naturalistic and interpersonal, can have higher loading from the “g”-factor[54]. The theory of multiple intelligence requires different intelligence modules to work relatively independently. However, there are many tasks which require complex intelligence[55]. There is also the circularity problem when a specific type of intelligence is described as intellectual ability. The other problem can reside with conceptual categories. For example, the popular Emotional Intelligence (EI) concept is not easily conceptualized and measured[56].

2.4. Intelligence assessment tools

Most theoretical models recognize the importance of basic intelligence, concentration, short-term and long-term memory, and the ability to plan and operate with the acquired information. Indirect psychometric tests are designed to assess intelligence. While biological intelligence can be assessed by anatomic brain integrity and genetic, biochemical and neurophysiological methods, psychometric phenotypical intelligence, mainly social, is also influenced by education, family and cultural environment, and socio-economic factors[57].

There are several ways to assess cognitive functions. They range from simple tests, made by family medical practitioners, to the novel methods of optogenetics and transcranial brain function registration and modulation. Several questionnaires have been developed for medical practitioners, psychiatrists, clinical psychologists, and educationalists to assess short-term and long-term memory, education level, logical and operational abilities[58]. A wide range of tests is routinely used in medical practice and serves as the first line in the diagnosis of cognitive dysfunction. The Mini-Cog is 3 3-minute test which registers delayed free verbal recall. The classical MMSE, Mini-Mental State Examination consists of 15 questions and basic tasks but misses verbal fluency and reasoning functions. Mild Cognitive Impairment is not usually registered by MMSE and gives results of at least 24 out of 25. The CASI, Cognitive Abilities Screening Instrument, helps to check a broader range of cognitive abilities and is more sensitive.

More specialized cognitive psychometric tests include the Wechsler Adult Intelligence Scale (WAIS) and the shorter Wechsler Abbreviated. Developmental tests used for children are the Scale of Intelligence Raven's Progressive Matrices, Stanford–Binet Intelligence Scales, and Kaufman Assessment Battery for Children (KABC)[59]. There are wider population tests and methods to assess the intelligence of large groups simultaneously. At the same time, intelligence tests do not register all conceptual intelligence frameworks or abilities and are prone to certain levels of cultural and other biases, even tests designed to minimize cultural and linguistic influence, such as Raven Progressive Matrices. There is some degree of disagreement among specialists on which basic cognitive types better demonstrate real measures of general intelligence: analytic, creative, practical or specific combinative forms[60].

There are many variants of IQ or intelligence quotient scales. Some of them are mentioned above, and many more are used in different areas, from diagnostics to education and employment. IQ scales differ in the level of reliability, internal consistency, spectrum and scope of the measured cognitive values, and depth of every measurement. IQ correlates with age, general health condition, social status, educational level, profession, and a few other categories[61].

IQ psychometry is often criticised for partial inconsistency between different tests, for the arbitrary nature of the "intelligence" model, a different approach to so-called "crystallized" intelligence and "fluid", inventive intelligence. There are deviations in cultural and educational specificity, different points for memory, and different types of tasks. Some tests ignore background differences. However, some approaches help to equalize differences and standardize results[62].

There are more instrumental methods to assess cognitive functions and intellectual levels. It is possible to estimate anatomical integrity on macro and micro levels, functional activity, genetic and general health background. The anatomic structure is assessed with the help of X-ray, CT, and MRI methods. It is possible to make a general analysis when the obtained pictures are compared to supposedly normal brain structure or anatomical pathology data. Today, it can be done with the help of machine learning and other diagnostic software. Damage or devolution of brain structures or tissue may affect functional activity. Clinical data on anatomical and functional disabilities are rich enough to make conclusions on the basis of indirect information[63].

MRI uses less damaging physical processes than X-rays or CTs, and it develops quickly. Today, resolution, which depends on the magnetic impulse intensity, grows rapidly. The highest possible level is achieved in CERN with a magnetic flux density of 11.8 Tesla. However, the resolution is still not on the cellular level, with thousands of neurons in one voxel. The microstructural analysis is effective for fields of neurons and white matter connectogramms. Diffusion MRI, especially DTI, is the most effective. The functional diagnostic is possible with fMRI, which analyses blood flow in the brain parts. The drawback is not only relatively low spatial precision but also a difference in neuronal effectivity of different people. A trained person will use less energy per neuron for a known task. The level will be comparable only in the case of the novel task.

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Other methods of functional activity registration are the electroencephalogram (EEG) and magnetoencephalogram (MEG), which register the electrical or magnetic activity of brain cells. They are non-invasive, technically relatively inexpensive and straightforward. The problem is the resolution level[64]. Positron-Emission Tomography, PET. PET was widely used in research and early diagnosis of dementia. The usage of positron-emitting glucose is limited by the radioactivity of the arterial one[65]. Other methods include near-infrared spectroscopy NIRS, which detects the oxygenation level of haemoglobin and some tissues. Diffuse Optical Imaging (DOI) gives an option to create a functional picture of the brain tissue. Event-related optical signals (EROS) register the activity of neurons directly[66].

In diagnostics, there are invasive methods such as direct observation during invasive procedures for macrostructures, brain tissue biopsy, less invasive electrode stimulation and non-invasive Transcranial Magnetic Stimulation (TMS). Diagnostically, only PET and biopsy give the most definitive answer at the micro level. Electric Stimulation (ES) and TMS are used more in research. Today, an additional technique of optogenetics is supposed to be a research option for animal models on the single neuron level[67]. In clinical practice, general health conditions, hormonal levels, electrolyte balance, and other indirect measurements are helpful in cognitive activity diagnostics. Novel genetic analysis helps to identify the activity of the competent loci responsible for brain activity, synapse modulation, neuromediator production, and memory abilities.

2.5. Pathology

The level of intelligence demonstrated in the premonitory phase and functional plasticity are protective factors against the development of cognitive impairment. For a highly intelligent individual, a decline in IQ to 90 or below requires a swift and aggressive pathological process. A number of conditions can cause quick and profound cognitive impairment. However, the illness progression usually takes years, if not decades, to develop[68].

Functional impairments typically arise from damage of underlying structures. It can stem from various acute or chronic causes: direct impacts on brain tissue such as trauma, haemorrhages, infections, local or metastatic tumours, immunologic, endocrine or metabolic diseases, impaired cerebrospinal fluid circulation, medication side effects, various toxicities or endogenous neurodegenerative processes. Indirect influences often involve disruptions to the blood supply, as seen in ischemic lesions. Additionally, systemic conditions affect all body tissues, including the so-called blood-brain barrier. Any compromise to this barrier can damage brain tissue[69][70].

DSM-5, the Diagnostic and Statistical Manual of Mental Disorder by American Psychiatric Association (APA), regards an MCI as MND (Mild Neurocognitive Disorder). It can be subdivided into two groups of conditions, amnestic and non-amnestic MND. APA proposed four subdomains: amnestic mono-domain, amnestic multi-domain, non-amnestic multi-domain, and non-amnestic mono-domain.

Acquired adult conditions have to be separated from inborn, perinatal or childhood developmental pathologies and social-environmental development retardation, such as inadequate education and cultural experience. The condition should be stable and of a non-transient nature. It has to be clearly differentiated from cognitive or memory impairment caused by other psychiatric disorders. Diagnosis of MND needs to be supported not only by neuropsychological assessment but also by thorough clinical investigation[70].

Impaired conditions usually develop due to Alzheimer's Disease (AD), Pseudobulbar Affect, Parkinson's Disease, Frontotemporal Lobar Degeneration, Lewy Body Disease, vascular diseases, traumatic brain injuries, substance or medication use, HIV infection, Prion disease, Huntington's disease or another medical condition[71]. Alzheimer's disease is one of the leading causes of dementia associated with ageing. While the main causes of the disease are not completely clear, they are the apoptosis of neurons and progressive atrophy of the cortical and some subcortical regions. Whether the leading cause is internal, genetic, connected to protein misfolding, or pathological production external (prions, toxins, immune mechanisms), the number of neurons and synapses is decreasing. This leads to the consequent loss of memory and cognitive functions[72].

There are specific signs of AD. The main macrostructures undergoing the negative volumetric change are the entorhinal cortex, amygdala, hippocampus, and cingulate gyrus. At some stages, it becomes visible on MRI and PET. On the histological level, the appearance of the amyloid-beta protein and the tau protein is usually supposed to be a sign of the pathological process. However, there is no direct correlation with them in every case of AD. Some researchers claim that proteostasis is the main reason for AD. Damaged lymph circulation damages protein clearance through the meningeal and cisterns system and the lymphatic system. AD is often associated with amyloid plaques (AP) and Aβ oligomers. There is a wide discussion about the diagnostic value of AP, as well as its intensity, distribution, and correlation with AD progress.

The pseudobulbar effect is an affective disorder characterized by uncontrollable outbursts of emotions. PA may be caused by different factors and is believed to develop due to damage to the prefrontal cortex[73]. Parkinson's Disease is a neurological condition which sometimes may be associated with dementia (in 20% of cases). Damage to Substantia Nigra in basal ganglia leads to the dopamine deficit and, consequently, neurological symptoms. Neurons demonstrate deposits of alpha-synuclein protein, so-called Lewy bodies[74].

Lewy Body Disease is a group of neurodegenerative conditions which can lead to cognitive impairment and various pathological neuropsychiatric symptoms and syndromes. It is caused by the Lewy bodies or deposits of synuclein in neurons. Another disease from the syno-nucleopathy group is Shy-Drager Syndrome, or Multiple System Atrophy (MSA)[75]. MSA can also lead to frontotemporal degeneration and dementia. Frontotemporal Lobar Degeneration (FTLD) is a group of proteinopatic conditions which lead to frontal and temporal cortical atrophy. There are tau-positive variants, such as Pick disease, FUS-positive and ubiquitin-positive variants[76].

Prion diseases, such as Creutzfeldt-Jakob disease (CJD), kuru, Gerstmann-Sträussler-Scheinker syndrome and Fatal Familial Insomnia (FFI) are caused by misfolding of the Prp protein and may lead to dementia and multiple CNS dysfunction[77]. Huntington's Disease is a hereditary neurodegenerative disorder. Neuropsychiatric symptoms include dementia and memory loss[78].

Alcohol abuse or Alcohol Use Disorder (AUD) may cause encephalopathy and frontal lobe deficiency. It is caused by direct neurotoxicity and liver dysfunction, and the effects are due to vitamin B deficiency. While cyanocobalamin or B12 is well known to neurologists and psychiatrists as an effective treatment for the relevant condition, other group B vitamin deficiencies may also be associated with dementia. The Wernicke-Korsakoff syndrome is often developed due to alcohol abuse and secondary thiamine (B1) deficiency. B3 (niacin) and B6 (pyridoxine) deficiencies are also associated with cases of dementia. Another alimentary factor is vitamin D (D2 and D3, ergocalciferol and cholecalciferol), which deficiency may cause or exacerbate dementia[79][80]. Other causes of dementia, as listed above, are traumatic, vascular, hypoxic, infectious (HIV) or substance or medication abuse aetiology. Medications may also cause dementia as a side effect. Reportedly, neuroleptics during prolonged treatment may lead to decreased cortical volume.

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3. Non-human intelligence

Intelligence is the capability "to operate successfully in a wide variety of environments"[81]. This ability is not limited to humans. Non-human intelligence is a wide category which includes the intelligence of non-human types and is not directly related to observable human intelligence. This will relate to animal cognition, artificial intelligence and extraterrestrial intelligence. In every category, we have to recognize blurry borders for the type. Animal cognition requires a clear taxonomic separation of Homo sapiens sapiens from other species. It could be relatively easy in the case of existing primates and "lower orders" creatures but less clear-cut for other previously existing Homo species. Artificial intelligence is judged by humans to perform cognitive tasks, and itself is a product of human cognitive efforts. Extraterrestrial intelligence, while not discovered yet, might be just one more variant of planetary biological type, which differs from terrestrial only by location. Even human intelligence has to be assessed for healthy adult individuals[82] with a full understanding of historical periods, places, health and social factors. While considering human intelligence, it is necessary to be aware of "unconscious" mental capabilities[83].

Non-human cognition can be radically different in form but similar in task-solving or forms of behaviour. There is evidence for possible signs of the "g" factor in animal studies[84]. Reasoning and "insight" have been demonstrated in a number of species: primates, racoons, rats, mice, corvids, and pigeons, to list just a few. There are also signs of developed complex cognitive abilities in some animal species. Human intellectual capabilities, when formally related to the activity of the prefrontal cortex, may induce meta-cognitive functions and not basic cognition and memory. There are still debates about the acceptability of protocols for animal cognition and reasoning ability[85]. While it was demonstrated in chimpanzees and corvids, it has to be recognized as the ability to perceive at least the same species' behaviour and evaluate their reasoning ability. Is it possible for us to judge reasoning in non-human intelligence correctly, and on what basis should it be placed?

3.1. Minimal biological intelligence

Non-human intelligence is certainly divided in accordance with levels of species' minimal cognitive and operative abilities, which is based on fundamental data processing. There are formal reasons to consider sensory perception, sensory-motor coordination, primitive forms of memory and learning, basic decision-making and problem-solving as signs of minimal intelligence[86]. We also cannot avoid the correlation between the complexity of the structural "processing tissues" organization, especially of

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neuronal basis, and sophistication in behavioural and adaptive capabilities. While we are pretty well informed about human intelligence and some non-human animal forms of intelligence, there is a conceptual place for the encompassing intelligence scale with a starting minimal level of intelligence.

Number of studies on procaryotes, such as Gram-negative group of proteobacteria M. xanthus, underline marks of communicative and cooperative behaviour, which leads to evolutionary gain[87]. Rudimentary levels of data collection and processing are natural for most elementary life forms, at least cellular. Predictive non-random adaptive mechanisms are generally beneficial, and the specific sensitivity to intercellular interactions led to the emergence of multicellular organisms[88]. Those autopoietic features can be interwoven with the primary abilities of the most basic biological intelligence. If the widely cited statement, which describes intelligence as "all processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used"[89], the definition will include many non-human and even non-biological forms. Automata and plants are not routinely included but can be formally considered as sufficiently representative[90].

Embodied cognition can be strictly recognized as sensorimotor coordination. Biochemical metabolic basis supports active exploitation of spatiotemporal metabolically relevant environmental features. The embodied sensorimotor system can operate as a single unit under direct stimulus control, with necessary "offline" controlling structures. We can comprehend it in the case of insects or animals, but plants are rarely considered to be sufficiently intelligent. There is a place for an internal information plant system, or informative network, falling short of the root-brain envisioned by Charles Darwin, with elements of minimally rational root distribution. At the same time, there should be a mechanism of "thinking" or cognitive modelling. Perception-action is suitable for online problem solving and action, and thinking might be the offline part of the cognitive process. It might be a necessity to avoid radical embodiment as the only source for the minimal cognitive processes[91].

A sufficiently abstract definition of the minimal basis of cognition could be better explained by Dynamic System Theory or Dynamic Hypothesis[92]. If successful, it could be applied to artificial intelligence systems. There is still an ontological gap between dynamic systems and cognitive systems. The cognitive element is intrinsic and cannot be directly equal to the dynamic one[93].

A sufficient number of non-biological physical dynamic causal systems or structures go through bifurcations superficially similar to the decision-making tree process, but without possessing any cognitive basis for it. The cognitive system will demonstrate purposeful behaviour, but it can also be applicable to non-biological systems. The problem might be to define purpose in purely external behaviouristic terms without the intrinsic internal teleology of it. Biological organisms are metabolic, self-sustainable, Far-From-Equilibrium (FFE) systems. It could be the fundamental basis or driving force for embedded and more developed forms of cognition, the "conatus" in Spinozist terms. Biological systems require a higher restrictive order than dynamic causal systems. With complexity growth, internal regulatory factors play a higher role in embedded cognition. Embedded emotions are biochemically and neurally explainable, and, possibly, they play an important part in minimal cognition of autopoietic systems as well. Still, there is a place for formal modelling of hypothetical minimally cognitive protocells[94].

There are also conceptual proposals for the Internet of Bio Nano Things (IoBNT), where cyborg nanosystems will combine autopoietic biological features with allopoetic synthetic abilities[95]. Still, biological systems can be defined as FFE self-maintaining chemical systems capable of reproducing their own functional components and creating physical boundaries with the environment[96]. Metabolic self-maintenance and self-reproduction are critically important. Basic self-maintaining metabolic networks are pre-biological prerequisites for any biological system. An internally meaningful system is the basis for purposeful adaptive response and, as such, minimal cognitive-like properties.

Experiments with Physarum polycephalum showed a certain degree of rational behaviour, an ability for basic externally enhanced memory, and possibly decision-making based on absolute valuation[97]. It might be tempting to consider minimal cognition as pre-neural, and neural-based cognition as a higher level of cognitive abilities. The really fundamental level of any cognitive system is recognized as a quantum informative theory, where quantum reference frames and scale-free Markov Blanket can give explanatory power for different levels of cognition[98]. The cell membrane in any cellular organism and organelle membranes in eukaryotic cells are implementational elements of the most fundamental biological Markov Blankets.

3.2. Animal intelligence

Daniel Dennett divided biological intelligence into four hierarchical types: Darwinian, evolutionary competent but unable to add intelligence through learning; Skinnerian, capable of learning in strict behaviouristic terms; Popperian, able to use imagination as a virtual tool; and Gregorian, possessing various thinking tools and systems, such as science[99]. While minimal cognition is clearly Darwinian, there are attempts to see a level of intelligence in some creatures, such as arthropods, as Popperian and not Skinnerian type[100].

Biological intelligence is derivative of an autopoietic biological basis and is supposed to be evolutionarily emergent across species. Non-human intelligence has to be assessed in an appropriate way to be recognized as such. It cannot be just an attribute or distinct property by itself, and it should be demonstrable as “intelligent behaviour”. IQ measurement is only a subdomain estimation of the much more extensive domain. Behaviour applies to animals and humans to support the understanding of it. Another condition is context because behaviour is usually context-dependent[101].

Non-human biological intelligence is widely tested, especially in larger-brained vertebrate species. There are tests on problem-solving, self-awareness, memory, numerical competence, and social intelligence. However, many tests could not be successfully used across the taxa or even species without significant adaptation because of variations in sensory-physiological and morphological features[62]. It is quite problematic to compare the results of tests directly between vertebrates and invertebrate taxa such as cephalopods or insects. Besides that, there are clear requirements for every tested specimen to perceive the test apparatus and distinguish the test stimuli easily, possess the necessary motor skills to handle it and have sufficient participative motivation[102].

There is a tendency to test mostly vertebrate taxa and species with developed brains, and there are other difficulties in proper evaluation. Animal intelligence has to be explained by widely distributed intelligence because animals represent just 0.01% of Earth's life forms and cannot possess intelligence as a rare phenomenon without a pre-cognitive basis and interaction with the biological environment[103].

All life forms possess some form of information exchange within their species and outside. Data processing allows the organism to gain information, process it, and translate it into a phenotype form, being subject to a natural selection filter. In this case, it is possible to speak about distributed biological intelligence, not limited by certain species or animal forms only. Still, such a broad intelligence vision could be subdivided into adaptive intelligence and a more general form of it[104].

General intelligence, if separated from adaptive intelligence, can be assessed regardless of evolutionary adaptation or disadaptation of the species, so the natural selection filter can be ignored. Moreover, general intelligence is supposed to have an element of individuality and be open to comparison[105]. An individualized approach is less applicable for social creatures, unlike primates, cetaceans, or many other mammals and birds. Octopi are not very social, live alone, have a relatively short lifespan of five years, and have little parental care[106].

Rapid learning is facilitated by 500 million neurons, 20 times more than in such social insects as ants. Cephalization and brain morphology can provide guidance for the evaluation of cognitive capabilities, general and specialized. Besides a number of general and cortical neurons, Information Processing Capacity (IPC) is a good measurement of cognition. It is the highest number of humans and great apes, followed by Old World and New World monkeys. Elephants and cetaceans have large brains with a significant number of neurons, but the thin cortex limits IPC[107].

Corvid and psittacid birds have higher neuron packing density, which is explanatory for their cognition. Another metric is axonal speed. There are multiple in-species neural system morpho-physiology. At least 200 evolutionary brain changes create a chasm between theropod dinosaurs and humans, which is not easy to get over[108]. It does not mean that with contemporary genetic engineering techniques and chimeric tissues, it is impossible to create super-intelligent animals. Moreover, they may appear before any upgrade of human intelligence, as animal models will be tested first[109].

3.3. Artificial intelligence

Symbolic reasoning is fundamental for mathematical and logical operations. It was developed for many centuries[110] before being distilled into the binary computational basis for machine operations[111]. Boolean algebra can be treated as a certain equivalent to propositional calculus[112] and, in this way, is applicable to the theory of Finite State Automata (FSA) and for the creation of finite state machines, deterministic and non-deterministic. The distance between FSA and Turing Machine (TM) includes Pushdown Automata (PDA) and Linear-Bound Automata (LBA) or restricted TM. FSA, PDA, LBA, and TM are related to regular, context-free, context-sensitive, and computably enumerable recursive languages[113] (see Table 1).

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Language	Automata or machine
Regular	Finite State Automata (FSA)
Context-free	Pushdown Automata (PDA)
Context-sensitive	Linear-Bound Automata (LBA)
Computably Enumerable Languages	Turing Machine (TM)

Table 1. Automated machine languages

Natural languages span several levels of the model with elements of context-free and context-sensitive levels. Natural Language Processing (NLP) often requires the addition of finite state approximation with finite state models and regular expressions. While TM allows recursive reasoning and decision-making, natural languages are less open to it. Table 2 reflects the differences between NLP and symbolic reasoning in terms of scalability, adaptability, interpretability, and other characteristics.

Aspect	NLP	Symbolic Reasoning
Approach	Data-based: statistical	Rule-based
Scalability	High	Medium, rule-dependent
Adaptability	High	Low/Medium, Knowledge Base -related
Interpretability	Black box	High, transparent, explicit
Context handling	Successful with transformers models	Low/Medium, rule-dependent
Applicability	Text processing, automated translation, chatbots, LLM	Knowledge representation ontologies, formal verification, expert systems

Table 2. The main aspects of NLP and Symbolic Reasoning

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In the machine environment, Neuro-Symbolic AI is seen as an instrument that closes the gap[114].

However, there is no strong direct relation between Neuro-Symbolic AI and human intelligence, which is comparable to the Chomsky hierarchy with related automata or machines. Image recognition is a statistically based approach that can be enhanced by Knowledge Graphs for reasoning and human-readable ontological categorization[115][116].

Statistical reasoning and symbolic reasoning are complementary. Statistical analysis is built on quantitative data and probabilistic models, while symbolic reasoning works with symbolic representation and logical inference. Mathematical reasoning allows quantitative formalization and mathematical categorical operations. All these types of reasoning are applicable in machine calculations, robotics and AI. Still, there is a necessity to define machine intelligence appropriately: does it mean a minimally sufficient level of algorithmic reasoning in calculators, logical processors, motoric tasks in robotics, pattern recognition in ML or AI, the ability to solve human intellectual problems: NLP, game analysis, intuitive reasoning, etc. We experience the same categorization problem as natural intelligence, from minimal to the highest level. One of the methods was to base intelligence assessment on the information and complexity theory[117]. In this approach, intelligence can be seen as a compression[118].

Conversely, there is minimal explanatory load, formalized as Minimum Description Length (MDL), counterbalancing compression. There is a proposal to see intelligence as an ability of explanatory compression[119]. It has to be recognized that this approach makes understanding intelligence applicable to any intelligent system, but denies us the possibility of a full explanation. There is an opinion that “The computer is a physical embodiment of the symbolic calculations envisaged by Hobbes and Leibniz. As such, it is not a thinking machine, but a language machine.”[120]

At the same time, the author declares, “There is no reason but hubris to believe that we are any closer to understanding intelligence than the alchemists were to the secrets of nuclear physics”. Indeed, if we try to explain intelligence in terms of language, we have to find a connection between pattern recognition and successful task solutions (performance), not only in formal and human-understandable reasoning but also in image processing and mechanical operations. It is impossible to discard the operative or “behavioural” element of intelligence in AI and simply replace it with symbolic or any other reasoning. The interactive nature of intelligence requires the inclusion of higher levels of operability than algorithmic reasoning or simple automatic response. Long-term memory possessed by any system allows learning, not only anapoiesis or recreation, but practopoiesis, the ability to adapt in learning and operative terms. The ability for meta-learning, or tuning of the learning process, is a significant part of practopoiesis and intelligent functioning, from sensorimotor to symbolic or other reasoning[121].

Autopoiesis is a process of self-reproduction in the widest terms, including the ability to adapt itself to environmental changes through self-change for the basic internal homeostatic support, where learning is part of the multilevel reaction, from molecular to organismic and supra-organismic level[122], practopoiesis does not require ultimate reproduction or highly developed homeostatic ability. In this way, developed artificial intelligence systems can be seen as cognitive anapoietic and practopoietic adaptable entities. Environmental, systemic changes can be seen as disturbances in terms of the Ashby Requisite Variety Theorem, where the system is sustainable in the case of sufficient or requisite internal complexity: the ability to counteract disturbances with an adequate number of internal state changes[123].

Biological systems are different from non-biological ones in some systemic elements. While Shannon's theory approach requires ergodicity as a necessary systemic feature, biological systems tend to be non-ergodic. Variety is also better applicable to biological systems than the probability to non-biological cases, such as in communication theory. There are some parallels in intelligent processes between AI and natural intelligence. Artificial Intelligence in most developed forms is usually extensively trained on Big Data sets. In contrast, natural intelligence often allows quick learning through the intensive transfer learning mechanism when previous tasks' meta-learning elements are successfully applied[124].

The success of AI systems is apparent, manifesting in their evident ability to achieve goals with remarkable precision and efficiency. We certainly cannot compare the ability of natural intelligence to over-perform in time and complexity standard calculation tasks, let alone combinatory search or gameplay, while some other aspects, such as sensorimotor functioning and context-related general reasoning, are still well-performed by humans if compared to AI. We can distinguish autopoietic biological cognition-processing systems from artificial ones through the character of intellect's interaction with the supporting systems. In autopoietic systems, every level is autopoietic, while in artificial cognitive systems, intellectual tasks are detached. If artificial systems acquire autopoietic abilities, they will be comparable to natural systems. Otherwise, AI is cognition and reasoning abilities detached from the supportive tasks, and the difference is in the underlying nature and autonomous capabilities, but not in the task-solution abilities. If we want to compare different types of intelligence, we need a generalized framework with common reasoning and task-related abilities.

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4. Embodied and distributed intelligence

Embodiment might be the most important step on the way to artificial consciousness and toward full autopoietic functionality. A combination of cognitive architecture, perception and actuators in one device or group of devices can provide a desirable level of autonomy[125]. Morphological computation is a necessary step in robotics, added by embodied cognition and developmental robots. Robotic ecology[126] can be a minimal requirement before the next level: smart devices or vehicles in the natural environment, with a distributed cognitive network of sensors and actuators embedded into nature. A more restricted view of embedded AI development can be provided by the Multi-Level Evolution (MLE) framework. A bottom-up automated development includes robots` design on multiple levels and in robotic ecological niches according to tasks and environmental conditions[127].

It could be notable that artificial intellectual functions are achieved quicker and require less computation than sensorimotor calculations, the phenomenon known as Moravec`s paradox[128]. This can shed light on the natural intelligence, whose emergence might depend on embodiment. There is a whole school of thought about emerging intelligence: it requires embodiment as a prerequisite and constant interaction with an environment to form and support necessary cognitive abilities[129].

The data stream from the environment and from within the perceiving, self-regulating system is akin to the stream of consciousness described by W. James. Conscious mind, in the words of A. Damasio and H. Damasio require at least three processes to be in place: a continuous generation of interoceptive and proprioceptive feelings and the resulting organism's internal operations; continuous production of images connected to the organism's sensory perspective in surroundings; and a combination of feeling, experience, and perspective resulting in subjectivity relative to the image contents[130].

The peripheral and central physiology of interoception and exteroception is responsible for the first two components, whereas the Central Nervous System completes the third task. There are signs that cognition is not functioning based on the symbol alone and requires relevance to the body's actions. Embodiment can be seen as grounded cognition[131]. There are several implications of such an approach to intelligence. First, it allows the emergence of intelligence in constant dynamic interaction with an environment. Second, it can be cognitively “embedded” in the physics and phenomena of the surrounding environment[132].

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Third, shared or similar structures perform the same or similar cognitive tasks in different taxonomies. We can scale intelligence emergence in accordance with morphological and architectural principles, in addition to behavioural ones. Embodied intelligence exhibits significant similarities precisely due to its functional similarity within the same or similar environment. Sensory illusions and subjective variance in reactions pose limitations for embodied intelligence and reopen the discussion about the importance of symbolic and abstract thinking. These cognitive abilities, in turn, can emerge from the foundation of embodied intelligence itself. An embodiment may lead to the ability to understand other people's behaviour, those solving "other minds" problems[133]. This is also reflected in language, where abstract concepts are often described in terms borrowed from concrete experiences[134]. An embodiment of natural intelligence allows the functioning of the biological Goal Creation System[135]. Early pre-designed automata-like robots were hardly intelligent in human view, and Evolutionary Robotics proposed self-organized evolving robots. Still, in many respects, they are far behind insects, especially social ones, in solving tasks and, indeed, level of autonomy[136].

There are certain trends in robotics when intelligent unit systems are based on non-von Neumann principles and imitate biological systems, such as neuromorphic systems with parallel processing and separation of storage pathways. Situatedness is connected to intelligence, as well as embodiment. Emergence signifies the unclear nature of intelligence in these systems: it comes from embodiment and interaction within the system with the outside environment[137]. There are several conceptual levels of embodiment. The principles described above are suitable for the first-order embodiment[138].

Second-order embodiment includes understanding intelligence and behaviour as representational systems, self-representation as an embodied system and an understanding of intelligent systems in neuropsychological terms applied to robots. Third-order embodiment requires direct self-mapping or phenomenal self-modelling during interaction with the outside environment. There is an option for the fourth-order embodiment. Distributed computing and multi-unit collective action can be upgraded in swarm robotics with distributed intelligence. When projected onto biologically intelligent species, especially humans, we can discuss the concept of supra-intelligence or collective cognition. Social dimensions add a significant layer of verbal and non-verbal interaction, which cannot be excluded from intelligence analysis[139].

Children who accidentally grew up with animals from an early age demonstrated significant impediments not only in interaction but also in intellectual functions. Social learning includes not only

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synchronicity but also diachronic elements[140]. We can see human intelligence as synchronic in terms of contemporary humankind and diachronic from a historical perspective. We possess biological evolutionary "knowledge" and intellectual abilities as well as civilizational ones, as a collective in the broadest sense. It is impossible to separate them except for Mowgli-like cases.

Artificial intelligence is a creation of human civilization and could also be seen not as a separate entity but as an extension. It is formalized as having 4E qualities: extended, embedded, enacted, and embodied, and it allows for the possibility of non-biological or artificial experiences[141].

5. Discussion and conclusion

Intelligence is a phenomenon with many facets and contextual backgrounds. There are multiple challenges in the attempts to measure intelligence across humans, animals, and biological and non-biological intelligent actors. Despite some signs of universal intelligent abilities, certain symbolic and operative universality on the basic level and relatively common range of contexts, significant morphological and functional differences preclude the creation of universally accessible intelligence regardless of its embodiment type. One of the primary issues here is the lack of a universally accepted categorical definition for intelligence that fully covers it in these three domains. Human intelligence is usually assessed through tests with IQ metrics, which focus on various linguistic, mathematical, and logical reasoning abilities. These tests are not sufficiently universal for different age and cultural groups, let alone other intelligent species or non-biological intelligent agents. Moreover, the modular nature of intelligence requires specific types of tests able to register creativity, social adaptability and some other forms, less reflected by symbolic and mathematical reasoning in some traditional tests.

In contrast, animal intelligence is typically evaluated on strong applied problem-solving abilities, specific learning capacity, and adaptability to environmental changes. Animal and biological intelligence is highly context-specific and species-related. Anatomy-physiological differences between species and taxa on the somatic and neural system levels create insurmountable problems for universal intelligence tests and assessments. Cognitive processes in modern humans and animals may differ for socio-linguistic reasons and the nature of required tasks. Any human-centric intelligence criteria, despite being primarily accessible and serving as a starting point for any potential scale, are restrictive and lead to inevitable bias if applied to wider assessment.

The problem may look even more complex in the case of AI assessment. AI systems are inherently designed for specific goals and usually operate within predefined parameters. Data processing, pattern recognition and the ability to play combinatory games are often highly efficient. Still, we cannot directly compare them to human or animal abilities without taking into account consciousness, emotional understanding and general adaptability beyond programming. It is also important to remember that AI is a product of certain types of human intelligence and system efforts of civilization, and not a self-developed phenomenon. For AI, the problem lies in the insufficient holistic approach to evaluating general intelligence, as current metrics often focus on specific capabilities rather than overall adaptability and problem-solving skills.

At the same time, these limitations can show the direction in which work can be done. There are several ways to assess universal intelligence. The first is purely minimalist and requires building a minimal cognitive scale beforehand. The capability of basic data processing does not necessarily require an interactive nature of intelligence when behavioural assessment is necessary. The minimal intelligence scale is easily formalized and can have related scales of physical or biological structures responsible for logic gate functioning. The next level is applicable to automata-like properties before it can be scaled to higher degrees. Behavioural scales, in turn, can be task-related and context-adjusted. It still lacks universality but can be successfully applied across different domains, avoiding the pitfalls of the Turing test. Data processing capabilities are measurable, while task solutions are comparable in speed and efficiency. Multiaxial and modular categorisations can easily accommodate data processing and problem-solving metrics, leaving space for adjustments, contexts and flexible frameworks.

The general intelligence scale will require a cumulative type of system for the calculation of different symbolic analytical abilities and task-related capabilities. Certain cognitive functions will be recognized in accordance with the complexity of tasks and outcomes to be rated and summarized. There is a highly attractive approach to building these particular complementary scales in relation to morphological complexity and energy spending, which places it on a stronger physical and computable basis. There is more than one way to construct the universal intelligence assessment framework; it can be approached from several directions simultaneously. While it is still a task for the future, it looks achievable in the observable future.

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