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Design And Evaluation Of The System Performance Of Sica-Based Optimized Social Intelligent Agents

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Abstract:
Agent-based simulations have been increasingly popular in the last few years for studying social systems in a variety of fields, including economics and sociology. These simulations must incorporate complicated agents to match the behavior of the simulated individuals because they are meant to replicate real-life scenarios involving humans. Concepts like cognition, emotions, personality, social relationships, or norms must therefore be considered; however, at this time, no agent architecture exists that could combine all of these characteristics and be utilized by the vast majority of modelers, including those with limited programming expertise. The social intelligent agent architecture is presented in this study to address this problem. The Belief-Desire-Intention model of cognition serves as the foundation for this modular architecture, which includes modules to enhance agent behavior with emotions, personality, social relationships, and emotional contagion. The primary benefit of the suggested device is its potential for use in military applications.
Keywords: *SICA, Social Simulation, Social Agent, and Communication*

1. INTRODUCTION

Particularly in the social sciences, agent-based simulations have emerged as a potent tool for researching scenarios involving human players in recent years. The community is already discussing social simulations in this same setting, which involve social agents mimicking human behavior (Gilbert & Troitzsch 2005). These social agents must make difficult choices while taking social and psychological concepts into consideration in order to replicate human behavior in a circumstance under study. Adding social characteristics to agents' behavior is necessary to create credible agents [1]
According to the EROS principle, simulating a real-life scenario involving humans yields more credible outcomes when psychological theories are incorporated into the specification of agent behavior. To confront these challenges of realism, numerous architectures, each encompassing distinct parts of human activity, have been proposed: from reflexive agents, researchers progressed to cognitive agents, emotional agents, agents with a personality, and normative systems. Nonetheless, the social simulation community still hardly uses these structures.Indeed, the researchers in this community come across a wide variety of agent architectures, some of which are domain-specific or don't work with well-known simulation platforms. Moreover, understanding the distinctions between these structures—which take into account a range of social traits—is difficult. Finally, many existing behavior designs need a rather high level of programming expertise. According to this research, the SICA architecture is designed to solve these issues. It can be utilized by modelers to create agents that imitate human actors with social traits including emotions, relationships, and thought processes. Actually, adding social elements not only makes agents act more realistically, but it also offers a comprehensive understanding of how they

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behave[2].

Examples of architectures that rely on psychological and neurological research include SOAR (Laird et al. 1987), Clarion (Sun et al. 2001), and ACT/R (Byrne & Anderson 1998). They make a distinction between the agent's mind and body, with the body serving as a conduit between the mind—the reasoning engine—and the surroundings. The many components of this reasoning engine allow an agent to function in the short term while taking its long-term goals into consideration. However, to the best of our knowledge, these structures have never been used in scenarios with hundreds of social agents in the real world. A different viewpoint on cognition is provided by the BDI (Belief Desire Intention) paradig[3].

The categories of beliefs, desires, and intentions are defined, together with the logical connections needed to select a course of action that will address the agent's intents, using modal logic as a formalization (Cohen & Levesque 1990). This paradigm has been adapted into the PRS (Procedural Reasoning System) (Myers 1997), which uses a set of rules to manipulate high-level concepts and decides an agent's course of action based on its perceptions and present state. Since then, this procedure has been used in agent architectures including JADEX (Pokahr et al. 2005) and JACK (Howden et al. 2001). BDI architectures are those that are built on the BDI paradigm[4].

Reflectively considering problems in their physical, social, and psychological dimensions is possible using the EM-ONE architecture for common sense computing. The EM-ONE architecture incorporates intricate relationships between the physical, social, and psychological dimensions as well as between many "actors." Here, we use the artificial environment Roboverse as an example of an AI architecture in a built world.There are multiple actors inhabiting this virtual universe, which has stiff body physics. The cognitive architecture of EM-ONE directs these actors. Together, these performers use straightforward, modular materials like sticks and boards to construct tables and chairs. The components resemble little toys and can be connected to each other by their ends and corners[5].

As simulated robots, the actors have a perceptual system that allows them to move. They have a single arm and resemble humans in general. It is possible to turn the hands on and off. By drawing in the closer items, these hands will function similarly to magnets. Green (left) wants to construct a table and observes any partially constructed tables so that additional legs can be added to finish the table. Green moves closest to the table after grabbing a stick. Green attempts to use its lone arm to construct a table.

The cognitive architecture is composed of six layers, including the reflective, reacting, and deliberative layers. The following three levels, which are made up of three distinct types of self-reflective layers, are framed by these layers. The mental critics who deal with problems in the external environment are found in these layers. The reactive layer's self-reflective layer offers solutions based on goals and external observations. The deliberative layer helps with scenario analysis and makes predictions about possible outcomes, while the reactive layer recommends actions. While monitoring the reasoning process at the deliberative layer, the reflecting layer employs the reflective critic to evaluate the effectiveness of deliberation.[6]

The highest levels are composed of critics who make it possible for actions to be carried out by adhering to certain standards and guaranteeing conformity with their predetermined model. The management of these critics is supervised by meta managerial critics, who select a subset that aligns with the problem and the recommended fix. Reflective, deliberative, and reactive processes can be programmed using EM-One. Its database, which is structured as a library of mental critics that employ this specific knowledge to solve problems, contains Commonsense knowledge. To solve problems, both stored information and common knowledge are used. As previously mentioned, each layer of EM-One contains a variety of mental critics[7].

Reactive critics take the initiative to actively engage with their environment by pointing out the discrepancy between the intended goal and the existing situation. On the other hand, the Deliberative Critics mirror the external conditions and the actions suggested by the Reactive Critics. Since they are based on specific beliefs, they are used to evaluate if the recommended actions will result in the intended outcome or whether these concepts are consistent with common sense. Reflective critics examine recent actions that demonstrate how the mind works in the interim. They identify problems with past activities, such blunders, and have the power to hold the critics accountable for them in order to stop them from happening again. The deliberative layer, which is derived from the Reflective Critics, includes critics who are self-ideal, self-conscious, and self-reflective[8].

Much research in the "theory of mind" field has focused on how one becomes proficient at reasoning about mental states. Children Reasoning about Intentions, Beliefs, and Behavior (CRIBB architecture) is a cognitive model that mimics the knowledge and reasoning processes of a capable child while tackling theory of mind problems. CRIBB's repositioning results in a conclusion. Once the belief's consistency has been evaluated, it is added to the current set of beliefs. The belief is then included if there are no inconsistencies. The consistency mechanism finds and corrects inconsistencies in the system's belief system. Any beliefs deemed to be false become secondary representations, Beliefs may originate from perceptions and preconceived notions. The CRIBB receives a suggestion and renders a decision. It looks at how well the belief fits into the existing belief system[9].

Depending on a specific set of true or false beliefs, the dynamic values in the A-CRIBB model can be increased or decreased. The affective reaction is linked to the system's drives. The A-CRIBB model is based on the goal-oriented theories of emotion. This covers goal-oriented, goal-based, and goal-achievement systems. The A-CRIBB subsystem uses feedback as a tool to accomplish the objective. The A-CRIBB model includes the central monitoring system. This is responsible for overseeing the semantic messages and promoting inter-subsystem communication. The concept of the mind as a control system is demonstrated by the Society of Mind Cognitive Architecture (SMCA) using the metaphor of a "Society of Agents." This notion describes the collective behavior of basic but extremely intelligent agents. The "Society of Mind" agents are deliberate and goal-oriented. Developing a self- configurable computational model that considers metacognition is the initial step. There are six levels to this architecture. The SMCA control model is built on a society of agents that use metrics consistent with artificial economic notions, as shown in animal cognition[10].

Metacognition is examined by the SMCA as a potent instrument for self-regulation, integration, and reflection. All BDI models will use metacognition to improve performance, with an emphasis on learning, problem-solving, self-reflection, orchestration, reasoning, decision-making, and the entire cognitive process. One strategy to include metacognition into the SMCA model is to distinguish between metacognitive tools, meta components, and metacognitive processes. Metacognitive processes include remedial exercises such as meta comprehension, self-management techniques such as meta management, and schema training, which teaches cognitive systems holistically. Meta-components are tools for conceptual expression. To create an efficient, wise, and perfect agent, metacognition necessitates a multi-layered control model that encompasses a range of agent actions and behaviors, from basic to complex. Six levels are used in the design and implementation of this paradigm: metacognition, Q-learning, reflexive, reactive, and deliberative for BDI[11].

In the 1970s, Marvin Minsky first introduced the Society of Mind idea at MIT's AI lab. He worked with Seymour Papert and his students to develop one of the earliest autonomous hand-eye robots. This robot builds constructions out of the building blocks by manipulating them with a robotic hand and using cameras to provide visual input. This article was the first time Minsky used the phrase "Society of Mind." He suggested using a television camera and a mechanical hand to put together block structures. The cognitive processes involved, including movement, grasping, and perception, have been the subject of years of research. The concept of the "Society of Mind" was made conceivable by this evolution, according to Minsky[12]

According to him, intelligence is a complicated social interaction between a variety of specialized cognitive processes rather than just a simple algorithm for cognition. According to him, each mind operates as a "Society of Mind."Each agent has a unique history and performs a specific task. Each actor in the society of mind, which is the result of particular cognitive processes, is represented by a basic code. Numerous generic and metacognitive agent types serve as the foundation for the generic framework employed by the Society of Mind approach to Cognitive Architecture (SMCA). Integrating these things is the primary objective in order to replicate cognitive abilities and function[13].

2. PROPOSED WORK

We are creating a self-configurable computational model by utilizing ideas from social intelligence and cognition. The agents work together to accomplish the job under this architecture. We are putting forward the SICA architecture by employing SMCA as the foundation design. The suggested SICA architecture is shown in Figure 2. The simulation is used to thoroughly examine social intelligence ideas in relation to performance, motivation, and coordination.

It also examines the differences in performance through appropriate incentive and cooperation.

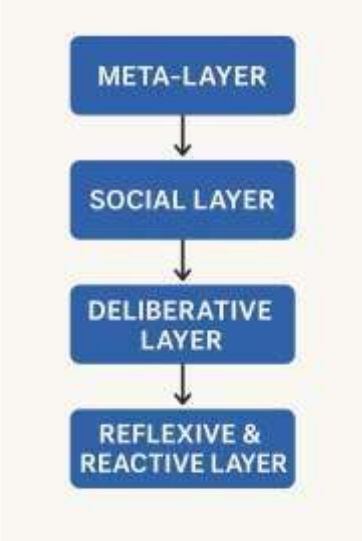

Figure 1: Proposed SICA

- **Meta-layer**: This layer discusses the concept of metacognition, or thinking about thinking. Within this cognitive layer, the agent has learned to focus solely on goal gathering. However, if the agent ignores an objective because they think it is incorrect, performance may be moderated. Using this core job, we began by clearly defining the agents' objectives. When an agent approaches and attempts to gather an objective, the reactive layer signals that an energy adjustment is required. If the purpose does not meet the agent's expectations, it begs the question of whether they should pursue it. The agent consequently hesitates when making choices[14-15]. Examples of such hesitancy are recognized, and these particular goals are assigned a lesser priority. Instead of speaking directly to one another, actors in a networked environment exchange information via a global array. To enable centralized agent monitoring[16], we established a networked area on the deployment field. This approach eliminates the need for human oversight by utilizing advanced monitoring systems. In these unique circumstances, agents can use the global array to transmit messages that include parameters such as "location, action, and action result." The network increases overall efficiency by preventing later agents from nearing the targeted objective by alerting all agents in the vicinity of this information. This system effectively manages unusual circumstances and keeps an eye on agent activities. Metacognitive agents, for example, can choose, customize, update, and reason about any meta control task within the specified testbed. Understanding natural brains and applying their concepts to the simulation of artificial minds is the aim. This idea includes abstract frameworks designed to improve cognitive and mental processes. From small to massive computational entities, a variety of agents must be built in order to develop and implement a physical architecture that complies with the principles of both artificial and human cognition. Through planned solutions and general cognitive processes intended to improve performance, visual assessments are employed to evaluate these agents' ability to coordinate toward their goals [17-19].
- **Social Layer**: W Agents set their own paths and function as a team within the deliberative and learning levels. In this stratum, agents move as a single, cohesive entity to reach their target and then the treasure. By demonstrating a variety of control mechanisms and strategies, this behavior exemplifies

the idea of "Social Intelligence." Social interactions within a group can be used to analyze the behavior of agents while accounting for the environment. In this scenario, the engagement will occur indirectly.

- **Agent's Mechanism**

According to our concept, an agent's interaction with the environment is defined by its ability [20] to sense the surroundings and take action. But instead of going through the traditional perceive, think, and act cycle, we argue that socio-cognitive agents should be required to do a few more steps. A five-stage process—perceive, interpret, update, execute, and act—is how we propose to define the agent's mechanism. The various ideas found in the agent's architecture are manipulated by each of these stages. Beginning with the agent's perception of its surroundings and ending with its action on the world, Algorithm 1 outlines the fundamental stages of its process.The algorithm is given below and working environment is shown in figure 2. In order to collect new data, this cycle starts with environmental sensing. It then analyzes these impressions in light of current crucial aspects to determine what matters. In response to the circumstances, the system makes resource decisions and modifies its priorities (CSF). After taking into account the resources and context that have been updated, it plans actions and then carries them out, changing the environment and getting ready for the next cycle[21].

Algorithm1 CYCLE(environment)

Step 1: Sense the environment
Step 2: Interpret what was perceived, given current critical
Step 3: Update critical success factors and decide on resources to use
Step 4: Decide on actions based on context and available resources5: Actions = Step
5: Execute the planned actions

End Function

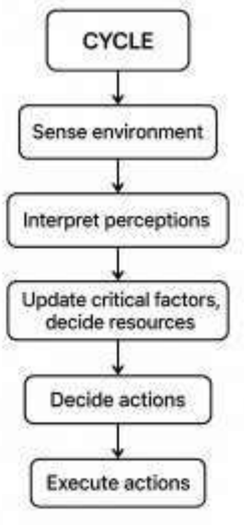

Fig 2: Agent Mechanism

- **Agent's Interpretation**.

In this stage Current perceptions and crucial success factors (CSFsalient)[22] are inputs to this function.
An empty social context is where it begins. It calculates how each crucial factor construes (or interprets) the senses. Together, these interpretations form the broader social framework.
The function then returns this updated social context, which shows how the environment is interpreted in relation to the priorities of the system and the steps are listed in algorithm 2

Algorithm 2: Interpreteation

Step 1: Make the social context a blank set at first.
Step 2: For each of the salient key success factors (csfs) on the list
:• Determine how the perceptions are interpreted (construed) by this CSF

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.• Include the social context with this interpretation.

Step 3: Return the aggregated social context once all csfs have been processed.

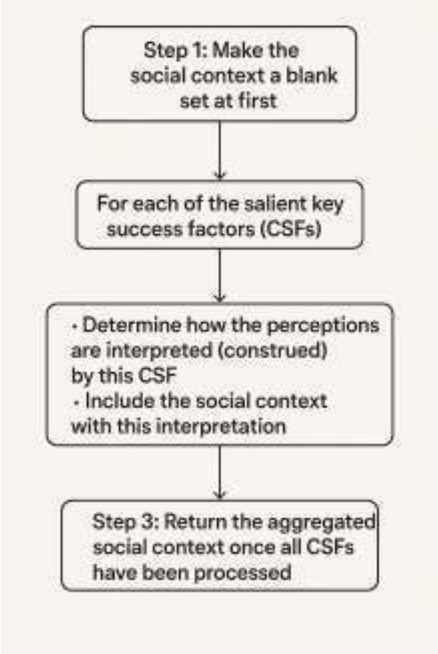

Fig 3: Agent Interpretation

- **Update** The agent has a formal representation that explains its viewpoint on the external world after creating the social environment. As a result, it's possible that the earlier prominent cognitive social frames are no longer relevant. The cognitive social frames in the long-term memory that meet the fitness criteria are chosen by this process. However, the agents' individual preferences also influence salience.
- **Execute**: No fundamental components of the architecture that are directly related to the cognitive social frameworks model are altered by the agent during this phase. Rather, the new social context that is stored in working memory is accessed by the updated collection of cognitive resources that have been deployed. The agent's units of cognition that focus on particular problem-solving, decision-making, reasoning, and other skills are known as cognitive resources, as was previously explained. They may include methods or knowledge. The only processes that will be executed are those that are executable. However, the other sort of cognitive resources can also manipulate the knowledge-holding cognitive resources without executing any procedures.
- **Deliberative Layer**: The deliberative layer includes elements related to or meant for contemplation or debate. The information learned from earlier stages and the agent's energy level or functionality are both represented by the internal state in this case. Here, the agent's avoidance behavior is further refined. An agent with a limited ability to maintain goals can only go up to a specific level, referred to as the initial threshold. After reaching this level, the agent continues to move and begins searching for objectives, a tactic it acquired in the reactive layer. A higher goal retention capacity allows an agent to get closer to a second threshold, where it looks for more goals to improve its decision-making. The agent has learned to refrain from pursuing objectives that would reduce its energy metrics based on its internal state, which is influenced by information from lower layers. When a social agent[22] (one with limited ability) is involved, its behavior is restricted and must stop at the specified threshold. The smaller agent will gather the closest goal, be it ore or gold, if any are discovered. The agent will stop moving at the threshold if no goals are specified.
- **Reflexive & Reactive**: An action carried out without conscious thought in response to a stimulus is called a reflex. The agent is instructed to take a predetermined route that has been programmed into it in order to reach its goal. Following this path, the agent responds to outside stimuli in line with reflexive behavior. When impediments are encountered, the agent demonstrates reactive behavior by rerouting or moving around to avoid them. Regardless of the type of obstacle, the agent must overcome it

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to reach its goal. In this single-agent situation, the reflexive response is the first action observed whenever the agent comes across an obstacle. There are several factors to consider because there is only one agent and it needs to go to its target. Obstacles are represented by the color cyan, and once they are identified, the agent must avoid them. The agent must also be able to identify several obstacles and, if any, steer clear of them all in order to effectively reach its goal. The agent should proceed directly to its goal if there are no obstacles. Our version of the code illustrates a scenario in which a single agent moves forward toward a destination while moving in a straight line through an environment with two barriers. The agent will eventually learn to avoid obstacles, reach all of its objectives, and take note of any positional changes that affect its overall behavior. There are real-world applications for this concept; for instance, a robot deployed to a field could need to dodge obstacles to reach a preset goal. This is the initial learning phase, and the acquired knowledge permeates all operational layers. In the Reactive Layer, the term "reaction" refers to an agent's response to stimuli. In this case, the agent's actions are consistent with specific objectives. This environment is characterized by a single agent that responds differently to its aim. The outcomes of its operations are documented once it reaches a predefined goal. We use an energy analogy, which is merely a parameter to be considered and is ultimately linked to performance measurements, to indicate the accomplishment of a result. It is expected that the agent will traverse the test bed, avoiding obstacles and heading in the direction of the destination, using the information gathered from previous experiences. Upon encountering a goal, the agent will evaluate the collected objectives. Through categorizing all of its replies, the agent will be able to comprehend the nature of the goal and the repercussions of its actions once it has been achieved. Consequently, the agent will get the ability to identify goals according to their purpose. The internal state of an agent is shown here, along with the knowledge the agent has acquired in this layer. Intelligent behavior integration is further developed by the subsequent layers.

3. RESULT

Individual agent behavior in a group environment and the impact of these behaviors on the performance of the entire group are evaluated by the SICA architecture. To examine agent behavior, a number of measures can be used, including competition, life expectancy, and social interactions in connection to environmental factors. The simulation results, displayed in graphs 1, 2, and 3, highlight the complex interactions between various agent kinds, with particular attention to how they behave in terms of energy usage and decision-making time.

To determine which agents are the most successful and to comprehend the traits that make them such, it is essential to evaluate them. By helping to create a high-performing group, this analysis improves the performance of the entire group. It is clear from comparing the three types of agents that deliberative agents, or Social agents 3, are highly motivated, reactive agents, or Social agents 1, are less enthusiastic, and reflexive agents, or Social agents 2, are either very enthusiastic or not at all.

The results show that deliberative agents—social agents—have the capacity to evaluate their current situation, reason about their goals, and accomplish them, exhibiting the capacity for intelligent behavior and decision-making. When energy levels fall below a particular threshold, for example, the experiment's decision-making process shifts to food consumption; when energy levels are adequate, the main objective of diamond collection is resumed.

This conduct is a reflection of both intelligence and psychology. Compared to cognitive agents, deliberative agents—Social agent3—are better at controlling their energy levels, which leads to a greater number of goals accomplished. Reactive and reflexive agents, on the other hand—social agent 2—find it difficult to control their energy and frequently exhaust it before finishing the allotted number of cycles. Thus, in goal collection, deliberative agents—social agent 3—performed better than cognitive agents.

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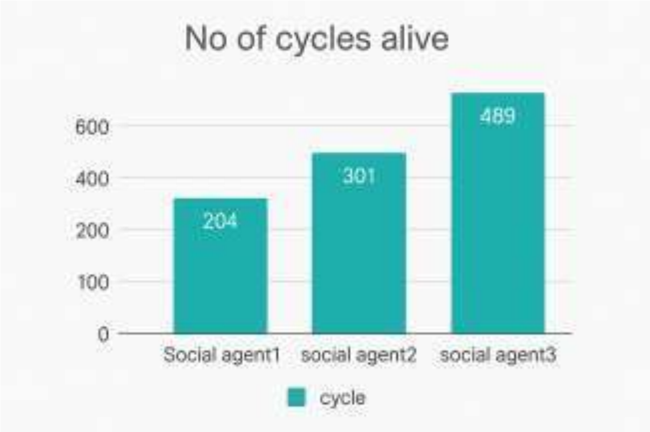
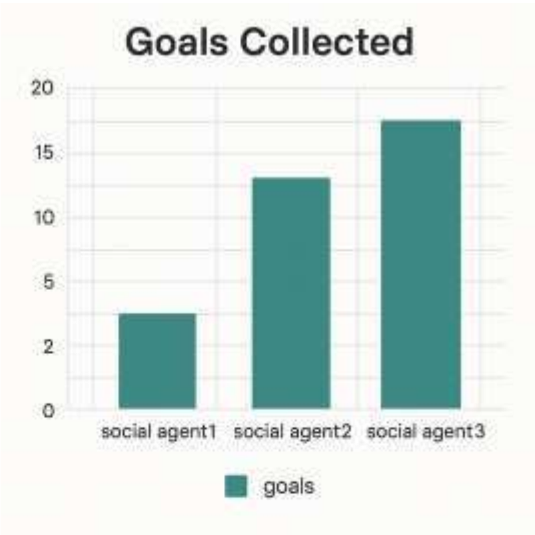


Graph 1: No of cycles lived

The number of cycles that each social agent survived is shown in the graph 1. The lifespans of social agents 1 and 3 were 204, 301, and 489 cycles, respectively. According to the statistics, agent 3 had the longest lifespan, which suggests that it was more resilient or efficient in its surroundings.



Graph 2: No of goals collected

Three social agents' goal totals are displayed in the graph 2 The fact that social agent 1 gathered two goals, agent 2 collected fifteen, and agent 3 collected eighteen indicates that agent 3 was the most successful at collecting goals. Their performances are clearly compared visually by the teal bars.

4. CONCLUSION:

A collective of agents works together on common duties in the suggested SICA architecture. According to research, when a clear aim is set, group performance is greatly improved, which raises performance levels overall. Additionally, because it encourages agents to reach the goals, the group goal-setting process improves individual performance. The increased sense of accountability people have while cooperating is thought to be the reason social agents in SICA are so effective. As a result, highly motivated agents that are in line with a well-defined objective perform at their best. The SICA model demonstrates that improving performance requires more than just communication between agents; rather, elements like the task's nature (specific goals), each agent's motivation, and the group's makeup (the kinds of people participating) are important. High-motivated agents have been found to perform better than those with low motivation. In SICA, a low-level communication system is set up between the agents. The suggested approach makes it easier for agents to collaborate and work toward shared goals. Research shows that when agents are guided by clear objectives, collective performance peaks,

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which in turn increases individual contributions. Better performance results are obtained when there is a clear objective and agents are categorized according to their level of motivation. It is often known that when there are specific goals, individual performance thrives. When a group has a shared goal, motivation is further increased, leading to improved performance overall. The SICA design offers a distinct method when compared to other cognitive architectures that are currently in use, such as EM-ONE, CRIBB, and SMCA.

REFERENCES

[1] Chandana, S., Nagarathna, C. R., Amrutha, A., & Jayasri, A. (2024, January). Detection Of Image Forgery Using Error Level Analysis. In *2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)* (pp. 1-5). IEEE.

[2]. Cognitive Architectures: Research Issues and Challenges Pat Langley Computational Learning Laboratory Center for the Study of Language and Information Stanford University, Stanford, CA 94305 John E. Laird EECS Department the University of Michigan 1101 Beal Avenue, Ann Arbor, MI 48109 Seth Rogers Computational Learning Laboratory Center for the Study of Language and Information Stanford University, Stanford, CA 94305.

[3]. Madsen, J.K.; Bailey, R.; Carrella, E.; Koralus, P. Analytic versus computational cognitive models: Agent-based modelling as a tool in cognitive sciences. Curr. Dir. Psychol. Sci. **2019**, 28, 299–305. [CrossRef]

[4]. ACT-R: A cognitive architecture Terese Liadal liadal@stud.ntnu.no Seminar AI Tools Universität des Saarlandes, Winter semester 06/07 Dozenten: A. Ndiaye, M. Kipp, D. Heckmann, M. Feld

[5] Ye, P.; Wang, T.; Wang, F.Y. A survey of cognitive architectures in the past 20 years. IEEE Trans. Cybern. **2018**, 48, 3280–3290.

[6]. Wang, F.Y.; Ye, P.; Li, J. Social intelligence: The way we interact, the way we go. IEEE Trans. Comput. Soc. Syst. **2019**, 6, 1139–1146.

[7]. Himaja, G., Kundan, K. M., & Nagarathna, C. R. (2024). Car parking slot detection using Hough line transform and CNN model. In *Computer Science Engineering* (pp. 703-711). CRC Press.

[8]. Preetham, A., Vyas, S., Kumar, M., & Kumar, S. N. P. (2024). Optimized convolutional neural network for land cover classification via improved lion algorithm. *Transactions in GIS*, *28*(4), 769-789.

[9]. S. Chandana, C. R. Nagarathna, A. Amrutha and A. Jayasri, "Detection Of Image Forgery Using Error Level Analysis," *2024 International Conference on Intelligent and Innovative Technologies in Computing, Electrical and Electronics (IITCEE)*, Bangalore, India, 2024, pp. 1-5, doi: 10.1109/IITCEE59897.2024.10467523.

[10]. An Introduction to Soar as an Agent Architecture Robert E Wray Soar Technology 3600 Green Road Suite 600 Ann Arbor MI 48105 wrayre@acm.org Randolph M Jones Colby College & Soar Technology 5857 Mayflower Hill Waterville, ME 04901-8858.

[11]. Nagarathna, C. R., & Kusuma, M. (2021, November). Comparative study of detection and classification of Alzheimer's disease using Hybrid model and CNN. In *2021 International Conference on Disruptive Technologies for Multi-Disciplinary Research and Applications (CENTCON)* (Vol. 1, pp. 43-46). IEEE.

[12]. Debnath, S., Preetham, A., Vuppu, S., & Kumar, S. N. P. (2023). Optimal weighted GAN and U-Net based segmentation for phenotypic trait estimation of crops using Taylor Coot algorithm. *Applied Soft Computing*, *144*, 110396.

[13]. Bhavyashree, H. L., Nagarathna, C. R., Preetham, A., & Priyanka, R. (2019, March). Modified cluster based certificate blocking of misbehaving node in MANETS. In *2019 1st international conference on advanced technologies in intelligent control, environment, computing & communication engineering (ICATIECE)* (pp. 155-161). IEEE.

[14]. Castelfranchi, C. Guarantees for autonomy in cognitive agent architecture. In International Workshop on Agent Theories, Architectures, and Languages; Springer: Berlin/Heidelberg, Germany, 1994; pp. 56–70.

[15]. Dignum, F.; Prada, R.; Hofstede, G.J. From autistic to social agents. In Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems. International Foundation for Autonomous Agents and Multiagent Systems, Paris, France, 5–9 May 2014; pp. 1161–1164.

[16]. Rangegowda, N. C., Mohanchandra, K., Preetham, A., Almas, M., & Huliyappa, H. (2023). A Multi-Layer Perceptron Network-Based Model for Classifying Stages of Alzheimer's Disease Using Clinical Data. *Revue d'Intelligence Artificielle*, *37*(3), 601.

[17]. Adam, C., Taillandier, P., Dugdale, J. & Gaudou, B. (2017). BDI vs FSM agents in social simulations for raising awareness in disasters: A case study in Melbourne bushfires. International Journal of Information Systems for Crisis Response and Management, 9(1), 27–44.

[18]. Nagamalla, V., Kumar, B. M., Janu, N., Preetham, A., Parambil Gangadharan, S. M., Alqahtani, M. A., & Ratna, R. (2022). Detection of adulteration in food using recurrent neural network with internet of things. *Journal of Food Quality*, *2022*(1), 6163649.

[19]. Preetham, A., & Battu, V. V. (2023). Soil Moisture Retrieval Using Sail Squirrel Search Optimization-based Deep Convolutional Neural Network with Sentinel-1 Images. *International Journal of Image and Graphics*, *23*(05), 2350048.

[20]. Wang, F.Y.; Ye, P.; Li, J. Social intelligence: The way we interact, the way we go. IEEE Trans. Comput. Soc. Syst. **2019**, 6, 1139–1146. [CrossRef].

[21]. Kotseruba, I.; Tsotsos, J.K. 40 years of cognitive architectures: Core cognitive abilities and practical applications. Artif. Intell. Rev.2020, 53, 17–94. [CrossRef].