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A universal knowledge model and cognitive architectures for prototyping AGI

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ABSTRACT

The article identified 56 cognitive architectures for creating general artificial intelligence (AGI) and proposed a set of interrelated functional blocks that an agent approaching AGI in its capabilities should possess. Since the required set of blocks is not found in any of the existing architectures, the article proposes a reference cognitive architecture for intelligent systems approaching AGI in their capabilities. As one of the key solutions within the framework of the architecture, a universal method of knowledge representation is proposed, which allows combining various non-formalized, partially and fully formalized methods of knowledge representation in a single knowledge base, such as texts in natural languages, images, audio and video recordings, graphs, algorithms, databases, neural networks, knowledge graphs, ontologies, frames, essence-property-relation models, production systems, predicate calculus models, conceptual models, and others. To combine and structure various fragments of knowledge, archigraph model are used, constructed as a development of annotated metagraphs. As other components, the reference cognitive architecture being developed includes following modules: machine consciousness, machine subconsciousness, interaction with the external environment, a goal management, an emotional control, social interaction, reflection, ethics, worldview, learning, monitoring, statement problems, solving problems, self-organization and meta learning. Based on the composition of the proposed reference architecture modules, existing cognitive architectures containing the following modules were analyzed: machine consciousness, machine subconsciousness, reflection, worldview.

1. Introduction

1.1. From analytics of cognitive architectures to theory of ones

Having grown out of advanced production systems, the first cognitive architectures appeared in the second half of the 1970s. (Anderson, 1983). The main capabilities of an intelligent information system, such as perceptual abilities, attention mechanisms, choice of actions, learning, memory, reasoning, and their practical application are determined by the cognitive architecture used in the system (Langley et al., 2009). If we consider the basic principles of functioning, then cognitive architectures are the opposite of expert systems. Expert systems provide solutions to intellectual tasks in a narrowly defined context, in the segment of activity for which they have knowledge, in contrast, cognitive architectures aim to providing a wide coverage, solving a diverse set of tasks in different fields. More importantly, cognitive architectures provide intelligent behavior at the system level, rather than at the level of methods of individual components designed to solve specialized tasks (Langley et al., 2009).

The results of research in the field of biology were the second source of the emergence and development of cognitive architectures (level of algorithms, Marr, 1982) and psychology (human associative memory, (Anderson and Bower, 1973). Additional information about the impact of the results of these studies on the development of cognitive architectures can be found in (Taatgen & Anderson, 2009). The new direction aroused interest not only in the academic environment; a number of studies were funded by military departments interested in the development of robots and unmanned systems. After a while, the first analytical reviews on cognitive architectures appeared (Anderson, 1988; Anderson, 1991; Laird, 1991; Pew & Mavor, 1998; Morrison, 2003; Ritter et al., 2003).

The article (Sowa, 2011) can also be considered an early review of

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cognitive architectures, since it examines the Conceptual Structures architecture, dating back to the mid-1980s, and compares it with four other architectures that existed at that time.

The next stage in the development of analytics on cognitive architectures begins with a conference and the publication of a collection of articles (Gray, 2007). A distinctive characteristic of this new stage is the large number of articles on cognitive architectures, the presentation of several dozen reports at conferences, and the formation of collections of conference articles from them. In the collection (Gray, 2007), in addition to articles on individual architectures or their components, there is an analytical article on several architectures (Pew, 2007). The publication of collections does not exclude the publication of individual articles in other issues (Taatgen & Anderson, 2008, 2009; Duch et al., 2008; Langley et al., 2009). The following year, also as part of the collection of articles of the specialized conference, which later became an annual one, Alexey Samsonovich (Samsonovich, 2010) published a large review, which included 26 cognitive architectures, with the participation of 35 co-authors.

The article (Thórisson & Helgasson, 2012) opens the next stage in the development of cognitive architecture analysts, the key feature of which is the comparison of functionality and other characteristics of architectures presented in the review, as opposed to a simple description of individual architectures. This trend manifested itself even more in 2016 with the publication of the first version of the preprint of the article (Kotseruba & Tsotsos, 2020). The same approach was adopted in (Kugurakova et al., 2016; Ye et al., 2018; Panella, 2021). Methodological aspects for cognitive architectures construction are considered in the article (Jiménez et al., 2021).

The preparation and publication of the monograph (Kotseruba & Tsotsos, 2024) is a step to a new level. The disparate analysis of cognitive architectures turns into a full-fledged engineering discipline "Theory of cognitive architectures", which can be taught as one of the basic courses in the master's degree in Artificial Intelligence.

1.2. Cognitive architectures for creating AGI

In recent years, there has been a rapid and multidirectional development of intelligent information systems developed by people (Ghosh & Singh, 2020). The ultimate direction of artificial intelligence is the creation of artificial intelligence systems in the future with the same capabilities as humans. Back in his famous lecture "Unified Theories of Cognition", Allen Newell (1990) assumed that a relatively distant extrapolation of the functionality of these developments would be the creation of an artificial intelligence comparable to human intelligence. He used the term General intelligence. Later, in the early 2000s Ben Goertzel and his colleagues popularized the term AGI for denoting such artificial intelligence (Goertzel, 2014a).

Despite the existence of publications devoted to cognitive architectures for creating AGI, such as publications (Laird and Wray, 2010; Lieto et al., 2018) or (Samsonovich, 2012), dedicated to the roadmap proposed by Dr. James Albus for a national program unifying artificial intelligence, neuroscience and cognitive science, only in two reviews (Ye et al., 2018; Kotseruba & Tsotsos, 2020) are architectures for creating AGI explicitly highlighted. In these two reviews, which cover about 140 architectures, cognitive architectures designed to create AGI were noted, we have emphasized them and supplemented the list with the results of a bibliographic search.

Unlike the authors of these reviews, authors of other publications featured in the previous section considered cognitive architectures for creating AGI or, as it was indicated in (Langley et al., 2009), for supporting the same capabilities as humans but also included in the review the architectures that were not intended for this purpose and did not isolate the former from the latter. We consider it important to analyze precisely cognitive architectures that are declared as architectures intended for creating AGI, since additional requirements are imposed on them (Laird and Wray, 2010). Other cognitive architectures could be developed to test some technical solutions or to solve more utilitarian tasks, for example, for image processing or controlling a transport robot transporting workpieces in the workshop.

Moreover, in this review we included some cognitive architectures not explicitly defined by their authors as designed for AGI creation. However, the features they exhibit, such as curiosity or self-organization, were previously unique to humans and animals. In other words, the goals of these architectures are to model human-like behavior or to focus on the complex functions inherent in humans. This motivated us to assume that the authors, without clearly specifying, aimed at developing their research in the direction of creating AGI, so we included such architectures in the general list of architectures under consideration. These architectures can be identified by the citations based on which they were included in the review.

The final list of cognitive architectures for analysis includes 56 entries presented in Table 1. If the architecture does not have a name, it is presented simply with a link to the publication. For each architecture this table contains citations indicating why we consider that the architecture is intended to enable AGI.

When analyzing the architectures, the following 16 functional components were identified. They were divided into 6 categories as shown in Table 2:

The listed set of functions is an extension of the set used in (Samsonovich, 2013), however, such an extension is justified, since a deeper understanding of many aspects has emerged over the past time. If we really want to see artificial intelligence comparable to human intelligence, all these functions are necessary for it. As ten years ago, in a study by Alexey Samsonovich (2013), all existing cognitive architectures were acclaimed as limited, we could not find more than 60% of the necessary functions anywhere. This served as a prerequisite for the development of a new cognitive architecture, which will have the necessary functionality.

The decision to make a new cognitive architecture was also dictated by the fact that we proposed a new, previously unknown method of organizing memory for storing knowledge, as well as a common bus method for knowledge exchange between functional components of the architecture (which is new for cognitive architectures, but widely used in software system architectures).

In 2019, a cognitive architecture was proposed, which is a very general sketch of the AGI structure (Sukhobokov et al., 2020), annotated metagraphs were used to represent knowledge in the architecture (Tarassov & Gapanyuk, 2020). Later in (Sukhobokov & Lavrinova, 2021), an approach was proposed on how to create intelligent information systems based on this architecture, including individual components from the AGI composition. Due to the rapid progress of research in areas such as metagraphs, machine ethics, machine emotions, machine thinking, there is a need to reconsider this previously developed cognitive architecture. The need to develop a new cognitive architecture was the reason to reflect all the necessary functionality in the second version of this architecture. Due to its broad, comprehensive functionality, we have named this second version the reference cognitive architecture.

1.3. Development of the theory of machine consciousness

Consciousness, its nature has led to millennia of analyses, explanations and debate by philosophers, theologians, and scientists. Opinions differ about what exactly needs to be studied or even considered consciousness. The disparate range of research, notions and speculations led to the appearance of one of the longest articles in English-language Wikipedia. According to Merriam-Webster (Merriam-Webster Dictionary, 2024):

2: consciousness

a : the quality or state of being aware especially of something within oneself

b : the state or fact of being conscious of an external object, state, or

Table 1
Cognitive architectures aimed to create AGI, and author citations confirming this

#	Name	Link(s)	Citations about purpose of cognitive architecture
1	Unified Theories of Cognition	Newell (1990)	Areas to be covered by a unified theory of cognition:Problem solving, decision making, routine action;Memory, learning, skill;Perception, motor behavior;Language;Motivation, emotion; Imagining, dreaming, daydreaming, ...
2	Soar	Laird (2019)	Soar … have used … to build complex integrated AI agents, and to create detailed models of human behavior. … We have found that combining what is known in psychology, in neuroscience, and in AI is an effective approach to building a comprehensive cognitive architecture. … Our bet is that achieving human-level intelligence is a long path of incremental experiments, discoveries, tests, reformulations and refinements.
3	ACT-R	Anderson et al. (2004); Lebiere et al. (2013)	This paper explores requirements on cognitive architectures for artificial general intelligence. The goal of the analysis is to determine the requirements for cognitive architectures that support the full-range of human-level intelligent behavior.
4	NARS	Wang (2013);Wang et al. (2018)	… system aimed at the realization of Artificial General Intelligence (AGI).
5	LIDA	Faghihi & Franklin (2012)	… we ... argue that Learning Intelligent Distribution Agent (LIDA) … may be suitable as an underlying cognitive architecture on which others might build an AGI.
6	Haikonen cognitive architecture	Haikonen (2007)	The author visions autonomous robots that perceive and understand the world and act in it in a natural way, without programs and numerical representation of information. This approach considers the cognitive machine as a system that is seamlessly interactive, both internally and externally, in respect to its environment and experience. This approach should result in robots that know and understand what they are doing and why, robots that can plan and imagine their actions and the possible outcome of these. Robots that exhibit properties like these are said to possess machine consciousness, which may or may not have common deeper properties with animal and human consciousness.
7	SiMA (previously ARS)	Schaat et al. (2015)	… most of humans' behavior is covered by every-day capabilities. … our experience with the cognitive architecture SiMA showed that – especially when the foundations of the human mind are at stake – every-day behavior is more suitable to analyze the basic functions of the human mind.
8	Sigma	Pynadath et al. (2014)	We … expect that a system capable of artificial general intelligence (AGI) would provide natural support for Theory of Mind. We are interested here in how Theory of Mind capabilities may be realized within Sigma (Σ), a nascent cognitive system—an integrated computational model of intelligent behavior— that is grounded in a cognitive architecture, a model of the fixed structure underlying a cognitive system.
9		Raizer et al. (2012)	The platform used as an specific domain for the initial experiments is the iCub humanoid robot simulator, but the architecture is built so it can be applied to different platforms and applications. This platform was chosen because it provides a "Human-Like" architectural level …
10	CogPrime	Goertzel et al. (2014a); Goertzel et al. (2014b)	Part 1 of the book … sketches the broad outlines of a novel, integrative architecture for Artificial General Intelligence (AGI) called CogPrime …Part 2 of the book concludes with a chapter summarizing the argument that CogPrime can lead to human-level (and eventually perhaps greater) AGI …
11	Ikon Flux	Thórisson & Nivel (2009); Nivel & Thórisson (2009)	Ikon Flux is a fully implemented prototypical architecture for self-programming systems - a prototype being an abstract type to be instantiated in a concrete domain. … A system continuously modeling its own operation has to do so at multiple levels of abstraction, from the program rewriting up to the level of global processes (e.g. the utility function), thus turning eventually into a fully self-modeling system. ,,, We believe peewee granularity is a promising way to simplify operational semantics and reach a computational homogeneity that can enable automated architectural growth – which in itself is a necessary step towards scaling of cognitive skills exhibited by current state-of-the-art architectures. Only this way will we move more quickly towards artificial general intelligence.
12	eBICA	Azarnov et al. (2018); Samsonovich (2020)	This work continues the effort to design and test the cognitive architecture eBICA: a general model of emotionally biased behavior control and decision making, with the focus on social emotional relationships. … We also presented the study of an implemented Virtual Actor based on the eBICA model. … The overall conclusion is that the implemented Virtual Actor performs at a human level.
13	D-LANCA	Panella, (2021)	This work suggests a novel approach to autonomous systems development linking autonomous technology to an integrated cognitive architecture with the aim of supporting a common artificial general intelligence (AGI) development.
14	ICOM	Kelley & Twyman (2020)	This paper articulates the methodology and reasoning for how biasing in the Independent Core Observer Model (ICOM) Cognitive Architecture for Artificial General Intelligence (AGI) is done.
15		Vityaev et al. (2020)	We consider a task-oriented approach to AGI, when any cognitive problem, perhaps superior to human ability, has sense given a criterion of its solution.
16	LIS	Nakamura & Yamakawa (2016)	… the LIS Framework … provides a way to approach AGI learning in a flexible and easy-to-use manner by combining multiple, interchangeable components. The framework allows AGI workers including beginners to combine pre-installed LIS Framework components and begin AGI development with ease.
17		Strannegård et al. (2013)	This paper is concerned with artificial general intelligence (AGI). Our ultimate goal is to create a computational model that may operate in any environment and develop intelligence adapted to that environment in a fully automatic fashion.
18	MBCA	Schneider (2020)	The biologically inspired Meaningful-Based Cognitive Architecture (MBCA) integrates the sensory processing abilities found in neural networks with many of the symbolic logical abilities found in human cognition. … MBCA can functionally produce a variety of behaviors which can help to better hypothesize and understand mammalian cortical function, and provide insight into possible mechanisms which link such mesoscopic functioning to the causal and symbolic behavior seen in humans.
19		Komarovsky (2022)	We introduce an AGI, in the form of cognitive architecture, which is based on Global Workspace Theory (GWT).
20	PySigma	Zhou & Ustun (2021)	The Sigma cognitive architecture is the beginning of an integrated computational model of intelligent behavior aimed at the grand goal of artificial general intelligence (AGI). However, whereas it has been proven to be capable of modeling a wide range of intelligent behaviors, the

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Table 1 (*continued*)

#	Name	Link(s)	Citations about purpose of cognitive architecture
			existing implementation of Sigma has suffered from several significant limitations. ... In this article, we propose solutions for this limitation ... The resulting design changes converge on a more capable version of the architecture called PySigma.
21	Unified Structured Framework for AGI	Xu et al. (2023)	Artificial General Intelligence (AGI) is a long-standing goal to fulfill for mankind. Achieving AGI requires a thorough understanding of how the human brain processes information in the function level and in the underlying dynamics level along with complex structure. Till now, neuromorphic computing and cognitive modelling are two fields that have been gaining significant attention in recent years due to their potential to revolutionize artificial intelligence (AI). Neuromorphic computing aims to replicate the functioning of the human brain by designing neuromorphic algorithms and compute chips that emulate the behavior of neurons and encephalic regions, while cognitive modelling focuses on building computational models of human cognition and mentality in higher level. Despite their different origins, both approaches share the common goal of achieving AGI.
22	GLAIR	Shapiro & Bona (2010)	GLAIR (Grounded Layered Architecture with Integrated Reasoning) is a multilayered cognitive architecture for embodied agents operating in real, virtual, or simulated environments containing other agents. … The motivation for the development of GLAIR has been "Computational Philosophy", the computational understanding and implementation of human-level intelligent behavior without necessarily being bound by the actual implementation of the human mind.
23	The Piagetian Modeler	Miller (2019); Miller (2021)	I'll be using the term my cognitive system, cognitive architecture, artificial general intelligence, and AGI interchangeably.
24	H-CogAff	Sloman & Chrisley (2005)	H-CogAff, a special case of CogAff, is postulated as a minimal architecture specification for a human-like system.
25		Serov (2022)	Our approach is to use a functional core to simulate the development of cognitive functions of autonomous agents. … The most important goal in the field of AGI is the development of control systems for cognitive agents, which, in terms of their intellectual performance, are not inferior, and perhaps even surpass humans. Developmental psychology studies show that the most significant changes in Innenwelt occur at the sensorimotor stage, which is the first in the postnatal ontogenesis. … . According to Piaget, this period of development is one of the most important in the creation of human mental abilities. The proposed architecture makes it possible to simulate the process of evolution of cognitive abilities, including the stage of sensorimotor development of autonomous agents.
26	EM-ONE	Singh (2005)	The design of EM-ONE draws heavily on Minsky's Emotion Machine architecture hence the name EM-ONE … I have also drawn ideas from Sloman's H-CogAff architecture, which resembles Minsky's architecture in many respects … Both Minsky and Sloman developed their architectures to provide rich frameworks with which to explain the diversity of complex and subtle aspects of human cognition, especially our capacity for common sense and our variety of emotions. … My goal with EM-ONE is primarily to support more intricate forms of reflective commonsense thinking, although in the long run I hope it will help to explain a broader array of types of thinking including such feelings as love, confusion, anger, and hope.
27		Dushkin (2022)	The article describes the author's proposal on cognitive architecture for the development of a general-level artificial intelligent agent («strong» artificial intelligence).
28	CAMAL	Davis (2002); Davis (2003); Davis (2008)	With the distributed model specific agents can change... The distributed agent requests those elements of itself (i.e. its component agents) that are associated with the current learning task to modify themselves. ... Currently we are looking at the nature of communication between agents with shared motivations and are using distributed blackboards. ... We have designed and implemented agents that display motivational qualities and address important questions about the nature of emotion and autonomy. ... We have demonstrated emotive qualities in our research agents. ... compromises can lead to the design of agent systems with inherent conflicts. ... By designing agents with the qualities described in this chapter an agent is given the means to represent and reason about these conflicts when they do arise. This research continues to raises questions about what agent is, what a mind is, and what are emotion and motivation.
29	SMCA	Venkatamuni (2008)	Artificial Intelligence originated with the desire to develop artificial minds capable of performing or behaving like an animal or person. ... Cognitive architectures are designed to be capable of performing certain behaviors and functions based on our understanding of human and non human minds. ... developing SMCA (Society of Mind Cognitive Architecture) can be viewed from the perspective of Minsky, which leads to the development of many different types of simple agents, with different behaviors. Metacognition is useful for framing the constraints for this swarm intelligence. Swarm intelligence requires the inclusion of a mathematical theory of how the group of agents work together to achieve a common goal. Swarm intelligence uses different mathematical algorithms so as to cover all processing and functioning associated with the adopted architecture or mind model.
30	MicroPSI	Bach (2009)	This book is completely dedicated to understanding the functional workings of intelligence and the mechanisms that underlie human behavior by creating a new cognitive architecture.
31	LISA	Hummel & Holyoak (2003)	Human mental representations are both flexible and structured – properties that, together, present challenging design requirements for a model of human thinking. The Learning and Inference with Schemas and Analogies (LISA) model of analogical reasoning aims to achieve these properties within a neural network.
32	CIT	Chandiok and Chaturvedi (2018)	The paper proposes a novel cognitive architecture that combines cognitive computing and cognitive agent technologies for performing human-like functionality. The system architecture is known as CIT (Cognitive Information Technology).
33	Companion	Forbus & Hinrich (2017)	The Companion cognitive architecture is aimed at reaching human-level AI by creating software social organisms – systems that interact with people using natural modalities, working and learning over extended periods of time as collaborators rather than tools.
34		Augello et al. (2016)	The paper proposes a novel cognitive architecture for computational creativity based on the Psi model and on the mechanisms inspired by dual process theories of reasoning and rationality.
35	Polyscheme	Cassimatis (2001)	This thesis describes a new framework for understanding and creating human-level intelligence by integrating multiple representation and inference schemes.

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Table 1 (*continued*)

#	Name	Link(s)	Citations about purpose of cognitive architecture
36		Larue et al. (2012a); Larue et al. (2012b)	We present a three level Cognitive architecture for the simulation of human behavior based on Stanovich's tripartite framework.
37	Clarion	Sun (2016)	The goal of this work is to develop a unified framework for understanding the human mind, and within the unified framework to develop process-based, mechanistic explanations of a substantial variety of psychological phenomena.
38	OSCAR	Pollock (2008)	The basic observation that motivates the OSCAR architecture is that agents of human-level intelligence operating in an environment of real-world complexity (henceforth, GIAs — "generally intelligent agents") must be able to form beliefs and make decisions against a background of pervasive ignorance.
39	OntoAgent	Nirenburg et al. (2011)English & Nirenburg (2020)	This paper presents an overview of a cognitive architecture, OntoAgent, that supports the creation and deployment of intelligent agents capable of simulating human-like abilities.
40	INCA	Oentaryo and Pasquier (2008)	Artificial intelligence research is now flourishing which aims at achieving general, human-level intelligence. Accordingly, cognitive architectures are increasingly employed as blueprints for building intelligent agents to be endowed with various perceptive and cognitive abilities. This paper presents a novel integrated neuro-cognitive architecture (INCA) which emulate the putative functional aspects of various salient brain sub-systems via a learning memory modeling approach.
41	ISAAC	Crowder et al. (2014)	A foundational component of an ISAAC processing framework is the concept of "mixture of experts" architecture and methodology, similar to a human brain.
42		Reser (2022)	This article provides an analytical framework for how to simulate human-like thought processes within a computer. ... Iterative updating is conceptualized here as an information processing strategy, a model of working memory, a theory of consciousness, and an algorithm for designing and programming artificial general intelligence.
43	Aigo	Voss & Jovanovic (2023)	Here we outline an architecture and development plan, together with some preliminary results, that offers a much more direct path to full Human-Level AI (HLAI) / AGI.
44	CCA1 –CCA5	Schneider (2021); Schneider & Bołtuć (2023)	The brain-inspired CCA1 tightly integrates the sensory processing capabilities found in neural networks with many of the causal abilities found in human cognition. Above we presented the Causal Cognitive Architecture 5 (CCA5). While no claims are made for the CCA5 as being a functioning AGI, conceptually it meets the above definitions for an AGI. As well, it meets the criteria above of the definition of a natural-like AGI including being a human-like AGI. Thus, for the sake of example, we consider the CCA5 as a natural-like AGI and a human-like AGI.
45	AERA	Nivel et al. (2013)	This document describes the model of the system being developed in the HUMANOBS project: a system able to learn socio-communicative skills by observing people.
46	Vertical-Horizontal Integrated Neuro- Symbolic Framework	Li et al. (2023)	The "hybrid approaches" towards building an artificial general intelligence (AGI) aim to combine different artificial intelligence (AI) techniques to form a system that has more abilities than the sum of its parts. The neuro-symbolic approach is one of the most promising hybrid approaches towards AGI…
47	ADAM	Shumsky & Baskov (2023)	We present a working prototype of an intelligent agent (ADAM) based on a novel hierarchical neuro-symbolic architecture (Deep Control) for deep reinforcement learning with a potentially unlimited planning horizon.
48	General-Purpose Minecraft Agent	Potapov et al., (2023)	We consider the problem of creating general-purpose Minecraft agents capable of solving a wide range of goals in a complex environment as a testbed for studying hybrid neural-symbolic architectures for Artificial General Intelligence (AGI). We analyze the desirable behavior of such agents and sketch out an architecture for it.
49	ECA	Georgeon et al. (2013)	… agent constructs its own ontology of the environment from its experience interacting with it, in sharp contrast to traditional rule-based cognitive architectures that require the modeler to specify the semantics of symbols, which amounts to defining the ontology of the environment a priori. ECA (enactivist cognitive architecture) allows implementing self-motivation in the agent. In the future, we envision implementing other behavior-selection mechanisms to generate additional forms of motivation such as curiosity. ECA allows the agent to program itself by learning a series of sensorimotor interactions and executing them as a single composite interaction. Self-programming allows constitutive autonomy, which theoreticians of enaction have identified as an important requirement for autonomous sense-making and intrinsic teleology.
50	Multiple Time-scales RNN (MTRNN)	Nishimoto & Tani (2009)	How can humans as well as artificial agents acquire diverse skills for goal-directed actions in a flexible, fluent, robust, and context-dependent manner? As a common sense, we know that day. Then, question is what are the underlying developmental principles of transforming such experiences to skills?Our group has investigated possible neuronal mechanisms of learning goal-directed skilled actions by conducting synthetic neuro-robotics experiments and by analyzing their results with utilizing the dynamical systems framework. Especially, the studies have focused on the possibility that the anticipation learning paradigm embedded in neuro-dynamics with rich sensory–motor interactions could result in acquiring generalized dynamic structures for performing a set of desired goal-directed actions. The essential idea is that anticipatory learning of direct sensory feedbacks associated with each intended action would result in self-organization of "internal reality" those are truly grounded to the actual experiences of the agents.
51	VERSES.AI	Albarracin et al. (2023)	… we have highlighted the importance of active inference models as a foundation for designing more human-like AI systems, seemingly capable of introspection and finessed (epistemic) collaboration with human users. This novel approach bridges the gap between AI and cognitive neuroscience by incorporating biologically inspired mechanisms into the design of AI systems, thus promoting a deeper understanding of the nature of consciousness and its potential applications in artificial intelligence. As we move forward in the development of AI systems, the importance of advancing explainable AI becomes increasingly apparent. By designing AI systems that can not only make accurate and efficient decisions, but also provide understandable explanations for their decisions, we foster (epistemic) trust and collaboration between AI systems and human users. This advancement ultimately leads to more transparent, effective, and user-friendly AI applications that can be tailored to a wide range of real-world scenarios.
52	LEELA.AI	Komrusch & Minsky (2022)	This paper will present and evaluate ideas for using symbolic learning concepts to guide learning of a neural network in a constructivist way. We aim to show how a neural network with internal feedback

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Table 1 (*continued*)

#	Name	Link(s)	Citations about purpose of cognitive architecture
			can be used - somewhat like the brain - to suggest the proper actions to take and predict the results of those actions. In other words, the system will create an internal model of the world on which it can reason. The neurosymbolic system we consider is inspired by the symbolic learning system from Gary Dresher and neural network cortical columns as discussed by Jeff Hawkins. The hybrid system aims to create a synthesis which can generalize on real-world concepts while also quickly learning from few examples as the world changes and prior experience is found to be inaccurate.
53		ter Doest (2023)	… this paper presents a proposal for a symbol-based narrow AGI that uses a problem-driven mechanism within a certain domain.
54		Sabat (2023)	In this work, we will i) analyse [*sic*] the issue of ambiguity of the AGI paradigm and ii) propose a framework to define unified strategies towards AGI. The ultimate goal of this work is to ensure all contributions to AGI are complete enough to provide value to the community, while keeping an accessible model that also narrows the gap between the design of current AI systems and the design of an AGI.
55	Cerno-CAMAL	Miri (2012)	The motivation and impetus for extending CAMAL and developing CernoCAMAL is the considerable evidence that probabilistic thinking and reasoning is linked to cognitive development and plays a role in cognitive functions, such as decision making and learning. This leads us to believe that a probabilistic reasoning capability is an essential part of human intelligence. Thus, it should be a vital part of any system that attempts to emulate human intelligence computationally.
56	RCS	Albus & Barbera (2005)	Real-time control system (RCS) is a cognitive architecture designed to enable any level of intelligent behavior, up to and including human levels of performance.

Table 2
Functional components of the AGI cognitive architecture

#	Functional module	Category
1	Consciousness for agent management in real time	Control
2	Subconscious mind for performing routine operations	
3	Goal management	
4	Emotional management	Policing
5	Formation and application of ethical assessments	
6	Monitoring	
7	Learning	Development
8	Self-development and meta-learning	
9	Problems statement	Problems solving
10	Problems solving	
11	Social interaction	Modeling the outside world and itself in it
12	Reflection	
13	Formation and use of a worldview	
14	Multimodal receipt of information from the external environment	Direct interaction with the outside world
15	Multimodal delivery of information to the external environment	
16	Control of movement organs and manipulators	

fact

> **c**: AWARENESS
> *especially* **:** concern for some social or political cause
>
> The organization aims to raise the political *consciousness* of teenagers.
> **2 :** the state of being characterized by sensation, emotion, volition, and thought **: MIND**
>
> **3 :** the totality of conscious states of an individual
> **4 :** the normal state of conscious life
> regained *consciousness*
>
> **5 :** the upper level of mental life of which the person is aware as contrasted with unconscious processes

The words “conscious” and “consciousness” in English date to the 1600s being derived from Latin, and were used by Cicero and Seneca, albeit with somewhat different meanings (Cassin, 2014; Molenaar, 1969). The origin of the modern meaning of consciousness is attributed to John Locke who defined the word in his “Essay Concerning Human Understanding”, published in 1690, as “the perception of what passes in a man’s own mind” (Locke, 1690; Consciousness (Science & Technology), 2024). The essay strongly influenced 18th-century British philosophy. Since then, for more than 300 years, there have been discussions among philosophers about the nature of consciousness. They have especially intensified since the 1990s (Hameroff et al., 1996; Hameroff et al., 1998; Hameroff and Kaszniak, 1999; Block et al., 1997).

Ned Block (1997) offered an opinion that discussions of consciousness often fail because participants do not distinguish properly between phenomenal (P-consciousness) and access (A-consciousness) (terms used before Block). P-consciousness, according to Block, is raw experience: it is moving, colored forms, sounds, sensations, emotions and feelings with our bodies and responses at the center. These experiences, considered independently of any impact on behavior, are called qualia. A-consciousness, on the other hand, is the phenomenon whereby information in our minds is accessible for verbal report, reasoning, and the control of behavior. For example, when we perceive, information about what we perceive is access conscious; when we introspect, information about our thoughts is access conscious; when we remember, information about the past is access conscious, and so on. David Chalmers (1995) has written on this point that A-consciousness can in principle be understood in mechanistic terms, but P-consciousness is much more difficult to understand. He called this the hard problem of consciousness.

Other philosophers, such as Daniel Dennett (1991), have disputed the validity of this distinction. In this work, he denied the existence of a single central place deputed to consciousness, describing the brain as a “bundle of semi-independent agencies.” In the latter (Dennett, 1996), he led the reader through a fascinating journey in the evolution of living beings to delineate the development of an intelligent conscious mind. He identified this phenomenon with the emergence of capabilities and means that turned out to be advantageous for the interaction between their possessor and the specific environment in which he lives. Therefore, consciousness is explained as the emergence of a set of inner mental representations, which results in the form of intentionality. Clearly, an agent cannot develop any form of intentionality, beliefs, desires, and hence any kind of consciousness, without an autonomous mechanism, which lets him discriminate the entities that share the same environment.

Later, authors of publications on intellectual robots (Chella & Manzotti, 2009; Manzotti & Chella, 2018) justified the urgent need for the adoption of a robust conceptual framework alternative to the Hard Problem and its cognates. They offer a new basis for robot consciousness. There will no longer be an elusive property concocted by some particular process inside the body of a robot agent; neither will it be a hard problem. Consciousness is the network of objects and events that, thanks to a body with sensory-motor-cognitive capability are brought to interact together. Consciousness is not an internal property, but the collection of objects that, thanks to the body, are causally responsible for what the body does. The study of robot consciousness will thus shift the focus from internal processes and structures to the analysis of the ontogenetic and epigenetic relations that a body develops and maintains with the external world during its life.

Now let us move on from the history of the philosophy of consciousness to the history of work on its realization in computer systems. Our search for primary sources showed that for the first time the problem of machine modeling human consciousness was put forward in (Hofstadter, 1979) and the first approaches to how this can be done were proposed there too.

Bernard Baars, (1993) suggested that consciousness implements a set of specific functions: Definition and Context Setting, Adaptation and Learning, Editing, Flagging and Debugging, Recruiting and Control, Prioritizing and Access-Control, Decision-making or Executive Function, Analogy-forming Function, Metacognitive and Self-monitoring Function, and Autoprogramming and Self-maintenance Function.

Igor Aleksander, (1995) proposed 12 principles of artificial consciousness in neurosystems: The Brain is a State Machine, Inner Neuron Partitioning, Conscious and Unconscious States, Perceptual Learning and Memory, Prediction, The Awareness of Self, Representation of Meaning, Learning Utterances, Learning Language, Will, Instinct, and Emotion. The proposed list was not exhaustive: it was important to keep the list open to encourage further development and refinement of the theory. The purpose of the theory of artificial consciousness formulated in (Aleksander, 1995) is to determine whether and how these and other aspects of consciousness can be synthesized in an engineering artifact such as a digital computer.

In (Paul & Cox, 1996), along with modeling human consciousness, the problem of creating artificial consciousness was raised. Since that time, a small (Ascott, 1998; Schlagel, 1999; Jones, 2001), and then an increasingly massive flow of scientific publications on this topic began. Next, in chronological order, we will cite several of such publications.

In (Kelemen, 2006), a functional-computational typological scale of agents is proposed, starting from the reactive and up to minimally conscious. A method of computational characterization of conscious agents using the concept of hypercalculations (parallel computations) is described. In the article collection «Artificial Consciousness» under edition of Antonio Chella and Manzotti, (2007) the problems of the race for artificial consciousness, design and implementation of an artificial consciousness, the comparison of artificial and natural consciousness were considered.A generalized conclusion that follows from the collection: consciousness is an integral and crucial element in the creation of artificial systems with human capabilities.

Antonio Chella and Gaglio, (2007) investigated the role of self-consciousness in AI. How can a robot obtain self-consciousness – that is, the ability to reflect on itself, its perceptions, and actions during its operation life? They suggested that the robot's self-consciousness is based on a higher-order perception that the robot has. In their model there is an external world and an internal world inside the robot. Self-consciousness is the perception of such an inner world. The robot can perceive its status and, thus, create an idea of itself of a higher order.

In (Zeki, 2007) a hierarchical structure of consciousness was suggested. In (Cleeremans, 2007), author put forward a thesis that consciousness appears as a result of learning from continuous attempts to predict the external environment state and one's own ideas about it. In (Aleksander and Morton, 2007), the architecture of consciousness as an information system is formulated. In (Arrabales et al., 2008), a taxonomy and some functional criteria are proposed that can be used to assess the level of consciousness of an artificial intelligence agent. In addition, the article provides a scale of consciousness, a list of measurable levels of artificial consciousness, as a tool for determining the potential level of consciousness of an agent.

In (Wiedermann, 2009), a simple but cognitively powerful architecture of a conscious agent with a material form is described. In (Taylor, 2011), eight basic and several additional models of consciousness are considered, and four criteria that models of consciousness should satisfy are enumerated. It is demonstrated that only one attention-based model satisfies all the aforementioned criteria: CODAM. In (Chella & Manzotti, 2011), an overview of various approaches to the implementation of machine consciousness is made, also an consciousness-oriented architecture and intentional architecture of consciousness are proposed based on Taylor's CODAM (Taylor, 2003, 2007) which is shown to perform better than other architectures in several properties.

In (Goertzel, 2014b), the thesis is formulated that AI systems, in concept, can demonstrate completely different types of consciousness, but if an AI system is going to demonstrate intelligence close to human, it will almost certainly also require to demonstrate consciousness close to human. Key factors of humanoid intelligence: dynamic representation, focusing of energy resources, focusing of information resources, dynamics of the global workspace, integrated information, correlation of concentration of attention with self-modeling. The article (Jonkisz, 2015) is of special significance. It formulates an abstract and unifying version of the concept of consciousness. It is argued that consciousness, characterized as dually accessible (cognizable from within and from without), hierarchically referential (semantically ordered), bodily deterministic (embedded in the working structures of an organism or conscious system), useful in action (pragmatically functional), is graduated, and not an all-or-none phenomenon. Reasonable and empirically based restrictions are imposed on the gradation approach to determine how wide the range of varieties of consciousness can be. It is argued that conscious systems are globally limited by the ability to individualize information, whereas local limitations establish an action orientation.

In (Dehaene et al., 2017) a hypothesis was formulated that the word "consciousness" conflates two different types of information-processing computations in the brain: the selection of information for global broadcasting, thus making it flexibly available for computation and report (C1, consciousness in the first sense), and the self-monitoring of those computations, leading to a subjective sense of certainty or error (C2, consciousness in the second sense). They argue that despite their recent successes, current machines are still mostly implementing computations that reflect unconscious processing (C0) in the human brain. After that they review the psychological and neural science of unconscious (C0) and conscious computations (C1 and C2) and outline how they may inspire novel machine architectures.

In (Boogaard et al., 2017), a network model of consciousness based on the theory of the attention scheme of neuroscientist Graziano is demonstrated. In this theory, the attention schema contains an internal model of the attention process that supports attention control. To implement the scheme, Jan Treur (2016) proposes to use a temporal-causal network. Temporal-causal network itself consists of states and causal relations between them. The specificity of this model is that simultaneously there are activities occurring in every state so that some states are more active and some less active. The relations represent which states are affected by other states with a weight value. Weights typically range from –1 to 1, where negative value means opposite influence on the following states. Due to the fact that the model reflects dynamic processes, states carry a speed of change value, which represents how fast changes from previous states will be reflected on the current one. Every state has its own combinational function, which defines exactly how a state must react to incoming values from previous states (Treur, 2016). In addition, in this article, a possibility of modeling cycles is described, which means that states can be connected in a loop.

In (Bringsjord et al., 2018), a methodology is proposed that allows to model consciousness and closely related phenomena based on formal methods so that the created models can be implemented. The methodology, according to the authors, was in its infancy at the time of writing. In a later article (Barendregt & Raffone, 2022), consciousness is presented axiomatically as consisting of a stream of configurations that are composite, discrete and (non-deterministically) computable. In this context, the notions of self, concentration, mindfulness, and various forms of suffering are defined. As an application of this attitude, it is shown how the combined development of concentration and mindfulness can attenuate and eventually eradicate some forms of suffering.

In (Sukhobokov et al., 2020), a cognitive architecture of the agent is proposed, within which two main blocks – the Consciousness and the Subconsciousness – solve the same classes of tasks but use different methods. The Consciousness uses conscious memory and inference mechanisms. The subconscious uses narrow AI models and methods and unconscious memory. Emotions, insights, intuitive solutions, algorithms or sequences of actions, expectations, feelings, desires or their hierarchies, abstractions, and areas of attention are used to transfer information from the Subconscious ness to the Consciousness. Both conscious and unconscious memory use the metagraph model of knowledge. The acquisition of knowledge from information coming from external channels is carried out in parallel by conscious and unconscious memory. In the same way, the output of information to external channels and the performance of actions are based on the knowledge of both conscious and unconscious memory. The proposed architecture is an attempt to make a bridge for the existing gap between AGI and narrow AI.

Jiří Wiedermann and Jan van Leeuwen (Wiedermann & Leeuwen, 2019; Wiedermann & Leeuwen, 2021) a finite state machine with feedback considered, which is a new model of the machine from the point of view of the scenario of cognitive computing. The model is developed in the spirit of automata theory and is a mixture of Alan Turing finite automata and Norbert Wiener automata with feedback. The concepts of minimal machine consciousness and machine qualia are formulated for the proposed model. The main components of minimal machine consciousness are global availability of information (self-informing), self-knowledge, self-control, and self-awareness. The emergence of minimal machine consciousness became possible thanks to the special architecture of the cognitive machine with internal feedback between its sensory units and its control in the final state, as well as between its motor units and its control in the final state. For the model, a test is designed that distinguishes minimally conscious machines from unconscious ones (“zombies”) on a given cognitive task. The developed model confirms that consciousness is a computational phenomenon that depends not only on suitable software, but also on a special architecture.

In (Popov et al., 2022), a mechanism of stream production systems was proposed for the realization of minimal consciousness. One of the main features of stream production systems, unlike cycle systems, is the rapid processing of all incoming information from sensors and the emission of commands to action actuators. Indirectly, the expediency of combining production systems and stream data processing methods is confirmed in (Bhattacharyya et al., 2021), where it is shown that the production system successfully simulates the activity of a human driver only in combination with stream data processing methods. In stream systems the left hand sides of the production rules are formed from variables. If they emit the truth, then the right hand sides of the production rules are executed, which may change the values of variables or generate commands for executive mechanisms. Production rules do not wait for each other to be calculated, in other words, as soon as the value of a variable changes, the calculation of the left hand sides of the rules which the variable immediately begins. The commands to the actuators are queued FIFO (for each mechanism its own queue) and executed in the order of appearance. Only privileged commands can be executed bypassing queues, for example, an immediate stop command. The presented architecture of a stream production system allows to consider it as a composition of parallel finite-state machines with feedback and finite automates, in which finite-state machines with feedback are responsible for parallel running productions, and finite automates are responsible for the queues for the actuators.

In (Blum & Blum, 2022) another, more powerful mechanism for implementing machine consciousness was proposed – the Conscious Turing Machine (CTM). The CTM is influenced by Alan Turing’s simple yet powerful model of computation, the Turing machine (TM), and by the global workspace theory (GWT) of consciousness originated by cognitive neuroscientist Bernard Baars and further developed by him, Stanislas Dehaene, Jean-Pierre Changeux, George Mashour, and others. Phenomena generally associated with consciousness, such as blindsight, inattentional blindness, change blindness, dream creation, and free will, are considered. Explanations derived from the model draw confirmation from consistencies at a high level, well above the level of neurons, with the cognitive neuroscience literature.

In “In the Theater of Consciousness”, Bernard Baars (1997) describes consciousness through a theater analogy as the activity of actors in a play performing on the stage of working memory, their performance under observation by a huge audience of unconscious processors sitting in the dark. In the CTM, the stage of GWT is represented by short-term memory (STM) that at any moment in time contains CTM’s conscious content. The audience members are represented by enormously powerful processors—each with its own expertise—that make up CTM’s long-term memory (LTM). These LTM processors make predictions and get feedback from CTM’s world. Based on this feedback, learning algorithms internal to each processor improve that processor’s behavior. LTM processors, each with their own specialty, compete to get their questions, answers, and information in the form of chunks on the stage for immediate broadcast to the audience. Conscious awareness—elsewhere called attention—is defined formally in the CTM as the reception by the LTM processors of the broadcast of CTM’s conscious content. In time, some of these processors become connected via links that turn conscious communication (through STM) into unconscious communication (through links) between these LTM processors. Communication via links about a broadcasted chunk reinforces its conscious awareness, a process that Dehaene & Changeux (2005) call ignition.

While these definitions are natural, they are merely definitions; they do not provide a proof that the CTM feels conscious. Lenore and Manuel (Blum and Blum, 2022) argue, however, that these definitions, together with explanations derived from the CTM model, capture commonly accepted intuitive concepts of consciousness and agree, at a high level, with cognitive neuroscience explanations of phenomena generally associated with consciousness.

The general theory of entities possessing consciousness is presented in the publications of Murray Shanahan (2016; 2024). With reference to the philosopher Aaron Sloman, he describes ‘the space of possible minds’ meaning humans, animals, conscious artificial intelligence systems and various hypothetical life-forms including extraterrestrial or artificial or both, with superhuman intelligence and a superhuman capacity for consciousness). Shanahan’s articles, based on Wittgenstein’s later works, present a critique of the usual dualistic approach, which inherently separates the mental from the physical and assumes a private, inaccessible sphere of consciousness.

A significant portion of the papers is devoted to the idea of “engineering encounters” with AI, drawing parallels with exotic forms of life that challenge our standard criteria for ascribing consciousness. Papers discusses the potential for AI systems, especially those with virtual or robotic embodiments, to participate in social interactions that might prompt humans to ascribe consciousness to them. These encounters, however, should not lure us into anthropomorphizing AI or mistaking sophisticated mimicry for genuine conscious experience. In exploring the future of human-AI interaction, M. Shanahan imagines a scenario where AI systems do not just replicate human behavior but also create a multiverse of narratives and personas. This complex simulation brings forth the challenge of addressing AI entities as conscious beings. “The kinds of AI agents we have been imagining offer the merest glimpse of the extraordinary menagerie of exotic forms of AI that might appear as we reveal more of the space of possible minds with our technology. … In a mixed reality future, we might find a cast of such characters – assistants, guides, friends, jesters, pets, ancestors, romantic partners – increasingly accompanying people in their everyday lives.” (Shanahan, 2024).

Shanahan’s papers (2016; 2024) were widely discussed in social networks and science publications, e.g.: (Paul-Choudhury, (2016, June

22).; Karelov, 2024). As a result of those discussions, there appeared several diagrams that modify the author's original diagram depicting his classification of conscious entities. From various representations, we have compiled the most adequate, in our opinion, version and presented it in Fig. 1.

1.4. Development of the theory of subconsciousness

There is some general ambiguity in the terms 'subconscious' and 'unconscious'. Initially, psychologists and philosophes wrote only about 'conscious' and 'unconscious'. Then Janet introduced the term 'subconscious' and separated 'subconscious' and 'unconscious'. Freud, at the beginning of his activity, distinguished 'conscious' and 'subconscious', but then switched to using three categories: conscious, preconscious, and unconscious. Freud stressed the importance of unconscious fantasies, and that unconscious representations must go through a stage of verbalization at the preconscious level before becoming conscious (Ellenberger, 1970). However, later these concepts were a little mixed up and simply diverged into different fields of activity: subconscious is more often used in sociology, social communications, media theory, AGI and cognitive architectures; while unconscious is used in classical psychoanalysis, psychology and philosophy. Although there are quite a few exceptions, for example (Lanius et al., 2017). In this subsection, since the results of research in the field of philosophy and psychology are presented here, we will adhere to the terminology characteristic of these sciences.

Ideas about the important role that subconsciousness plays in cognitive activity appeared much later than the concept of consciousness arose. John Norris (1708) came very close to the concept of the unconscious when he wrote that not all our thoughts were conscious, but stopped and did not introduce the concept. John Norris was chosen as an example because his essay is digitized in two parts and is available in the Google Archive. This is an example of one of dozens of thinkers who, since the times of ancient Greece and ancient Rome, have been looking for approaches to the problems of the unconscious, but have not received any serious results (Whyte, 1962).

The definition of the unconscious was developed in the depths of German romantic philosophy. First attempt to give a complete and objective theory on unconscious psychological life was the book *Psyche* (Carus, 1846) from Carl Gustav Carus (Ellenberger, 1970). In it, he formulated the characteristics of the unconscious:

- The unconscious has "prometheic" and "epimetheic" aspects, it is turned toward the future and toward the past hut does not know of the present.
- The unconscious is in constant movement and transformation; conscious thoughts or feelings, when becoming unconscious, undergo continuous modification and maturation.
- The unconscious is indefatigable; it does not need periodic rest, whereas our conscious life needs rest and mental restoration which it finds by plunging into the unconscious.
- The unconscious is basically sound and does not know disease; one of its functions is "the healing power of Nature."
- The unconscious works along its own ineluctable laws and has no freedom.
- The unconscious possesses its own inborn wisdom; in it, there is no trial and error, no learning.
- Without being consciously aware of it, we remain in connection through the unconscious with the rest of the world, particularly with our fellow beings.

The theory of the unconscious has been further developed in Eduard von Hartmann's famous *Philosophy of the Unconscious* (von Hartmann, 1869). Von Hartmann collected numerous and relevant facts concerning perception, the association of ideas, wit, emotional life, instinct, personality traits, individual destiny, as well as the role of the unconscious in language, religion, history, and social life.

The most important contribution to the concept of the unconscious was the work of Pierre Janet, who conceptually outstripped his followers Freud, Adler, and Jung, who partially remained within the framework of the philosophy of romanticism, while Janet developed his own philosophical system (Ellenberger, 1970). Janet defended his doctoral dissertation on experimental psychology (Janet, 1889), in which he proved that the subconscious mind is responsible for the actions performed automatically. He put forward the idea that under the conscious mind lies another, which controls the body when the conscious mind is distracted, under hypnosis or ill. In his work, Janet showed that with the help of distractions, it is possible to impress a subject with suggestions or even hallucinations, which leads to curious confusions and interactions between conscious and subconscious manifestations. Exploring automatism, he identified variants of total and partial automatism and in the latter case assumed the presence of rudimentary consciousness when the subconscious mind controls the body (Ellenberger, 1970).

By 1896, Freud had built a new theory of neuroses explaining every detail of their symptoms and origins. This became the starting point for him to create a theory that became known as depth psychology. Depth psychology claimed to provide the key to exploring the unconscious and, through it, to an updated knowledge of the conscious mind with broader possibilities for understanding literature, art, religion and culture. The main aspects of depth psychology were Freud's dream theory and his theory of parapraxes, the first two generalizations of the pattern he had worked out for hysteria. These theories were elaborated simultaneously and presented in two of his best-known books: The Interpretation of Dreams, in 1900 (Freud, 1913, in translation), and The Psychopathology of Everyday Life in 1904 (Freud, 1920, in translation). Freud's theory of dreams has been told so often that it has become common knowledge (Ellenberger, 1970).

The seminars of French psychoanalyst and psychiatrist Jacques Lacan held in Paris from 1952 to 1980 in 1957-58 examined the structure of the unconscious (Lacan, 2017). For S. Freud, the unconscious is a separate entity in the human mind, formed from suppressed emotions and memories, which can project itself into more conscious (aware) activities, such as dreams, whereas Lacan, adopting the idea of the unconscious as a localized separate entity of the mind, is guided by ideas of French structuralism and assigns to it the property of structure, comparing this internal hierarchy with the structure of language (Günday and Kaçar, 2022).

In his posthumously published work, Carl Jung, (1964) argued that since there is a limit to what can be held in consciousness, an alternative repository of knowledge, dreams, imaginary situations and previous experiences is needed. A significant part of the signals, premonitions and ideas a person receives from the unconscious. By providing information, the unconscious influences conscious behavior. There may be situations when the conscious does not yet know, but the unconscious has already been informed, has processed the information, has come to a conclusion and has made a choice. This is done instinctively.

In the book (Lakoff & Johnson, 1999), the authors write the following regarding the cognitive unconscious: 'Cognitive science is the scientific discipline that studies conceptual systems. It is a relatively new discipline, having been founded in the 1970s. Yet in a short time it has made startling discoveries. It has discovered, first of all, that most of our thought is unconscious, not in the Freudian sense of being repressed, but in the sense that it operates beneath the level of cognitive awareness, inaccessible to consciousness and operating too quickly to be focused on.' Lakoff and Johnson (1999) distinguish between two areas of the unconscious. The first has to do with all our automatic cognitive operations: visual and auditory processing, and motor operations among them. The other, particularly relevant when we deal with memory, is what they call 'our implicit knowledge' and they claim that 'all of our knowledge and beliefs are framed in terms of a conceptual system that resides mostly in the cognitive unconscious'.

The review (Snodgrass et al., 2004) examines unconscious

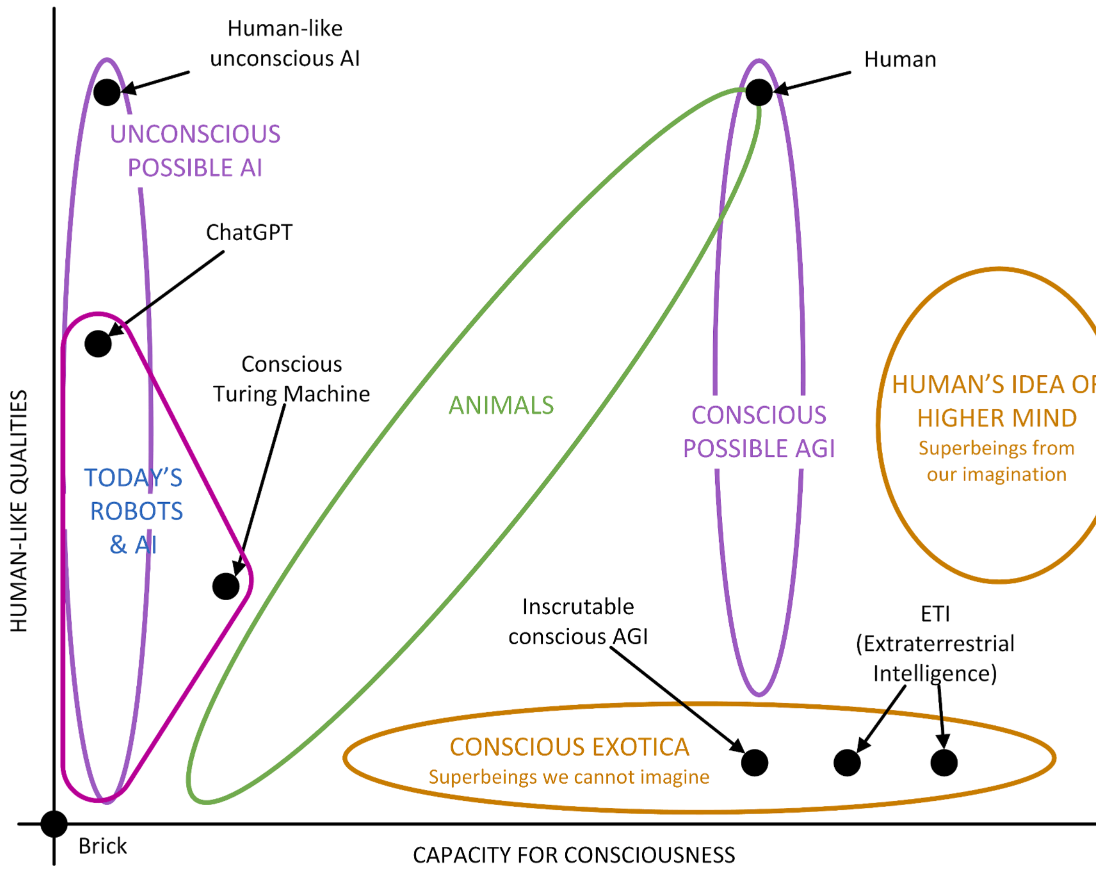

Fig. 1. Classes of conscious entities (adaptation of M. Shanahan's diagram and its variations).

perceptual effects in conditions where they are influenced by conscious perception. A novel methodological framework is presented in the article, stressing the centrality of specifying the single-process conscious perception model. Various considerations suggest that conscious perception functions hierarchically, in such a way that higher level effects (e.g., semantic priming) should not be possible without lower level discrimination (i.e., detection and identification). Relatedly, alternative conscious perception accounts predict positive relationships between direct and indirect measures. Contrariwise, this review suggests that negative and/or nonmonotonic relationships are found, providing strong evidence for unconscious perception and further suggesting that conscious and unconscious perceptual influences are functionally exclusive, in such a way that the former typically override the latter when both are present. Consequently, unconscious perceptual effects manifest reliably only when conscious perception is completely absent, which occurs at the objective detection (but not identification) threshold.

The article (Ekstrom, 2004) provides an overview of the works of Roger Schank from Northwestern University Institute for Learning Sciences about the conceptualization of the unconscious which has come from his work:

- According to Schank (1999), a wide range of scripts or stories serve in memory storage. They do so because they are the most efficient way to remember a great number of events and because they can be continuously updated and indexed. However, much of the indexing happens without our awareness, non-consciously, and, as most cognitive scientists, Schank, (1990) has found little reason to believe that unconscious activities primarily are the result of Freudian repression. Instead, he proposes that there is plenty of unconscious processing going on in the mind/brain of humans, not because we have to filter out threatening stimuli or impulses, but because many cognitive operations go on without conscious participation.
- The narrative explanation of memory structures is the outcome of many years of frustrating experimentation, but the first step came when Schank and Abelson (1977) were able to describe certain basic memory scripts. The next step, documented in Schank's Tell Me a Story (1990), for the first time took advantage of the narrative understanding in literary criticism, narratology in particular.
- To Schank, most learning begins with telling a story, which is also creating it. Once a story is created we can re-use it. This in turn makes reconstruction of missing or loosely connected details easier than creating a new story each time.
- Memorizing and learning are therefore tied to various types of narratives and these memory packets may be constructed in many different ways. However, they are all based on two particular activities which keep occurring once a narrative has been created: something unexpected and being reminded.
- In the earlier version of his major work, Dynamic Memory, Schank, (1982) focuses on how learning depends on what he calls expectation failures. Confronted by such failures, we attempt to explain deviations from the original memory structure by further refining and elaborating and we do so by indexing memory structures we have already created.
- He bases this idea on the fact that we take particular notice every time the expected does not happen. Without consciously having to decide, a new index will be created each time the unexpected occurs, so that any future occurrence of this circumstance can be accounted for.
- The other memory mechanism, reminding, is further expanded in a later version of his work on memory, Dynamic Memory Revisited (1999). Since no two stories are exactly alike, Schank argues, retrieval must take place by searching for memory scripts with

similar features and a match is made when we are reminded of a story of our own which is similar enough. We feel we have heard the other person and that we understand.

The article (Bargh & Morsella, 2008) examines the evolution of ideas about the unconscious. The unconscious mind is still viewed by many psychological scientists as the shadow of a "real" conscious mind, though there now exists substantial evidence that the unconscious is not identifiably less flexible, complex, controlling, deliberative, or action-oriented than is its counterpart. This "conscious-centric" bias is due in part to the operational definition within cognitive psychology that equates unconscious with subliminal. We review the evidence challenging this restricted view of the unconscious emerging from contemporary social cognition research, which has traditionally defined the unconscious in terms of its unintentional nature; this research has demonstrated the existence of several independent unconscious behavioral guidance systems: perceptual, evaluative, and motivational. From this perspective, it is concluded that in both phylogeny and ontogeny, actions of an unconscious mind precede the arrival of a conscious mind—that action precedes reflection.

In the article (Augusto, 2010) the main argument is that whereas complexity greatly interferes with conscious thought, thus often resulting in bad choices, the unconscious is not affected by it. The assumptions underlying this conclusion are in fact not far from some of those shared by other theories of unconscious knowledge: For instance, as seen above, research in artificial grammars rests in large measure on the assumption that complex grammatical rules are more easily learned unconsciously. Studies corroborate one of the major tenets of unconscious cognition, to wit, that unconscious knowledge is solely procedural, remaining inaccessible to consciousness and verbalization. Although at first sight not primarily, or at all, concerned with issues of unconscious knowledge, the somatic marker hypothesis and what is known as unconscious thought theory might be seen as contributing to the assumption that one can decide, securing beneficial results, by resorting to unconscious forms of knowledge processing alone.

The article (Soon et al., 2013) describes experiments showing that the outcome of a free decision to either add or subtract numbers can already be decoded from neural activity in medial prefrontal and parietal cortex 4 s before the participant reports they are consciously making their choice. These choice-predictive signals co-occurred with the so-called default mode brain activity pattern that was still dominant at the time when the choice-predictive signals occurred. Our results suggest that unconscious preparation of free choices is not restricted to motor preparation. Instead, decisions at multiple scales of abstraction evolve from the dynamics of preceding brain activity.

According to (Hassin, 2013), understanding the division of labor between conscious processes and unconscious ones is central to our understanding of the human mind. This article proposes a simple "Yes It Can" (or YIC) principle: It argues that unconscious processes can perform the same fundamental, high-level functions that conscious processes can perform. The author presents considerations of evolutionary pressures and of the availability of mental resources that render YIC a reasonable hypothesis. Evidence is then reviewed from various subfields of the cognitive sciences, which shows that functions that were traditionally thought of as requiring consciousness can occur nonconsciously. On the basis of these data and arguments, it is proposed that an answer to the question "What is it that consciousness does?" would not be in the form of "Consciousness is necessary for *F*," where *F* is a fundamental, high-level cognitive function. In Marr's (1982) terms, the argument is that computationally conscious and unconscious processes are very similar. Yet differences in how these processes kick in and in the ways in which they play out (Marr's algorithmic-representational level) are likely to have interesting implications for human cognition, motivation, and emotion.

In (Prinz, 2015) it is discussed that before the twentieth century, there was little appreciation of the fact that mental activity can occur without consciousness. Now unconscious mentality is widely accepted. This owes, in part, to Freud who emphasized unconscious motivations, but belief in the unconscious became more deeply entrenched with the rise of experimental psychology, and the discovery that human behavior is often best explained by appeal to processes that take place without awareness. Unconscious perception is one of the most extensively studied phenomena of this kind. There is extensive evidence that we respond to stimuli presented to our senses without awareness. Author has argued that there are unconscious perceptual states. Indeed, such states are very much like conscious perceptual states in terms of the information they carry, but they present that information without qualitative character, and they don't let it travel very far. Unconscious perception is no dumber and no smarter than reptilian Unconscious Perception 387 perception. It is a sensory lizard that resides in each of us, and takes the reigns when we are not paying attention.

Heated debates, similar to those that took place in the late 1990s about consciousness, take place on various aspects of the unconscious in the late 2010s and early 2020s (Phillips & Block, 2017). Cases of two types ground much contemporary belief in unconscious perception. First, clinical cases in which perception appears preserved despite loss of consciousness. Second, paradigms in which a stimulus continues to influence responding despite apparently being suppressed from conscious awareness. Seeing is a single fundamental natural kind, of which conscious and unconscious seeing are sub-kinds. This fact provides difficulties for some of the major theories of perception. Unconscious perception must be both unconscious and perception, but there is a potential conflict between these desiderata. Ned Block's opening statement describes his "Favorite case of unconscious seeing": continuous flash suppression. Ned Block suggests a wider significance: unconscious perception threatens naïve realism. Block's view rests on two contentions: that conscious and unconscious seeing are of the same fundamental kind, and that unconscious seeing "must be a matter of perceptual representation". A. Phillips says unconscious perception of low-level features associated with gender might explain the result.

The article (Michel, 2023) continues the debate about the unconscious. Recent work questions whether previously reported unconscious perceptual effects are genuinely unconscious, or due to weak conscious perception. Some philosophers and psychologists react by rejecting unconscious perception or by holding that it has been overestimated. Author argues that the most significant attack on unconscious perception commits the criterion content fallacy: the fallacy of interpreting evidence that observers were conscious of something as evidence that they were conscious of task-relevant features. This fallacy is prevalent in consciousness research: if unconscious perception exists, scientists could routinely underestimate it. Author concludes with methodological recommendations for moving the debate forward.

2. Material and Methods

During the work, materials from several hundred scientific publications were used, the most significant of which are listed in the list of references. We often discussed which of several publications on the same topic to indicate in the link, and tried to bring the one that most fully reflects the information or more clearly sets out the material. Two publications in the same link were listed together under different numbers if they significantly complement each other.

The source of ideas for designing a universal knowledge base was the parallel development of works on the design of multi-paradigm data lakes, in which several data models are supported; references are given further in the text. The knowledge base management system for AGI is a significantly more complex one, since it must simultaneously support several dozen methods of knowledge representation.

Our own activities were an important source of ideas regarding the assignment of modules as part of the referential cognitive architecture. After all, we are designing AGI, and it should be able to do a lot of things that a human can. Therefore, we analyzed our daily actions and listened to ourselves sensitively, trying to understand how we work with knowledge, and what functional components should be present as part of the cognitive architecture of AGI.

The list of cognitive architectures, which are aimed at creating an AGI, was compiled as follows:

- In review (Kotseruba & Tsotsos, 2020) the authors highlighted 7 architectures for creating an AGI; 3 more were added by us from review (Ye et al., 2018).
- 40 architectures were found through a Google Scholar search.
- 6 architectures were proposed by the reviewers during the first round of the article review.

Initially, a Google Scholar search was conducted based on the presence of two terms in the publication: AGI and "cognitive architecture"; then human and "cognitive architecture". All the articles and books found were analyzed according to their content. Those that did not meet the requirement of having a cognitive architecture aimed at creating AGI were discarded; otherwise, they were included in the list. The viewing continued in depth while Google Scholar provided articles that met the requirement. The justification for the selection of each architecture is given in Table 1. Within the limits of one search, 100-150 publications were viewed, until no suitable one was found on two consecutive pages (10 publications each). If the search yielded an article from a specialized issue of a journal or collection of the conference on cognitive architectures, then in some cases it was viewed in its entirety. Thus, 21 cognitive architectures were found.

After that, a search was conducted for the presence of individual modules as part of cognitive architectures. We searched for pairs of terms Conscious and "cognitive architecture", Subconscious and "cognitive architecture", Worldview and "cognitive architecture", Reflection and "cognitive architecture". The searches were conducted with the same search termination condition as before. In these searches, in addition to the fact that architectures containing the required modules were found, 19 architectures designed to create AGI were also found.

During our search and selection of sources, we examined not only articles from peer-reviewed scientific journals, but also preprints and publications on websites. In some cases, the topics of the preprints are not examined in depth, and scientific conclusions are not sufficiently justified: as such an example we can cite the preprint (Voss & Jovanovic, 2023), the usefulness of including which in the review was an internal dispute. Nevertheless, the information contained in the preprints can be used to further develop theoretical aspects or design AGI prototypes. Wherever, according to the results of the preprint, the final published version of the article was subsequently published, we indicated a link to it.

3. Results

In the process of the research, a preliminary design of a knowledge base has been developed that will be able to operate with any forms of knowledge representation. Using it, a preliminary design of a cognitive architecture has been developed, based on which AGI prototypes can be created.

3.1. The Universal Knowledge Model

3.1.1. Archigraph as the Foundation of a Universal Model of Knowledge

The basis of cognitive architecture is the representation of knowledge. Like a human, an agent must be able to work with different forms of knowledge and switch from one to another if it is possible. In (Sukhobokov et al., 2022), a universal data model was proposed that allows storing data in a data lake structured according to different data models: relational, multidimensional, graph, and others. For this purpose, the metagraph data model based on annotated metagraphs has been expanded. Further, we will consider the proposed ways of this expansion in more detail.

The first time the term "metagraph" was mentioned in the monograph by Basu and Blanning, (2007). Their definition of a metagraph included:

- Ability to combine vertices into arbitrary groups and inside these groups to have nested groups of vertices.
- Ability to connect by edges both individual vertices and groups of vertices, including any nesting penetrating group boundaries.
- The presence of variables on the edges to which values can be assigned.

Thereafter, various modifications of the metagraph model appeared: a model with metavertices (Globa et al., 2015), a hierarchical model with metavertices and metaedges (Astanin et al., 2012), and an annotated model (Samokhvalov et al., 2015; Chernenkiy et al., 2017; Tarassov & Gapanyuk, 2020; Gapanyuk, 2021). The extension of the Bazu-Blanning model proposed in the annotated metagraphs at first did not have such a name (Samokhvalov et al., 2015; Chernenkiy et al., 2017). Later this model was named annotated because metavertices or metaedges containing the same internal objects as other metavertices or metaedges annotating these objects, allowing some additional attributes to be added to them in the new representation (Tarassov & Gapanyuk, 2020; Gapanyuk, 2021).

Technically, the metagraph itself is defined as: $MG = \langle V, MV, E, ME \rangle$, where MG – metagraph, V – set of metagraph vertices, MV – set of metagraph metavertices, E – set of metagraph edges, ME – set of metagraph metaedges.

A **vertex** is defined as: $v = \langle \{atr_1, \dots, atr_k\} \rangle, v \in V$, where v – metagraph vertex, $atr_1, \dots, atr_k$ – vertex attributes.

An **edge** of a metagraph is described as: $e = \langle vbegin, vend, eo, \{atr_1, \dots, atr_k\} \rangle$, $e \in E \wedge eo \in \{true, false\}$, where e – metagraph edge, $vbegin$ – start vertex (metavertex) of the edge, $vend$ – end vertex (metavertex) of the edge, $atr_1, \dots, atr_k$ – edge attributes, eo – edge directional sign ($eo = true$ – directed edge; $eo = false$ – undirected edge).

Fragment of metagraph in a general form is defined as: $EV = \langle \{ev \mid ev \in (V \cup E \cup MV \cup ME)\} \rangle$, where EV – fragment of metagraph, ev – element that is either an edge, a meta edge, a vertex, or a meta vertex.

A **metavertex** is defined as: $mv = \langle EV, \{atr_1, \dots, atr_k\} \rangle, mv \in MV$, where mv – metagraph metavertex, $atr_1, \dots, atr_k$ – metavertex attributes, EV – fragment of metagraph.

A **metaedge** is defined as: $me = \langle vbegin, vend, eo, \{atr_1, \dots, atr_k\}, EV \rangle$, $me \in ME \wedge eo \in \{true, false\}$, where me – metagraph metaedge, $vbegin$ – start vertex (metavertex) of the edge, $vend$ – end vertex (metavertex) of the edge, $atr_1, \dots, atr_k$ – edge attributes, eo – edge directional sign ($eo = true$ – directed edge; $eo = false$ – undirected edge), EV – fragment of metagraph.

Thus, the annotated metagraph is characterized by the following properties:

- The structure of the metagraph includes, in addition to the usual edges and vertices, metaedges and metavertices;
- Each vertex, edge, metavertex and metaedge is characterized by a set of attributes that have a name and value;
- Metavertices and metaedges differ from ordinary edges and vertices in that they can contain fragments of a metagraph inside themselves, which by their properties also represent metagraphs;
- The contents of various metavertices and metaedges can overlap up to complete equivalence;
- The boundaries of the metavertices and metaedges are permeable to edges and metaedges to any nesting depth.

An example of an annotated metagraph which is the expansion of the example from (Gapanyuk, 2021) is shown in Fig. 2. The example from (Gapanyuk, 2021) is supplemented by the inclusion of a metaedge and a

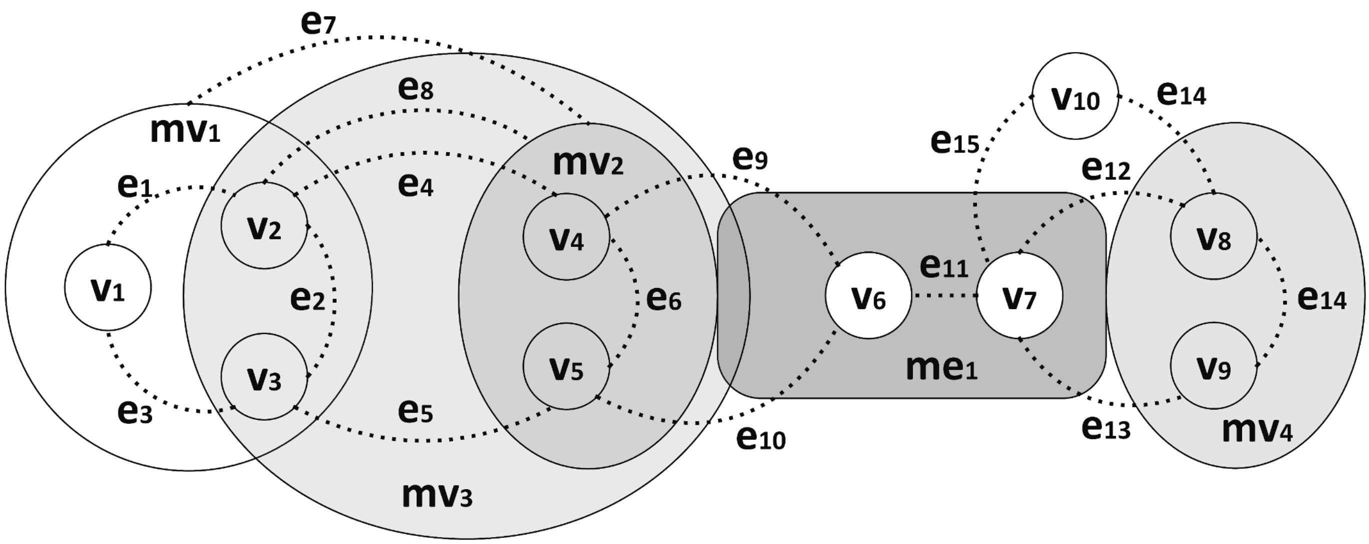

Fig. 2. Example of an undirected annotated metagraph.

vertex outside the metavertices and metaedges in order to show the possibilities of structuring objects and connections more fully.

The metagraph contains four metavertices: mv1, mv2, mv3, mv4, and one metaedge me1. Metavertex mv1 contains vertices v1, v2, v3 and connecting them edges e1, e2, e3. Metavertex mv2 contains vertices v4, v5, and connecting them edge e6. Edges e4, e5 are examples of edges connecting vertices v2–v4 and v3–v5 are contained in different metavertices mv1 and mv2. Edge e7 is an example of the edge connecting metavertices mv1 and mv2. Edge e8 is an example of the edge connecting vertex v2 and metavertex mv2. Metavertex mv3 contains metavertex mv2, vertices v2, v3, and edge e2 from metavertex mv1 and also edges e4, e5, e8, showing the holonic nature of the metagraph structure. Metavertex mv4 contains vertices v8, v9, and connecting them edge e14. Metaedge me1 connect metavertices mv2, mv4, and contains vertices v6, v7, and connecting them edge e11. Edges e9, e10 connect vertices v4 and v5 with vertex v6. Edges e12, e13 connect vertices v8 and v9 with vertex v7. Edges e14, e15 connect vertices v7 and v8 with vertex v10.

Though the original drawing from (Gapanyuk, 2021) has been expanded, Fig.2 still does not fully reflect all possible options for organizing a metagraph. For example, the following are not shown: a metaedge inside a metavertex, a metavertex inside a metaedge, and connections between a vertex and a metavertex by a metaedge. We decided to limit ourselves to what is shown in Fig.2 to avoid making the drawing too bulky.

The metagraph model provides an unlimited number of knowledge nesting levels and encapsulation of nested knowledge. These capabilities will allow you to work with knowledge at the top generalized levels and only access the details when it is needed. As a result, the organization of knowledge in the form of a metagraph allows one to work with very large and complex knowledge bases structured into any required number of nesting levels.

The use of the metagraph model can significantly expand the possibilities of knowledge representation using semantic networks and knowledge graphs (Terekhov et al., 2021). However, there are many other methods of representing knowledge that are difficult to represent by metagraphs. Consequently, it is necessary to extend this model. For this purpose, let address the notions of protograph and archigraph proposed in (Kruchinin, 2017a; Kruchinin, 2017b). These concepts were proposed to be able to describe various generalizations of graphs (metagraphs, hypergraphs, multigraphs, and others).

A **protograph** is called a set of elements $P = \{p_1, p_2, \dots, p_n\}$ and their adjacency matrix $M = \|m_{i,j}\|_{n\times n}$, $m_{i,j} \in \{0, 1\}$, where 1 means the presence of the adjacency of element p_i with element p_j, and 0 means its absence. A protograph can be considered as a graph with no edges; the role of edges is played by the adjacency of vertices to each other. Examples of protographs are: stack, queue, map, figures of the mathematical game “Life”. Examples of infinite protograph are a Turing machine tape. A protograph can be either undirected or directed. An example of various types of protographs is shown in Fig. 3.

A protograph is a minimal model and by dividing it into subsets it is possible to form a graph, a multigraph, and a hypergraph. For building a metagraph, and an archigraph as a protograph, it is necessary to use a multidimensional space in which the protograph will be located, and the more nesting levels there are in the archigraph or metagraph, the more dimensions are needed. It is also possible that a metagraph or an archigraph is transformed into an equivalent planar graph by adding

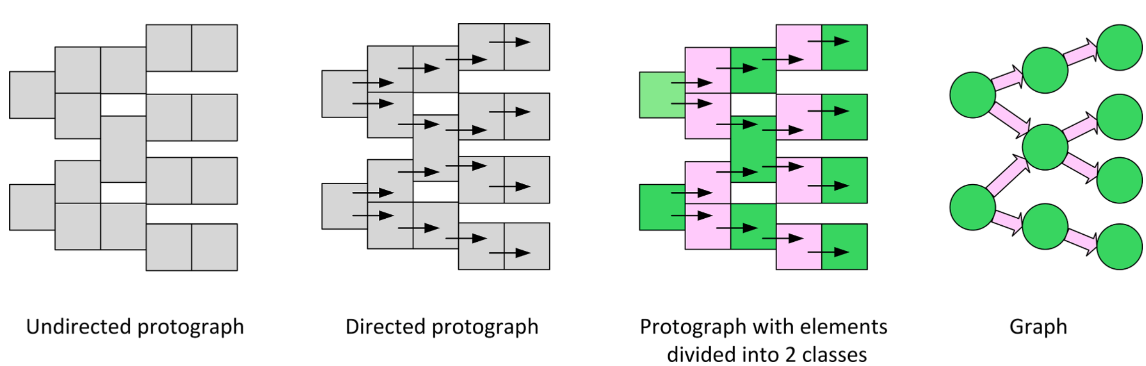

Fig. 3. Examples of a protographs.

additional edges, such as in (Chernenkiy et al., 2019), or in more complex cases, into a three-dimensional graph, and then they can be represented on a plane or in three-dimensional space. Then its transformation into a protograph will not require additional dimensions.

An **archigraph** is called a collection of sets between whose elements there exists an incidence relation. Formally, an archigraph is defined as: $G^n = \langle V_1, V_2, \ldots, V_n \rangle$, where G^n – archigraph, V_i – set of elements, n – number of such sets called degree of archigraph. Thus, it can be said that an archigraph consists of some number of classes V_i, where V_i contains the set of elements of the i-th class. Let us consider examples of archigraphs:

- $G^0=(\varnothing,\varnothing)$ – contains neither vertices nor edges;
- $G^1=(V,\varnothing)$ – a graph consisting only of isolated vertices;
- $G^1=(V,\varnothing)$ – a protograph without separated classes;
- $G^2=(V,E)$ – a graph, multigraph or hypergraph consisting of vertices and edges, and the rule applies that elements of the same class cannot be adjacent;
- an example of an archigraphs $G^3=(V,P,E)$ are port graphs used for modeling and analysis of telecommunication systems. In addition to vertices V corresponding to telecommunication devices, there are vertices P corresponding to telecommunication ports of the devices.

In this way, the previously described metagraph models can be systematized through the concept of archigraph. Thus, the first model proposed by A. Bazu and R. Blanning (2007), is an archigraph of degree 4 and can be represented as a protograph of 4 classes: vertices, vertex groups, edges and variables. And the annotated model is an archigraph with degree 5 and can be represented as a protograph of 5 classes: vertices, metavertices, edges, metaedges and attributes.

Therefore, it is possible to extend the archigraph representation of the annotated metagraph model to an archigraph of higher degree. In (Sukhobokov et al., 2024) presented the idea of creating multi-paradigm data lakes on a single technological platform and universal data model. It is based on the archigraph structure supporting graph, tabular and multidimensional data representation, text documents, and Search Engine search index. The archigraph proposed there is based on an annotated metagraph and consists of 9 classes: vertices, edges, metavertices, metaedges, multidimensional cubes, tables, indexes, documents, and attributes.

To make archigraph convenient to work with different kinds of knowledge available to humans, we propose:

- Use the annotated metagraph model as the basis. This will make it possible to use the powerful mechanism of the model for structuring entities and relationships between them.
- Include all the widely used various types of knowledge representation into the elements of the archigraph. This will allow the model to combine any forms of knowledge and ensure work with them. For that purpose it is necessary, by analogy with the universal data model (Sukhobokov et al., 2022; Sukhobokov et al., 2024), to add several dozen types of elements corresponding to different forms of

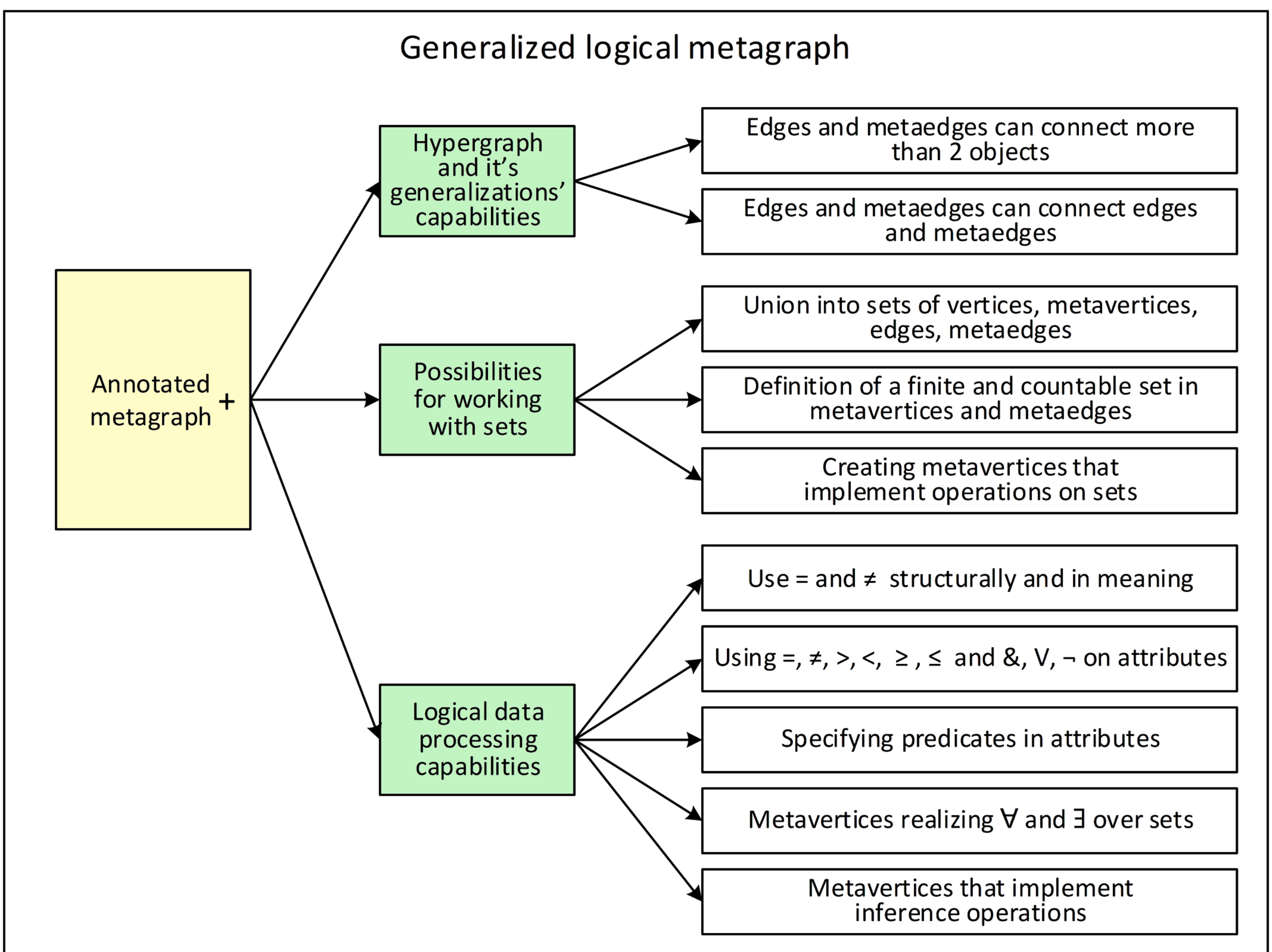

Fig. 4. An expansion of annotated metagraph.

knowledge representation to the archigraph. Then it will be possible to build archigraphs in which all knowledge from a certain subject area will be combined, regardless of the form of their representation. The edges and metaedges of such an archigraph will correspond to the relationship between entities. Metavertices will be used when these relationships are complex and need to be detailed with additional entities.

- In addition to edges and metaedges reflecting the content of knowledge, the archigraph will also contain edges and metaedges reflecting the history of which object was obtained from or based on which. For example, that this text is an abstract of that text. The appearance of such seemingly technical connections in the archigraph is completely justified – this is also knowledge. The use of metaedges in such technical cases may be due to the complexity of the conversion process.
- To expand the annotated metagraph model as shown in Fig. 4, in order to make it more versatile and to improve the capabilities for knowledge representation.

This expansion of capabilities will be done through the following steps:

1. Add hypergraph (Mahadev & Peled, 1995) and its generalizations capabilities:
— The ability to have edges and metaedges as in hypergraphs, which can connect more than 2 objects (can start on several objects and can end on several objects).
— The possibility that an edge or a metaedge can start not only from a vertices or a metavertices, but also from edges or a metaedges, and can also end not only with a vertices or a metavertices, but also with edges or a metaedges. Edges between edges were first considered in the early 2010s, for example (Matsumoto et al., 2013). In (Jung et al., 2023) these ideas were most fully represented, with the following edges being possible: edge-to-edge, edge-to-vertex, vertex-to-edge, vertex-to-vertex.
2. Add features for working with implicitly and explicitly defined sets. The idea of using sets in complex graphs also arose when working with hypergraphs, for example (Trotter & Wang, 2014; Yadav et al., 2022). However, we have not found publications, where working with sets on hypergraphs (and complex graphs in general) would be fully presented and it would be convenient to build the necessary models. Therefore, when expanding the ability to work with sets, new features were allocated in a separate direction and designed from scratch. These features include the following decisions on additional designs:
— To provide an opportunity to group vertices, metavertices, edges and metaedges into groups with similar ones due to their direct proximity to each other as in protographs. For any element of such groups, operations are possible: find out the number of elements in the group, get a link to the next member of the group.
— Provide an opportunity for any metavertex or metaedge to indicate that the objects of the first level included in them form a finite set. For such sets, operations are possible: find out the number of elements of the set, get a link to the first nearest element of the set, get a link to the next element of the set.
— Provide an opportunity for any metavertex or metaedge to indicate that the objects included in them form a countable set. For such metavertices or metaedges, two metavertices are created inside sets: one contains a finite set of object types, and the second contains a countable set of objects (further, when designing the knowledge base, various ways of representing countable sets will be proposed). For objects of a countable set, operations are possible: get a reference to the first nearest element of the set, get a reference to the next element of the set.
— Provide an opportunity to create metavertices that implement operations on sets: union, intersection, subtraction, despite the fact that the internal elements of the first level of such metavertices can only be metavertices and metaedges that form sets.
3. Add logical data processing capabilities:
— To provide the possibility of operators $=$ and $\neq$ above the objects in two versions: structurally (according to the internal structure and composition of attributes) and by value (in addition to the structure, the attribute values must match).
— Provide the ability to use standard operations $=, \neq, >, <, \geq, \leq$ for operations on attributes.
— Provide the ability to specify predicates in the attributes of vertices, edges, meta-vertices and metaedges.
— Provide the ability to perform logical operations (&, V, $\neg$) over the attributes of vertices, edges, metavertices and metaedges.
— Provide an opportunity to create metavertices that implement quantifiers $\forall$ and $\exists$ over sets, despite the fact that the only internal element of the first level of such metavertices can only be metavertices and metaedges forming sets.
— Provide the ability to create metavertices that implement logical inference operations on objects, specifying a set of source objects and their attributes with predicates, as well as the object and its attribute to which the result will be assigned.
— Create meta-vertices that implement a wide range of modal operators (aletic, epistemic, deontic, axiological, temporal) by specifying one or more objects and their attributes with predicates.

Archigraphs with such extensions can be used to implement first, second and higher order logic, as well as various modal logics, they only lack functions. Let's call them generalized logical archigraphs. To implement functions, we will add another type of object – a function in addition to vertices, edges, meta-vertices, and meta-edges. The resulting generalized logical archigraphs can become the basis for the presentation of knowledge.

Since a generalized logical archigraph can contain metavertices and metaedges, and it has inherited the following properties from the annotated metagraph:

- each vertex, edge, metavertex, metaedge and any other object of the archigraph is characterized by a set of attributes that have a name and value;
- the contents of various metavertices and metaedges can overlap up to complete equivalence;
- the boundaries of the metavertices and metaedges are permeable to edges and metaedges to any nesting depth;

it can be stated that it is also an annotated metaarchigraph.

As a storage environment for the proposed archigraphs, it is necessary to develop a specialized DBMS that supports the generalized logical archigraph data model. Its design and development can be considered as a further development of the work on the development of metagraph databases, approaches to the creation of which were considered in (Chernenkiy et al., 2018a; Sukhobokov et al., 2021) and the development of works on the creation of a data lake management system based on a universal data model (Sukhobokov et al., 2024).

All the knowledge presented in the archigraph can be divided into three large groups: unformalized, partially formalized and formalized.

3.1.2. Storage and Processing of Non-Formalized Knowledge

The informal knowledge processed in computers can be classified as:

- texts in natural languages, including technical, legal, prose, poetry, etc.;
- various graph schemes and drawings developed outside the automation systems of their development;
- maps made outside GIS;
- speech audio recordings;
- music, sound effects;

- images (photographs, paintings, portraits);
- videos and movies, including those with audio accompaniment.

There are many technologies for converting informal knowledge into formalized knowledge. For example, let's first consider the transition from natural language texts to formalized knowledge. In order not to delve too much into history, you can take as a starting point the popular and quite functionally complete NLTK library for Python (Hardeniya, 2015). During further development, neural networks and knowledge graphs began to be widely used for these purposes (Gomez-Perez et al., 2020; Liu et al., 2020). In addition to technologies for converting texts into semantic networks or into knowledge graphs (the latter provide opportunities for logical inference based on the knowledge contained in them), there are well-developed technologies for reverse conversion from graphs to texts (Gatt & Krahmer, 2018). One of the recent works in this field is devoted to the bidirectional transformation of texts into semantically loaded metagraphs and vice versa (Todosiev et al., 2023).

To formalize images, their representations are used in the form of scene graphs, which are structured representations of images in the form of graphs containing objects, their attributes and defining relationships between objects in the scene. There are currently two main approaches to scene graph generation (SGG):

- The first is to find objects, and then to find paired relationships between the found objects (Liao et al., 2019).
- The second is the simultaneous detection of objects and the relationships between them (Li et al., 2017b).

As a rule, SGG tasks are solved by using various types of neural networks: convolutional (CNN) (Dai et al., 2017), recurrent (RNN) (Xu et al., 2017), graph (GNN) (Li et al., 2018). Articles (Xu et al., 2020; Chang et al., 2023) provide a detailed overview of existing methods for generating scene graphs. The reverse transformation – the generation of images from scene graphs, as well as from other images or from text descriptions is also performed using neural networks. Generative adversarial networks (GAN) are mainly used (Elasri et al., 2022). A separate major area is the generation of images and related descriptions based on the results of medical diagnostic procedures such as MRI and PET (Singh & Raza, 2021). In these cases, the image acts as an external representation of the data processing results coming from the diagnostic equipment, masking the formalized representation of the semantics of the received data.

The task of formalizing video is relatively new. One of the solutions to this problem is based on the development of the idea of constructing a graph of image scenes – the construction of a graph of video scenes (Wang et al., 2024). Another approach used in (Mahon et al., 2020) involves the generation of knowledge graphs based on language annotations to videos. In the same article, the authors propose a model for generating knowledge graphs directly from video based on neural networks, trained on the dataset obtained in the first part of the work. Neural networks are also used for reverse conversion – generation of videos from knowledge graphs, sets of images or text descriptions. This topic attracts the attention of many researchers. Only in the preprint archive arxiv.org a search for the phrase "video generation" in the headlines of publications yields a list containing more than 380 articles. Some of the works on this topic are considered in the reviews (Liu & Yu, 2023; Aldausari et al., 2022).

The formalization of audio recordings of speech is usually performed in two stages. Based on the spectral characteristics of speech, it is quite difficult to immediately build a knowledge graph. In order not to form it directly from the spectral pattern of human speech sound waves, an intermediate stage of speech recognition is performed, for example, using voice assistants (Karim et al., 2022). After that, the problem is reduced to the task of formalizing texts in natural languages, which was considered earlier. Neural networks are widely used as speech-to-text translation tools: convolutional (CNN) (Kiranyaz et al., 2021), transformers (Dong et al., 2018) and, more recently, graph neural networks (GNN) (Kwon et al., 2022). About a dozen different methods have been developed for synthesizing speech from text (Tan et al., 2021). Currently, neural network–based methods are also the most promising: convolutional networks that do not have autoregression provide the highest speed of speech formation (Kaur & Singh, 2023), and networks with feedback – transformers (Kaur & Singh, 2023) and generative-adversarial (GAN) (Wali et al., 2022) are characterized by high acoustic speech quality, can generate speech with several voices and give it an emotional coloring.

To formalize musical works, their fragments and the sounds of musical instruments stored in musical databases (Goto et al., 2003; Hashida et al., 2017), as well as sound effects stored in special databases (Gygi & Shafiro, 2010), special formalization methods based on Markov processes (Xenakis, 1992), and algebraic methods (Andreatta, 2004; Papadopoulos, 2015) are used.

A separate major area of formalization of non-formalized knowledge is the formalization of multimodal representations combining two or more non-formalized streams of knowledge, such as those related to the main ones: text, image, video, audio, as well as various auxiliary ones: context, pose, intonation, facial expressions, smell, taste, touch. The knowledge graph obtained as a result of multimodal synchronous processing of several parallel streams of unformalized knowledge is not a simple combination and combination of knowledge graphs obtained by processing individual streams, additional knowledge may appear in it due to a deeper understanding of the subject area (Peng et al., 2023). In addition, knowledge from different streams fills in gaps and corrects errors in individual streams. It is shown that the connection of several modalities makes it possible to improve the formation and processing of knowledge graphs created on the basis of information selected from social networks (Wilcke et al., 2020). Interactive immersive generative multimodal interaction between a person and an agent in the form of a steady smooth exciting conversation accompanied by the display of images is considered as a prospect for the development of technologies of multimodal interaction with agents in (Park & Kim, 2023).

3.1.3. Storage and Processing of Partially Formalized Knowledge

The first group of partially formalized knowledge is data that has a structure, but there is no intensional that allows them to be used and interpreted. And there is also no understanding of the place of specific data in the metric of the relevant semantic space. Partially formalized knowledge can include:

- Data located in files organized using various access methods (sequential, direct, index-sequential, etc.);
- Data stored in files created without specifying access methods in various local, distributed and cloud file systems;
- Data in databases organized according to various data models (network, hierarchical, multivalue, multidimensional, relational, graph, object, vector, XML, key-value, wide column, documentary, tabular, time series, event, spatial, etc., as well as RDF used without describing semantics) (DB-Engines, 2023), including: data from various modules and subsystems of enterprise management, data from document management and content management systems, data from electronic trading platforms, test questions and training material from automated learning systems, data from library systems and scientific citation systems, data from research automation systems, etc.;
- Data from search engines indexes, both on the internet scale (Cambazoglu & Baeza-Yates, 2022) and corporate ones (Hilger & Wahl, 2022);
- Data from blockchain frameworks;
- CAD data on the products being designed;
- Neural network structures;
- Cartographic data in GIS;

- Tables and diagrams prepared in desktop and cloud applications, with the exception of diagrams describing certain sequences of actions (program flowcharts, business process diagrams, project plans, production flowcharts, etc.).

The second group of partially formalized knowledge is mathematical models that are not context–bound:

- linear and nonlinear equations and systems of such equations;
- differential equations and systems of such equations;
- partial differential equations and systems of such equations;
- probabilistic equations and systems of such equations;
- logical equations of propositional calculus and systems of such equations;
- tensor operators and equations;
- infinite-dimensional topological vector spaces and their mappings (Bowers & Kalton, 2014);
- algebras, groups, rings, fields, lattices, modules (Lee, 2018).

For both groups, the lists are clearly not exhaustive. However, they provide an understanding that allows you to assign similar cases, that are not included, in each group.

To turn data or abstract mathematical models into formalized knowledge, it is necessary to add connections that allow them to be used and interpreted, to correlate these objects with other ones.

The transformation between different forms of partially structured knowledge mostly makes sense for the first group considered. In fact, it comes down to the ability to upload files to databases and the ability to convert data from one model to another. Until the early 2000s, a limited number of data models was used in databases: network, hierarchical, multivalue, multidimensional, relational, graph, and object. Studies were conducted for the models, and the equivalence that the data could be transferred from one model to another without losses was justified (Borkin, 1979; Lien, 1982; Kalinichenko, 1990; Gangopadhyay, 1991). This may make the development or execution of programs more time-consuming, but the equivalence will be preserved. Since the early 2000s, with the advent of NoSQL databases, and then with the transition to working with big data, the number of data models used has multiplied (Mostajabi et al., 2021). Even to the point that variations of data models have appeared, which are supported by a single DBMS or a framework for working with big data. In such conditions, the study of the equivalence of models is conducted too slowly or not conducted at all. Despite this, there is still an intuitive confidence that it is possible to transfer data between different DBMS using different data models without losses.

3.1.4. Storage and Processing of Formalized Knowledge

The ways of presenting formalized knowledge are very diverse:

- Computer programs in traditional programming languages (programs that have source code, architecture, or algorithm descriptions available will have internal granularity).
- Computer programs in languages that implement logical programming based on a subset of first-order predicate logic or implement it along with other features (Prolog, Visual Prolog, Mercury, Oz, Strand, KL0, KL1, Datalog, etc.) (Körner et al., 2022).
- Diagrams describing some sequences of actions (program flowcharts, business process diagrams, project execution plans, production flowcharts, etc.) Prepared using specialized tools.
- Semantic networks (Sowa, 1992).
- Trained neural networks.
- Frames. During the first 15 years of their development, frame systems and languages were used for the structural representation of knowledge (Karp, 1992), but since the late 1980s, logical inference tools based on stored information have appeared in them (Weaver et al., 1989) and with subsequent development, the role of logic tools increases significantly (Hernandez, 2017).
- Knowledge graphs (Ehrlinger & Wöß, 2016).
- Descriptions using first-order predicate logic, including: in the languages of general logic (ISO, 2018), as well as in the languages CycL (Guha & Lenat, 1991), FO[·] (De Cat et al., 2018), KIF (KSL.Stanford, 1992; Genesereth & Fikes, 1992), etc.
- Descriptions using language families for the semantic web: RDF (W3C, 2014) and OWL (W3C, 2012) or simpler ones like SHOE (Heflin & Hendler, 2001).
- Description in ontology description languages and/or in systems such as LOOM (MacGregor & Burstein, 1991), Ontologua (Farquhar et al., 1997), DOGMA (Jarrar & Meersman, 2008), OntoUML (Guizzardi & Wagner, 2012), UFO (Guizzardi et al., 2022), etc.
- Production systems. In simplest cases, they can be implemented using traditional programming languages. For professional implementation, specialized development languages (Riley & Giarratano, 2005; Rattanasawad et al., 2013) or special systems for working with production rules (Varlamov, 2018) are used, they can be divided by type into clock and stream ones (Popov et al., 2022).
- Formal grammars (Gross & Lentin, 2012).
- Formal systems of concepts (Poelmans et al., 2013).
- Conceptual models of knowledge (Vykhovanets, 2021).
- Interconnected points in the Elements-Attributes-Relations space (Varlamov, 2002; Chuvikov & Nazarov, 2016).
- Complex networks (Boccaletti et al., 2006).
- Petri nets (Reisig, 2012).
- Finite state machines (Hadjicostis, 2020).
- Simulation models (Choi & Kang, 2013).

Traditionally, when listing ways to represent formalized knowledge, objects such as computer programs, neural networks, finite state machines, simulation models and complex networks are not considered. This is due, among other things, to the fact that in the absence of additional information, and sometimes even if it is available, it is impossible to explain the results obtained by accessing such objects. However, when creating a broad-purpose knowledge base for a projected AGI, the lack of detailed explanations of how the final result was obtained, as well as for a person, is not a reason to discard such objects. We can say that they contain "canned" knowledge, and when entering the initial data, they produce a result.

The above list of types of formalized knowledge is also not comprehensive, as is the composition of other groups, but it gives an intuitive understanding of what objects, not yet listed, could be included in this group.

The mutual transformations of formalized knowledge are more limited compared to other categories of knowledge. The most natural transformations are between different forms of declarative knowledge or between different forms of procedural knowledge. However, there are also certain approaches that allow converting declarative knowledge into procedural (Avdeenko et al., 2016) and vice versa – procedural knowledge into declarative (Fedorov & Shikov, 2020). In the absence of tools to perform the necessary transformations, the transformation of formalized knowledge into an unformalized textual representation in a natural language can be used, followed by the restoration of the required formalized model from it (Timchenko, 2013).

3.1.5. An Alternative Version of the Knowledge Base Organization, which was Abandoned

The proposed approach to the organization of the knowledge base using the archigraph is simply a way of structuring knowledge, without limiting the use of its various forms. Just as a human is able to operate various types of knowledge, so an AGI should be able to work with the whole variety of types of knowledge. We are not aware of other approaches that allow us to organize a knowledge base that supports all knowledge representations.

It was possible to avoid applying the concept of an archigraph with several dozen types of objects for different types of knowledge, but instead to focus on the model of a generalized logical metagraph, to which only functions could be added and a "Type" attribute could be introduced for each vertex, with which the type of knowledge contained in it could be determined. But for each type of knowledge, its own group of functions working with it will be used, which may overlap or not overlap with the functions of the other types of knowledge. In addition, technical edges or metaedges related to knowledge transformation would come into or out of each object. And for all these functions, edges and metaedges in this case, one would also need a special "Type" attribute. This would complicate the structure. Therefore, this option was abandoned.

3.2. A Preliminary Design of the Reference Cognitive Architecture Based on which AGI Prototypes Can Be Developed

When designing a cognitive architecture, it is necessary to identify the modules in its composition. Debates about the modularity of cognitive architecture of a human brain are described in (Robbins, 2013), which have been ongoing for at least the past three decades, since the publication of Fodor's book (Fodor, 1983). According to Fodor, modularity is essentially tied to informational encapsulation, and as such is only found in the relatively low-level cognitive systems responsible for perception and language. According to Fodor's critics in the evolutionary psychology camp, modularity simply reflects the fine-grained functional specialization dictated by natural selection, and it characterizes virtually all aspects of cognitive architecture, including high-level systems for judgment, decision making, and reasoning. Ultimately, the outcome of the discussion comes down to the hypothesis of 'minimal' modularity, according to which the architecture of the mind contains at least a relatively small number of modular systems at various levels.

In cognitive architectures of artificial intelligence, a modular structure is designed based on a statement of desired abilities (Jiménez et al., 2021). Frequently, a modular approach is coupled with decompositional analysis, which considers the analysis of the system in terms of its components. Each component performs some function, and complex interactions can take place between them, such as between learning and problem solving or between emotions and social interactions, but this is not a reason to combine everything into monolithic complex conglomerates. The purpose of the architecture is to isolate all components (functional modules) in such a way as to combine all functions working with common knowledge and minimize duplication of functions. The architecture of each of these modules, detailing the interactions between them, will require many independent articles.

Based on the set of functional modules presented in Table 2, a reference cognitive architecture is proposed, shown in Fig. 5, which

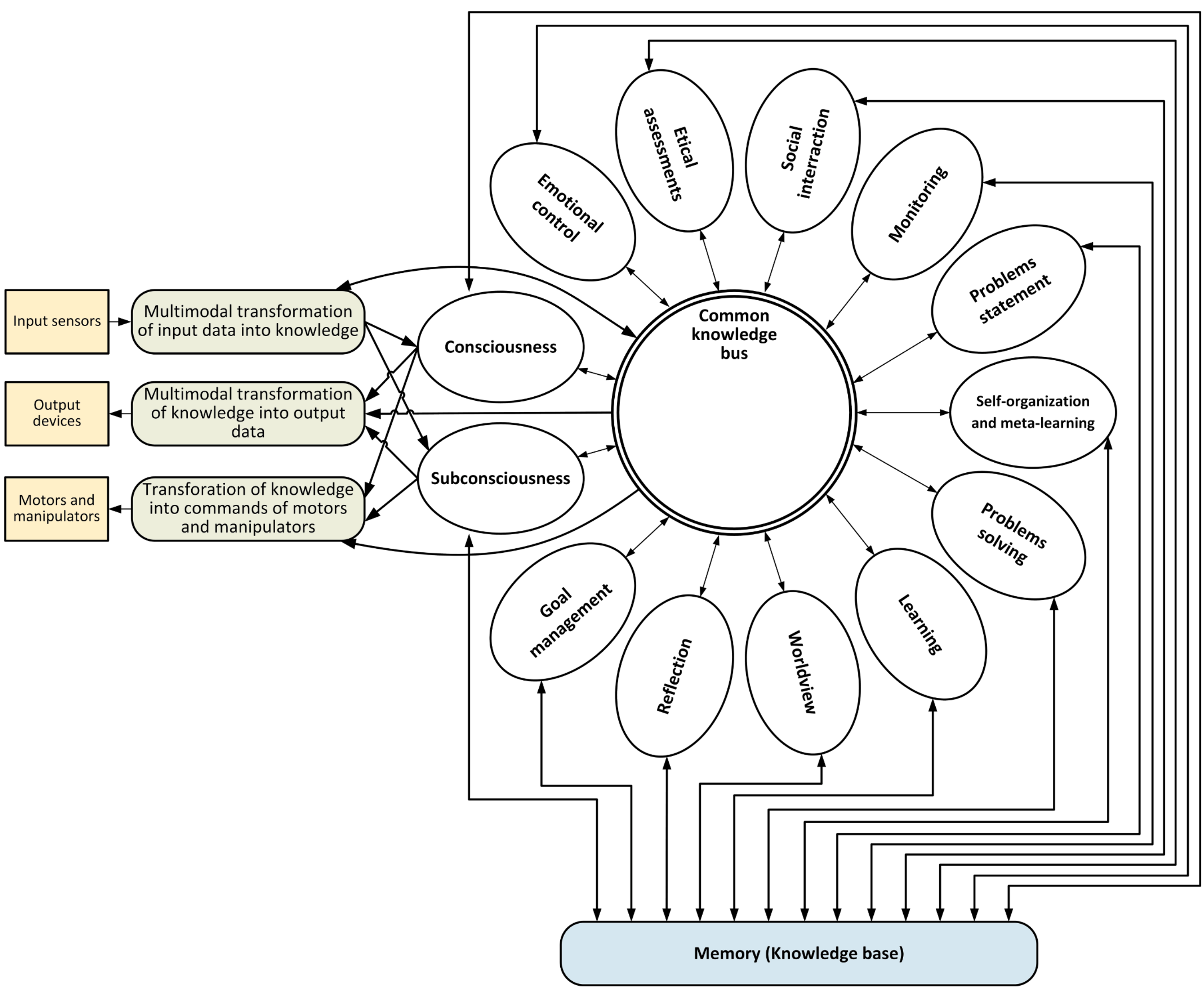

Fig. 5. A diagram of the reference cognitive architecture that can be used to develop AGI prototypes.

based on the suggested universal knowledge model and can be used to develop AGI prototypes.

All functional modules included in the reference cognitive architecture, except for modules interacting with the external environment, work with the knowledge base, which is the agent's memory. Each module interacting with the knowledge base has a separate section there, in which it stores the knowledge it needs, and can change them as it sees fit. If some knowledge is important for several modules, to eliminate duplication, they can be stored in a common section accessible to all of them. But then, to make changes to such knowledge, consent must be obtained from all modules that have access to them.

All functional modules of the reference cognitive architecture are integrated using a common knowledge bus. The knowledge sent to the common bus gets to all modules connected to the bus, then each module individually decides how to deal with them, save them in its knowledge base area and somehow use or ignore them. In addition, the shared bus can be used by modules to request knowledge from other modules. The response to the request also comes via a common bus. Knowledge on the common bus can be transmitted in all forms in which it can be stored in the knowledge base.

Using a shared knowledge bus is an alternative used in many cognitive architectures to the concept of working memory: SOAR (Laird, 2019), NARS (Wang, 2013), LIDA (Faghihi & Franklin, 2012), Sigma (Pynadath et al., 2014) and others. These options are comparable to the integration methods used in the architecture of software systems: integration over a common bus and integration over data. The advantages of using a common knowledge bus are that all modules are forced to process the incoming knowledge stream in parallel, except in situations where knowledge is sent to a specific module in response to its request. This is a mechanism that requires much more resources (both processor and memory), but this mechanism is based on active actions, it involves individual modules in knowledge processing and provides an up-to-date context for all of them. Unlike the general knowledge bus, when using working memory, in case of any situation, the module must look at what lies in the workspace. This is a passive mechanism. What if the necessary knowledge has already been removed from the workspace and replaced with something else?

The modules of consciousness and subconsciousness play a major role in interacting with interface modules that provide interaction with the external environment. The consciousness module is a control system that controls the movement of an agent in a complex space, which is a combination of ordinary three-dimensional space, time and any other spaces in which the agent operates (for example, media spaces, consumer goods spaces, scientific research spaces, etc.), with all the limitations inherent in these spaces (for example, you can only move from one floor to another by stairs or by elevator). The subconscious module allows you to implement ready-made routine sequences of actions stored in the knowledge base without connecting or with minimal connection of a relatively slow control system implemented by consciousness. Often the same sequences of actions performed by consciousness move over time into the subconscious.

Consciousness controls movement, focusing on the goals generated by the goal management module, and on the situation developing in the external environment. Knowledge about the situation in the external environment from the multimodal data and knowledge conversion module is transmitted not only to the modules of consciousness and subconsciousness, which are the main consumers this data, but also after being cleared of unnecessary details, it is transmitted to the common bus, from where all other modules receive them, including: monitoring module, goal management module, emotional management module. And the same in the opposite direction (but not symmetrically): the modules interacting with the external environment receive knowledge from the common bus, for example, emotions from the emotional management module, although the bulk of knowledge is transferred there from consciousness and subconsciousness.

The emotional control module is another control system besides consciousness, which does not act as precisely as consciousness can, but on all modules at once. The emotions generated are not some single objects with the meanings "sad", "joyful", "anxious", "ashamed", etc., but more complex knowledge structures where there are reasons, some previous history, perhaps: participants in the event and something else.

The ethical assessment module generates ethical assessments of all events and actions, including possible actions. These assessments can both encourage and deter these actions, and the level of support or deterrence may vary. If the actions and events have already taken place, then their ethical assessments are added to their characteristics. Just like emotions, ethical assessments are complex structures in which reasons may be present, justifying artifacts or chains of events, etc. Ethical assessments are formed on the basis of ethical principles stored in the knowledge base and amenable to modification either with human participation or as a result of repeated occurrence of sequences of events that reveal contradictions in these principles.

The reflection module is somewhat similar to the ethics module, it also generates assessments of actions and events, but only past ones, and not from the perspective of some ethical norms established by culture, religion or some authorities, but from the perspective of achieving the final result, side effects that arise, influencing one's own and others' plans, and etc. At the same time, very often, during the work of the reflection module, events that have occurred are modeled from the positions of other participants, their assumed (or confirmed by some facts) estimates of these events are formed, and own estimates are adjusted from these positions.

The social interaction module takes into account relationships with people and other agents, existing and possible roles in these interactions, emotions towards other agents, the course of processes and the results of previous interactions with them and, basing on all of this, adjusts action plans that are somehow related to other agents. In addition to plans, the module influences on actions and dialogues when interacting with people and other agents, forming additional knowledge for modules of interaction with the external environment.

The worldview module provides the formation and support of a special section in the knowledge base, which contains a picture of the agent's world and determines his place in it, the main goals of the agent's existence are formulated. This section is based on a scientific picture of the world, but to understand many aspects of history, art, and social relationships, other pictures of the world (mythological, several religious, and alternative scientific) are also stored in the section with explanations why they are not correct. The scientific picture of the world is modified as new scientific knowledge becomes available. Stored worldviews are used to gain new knowledge from different fields and compare them with those available in the database. In case of contradictions, various reactions are possible, both the re-clarification of the received knowledge and the assignment of assessments that they are false.

The monitoring module allows for various types of monitoring in a wide range of processes occurring in the external environment and in the modules of the agent's cognitive system. The occurrence of some events and changes in the values of the characteristics of some objects can be controlled, in the latter case both the achievement of some expected value and the finding of this value within some acceptable limits can be controlled. The initiation of monitoring processes is carried out by other modules of the cognitive architecture.

The learning module generates new knowledge in the knowledge base. This can happen both through the direct transfer of knowledge coming from the external environment with their subsequent comparison with existing knowledge and binding in the absence of contradictions, and through the formation of models based on the results of the agent's own actions. Both externally received and independently created models are tested and checked for compliance with the knowledge already available in the knowledge base. If there are inconsistencies, new knowledge can be discarded (if it strongly contradicts the worldview, ethical assessments, or already existing knowledge) or recorded in the knowledge base with the mark indicating the presence of contradictions. The formation of new knowledge can occur in all modules of the cognitive architecture working with the knowledge base, while access to the learning module is performed to replenish and/or adjust the knowledge base.

The problem formulating and problem solving modules carry out the formulation and solving of tasks. Requests to them are initiated from any module of the cognitive architecture, including the learning module for building new models and the problems formulating and solving modules themselves for setting and solving problems when a complex task is divided into subtasks.

With the help of the self-organization and meta-learning module, the agent should be able to rebuild and improve his activities, find and switch to using new more productive ways of learning. Decisions on the reorganization of activities or on the transition to new forms of activity, as well as decisions on the transition to new forms of education should be made based on the results of a purposeful search, modeling, and subsequent practical testing. For the first time, the need for such a functional component as part of the cognitive architecture for AGI was shown in (Samsonovich, 2009).

The presented description of the reference cognitive architecture in the light of (Osawa et al., 2019) can be considered as a top-level specification that can be used to further detail the cognitive architecture and develop an intelligent agent, however, we will not delve into this process due to its resource intensity. Our following descriptions of the individual modules will be related to an overview of the implementation of the corresponding mechanisms in other cognitive architectures.

3.3. Cognitive Architectures Containing Modules of Reference Cognitive Architecture

3.3.1. Consciousness Module

Of the 56 cognitive architectures considered by us, only 11 have an explicitly highlighted “Consciousness” component for building AGI. They are presented in Table 3. And also, MBCA (Schneider, 2020) has the Knowledge Layer in which conscious reasoning, planning, and act selection is performed.

There are much more cognitive architectures for simpler robots that have consciousness embedded in them, or architectures being developed as part of research projects on the realization of consciousness. Such cognitive architectures presented in Table 4. In these works, as a rule, a lot of attention is paid to the technical implementation of consciousness and its integration into the cognitive architecture, while its functionality is not worked out deeply enough, but only at a general level.

Table 3
Cognitive architectures containing consciousness module and intended to create AGI

#	Name of cognitive architecture	Link
1	LIDA (Learning Intelligent Distribution Agent)	Faghihi & Franklin (2012)
2	Haikonen cognitive architecture	Haikonen (2007)
3	The cognitive architecture with incremental levels of machine consciousness inspired by cognitive neuroscience	Raizer et al. (2012)
4	ICOM (Independent Core Observer Model)	Kelley & Twyman (2020)
5	GLAIR (Grounded Layered Architecture with Integrated Reasoning)	Shapiro & Bona (2010)
6	The cognitive architecture integrating computational creativity and dual process approaches	Augello et al. (2016)
7	Clarion (Connectionist Learning with Adaptive Rule Induction On-line)	Sun (2016)
8	OntoAgent (The cognitive agent architecture that supports content-centric modeling)	Nirenburg et al. (2011); English & Nirenburg (2020)
9	ISAAC (Intelligent information Software Agents to facilitate Artificial Consciousness)	Crowder et al. (2014)
10	The cognitive architecture for machine consciousness and artificial superintelligence	Reser (2022)
11	Aigo (Fully Integrated Cognitive Architecture using a Knowledge-Base Substrate)	Voss & Jovanovic (2023)

Table 4
Cognitive architectures containing consciousness module but not intended to create AGI

#	Name of cognitive architecture	Link
1	The cognitive architecture that combines internal simulation with a global workspace	Shanahan (2006)
2	The cognitive architecture for robot self-consciousness	Chella et al. (2008)
3	Baars-Franklin’s cognitive architecture	Becker et al. (2015)
4	MECA (The multipurpose enhanced cognitive architecture)	Gudwin et al. (2017)
5	The cognitive architecture of autonomous intelligent agent	Dyachenko et al. (2018)
6	The cognitive architecture for inner speech	Chella & Pipitone (2020)
7	The cognitive architecture based on an amygdala-thalamo-cortical model	Burrafato & Florio (2012)
8	The cognitive architecture for human-robot teaming interaction	Lanza (2021)
9	RoboErgoSum (The architecture of self-aware robot)	Chatila et al. (2018)
10	The artificial somatosensory system, embedded in a cognitive architecture	Augello et al. (2023)
11	COCOCA (The consciousness and common sense cognitive architecture)	Shylaja et al. (2013)
12	MLECOG (The motivated learning embodied cognitive architecture)	Starzyk & Graham (2017) Graham & Starzyk (2013)
13	The cognitive architecture for artificial consciousness	Chatterjee (2012)
14	The neural cognitive architecture	Huyck (2017)
15	CELTS (The cognitive tutoring agent with human-like learning capabilities and emotions)	Faghihi et al. (2013)
16	The cognitive architecture for the formal analysis of human behaviour [*sic*] and learning	Cerone (2018)
17	The cognitive architecture of an autonomous agent inspired by global workspace model	Garrido-Mercháin et al. (2022)
18	The cognitive architecture based hybrid intelligent information system approach	Chernenkiy et al. (2018b)
19	CERIL (Cause–Effect Reasoning in Imitation Learning)	Reggia et al. (2018)
20	The computational architecture based on *In Situ* representations	Van der Velde (2018)
21	The basic architecture of an autonomous adaptive system with conscious-like function for a humanoid robot	Kinouchi & Mackin (2018)
22	SEAI (Social Emotional Artificial Intelligence based on Damasio’s theory of mind)	Cominelli et al. (2018)
23	The architecture using a simulation-based internal model	Winfield (2018)

The key features of the modern understanding of machine consciousness were formulated in (Wiedermann and Leeuwen, 2019). Consciousness is considered as a control system for the agent’s current actions. To have minimal consciousness, it is necessary that the agent has the following capabilities:

- self-knowledge: Agent has complete knowledge of its current cognitive state as well as of the data produced by all its interfaces, sensor, and motor units.
- self-monitoring: Agent is completely informed about the performance and status of its sensory and motor units over time (including the quality of the sensations and the reports from all of them) and of its embedding in the environment as it is.
- self-awareness (or self-reflection): Agent behaves in a way that unambiguously reflects, respectively is determined by its current cognitive state and the information gained by its self-knowledge and self-monitoring abilities, and that is ‘aware’ of the internal and external changes that it causes.
- self-informing: Agent globally broadcasts its cognitive state, to all modules of the system and whenever changes of state occur.

Table 5
Cognitive architectures containing subconsciousness module and intended to create AGI

#	Name of cognitive architecture	Link
1	ACT-R (Adaptive Control of Thought, Rational)	Anderson et al. (2004) Lebiere et al. (2013)
2	LIDA (Learning Intelligent Distribution Agent)	Faghihi & Franklin (2012)
3	CogPrime (An Integrative Architecture for Embodied Artificial General Intelligence)	Goertzel et al. (2014a) Goertzel et al. (2014b)
4	ICOM (Independent Core Observer Model)	Kelley & Twyman (2020)
5	GLAIR (Grounded Layered Architecture with Integrated Reasoning)	Shapiro & Bona (2010)
6	MicroPSI. The MicroPsi agent architecture describes the interaction of emotion, motivation and cognition of situated agents based on the Psi theory of Dietrich Dorner.	Bach (2009)
7	The cognitive architecture integrating computational creativity and dual process approach inspired by dual process theories of reasoning and rationality.	Augello et al. (2016)
8	Clarion (Connectionist Learning with Adaptive Rule Induction On-line)	Sun (2016)
9	OntoAgent – the agent architecture that supports content-centric modeling.	Nirenburg et al. (2011) English & Nirenburg (2020)
10	ISAAC (Intelligent information Software Agents to facilitate Artificial Consciousness)	Crowder et al. (2014)

Table 6
Cognitive architectures containing subconsciousness module but not intended to create AGI

#	Name of cognitive architecture	Consciousness	Link
1	COCOCA (The Consciousness and Common sense Cognitive Architecture)	Yes	Shylaja et al. (2013)
2	MLECOG (The Motivated Learning Embodied Cognitive Architecture)	Yes	Graham & Starzyk (2013); Starzyk & Graham (2017)
3	The cognitive architecture for artificial consciousness	Yes	Chatterjee (2012)
4	The neural cognitive architecture	Yes	Huyck (2017)
5	CELTS (The cognitive tutoring agent with human-like learning capabilities and emotions)	Yes	Faghihi et al. (2013)
6	The cognitive architecture for the formal analysis of human behaviour [*sic*] and learning	Yes	Cerone (2018)
7	The cognitive architecture of an autonomous agent inspired by global workspace model	Yes	Garrido-Mercháin et al. (2022)
8	The cognitive architecture based hybrid intelligent information system approach	Yes	Chernenkiy et al. (2018b)
9	IFORs The framework for modeling emotions in an interactive, decision-making agent	No	Henninger et al. (2003)
10	The behavior-based cognitive architecture to enrich the e-learning with the pedagogical measures	No	Ekanayake et al. (2006)
11	The cognitive architecture for handling mental models	No	van Ments & Treur (2022)
12	The cognitive architecture for direction of attention founded on subliminal memory searches, pseudorandom and nonstop	No	Burger (2008)
13	DIARC (Distributed Integrated Affect Reflection and Cognition) architecture	No	Scheutz et al. (2019)
14	NCCA (Natural Constructive Cognitive Architecture)	No	Chernavskaya (2023)
15	The multi-agent neurocognitive architecture	No	Nagoev et al. (2020)

It can be expected that the further development of this theory from a minimal to a more advanced consciousness will make it possible to realize consciousness as a system of parallel control processes taking place in multidimensional, partially intersecting virtual spaces in which spatial and temporal constraints are set. If the actions that need to be performed based on the results of parallel management processes in the real space in which the agent operates contradict each other, they are checked for consistency in time distribution, ranked and queued. In the process of functioning, the consciousness module intensively interacts with all other AGI modules, receiving plans for further actions, applying for statements and solutions to problems of modeling possible situations, considering ethical assessments, checking with the worldview, etc.

3.3.2. Subconscious Module

The machine subconscious contains ready-made models and algorithms that can be quickly activated when corresponding situations arise. Unlike human memory, the volume of the machine subconscious can be quite large, and stored models can cover a wide range of fields of knowledge and activities. Among the architectures designed to create AGI, the ones have the subconscious presented in Table 5.

Some cognitive architectures, which do not have the immediate goal of creating AGI, are claimed to have both consciousness and subconsciousness. At the same time, there are cognitive architectures of this class, which have only subconsciousness without consciousness. This distinction is demonstrated in Table 6, where architectures containing subconsciousness but not intended to create AGI are presented.

The existence of the subconscious in the cognitive architecture is evidenced not only by the explicit indication of its presence. As was rightly noted in (Serov, 2022), all reactive cognitive architectures such as Soar (Laird, 2019), ICARUS (Langley & Choi, 2006), SW-CASPAR (Longo et al., 2021b) or individual reactive levels in complex combined architectures, such as the reactive layer in CogAff (Sloman & Chrisley, 2005), contain a certain set of behaviors for different situations and, in fact, act as a subconscious.

The perception of subconsciousness, that has developed among some researchers, as some kind of auxiliary system that helps consciousness (which is not entirely true) leads to the fact that the specific functionality of the subconscious in cognitive architectures is often left behind the scenes or distorted. So, in (Augello et al., 2016) and (Huyck, 2017) they take as a basis Kahneman's idea (Kahneman, 2011) about the dual nature of thinking processes and distinguish a fast subconscious mind that processes large amounts of incoming information and a slow consciousness that processes significantly less information. This is true, but with this approach, the functionality of the subconscious mind for the accumulation, storage and use of ready-made algorithms and models remains undisclosed.

Along with the fact that the functionality of the subconscious mind is not revealed, it can also be distorted. So, the article (Rauterberg, 2010) begins with the correct statements that the subconscious can handle tasks in the high dimensional problem-solving space while the consciousness can operate only in the low dimensional space. But then the author considers a way to transfer information from the subconscious mind to consciousness using emotions. The same idea is expressed in (Henninger et al., 2004). In our opinion, this is wrong, emotions are not signals of the subconscious mind. The emotional management system is a separate functional component of the cognitive architecture. In the architecture shown in the figure above, the subconscious mind can directly interact with the modules of interaction with the external environment. Consciousness, receiving information about these interactions, can suppress or correct them.

Similarly, attaching the functions of interaction with the external environment to the subconscious mind (Chernenkiy et al., 2018a), in our opinion, is also a distortion of its functionality; for this purpose, separate modules should be allocated in the cognitive architecture. The restriction on the methods of realization of the subconscious mind caused by this distortion (the use of neural networks and fuzzy logic) immediately

Table 7
Cognitive architectures containing worldview module and intended to create AGI

#	Name of cognitive architecture	Link
1	NARS (Non-Axiomatic Reasoning System)	Wang (2013); Wang et al. (2018)
2	Sigma – the cognitive architecture using different methods of multiagent reinforcement learning to make effective decisions on social interaction despite uncertainty about the potential behavior of others around them.	Pynadath et al. (2014)
3	MBCA (Meaningful-Based Cognitive Architecture) integrates the subsymbolic sensory processing abilities found in neural networks with many of the symbolic logical abilities found in human cognition.	Schneider (2020)
4	GLAIR (Grounded Layered Architecture with Integrated Reasoning) is a multilayered cognitive architecture for embodied agents operating in real, virtual, or simulated environments containing other agents.	Shapiro & Bona (2010)
5	H-CogAff, a special case of CogAff, is a minimal architecture specification for a human-like system. CogAff – architecture schema combines reactive, deliberative, and meta-management categories.	Sloman & Chrisley (2005)
6	EM-ONE is a cognitive architecture whose purpose is to support commonsense thinking required to produce the scenarios of activity. For selection of actions, mental critics apply which are procedures that recognize problems in the current situation.	Singh (2005)
7	CAMAL – Computational Architectures for Motivation, Affect and Learning allows to model the joint behavior of agents with different motivations, beliefs, drives, desires, goals, and intentions.	Davis (2002); Davis (2003); Davis (2008)
8	SMCA (Society of Mind Cognitive Architecture) Many different types of simple agents, with different behaviors work together to achieve a common goal.	Venkatamuni (2008)
9	Clarion (Connectionist Learning with Adaptive Rule Induction On-line)	Sun (2016)
10	OSCAR – cognitive architecture in which agents of human-level intelligence operating in an environment of real-world complexity must be able to form beliefs and make decisions against a background of pervasive ignorance.	Pollock (2008)
11	CernoCAMAL– the probabilistic extension of cognitive architecture CAMAL.	Miri (2012)

becomes invalid after the distortion is eliminated. This is confirmed by a few examples of the inclusion of the subconscious mind in the symbolist cognitive architectures presented in this section, based on the use of production rules.

3.3.3. Worldview Module

Worldview is important for advanced intelligent systems and for AGI in particular, because they will encounter large amounts of information on the Internet and interact with people who may have different worldviews that contradict each other. Moreover, different worldviews can form bizarre and sophisticated combinations in the mind of one person (Caruana, 2022).

Of the 56 cognitive architectures we have considered for building AGI, those that are presented in Table 7 possess a worldview module.

Cognitive architectures containing worldview module, which was developed for research and industry purposes, presented in Table 8. These architectures did not intend to create AGI.

The architectures listed in Tables 7 and 8 provide for the presence and use of many elements of worldviews. All these elements are either intuitive (laid down initially when creating an agent), or formed as a result of training, and they are all related to some operational aspects of the activity. Conflicting worldviews such as scientific, religious, and mythological are not considered.

Table 8
Cognitive architectures containing worldview module but not intended to create AGI

#	Name of cognitive architecture	Link
1	CogAff – the architecture schema combines reactive, deliberative, and meta-management categories.	Sloman & Chrisley (2005)
2	MECA (the Multipurpose Enhanced Cognitive Architecture) uses Dynamic Subsumption Motivational System, rule-based processing, and space-state exploration.	Gudwin et al. (2017)
3	ICARUS – the cognitive architecture influenced by results from cognitive psychology.	Langley & Choi (2006)
4	SW-CASPAR – the reactive-cognitive architecture based on Natural Language Processing for the task of decision-making in the open-world assumption.	Longo et al., (2021b)
5	CRIBB – the model Children's Reasoning about Intentions, Beliefs, and Behavior that simulates children's reasoning in solving false-belief-tasks.	Wahl & Spada (2000)
6	A-CRIBB – an extension to CRIBB to include an Affect and Affordance Model	Lewis (2004); Davis & Lewis (2004)
7	The Cognitive Architecture of Belief Reasoning in Children and Adults	Low et al. (2016)
8	SACA – the cognitive architecture to analyze the effect of intrinsic motivation with metacognition over extrinsic motivation on swarm agents	Kodipalli (2018)
9	The reflective-cognitive agent architecture which enables the agent to alter its own code in runtime according to the changes in the environment.	Foltyn et al. (2006)
10	CoJACK – the high-level architecture that provides insights on behavior variability, situation awareness, and behavioral moderators.	Ritter et al. (2012)
11	Thrive – the hybrid cognitive architecture designed to integrate recent discoveries regarding the underlying mechanism of trust into a computational model.	Patacchiola & Cangelosi (2020)
12	The cognitive architecture of an agent for human-agent dialogues	Baskar & Lindgren (2014)
13	MAMID – the symbolic cognitive architecture that unites both stable personality characteristics (traits) and transient emotions (states) influencing on cognition and behavior	Hudlicka (2002)
14	CogToM – the cognitive architecture designed to process the output of computer systems and to reason according to the Theory of Mind.	Grassiotto & Costa (2021)
15	Scruff – the cognitive architecture capable of implementing predictive processing models by incorporating key properties of neural networks into the Bayesian probabilistic programming framework.	Pfeffer & Lynn (2019)
16	CASPAR – architecture for building cognitive agents leveraging Natural Language Processing. Such agents will be able of deduction on facts and rules in First Order Logic inferred directly from Natural Language.	Longo et al., (2021a)
17	The cognitive architecture of conversational agents based on the principles of cognitive pragmatics	Gnaneswari & Vijayakumar (2017)
18	InnovA – the cognitive architecture for creative problem solving in analog circuit design that uses multiple knowledge representations organized using topological similarity and causality information.	Li et al., (2017a)

In (Heylighen, 2011), a method for the coordinated use of several contradictory worldviews is proposed, but it is quite primitive and not suitable for AGI: the agent acts as a character in a game journey full of challenges and mysteries that underlie myths. In (Bendaña and Mandelbaum, 2021) and (Egan, 2021), a fragmented worldview is considered. The fundamental basis for dealing with worldviews is the theory of Belief revision (Peppas, 2008; Olsson & Enqvist, 2011; Ribeiro, 2012).

For effective coordinated use of different worldviews in AGI, it is necessary, depending on the context, to ensure dynamic switching between different independent worldview models and to have knowledge (on a deeper layer of worldview common to all models) about the relevance of each model and the conditions of its application. At the same time, it is advisable to have one worldview as a basic reference (Vidal, 2014), and use the rest to understand the historical and cultural traditions of people, at the same time blocking the AGI from using another worldview as the main one.

When analyzing and designing the worldview module, it is also necessary to understand that the worldview is not only declarative knowledge that allows us to answer basic existential questions and explain the origin of the universe and man. It is also some procedural knowledge that regulates behavior in many situations related to religious rituals, protection of loved ones, death, self-sacrifice, etc.

3.3.4. Reflection Module

The reflection module builds models of this agent, reflecting its various aspects: activities, plans, knowledge, appearance, etc. At the same time, these models can be built in parallel and from different perspectives:

- From the point of view of some theoretical concepts: cost, safety, environmental protection, technical condition, etc.;
- From the point of view of some real or abstract individuals and/or organizations. In the process of building a reflexive model, an agent model is used, from which position this reflexive model is built. In this case, not one, but a small sequence of reflexive models can be built from the position of a particular agent and several of its models. In particular, the second reflexive model is built on the assumption that the external agent knows that the main agent understands what the external agent thinks about him. This is considered in the second external agent model. According to the same principle of multiple reflection, third and subsequent reflexive models and models of an external agent can be constructed.

In both variants, emotional assessments of concepts and subjects can be considered, from the point of view of which reflexive models are built.

The created reflexive models can be partial models of a given agent (reflect only one or several of its sides) and differ from the model of a given agent available in consciousness. They are used for self-assessment and adjustment of modelled aspects.

Cognitive architectures designed to create AGIs that have reflection functionality are presented in Table 9.

In addition, reflection functionality is used in the cognitive architecture of strong human-machine intelligence (Krinkin & Shichkina, 2023), as well as in cognitive architectures designed for simpler robots and research in the field of cognitive architectures presented in Table 10.

Table 9
Cognitive architectures containing reflection functionality and intended to create AGI

#	Name of cognitive architecture	Link
1	Soar is a general cognitive architecture that integrates knowledge-intensive reasoning, reactive execution, hierarchical reasoning, planning, and learning from experience.	Laird (2019)
2	Sigma – the cognitive architecture using different methods of multiagent reinforcement learning to make effective decisions on social interaction despite uncertainty about the potential behavior of others around them.	Pynadath et al. (2014)
3	eBICA (emotional Biologically Inspired Cognitive Architecture). In this architecture emotional elements are added virtually to all cognitive representations and processes.	Azarnov et al. (2018); Samsonovich (2020)
4	H-CogAff, a special case of CogAff, is a minimal architecture specification for a human-like system. CogAff – architecture schema combines reactive, deliberative, and meta-management categories.	Sloman & Chrisley (2005)
5	EM-ONE is a cognitive architecture whose purpose is to support commonsense thinking required to produce the scenarios of activity. For selection of actions, mental critics apply which are procedures that recognize problems in the current situation.	Singh (2005)
6	CAMAL – Computational Architectures for Motivation, Affect and Learning allows to model the joint behavior of agents with different motivations, beliefs, drives, desires, goals, and intentions.	Davis (2002); Davis (2003); Davis (2008)
7	SMCA (Society of Mind Cognitive Architecture) Many different types of simple agents, with different behaviors work together to achieve a common goal.	Venkatamuni (2008)
8	MicroPSI. The MicroPsi agent architecture describes the interaction of emotion, motivation and cognition of situated agents based on the Psi theory of Dietrich Dorner.	Bach (2009)
9	The cognitive architecture integrating computational creativity and dual process approach inspired by dual process theories of reasoning and rationality.	Augello et al. (2016)
10	Polyscheme – the cognitive architecture for integrating multiple representation and inference schemes.	Cassimatis (2001)
11	The three-level cognitive architecture for the simulation of human behavior based on cognitive/neurological dual-system theories.	Larue et al., (2012a); Larue et al., (2012b)
12	Clarion (Connectionist Learning with Adaptive Rule Induction On-line)	Sun (2016)
13	CernoCAMAL– the probabilistic extension of cognitive architecture CAMAL.	Miri (2012)

3.3.5. Other modules

The article considers in detail only 5 functional modules of the proposed cognitive architecture out of 17 including Knowledge base. Of course, it is necessary to describe them all.

There are many developments of cognitive architectures and high-quality publications on modules not presented in detail in this paper.

Table 10
Cognitive architectures containing reflection functionality but not intended to create AGI

#	Name of cognitive architecture	Link
1	CogAff – the architecture schema combines reactive, deliberative, and meta-management categories.	Sloman & Chrisley (2005)
2	DIARC (Distributed Integrated Affect Reflection and Cognition) architecture	Scheutz et al. (2019)
3	CRIBB – the model Children's Reasoning about Intentions, Beliefs, and Behavior that simulates children's reasoning in solving false-belief-tasks.	Wahl & Spada (2000)
4	A-CRIBB – an extension to CRIBB to include an Affect and Affordance Model	Lewis (2004); Davis & Lewis (2004)
5	SACA – the cognitive architecture to analyze the effect of intrinsic motivation with metacognition over extrinsic motivation on swarm agents	Kodipalli (2018)
6	The reflective-cognitive agent architecture which enables the agent to alter its own code in runtime according to the changes in the environment.	Foltyn et al. (2006)
7	MAMID – the symbolic cognitive architecture that unites both stable personality characteristics (traits) and transient emotions (states) influencing on cognition and behavior	Hudlicka (2002)
8	The three-level cognitive architecture for handling mental models, ensuring that they (1) be used for internal simulation, (2) can be adapted, and (3) can be controlled.	van Ments & Treur (2021)
9	The cognitive architecture for the simulation of intelligent virtual characters, for which the combinations of three behavioral models are proposed – reflexive, reactive and reflective.	Liew et al. (2009)
10	The multi-level cognitive architecture to model mental processes in clients of psychotherapeutic sessions involving self-referencing, self-awareness, and self-interpretation.	Treur & Glas (2021)

Here are some examples, although one might as well consider publications on other modules:

- components and solutions using emotions are presented in publications of Samsonovich (2020), Assunção et al. (2022), Zall & Kangavari (2022), Sica & Sætra (2024), Yan et al. (2021), Vallverdú et al. (2016), and others;
- components and solutions using ethics are presented in publications of Wallach et al. (2020), Yilmaz & Sivaraj (2019), Cervantes et al. (2020), Waser & Kelley (2016), Atreides et al. (2021), Bickley & Torgler (2023), Gidey et al. (2023), and others;
- components and solutions using goal management are presented in publications of Cox et al. (2017), Dannenhauer et al. (2019), Kondrakunta et al. (2019), Gogineni (2021), Cardona-Rivera et al. (2022), Kondrakunta (2021) and others.

However, this enumeration provides only brief incomplete lists without a detailed analysis of all cognitive architectures for creating AGI. To form a complete picture, reviews of each of the functional blocks presented in the architecture are necessary, at least to a minimum extent, as presented in this paper. However, the article is already quite large, and adding architecture reviews containing 12 functional modules will increase it significantly in size.

Depending on the circumstances, the authors plan to prepare next article in the future with a description of the remaining functional modules.

4. Discussion

4.1. Could this article have been written as a meta-analysis paper?

The short answer to the question in the title is yes, in theory; no, in practice.

It is very difficult to estimate how many cognitive architectures have been proposed in the world in varying degrees of elaboration; it is definitely at least several hundred. After discussion, we arrived at an intuitive empirical assessment of approximately 500 cognitive architectures, with a possible upward bias. This is much higher than the estimate in (Kotseruba & Tsotsos, 2024) because we do not impose such strict selection restrictions. Several dozen more architectures are added every year. In the most famous review (Kotseruba & Tsotsos, 2020), there was an attempt to collect all known architectures, but in a later fundamental work (Kotseruba & Tsotsos, 2024), the authors moved on to describing general concepts and did not build a list of architectures, obviously realizing the hopelessness of trying to collect and analyze them all by a team of two people.

The method we used while looking for cognitive architectures designed to create AGI is ill suited to the approach adopted in meta-analysis papers – to take the entire list of architectures and select from it those that are designed to create AGI. There is no such list.

However, this does not mean that it cannot be formed. To compile a list of articles that explicitly contain the term “cognitive architecture”, one needs a crawler similar to those used in global search engines like Google, but highly specialized, providing the creation of an index that contains only publications on cognitive architectures. If such a crawler is made intelligent so that it can discard repetitive cognitive architectures, then it will form the required list. If it is not intelligent, then manual processing of publications will be required.

However, it should be noted that authors often disguise cognitive architecture under the terms “framework”, “computational model”, “artificial intelligence model” etc. In addition, authors from related scientific fields, describing cognitive architectures, do not always use this term, but often write about methods of knowledge processing, recognition or decision-making. To detect such implicit cognitive architectures, the crawler will have to search for a wider range of keywords, and the processing of the found materials can only be partially automated and will require significant efforts.

At the same time, the practicability of forming a common list of cognitive architectures is questionable and the necessity of solving such a problem should be justified by reasonable arguments.

For a similar reason, it is not yet possible to take a list of cognitive architectures designed to create AGI and specify which modules are present in which of them. So far, the search has been conducted for only four functional modules, and the architectures in which they are present are listed in the relevant sections of this article. The presented list of 56 architectures is most likely incomplete. We are confident that the search for cognitive architectures containing other functional modules will simultaneously expand the list of cognitive architectures that were intended to create AGI to 70 or more.

4.2. Implementation of the proposed reference cognitive architecture

Also in this section, we want to exclude possible assumptions that we are implementing or plan to implement the proposed reference architecture. None of the co-authors deal with this problem in general (building an AGI prototype). Everyone’s research interests lie within one of the modules of the presented cognitive architecture or in the field of intelligent data lakes. This allows us to imagine how complex the implementation of each of the modules can be.

Writing this article was brought about by a feeling of dissatisfaction due to the presence of many private works and the lack of a common architecture for building AGI. We tried to imagine what this architecture might be like. We are not trying to implement the proposed architecture, but rather we are looking for a way to build a consistent, comprehensive conceptual picture without going into much detail about how individual functional blocks will be implemented.

We are not trying to make plans for the implementation of the proposed architecture also because we realistically assess our possibilities. The time when a group of enthusiasts could do something in their garage has passed. LLM implementations, which represent 3 architecture modules, are handled by large startups with multibillion-dollar investments. In our opinion, the rest of the architecture modules will require similarly large developments and huge investments.

The theoretical nature of the work does not allow us to make any assumptions about the timing of the implementation of the proposed architecture and the timing of the development of AGI prototypes.

The main result that we expect is a faster development of AGI. We expect review articles on ways to implement each of these individual modules will appear, and the advantages and disadvantages of used solutions to be analyzed after we have outlined the functionality of individual modules and collected lists of cognitive architectures that have got some functional module implemented. A stricter definition of intermodule interaction protocols could be a distinct result. All these results would entail the emergence of new prototypes that could improve the integration of components, increase the intellectual capabilities of individual modules and AGI as a whole.

5. Conclusions

The article proposes a model of knowledge representation that allows the upcoming AGI to work with different representations of knowledge and freely move from one to another. This model is used in the proposed reference cognitive architecture of AGI, which identifies functional blocks for all types of cognitive activity that the authors considered inherent in humans.

We hope that the proposed reference cognitive architecture and knowledge representation model will solve the problem formulated in the first part of the introduction, as well as allow us to answer some of the challenges that faced the theory of cognitive architectures according to (Lieto et al., 2018; Lieto, 2021), in particular:

- The need for robust integration of mechanisms involving planning, acting, monitoring and goal reasoning.
- The limited size and the homogeneous typology of knowledge that is encoded and processed by systems based on cognitive architectures.

In the first prototypes being developed, not all types of knowledge and not all functional blocks of the reference cognitive architecture may be supported. At the same time, the prototyping process and future theoretical research may reveal the need to expand the composition of blocks of reference cognitive architecture, to include blocks not provided for in this article.

6. Organizational Snippets

Author Contributions

Artem Sukhobokov: Conceptualization, Writing - Original Draft, Supervision. **Evgeny Belousov**: Resources, Writing - Original Draft. **Danila Gromozdov**: Writing - Original Draft, Validation. **Anna Zenger**: Writing - Original Draft, Writing - Review & Editing. **Ilya Popov**: Methodology, Writing - Original Draft.

7. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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CRediT authorship contribution statement

Artem Sukhobokov: Writing – original draft, Supervision, Conceptualization. **Evgeny Belousov:** Writing – original draft, Resources. **Danila Gromozdov:** Writing – original draft, Validation. **Anna Zenger:** Writing – review & editing, Writing – original draft. **Ilya Popov:** Writing – original draft, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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