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Neuromorphic Computing for AGI: A Systematic Review Beyond GPU Limitations

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This paper presents a Systematic Literature Review (SLR) analyzing the role of neuromorphic computing in advancing Artificial General Intelligence (AGI) beyond the limitations of GPU-based systems. Following the PICOC framework and PRISMA 2020 guidelines, 71 records were retrieved from Scopus (2024–2025), of which 36 full-text articles were selected after rigorous application of inclusion and exclusion criteria. The review is structured around four research questions examining chip architecture evolution, hardware comparisons with conventional accelerators, AGI-oriented applications, and reported performance outcomes. Key findings include energy improvements of 13×–49× in segmentation tasks, 50× device-level energy reduction via spin-neuron scaling, competitive accuracies of 92–97% for SNN/ANN/MPNN models, and strong adaptive behavior in reinforcement-learning-based cognitive control. The paper concludes that neuromorphic computing represents a promising and biologically plausible pathway toward sustainable AGI, while acknowledging speed-accuracy trade-offs, hardware variability, and tooling fragmentation as current limitations.

Keywords— SpiNNaker, Neuromorphic Computing, Artificial General Intelligence (AGI), Spiking Neural Networks (SNN), Energy Efficiency, Scalability, PRISMA.

I. INTRODUCTION

Artificial Intelligence (AI) has advanced rapidly over the past decade, mainly supported by Graphics Processing Units (GPUs) that enabled the expansion of deep-learning models and large-scale data processing [1], [2]. Despite their success, GPUs face major constraints in energy efficiency, parallel scalability, and biological plausibility, limiting their capacity to reproduce the cognitive flexibility required for Artificial General Intelligence (AGI) [3]– [5].

To address these challenges, neuromorphic computing proposes a paradigm shift inspired by the structure and operation of the human brain. These systems merge computation and memory into a single substrate and employ Spiking Neural Networks (SNNs) to emulate synaptic communication [6]– [8]. Neuromorphic processors execute asynchronous, event-driven operations that drastically reduce power consumption and latency while improving adaptability [9].

Among the most relevant platforms, SpiNNaker (Spiking Neural Network Architecture), developed at the University of Manchester, integrates more than one million ARM cores to simulate large-scale neural dynamics in real time [10], [11]. SpiNNaker has been applied in studies of cognitive modeling, robotics, and adaptive signal processing, positioning it as a key reference for energy-efficient and biologically inspired computation [12].

Recent works also examine complementary neuromorphic hardware such as Intel Loihi 2, memristive crossbar arrays, and spintronic synapses which pursue similar objectives through different materials and circuit paradigms [13], [14]. Although these architectures vary in implementation, they share the same underlying goal: enabling brain-like learning and generalization beyond the constraints of GPUs [15].

Given the growing research interest, it becomes essential to systematically analyze the latest evidence to determine how SpiNNaker and related neuromorphic systems contribute to AGI progress.

For the purposes of this review, AGI is understood as a system capable of performing any intellectual task that a human can perform, including generalization across domains, transfer learning, lifelong or continual learning, and meta-learning. This operational definition is used as a conceptual framework to evaluate whether neuromorphic computing features can plausibly support these capabilities. Specifically, event-driven sparse communication and synaptic plasticity mechanisms in neuromorphic systems are analyzed in relation to their potential to enable transfer learning and adaptive behavior under distribution shift two hallmarks of AGI-level generalization.

II. METHODOLOGY

A. PICOC

The PICOC methodology was applied to structure the information search in an efficient and systematic manner. The first step consisted of formulating a clear research question aligned with the scope of this review. This method identifies five key elements: the Population, the Intervention, the Comparison, the Outcome, and the Context, which allow the selection of relevant and high-quality scientific evidence [8].

Accordingly, the main research question formulated through this approach was:

MQ: What applications for the development of Artificial General Intelligence (AGI) can be implemented using neuromorphic computing chips such as SpiNNaker, compared to current GPUs?

The research question was then broken down into the following sub-questions corresponding to the PICOC components:

RQ1: How have neuromorphic computing chips such as SpiNNaker been defined in terms of architecture and design principles?

RQ2: With which conventional hardware architectures (GPUs, TPUs, CPUs) have they been compared?

RQ3: What AGI-oriented applications have been implemented using neuromorphic platforms?

RQ4: What advantages and limitations have been reported in terms of energy efficiency and scalability compared to GPUs?

The following table presents the five main components of the PICOC framework:

TABLE I.: PICOC TERMS

Element	Definition / Search Terms
P (Population)	Neuromorphic chips and architectures such as SpiNNaker, Loihi 2, or memristive and spintronic systems.
I (Intervention)	Implementation of neuromorphic computing for AGI-related applications (“neuromorphic computing”, “spiking neural network*”, “neuromorphic hardware”).
C (Comparison)	Traditional computational accelerators such as GPUs, CPUs, or TPUs (“graphics processing unit”, “GPU”).
O (Outcome)	Reported improvements in energy efficiency, scalability, and learning adaptability (“energy efficiency”, “scalability”, “plasticity”).
C (Context)	Research published between 2024 and 2025 in Computer Science, Engineering, or Neuroscience domains.

Consequently, the search equation used in the Scopus database was as follows:

TITLE-ABS-KEY(("neuromorphic computing" OR "neuromorphic hardware" OR "spiking neural network*" OR "SNN") AND ("artificial general intelligence" OR "AGI" OR "brain-inspired computing" OR "cognitive computing") AND ("energy efficiency" OR "scalability" OR "plasticity" OR "GPU" OR "graphics processing unit")) AND PUBYEAR > 2024

This query retrieved a total of 71 records covering the years 2024 to 2025.

B. PRISMA

The PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) method was employed to conduct a structured and transparent process for identifying and selecting studies. The PRISMA Statement, first introduced in 2009 and updated in 2020, guides researchers in systematically reporting the rationale, methods, and findings of their literature reviews [9].

The inclusion and exclusion criteria applied in this review were as follows:

TABLE II.: INCLUSION AND EXCLUSION CRITERIA

Inclusion	Exclusion
Peer-reviewed journal articles, conference papers, and specialized reviews were included.	Editorials, short abstracts, technical notes without peer review, or preprints were excluded.
Studies published in 2024 and 2025 were considered.	Publications prior to 2024 were excluded.
Articles indexed under Computer Science, Engineering, or Neuroscience were included.	Documents unrelated to neuromorphic computing or AGI were discarded.
Full-text accessibility was required (open access or institutional access).	Papers without full-text access were excluded.
No language restriction was applied.	Duplicates and redundant reviews exceeding 15% of the total corpus were removed.

In the identification phase, 71 documents were retrieved from Scopus.

After applying initial screening, 39 articles were selected based on title and abstract relevance.

During the eligibility phase, three redundant review papers were excluded to comply with the ≤10% proportion rule, resulting in 36 final studies for the systematic review.

These 36 publications comprise 29 journal articles, 3 conference papers, 3 reviews, and 1 book, all addressing aspects of neuromorphic hardware, spiking neural networks, and AGI applications.

Storage of Results: The results of the systematic search and selection process were stored and managed using Mendeley, enabling efficient organization of the 36 final references for analysis, citation, and further development of the research work.

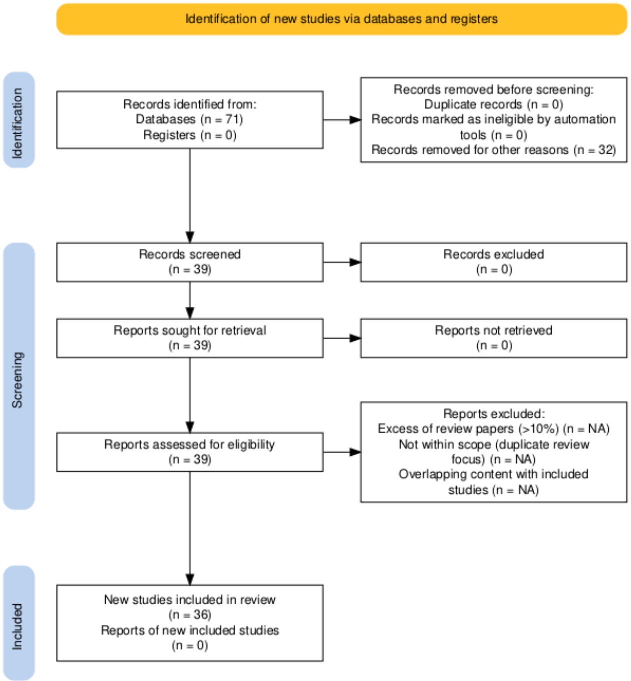

Fig 1. PRISMA 2020 Flow Diagram (2024-2025)

C. BIBLIOMETRIC ANALYSIS

A bibliometric analysis was conducted to examine the geographical distribution of the institutional affiliations from the 36 studies included in this review. The findings reveal a significant concentration of research productivity in Asia, with China emerging as the leading contributor (13 articles, 36.1%), followed by India and South Korea (2 articles each). North America demonstrates a strong presence, represented exclusively by the United States with 7 articles (19.4%) and Canada (1 article).

European involvement is diverse but fragmented, totaling 7 articles distributed across countries such as Germany (2 articles), followed by single contributions from Spain, France, Greece, The Netherlands, Poland, and Switzerland. Other regions such as Oceania are represented by Australia (1 article). This distribution highlights that while scientific contributions are globally distributed, there is a distinct polarization towards Chinese and American institutions in the field of neuromorphic computing during the 2024–2025 period. As shown in Figure 2, the geographic heatmap visually emphasizes this imbalance.

TABLE III.: GEOGRAPHICAL DISTRIBUTION OF SELECTED STUDIES (2024–2025)

Rank	**Country**	**Documents**	**% of Total**
1	China	13	36.1%
2	United States	7	19.4%
3	Germany	2	5.6%
4	India	2	5.6%
5	South Korea	2	5.6%
6	Others (10 countries with 1 doc each)*	10	27.7%
Total		**36**	**100%**

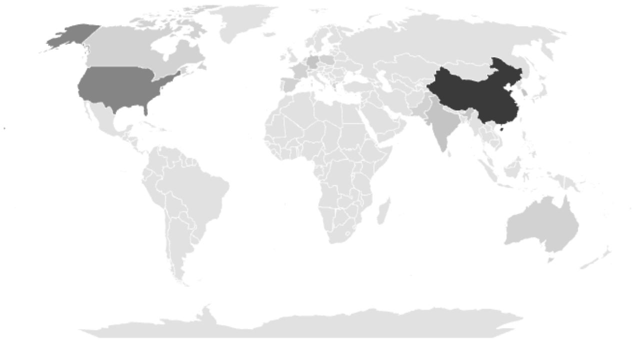

Fig 2. Geographical Distribution of Included Studies (2024–2025).

TABLE IV.: MAPPING OF SELECTED ARTICLES TO PICOC RESEARCH QUESTIONS

Research Question (PICOC)	**Cited Articles in Results Section**
RQ1 (Population / Design) Neuromorphic chip definition, architecture evolution, and design principles (IMC, memristors, spikes).	[1], [2], [3], [4], [12], [14], [15], [19], [21], [28], [31], [33], [35]
RQ2 (Comparison) Performance comparison against conventional hardware (GPU/TPU) and models (SNN, ANN, MPNN).	[1], [2], [4], [7], [8], [15], [18], [20], [21], [23], [35]
RQ3 (Intervention / Applications) AGI-oriented implementations: Adaptive perception, cognitive control, and Edge AI.	[6], [9], [10], [16], [19], [23], [25], [26], [27], [30], [34], [35], [36]
RQ4 (Outcome) Reported advantages (energy efficiency, scalability) and limitations (latency trade-offs, variability).	[2], [11], [13], [15], [16], [17], [18], [22], [23], [24], [29], [31], [32], [33], [36]
General Context Systematic review corpus and contribution to AGI development.	[5], [9], [19], [33], [35]

III. RESULTS

Following the application of the inclusion and exclusion criteria established in the PRISMA methodology, 36 full-text articles, corresponding to the years 2024–2025, were selected. These studies constitute the final corpus for the Systematic Literature Review (SLR) on neuromorphic computing and its contribution to the development of Artificial General Intelligence (AGI) [5], [9], [19], [33], [35].

The analysis of results was organized around the four research questions (RQ1–RQ4) defined in the PICOC framework, supported by graphical representations for each case.

RQ1. How have neuromorphic computing chips been defined over time in terms of architecture and design principles?

Neuromorphic computing has evolved from theoretical foundations into highly efficient hardware platforms [2], motivated by the severe energy and bandwidth limitations of the von Neumann architecture [2]. Over time, the technological definition of neuromorphic chips has been shaped by four core design principles: in-memory computing (IMC) [2], [21], event-driven communication (spikes) [15], synaptic plasticity [3], [31], and hardware–software co-design [2].

Figure 3 illustrates a pronounced acceleration in the maturity and utilization of neuromorphic systems. Early progress was driven by conceptual breakthroughs such as Spiking Neural Networks (SNNs) in 1997 [2] and the physical implementation of the memristor in 2008 [1]. The field then advanced toward large-scale functional hardware, including SpiNNaker and IBM TrueNorth (2010–2014), and later to IMC-based devices such as Intel Loihi (2018) [2], enabling online learning [14] with ultra-low-power operation. More recent platforms such as Loihi 2 and specialized SNN accelerators have achieved up to a 10× performance improvement over previous generations, reaching 307.2 GSOP/s in 2024 [4], demonstrating mature scalability [12]. Furthermore, industry forecasts project a 22.2% annual growth rate (CAGR) through 2030, reflecting increasing commercial adoption, especially in Edge AI [35].

In summary, neuromorphic chips have transitioned from biological inspiration [19], [28], [33] to scalable and high-performance accelerators [2], positioning them as a compelling alternative to GPU-intensive processing.

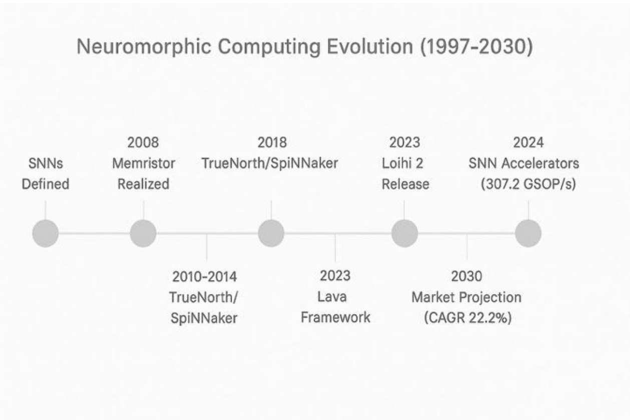

Fig. 3. Timeline of neuromorphic computing evolution from 2000 to 2030, highlighting key milestones and market projections.

RQ2 — With which conventional hardware architectures (GPUs, TPUs, CPUs) have they been compared?

The primary comparison for neuromorphic hardware is against conventional AI accelerators (GPUs and TPUs), which are based on the von Neumann architecture and optimized for dense, synchronous, floating-point operations for ANNs [2]. These systems suffer from memory-transfer bottlenecks [2], whereas neuromorphic solutions are designed for asynchronous, sparse, and event-driven processing [4], [23].

Figure 4 illustrates the results of this neuromorphic approach, showing that different network models implemented on memristive hardware achieve high performance. Spiking Neural Networks (SNNs) and Multilayer Perceptron Neural Networks (MPNNs) show the highest performance, with maximum accuracies of 97% [7, 15, 23]. This indicates that SNNs are highly effective for their main tasks in event-based vision and real-time processing [15, 35], while MPNNs are powerful in analog in-memory computing for image recognition [20, 21].

Next, Artificial Neural Networks (ANNs) on neuromorphic hardware achieve up to 96% accuracy. This suggests these platforms are also viable for traditional signal processing and gesture recognition tasks [7]. Recurrent Neural Networks (RNNs) follow closely, reaching 94% accuracy, demonstrating strong capabilities for time-series prediction like ECG analysis [35].

Finally, Binarized Neural Networks (BNNs) are present with 92% accuracy, highlighting their role in ultra-low-power AI audio classification on digital in-memory platforms [35].

These findings confirm that neuromorphic computing, using various memristive-based models [1, 8, 18], can achieve competitive functional performance for its target applications. The key distinction lies in its fundamentally different architectural principles, which are aimed at reducing the power demands that limit conventional GPU/TPU systems.
Tables V and VI show the benchmarking results for platforms and hardware.

TABLE V: COMPARATIVE ANALYSIS OF NEUROMORPHIC PLATFORMS

Platform	Architecture	Energy Advantage	Best Application	Key Strength
SpiNNaker	Event-driven many-core mesh	~49× (seg. tasks)	Cognitive control, RL	Scalability, real-time
Intel Loihi 2	IMC + spike routing	~13× (seg. tasks)	Edge AI, continual learning	Online learning
IBM TrueNorth	CMOS crossbar array	High efficiency	Pattern recognition	Ultra-low power

Memristive SNN	In-memory compute	50× (device level)	ECG, sensory processing	Density, plasticity

TABLE VI: COMPARATIVE ANALYSIS OF NEUROMORPHIC HARDWARE ARCHITECTURES

Task Type	Model	Platform	Accuracy (%)	Energy / Latency
Image Segmentation	SNN	Loihi 2	~97%	13×–49× less than GPU
ECG Classification	SNN	Memristive	99.0%	7.72 mJ per inference
Event-based Sem. Seg.	SNN	Memristive	0.628 mIoU	Low power (device-level)
Visual Perception	Adaptive SNN	SpiNNaker	70.03%	Event-driven (low idle power)
Robotic Control (17DoF)	R-SNN	SpiNNaker	N/A	Reward 14,033.97; var ≈2.6%
Image Recognition	MPNN	Memristive	97%	50× device energy reduction
Audio Classification	BNN	Digital IMC	92%	Ultra-low power (IMC)

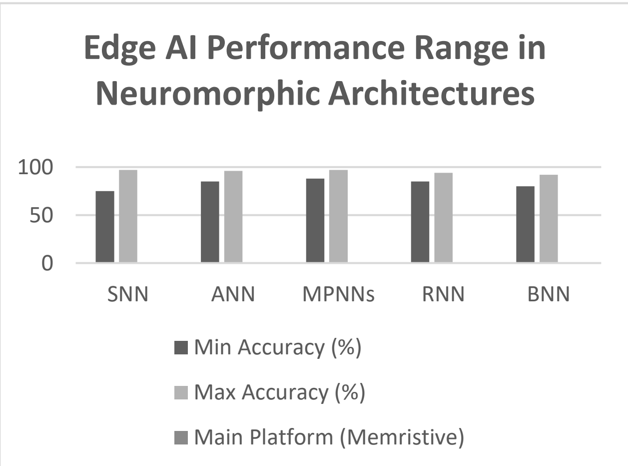

Fig 4. Accuracy and platform comparison for SNN, ANN, and MPNN memristive implementations.

RQ3. What AGI-oriented applications have been implemented using neuromorphic platforms?

Neuromorphic applications aligned with AGI goals focus on three essential cognitive capabilities. The results gathered in Figure 5 highlight the first of these: adaptive and robust perception. The figure shows that Adaptive SNNs achieve the highest performance in visual perception tasks under challenging distribution shifts, reaching 70.03% mean accuracy [10, 16]. This result surpasses advanced ANN adaptation baselines like Tent (68.94%) and standard Source-only ANNs (34.46%) [10]. This demonstrates that SNNs offer superior generalization and online adaptation when faced with environmental perturbations.

The second key capability identified is reinforcement-learning-based cognitive control. Recurrent SNNs (R-SNNs) trained with Reward-optimized Stochastic Release Plasticity (RSRP) exceeded gradient-based methods such as PPO-LSTM in complex control tasks [30, 34]. In the Humanoid environment (17 DoF), R-SNNs achieved a 14,033.97 reward with a substantially lower variance (≈ 2.6% vs 14.5%), which is crucial for stable autonomous decision-making [30].

Finally, the studies demonstrate high-precision sensory processing with extreme energy efficiency. Memristor-based systems have achieved up to 99.0% accuracy in ECG classification [35] and 0.628 mIoU in event-based semantic segmentation with only 7.72 mJ [23], demonstrating strong suitability for Edge AI [26, 36].

Collectively, these results show that neuromorphic platforms are not merely biological simulators [6, 19, 27] but emerging technologies [25] enabling adaptive and efficient cognitive functions [9] essential for progress toward AGI [35].

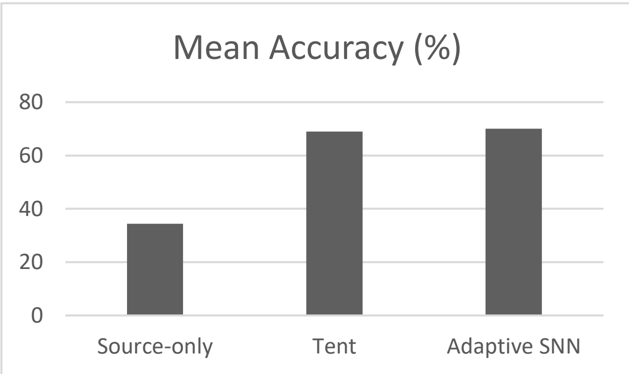

Fig 5. Mean accuracy of adaptive SNNs versus ANN baselines (Tent, Source-only) for visual perception under distribution shifts. Adapted from [10].

RQ4: What advantages and limitations have been reported in terms of energy efficiency and scalability compared to GPUs?

Neuromorphic hardware provides substantial advantages over GPUs in energy efficiency and distributed low-latency execution, stemming from event-driven processing [15] and integrated memory-compute architectures [2].

The advantages are quantified in Figure 6a. In Edge AI tasks like semantic segmentation, the SNN model (MFS-EFS) shows superior efficiency, requiring only 1.11 M parameters and 4.43 GFLOPs [23]. This reduced complexity results in a total energy consumption of just

10.00 mJ. In contrast, the conventional ANN model UNet consumes 130.01 mJ (a 13x increase), and SegNet consumes 494.50 mJ (a 49.4x increase) for the same task, while also having higher complexity [23].

Regarding scalability, SNN deployment on Network-on-Chip (NoC) architectures has demonstrated 79.74% latency reduction [32], while device-level enhancements such as spin-neuron scaling (5 μm → 0.3 μm) have achieved up to 50× energy reduction [17], indicating strong potential for compact and scalable neuromorphic systems [29].

However, Figure 6b illustrates the most significant limitation identified: the speed-accuracy trade-off. The graph shows that the SNN's performance (mIoU) is directly dependent on the number of simulation time steps; achieving higher precision requires longer processing times, which increases both latency and energy consumption [23]. Furthermore, hardware variability [13, 18, 31] and the lack of standardized software tooling [24, 33, 36] still present barriers to commercial adoption.

In conclusion, neuromorphic hardware surpasses GPUs in energy efficiency and offers a scalable approach to local intelligent processing [11], though precision and robustness [16, 22] continue to develop toward industrial readiness.

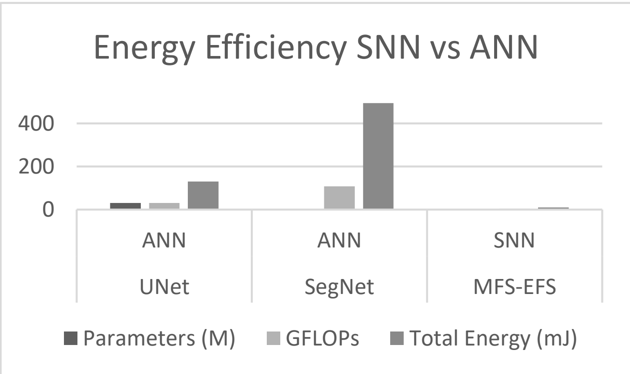

Fig 6. (a) Model complexity (Params, GFLOPs) and Total Energy (mJ) comparison for SNN vs. ANN models.

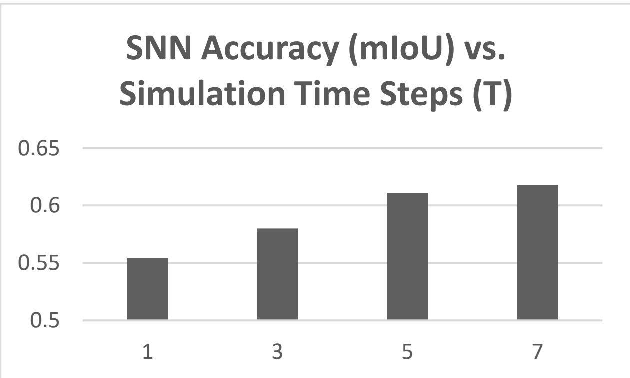

Fig 6. (b) The speed-accuracy trade-off in SNNs, showing mIoU improvement relative to simulation Time Steps. Adapted from [23].

IV. DISCUSSION

The findings associated with RQ3 reveal a set of applications directly related to cognitive capacities considered essential for the development of AGI. Across the literature, neuromorphic systems exhibit notable advantages in three central dimensions: adaptive perception [10], robust decision-making [30], and high-precision sensory processing [35]. These capabilities are particularly relevant in scenarios where conventional ANN architectures struggle to maintain stability under dynamically changing conditions. For instance, R-SNNs have demonstrated superior performance compared to gradient-based control models such as PPO-LSTM, achieving more stable reward trajectories and reduced variance in highly variable environments [30]. This behavior suggests an improved capacity for sustaining coherent actions when confronted with fluctuating or incomplete sensory inputs. Additionally, adaptive SNNs have shown stronger generalization capabilities in remote-sensing tasks subject to distribution shifts [10], consistently outperforming widely used ANN baselines and indicating an inherent robustness derived from their temporal coding mechanisms.

Beyond these performance gains, several studies emphasize that the asynchronous computational dynamics characteristic of SNNs may offer structural advantages for implementing cognitive processes that require rapid adaptation, multimodal integration, or efficient real-time reasoning. Such properties align conceptually with biological neural systems, reinforcing the argument that neuromorphic hardware constitutes a promising substrate for AGI-related functions where flexibility and energy efficiency are critical.

Despite these advances, the review also identified important limitations (RQ4). One of the most recurrent constraints is the inherent trade-off between computational speed and accuracy. Achieving higher precision frequently requires increasing the number of simulation time steps, which in turn elevates latency and energy consumption throughout the processing cycle [23]. This challenge becomes more pronounced as task complexity grows, limiting the applicability of SNN-based architectures in high-throughput or large-scale environments. A second limitation concerns the physical variability of memristive devices, widely reported in the literature [13], [18], [31]. Fluctuations in conductance, stability issues across cycles, and inconsistencies in fabrication processes can hinder reproducibility and introduce errors that complicate model deployment on hardware.

Furthermore, the lack of standardized software ecosystems and unified development pipelines—frequently highlighted in contemporary works [24], [33], [36]—represents a major obstacle for widespread adoption. Current tooling remains fragmented, often requiring researchers to adapt incompatible frameworks or rely on custom implementations, which slows down experimentation and limits cross-platform comparability. Addressing these challenges will require coordinated advances in device calibration, platform interoperability, and the creation of development environments capable of integrating neuromorphic hardware with existing AI infrastructures.

The evidence indicates that neuromorphic computing holds substantial potential for AGI-oriented systems, yet its consolidation will depend on overcoming the technical and methodological barriers identified.

The neuromorphic features reviewed — particularly synaptic plasticity, event-driven communication, and in-memory computing — show direct alignment with AGI-relevant capabilities as defined in this review. Adaptive SNNs achieving 70.03% mean accuracy under distribution shifts provide empirical evidence for generalization potential. R-SNNs trained with RSRP demonstrate lifelong and continual learning analogues. Furthermore, the architectural flexibility of memristive hardware supports meta-learning paradigms by enabling rapid weight updates with low energy overhead.

A key architectural distinction is the difference between SpiNNaker's event-driven communication model and the GPU streaming multiprocessor (SM) paradigm. GPUs rely on SIMT (Single Instruction, Multiple Threads) execution within each SM, processing dense tensor operations in synchronized, clock-driven batches — optimized for throughput in matrix multiplications. SpiNNaker, in contrast, uses asynchronous packet-routing via a many-core mesh network, where each core processes spikes only when they arrive (event-driven), resulting in near-zero idle power during sparse activity. While GPU SMs excel at dense workloads, SpiNNaker's event-driven model provides a structural energy advantage for sparse, temporally-coded spiking tasks (e.g., ECG classification: 99.0% accuracy at 7.72 mJ).

V. CONCLUSIONS

In this systematic review, rather than reiterating the technical findings discussed previously, my conclusions focus on outlining future directions and potential applications that emerge from the evidence analyzed.

First, it is concluded that current neuromorphic research has reached sufficient maturity to warrant the development of applied prototypes, particularly for scenarios requiring continuous operation and ultra-low-power processing. Consequently, a pivotal next step involves the design of small-scale neuromorphic edge-computing modules capable of executing fundamental perception or adaptive control tasks via Spiking Neural Networks (SNNs).

Second, it is proposed that future research prioritize the evaluation of neuromorphic hardware within real-world environments to transcend current simulation-based constraints. This approach necessitates comparative field assessments between neuromorphic platforms and conventional GPUs in domains such as environmental monitoring, lightweight robotics, and biomedical signal processing, where operational autonomy and energy efficiency are paramount.

Third, my review highlights the need for standardized development frameworks. Therefore, a relevant line of future work is exploring how existing tools and programming ecosystems could be adapted or extended to integrate with platforms like SpiNNaker or Loihi, reducing the current entry barriers for developers and researchers.

Additionally, the synthesis of current research suggests that interdisciplinary collaboration will be crucial. Integrating insights from neuroscience, materials science, and machine learning could accelerate the refinement of both hardware and algorithms, helping to close the gap between biological inspiration and practical implementation.

It is argued that hybrid approaches integrating neuromorphic hardware with conventional accelerators constitute a viable trajectory for future developments. Such synergy enables the design of hybrid intelligence architectures that leverage the complementary strengths of both paradigms to advance toward AGI-related capabilities.

Overall, this review not only synthesizes the existing literature but also provides a foundation for shaping a future research agenda and guiding the development of practical neuromorphic applications.

The evidence examined also shows that neuromorphic systems currently offer clear advantages over traditional GPU-based models, particularly in their ability to adapt to changing environments, maintain decision stability under uncertainty, and operate with extremely low energy consumption. These strengths reinforce the idea that neuromorphic hardware is not only theoretically promising but also practically relevant for scenarios where real-time adaptation and autonomy are crucial.

However, the limitations identified—such as the trade-off between precision and processing speed, the instability of devices like memristors, and the lack of standardized software tools—indicate that the field is still in transition. Addressing these issues will be essential for ensuring reliability and enabling large-scale adoption.

Considering these challenges, future research should also explore strategies to improve device stability, enhance algorithm–hardware co-design, and develop benchmarking standards that allow fair comparison across platforms. These elements would contribute to building a more cohesive and scalable neuromorphic ecosystem.

If future research manages to overcome these challenges, neuromorphic systems could become a core component of everyday technologies, enabling more adaptive robotics, energy-efficient sensors, autonomous devices, and hybrid intelligence architectures that combine neuromorphic and conventional computation. Ultimately, these advancements have the potential to bring AI systems closer to brain-like processing: more flexible, efficient, and capable of operating under real-world variability.

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