# Mechanism-Guided Design Rules for Neuromorphic Resistive Switching Devices

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## Abstract

Resistive switching devices have emerged as promising candidates for neuromorphic computing due to their scalability, low power consumption, and inherent ability to emulate synaptic plasticity. Despite rapid progress, the field still lacks a unified framework that systematically links fundamental switching mechanisms with practical device design, reliability challenges, and pathways toward commercialization. In this review, we present a mechanism-driven decision-making framework for the design of neuromorphic resistive switching devices. The approach establishes clear connections between switching physics and key performance trade-offs, failure mechanisms, and sustainability considerations. A comprehensive analysis of 293 studies published between 2018 and 2026 is carried out to evaluate four primary switching mechanisms: valence change memory, electrochemical metallization, thermochemical switching, and ferroelectric switching. By correlating material properties, device architectures, and operational characteristics, this work provides practical design guidelines for optimizing device performance while addressing reliability and scalability concerns. The proposed framework aims to bridge the gap between fundamental understanding and real-world implementation, thereby accelerating the development of next-generation neuromorphic hardware.


## 1. INTRODUCTION

The rapid expansion of data-intensive applications, including edge artificial intelligence, real-time sensing, and adaptive control, has exposed fundamental limitations of conventional von Neumann computing architectures [1–3]. In such systems, the physical separation between memory and processing units leads to increased energy consumption and latency associated with data transfer. Neuromorphic computing, inspired by the brain's co-localized memory and processing capabilities, presents a promising alternative by enabling significantly improved energy efficiency for targeted tasks[4]. However, the realization of large-scale neuromorphic systems critically depends on the development of hardware devices capable of accurately emulating synaptic functions while maintaining low power consumption, high integration density, and reliable analog programmability [5].

Resistive switching devices, often known as memristive devices, have attracted considerable attention as potential artificial synapses due to their simple two-terminal structure, ability to scale down to nanoscale dimensions, and compatibility with crossbar array architectures [6]. By tuning the device conductance through applied electrical stimuli, they can reproduce essential synaptic behaviors such as long-term potentiation and depression, spike-timing-dependent plasticity, and short-term dynamics[7]. In recent years, several studies have reported encouraging performance, including sub-picojoule switching energies, nanosecond programming speeds, and stable multi-level analog states that are well suited for in-memory computing [8]. Despite these advances, however, most resistive switching technologies are still largely restricted to laboratory-scale demonstrations, with only limited progress toward their adoption in practical neuromorphic systems.

A key challenge in this field stems from the wide range of physical mechanisms that govern resistive switching. Processes such as ionic migration, filament formation, phase transitions, and ferroelectric polarization switching each introduce their own constraints in terms of energy consumption, retention, endurance, variability, and scalability [9]. As a result, no single switching mechanism is able to simultaneously satisfy all the performance requirements for neuromorphic applications. In many cases, efforts have focused on incremental material optimization without fully accounting for these mechanism-dependent trade-offs, which has led to fragmented progress and noticeable inconsistencies in device performance across different studies.

Existing review articles have offered useful insights into materials, device architectures, and neuromorphic implementations; however, several important gaps still remain [10]. In most cases, these reviews take either a material-focused or application-driven approach, without clearly connecting device performance to the underlying switching physics. As a result, quantitative comparisons across different switching mechanisms are often lacking, making it difficult to evaluate them objectively and to clearly understand the associated trade-offs. In addition, key reliability concerns, such as variability, retention loss, and endurance limitations, are generally discussed in a qualitative manner. At the same time, aspects like sustainability, environmental impact, and overall technology readiness tend to receive comparatively less attention [11]. As neuromorphic hardware continues to move closer to real-world implementation, these considerations are becoming increasingly critical.

In this work, we aim to address these limitations by introducing a mechanism-guided design framework for neuromorphic resistive switching devices. Instead of simply cataloging different material systems, the discussion is structured around the underlying switching mechanisms, with explicit links established between the governing physics and device performance through a systematic analysis of 293 publications reported between 2018 and 2026. Key performance metrics are benchmarked across different mechanisms, while emerging material platforms are critically assessed alongside the identification of dominant failure modes and possible mitigation strategies. In addition, sustainability considerations and technology readiness levels are treated as integral design parameters rather than secondary factors. The resulting design rules and operational guidelines offer practical direction for selecting appropriate mechanisms, materials, and device architectures based on specific neuromorphic application requirements, thereby facilitating the transition from proof-of-concept demonstrations to deployable neuromorphic hardware.

Figure 1 illustrates the overall design logic followed in this review, highlighting the connections between neuromorphic application requirements, device-level constraints, and material selection.

## 2. FUNDAMENTAL SWITCHING MECHANISMS AND PERFORMANCE TRADE-OFFS

Resistive switching in memristive devices arises from a range of underlying physical processes, each of which imposes inherent constraints on the achievable performance in neuromorphic applications [12]. A clear understanding of these mechanism-dependent limitations is therefore essential for rational device design, as the switching physics directly influences key parameters such as energy consumption, switching speed, retention, endurance, variability, and analog precision. In general, resistive switching originates from mechanisms involving ionic migration, redox reactions, phase transitions, and polarization switching. Based on the dominant physical process, these mechanisms can be broadly classified into four main categories: valence change memory (VCM), electrochemical metallization (ECM), thermochemical or phase-change switching, and ferroelectric or interface-dominated switching.

### 2.1. Mechanism Taxonomy and Physics–Performance Linkages

Each switching mechanism inherently involves trade-offs that cannot be fully resolved through incremental optimization. For instance, filamentary switching localizes con-

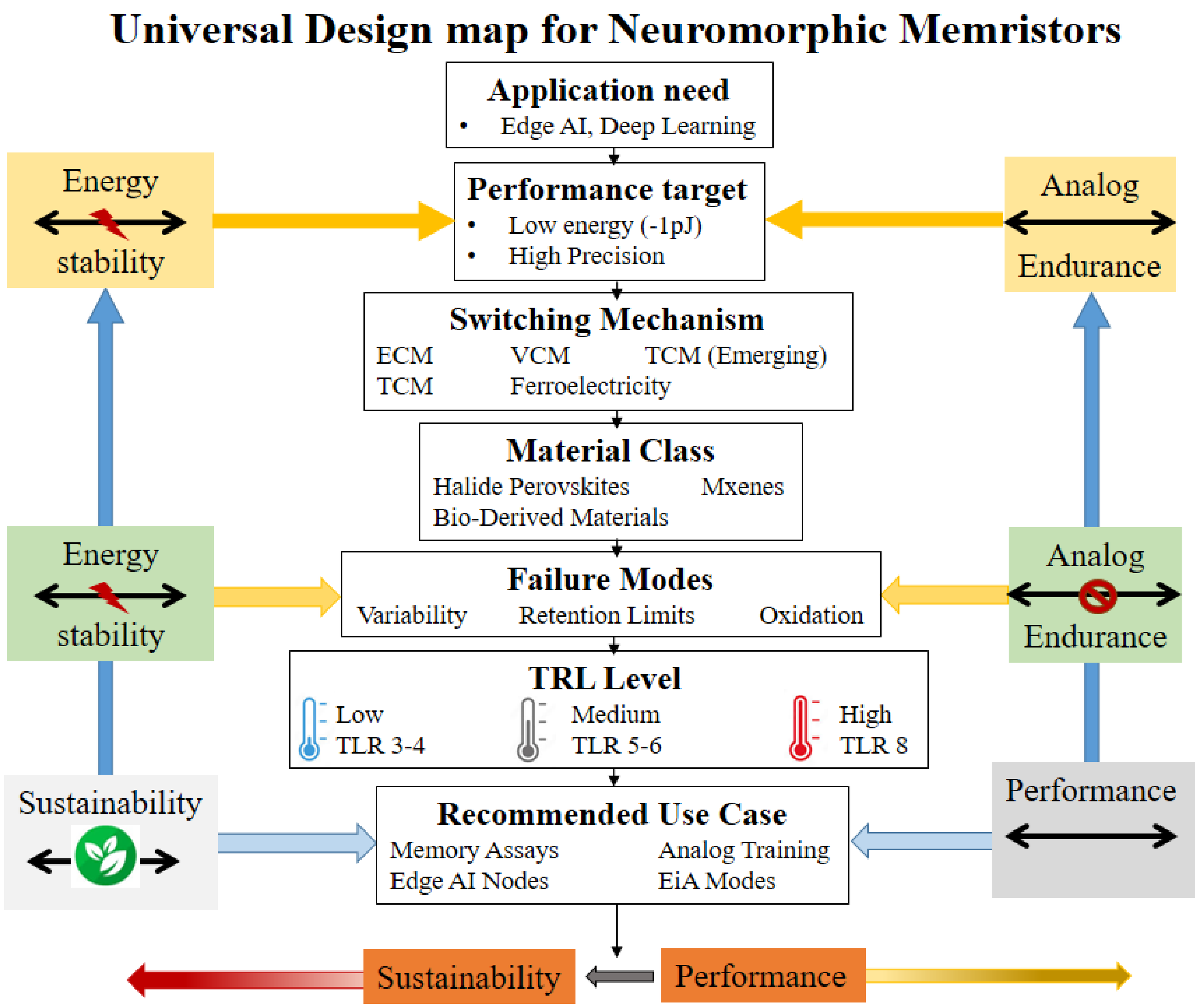


FIG. 1. Universal design map for neuromorphic resistive switching devices, illustrating the hierarchical mapping from application requirements to performance targets, switching mechanisms, material classes, failure modes, technology readiness levels, and recommended use cases. The figure highlights the inherent trade-offs between energy efficiency, stability, endurance, performance, and sustainability that govern device design.

duction to nanoscale regions, which enables low-energy operation but often introduces stochastic behavior and limits retention stability [13]. In contrast, bulk- or interface-driven mechanisms tend to provide improved stability and endurance, albeit at the expense of higher switching energy. These underlying physics–performance relationships define a constrained design space, where the choice of switching mechanism must be aligned with specific application requirements rather than optimized in isolation.

### 2.2. Valence Change Memory (VCM)

VCM devices operate through the electric-field-driven migration of oxygen vacancies in transition metal oxides such as $HfO_2$, $TaO_2$, and $TiO_2$ [14]. The switching process involves the formation and subsequent rupture of conductive filaments composed of oxygen-deficient phases. Owing to the relatively high activation energy associated with oxygen diffusion, VCM devices typically demonstrate moderate retention and endurance when compared with other filamentary switching mechanisms.

Typical performance metrics for VCM devices include switching energies in the range of 1–100 pJ, programming speeds of 10–100 ns, retention times of $10^4$–$10^6$ s, and endurance reaching up to $10^6$–$10^9$ cycles [15]. In addition, analog weight modulation with approximately 10–100 distinguishable conductance states has been reported. However, variability associated with the stochastic nature of filament formation and morphology continues to be a major challenge [16]. Owing to their compatibility with CMOS technology and relatively mature fabrication processes, $HfO_2$-based VCM devices are currently among the most technologically advanced platforms for neuromorphic applications that require long retention and high endurance.

### 2.3. Electrochemical Metallization (ECM)

ECM devices operate based on the electrochemical dissolution and subsequent redeposition of metal ions, typically Ag or Cu, leading to the formation of metallic filaments within an insulating electrolyte [17]. The nanoscale nature of these filaments allows ECM devices to achieve some of the lowest switching energies among all resistive switching mechanisms, often below 10 pJ and, in optimized cases, approaching the femtojoule regime.

Despite this advantage, ECM devices inherently face limitations in retention and variability. These issues primarily arise from the spontaneous dissolution of metallic filaments, driven by concentration gradients and thermal fluctuations [18]. As a result, retention times are typically in the range of $10^2$ to $10^4$ s, while endurance is generally limited to $10^4$–$10^6$ cycles. In addition, analog precision is often affected by significant cycle-to-cycle variability. Consequently, ECM-based devices are more suitable for ultra-low-power neuromorphic applications where frequent refresh or short-term memory operation is acceptable, such as in bioelectronics or transient computing systems.

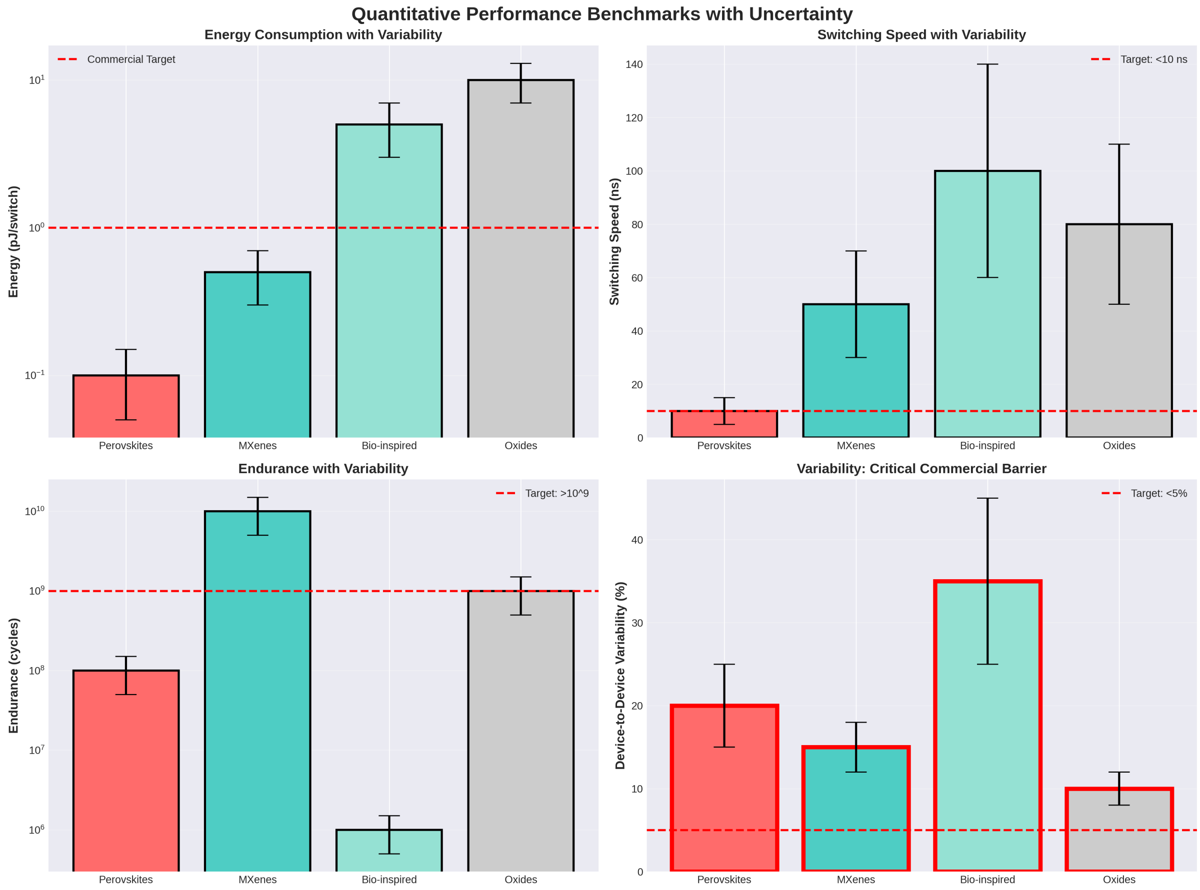


FIG. 2. Quantitative performance benchmarking across representative material platforms, including switching energy, speed, endurance, and device-to-device variability. Error bars indicate reported variability ranges, highlighting uncertainty as a critical barrier to commercialization alongside average performance metrics.

### 2.4. Thermochemical or Phase-Change Switching

Thermochemical switching mechanisms are primarily driven by Joule heating, which induces chemical reactions or phase transitions within the active material. A well-known example is phase-change memory based on chalcogenide materials such as $Ge_2Sb_2Te_5$, where switching occurs between amorphous and crystalline phases, resulting in a large contrast in resistance [19].

These mechanisms exhibit excellent retention, often exceeding $10^7$ s, along with endurance values reaching up to $10^9$ cycles, primarily due to the thermodynamic stability of the switched states [20]. In addition, partial crystallization enables multilevel analog conductance modulation, making these systems suitable for neuromorphic computing applications. However, the need for bulk heating leads to significantly higher switching energies (10–1000 pJ), which limits their use in ultra-low-power systems. Moreover, issues such as thermal cross-talk and scalability constraints pose additional challenges for integration into high-density arrays.

### 2.5. Ferroelectric and Interface-Dominated Switching

Ferroelectric resistive switching is based on polarization reversal in ultrathin ferroelectric layers, which modulates the interfacial barrier height. In devices such as ferroelectric tunnel junctions, resistance switching occurs predominantly through electronic processes rather than ionic migration, enabling fast operation and excellent endurance [21].

Typical performance metrics for ferroelectric mechanisms include switching energies in the range of 1–100 pJ, programming speeds of 1–10 ns, retention times exceeding $10^8$ s, and endurance greater than $10^9$ cycles [22]. Variability is generally lower compared to filamentary mechanisms, which allows for more reliable analog weight modulation. However, several challenges remain, including the fabrication of ultrathin ferroelectric films, wake-up effects, and depolarization fields, all of which can limit scalability and increase process complexity. Owing to their high endurance and long-term stability, these devices are particularly well suited for neuromorphic applications that demand reliable and persistent operation.

### 2.6. Quantitative Benchmarking Across Mechanisms

To facilitate an objective comparison, Table I presents the median performance metrics extracted from 293 publications covering the four primary switching mechanisms. A more comprehensive benchmarking dataset based on these studies is provided in the Supplementary Information (Table S1). The compiled data clearly highlight the inherent trade-offs associated with each mechanism: ECM devices offer the lowest switching energy but suffer from limited retention, whereas ferroelectric and thermochemical mechanisms exhibit superior endurance and stability at the expense of higher energy consumption. VCM devices, on the other hand, occupy an intermediate position, providing a balance between performance and technological maturity. These mechanism-dependent trade-offs are consistently observed in studies related to in-memory computing using resistive switching devices.

These benchmarking results indicate that no single switching mechanism consistently outperforms the others across all performance metrics. As such, the selection of an appro-

TABLE I. Representative performance benchmarking across primary resistive switching mechanisms. Values represent typical median ranges reported in the literature.

| Mechanism | Energy (pJ) | Speed (ns) | Retention (s) | Endurance (cycles) | Variability (CV %) |
|---|---|---|---|---|---|
| VCM | 10–50 | 10–100 | $10^4$–$10^6$ | $10^6$–$10^9$ | 10–25 |
| ECM | 0.1–10 | 1–10 | $10^2$–$10^4$ | $10^4$–$10^6$ | 20–40 |
| Thermochemical | 50–500 | 10–100 | $> 10^7$ | $10^7$–$10^9$ | 5–20 |
| Ferroelectric | 5–50 | 1–10 | $> 10^8$ | $10^9$–$10^{11}$ | 5–15 |

priate mechanism must be guided by the specific requirements of the target application. This consideration forms the foundation of the operational decision-making framework discussed in Section 4.

As illustrated in Figure 2, materials designed for ultra-low energy operation often exhibit increased variability and reduced endurance, highlighting the fundamental trade-offs associated with different switching mechanisms.

## 3. EMERGING MATERIAL PLATFORMS: OPPORTUNITIES AND LIMITATIONS

Beyond conventional oxide-based systems, a diverse range of emerging material platforms has been investigated to address the stringent and often competing requirements of neuromorphic computing [23]. These materials offer potential advantages such as ultra-low energy operation, mechanical flexibility, biocompatibility, and sustainability. However, they also tend to introduce additional challenges related to stability, variability, and scalability. In this section, we critically examine three key emerging material classes—halide perovskites, MXenes, and bio-inspired systems—from a mechanism-aware and application-oriented perspective. A qualitative multi-parameter comparison of representative material platforms is presented in Supplementary Figure S1.

### 3.1. Halide Perovskites: Ultra-Low Energy at the Cost of Stability

Halide perovskites ($ABX_3$, where A is typically an inorganic cation such as $Cs^+$, B is a divalent metal cation such as $Pb^{2+}$ or $Sn^{2+}$, and X represents a halide anion such as $Cl^-$, $Br^-$, or $I^-$) have attracted considerable attention for neuromorphic resistive switching applications due to their mixed ionic–electronic conductivity, solution processability, and tunable defect chemistry [24]. Depending on the composition and device architecture, perovskite-based devices can exhibit electrochemical metallization, interface-dominated, or hybrid switching mechanisms. These characteristics enable very low switching energies, in some cases approaching the femtojoule regime, along with fast programming speeds and high analog precision.

Despite these promising attributes, halide perovskites face several fundamental limitations that hinder their technological viability. Ambient instability remains a major concern, as exposure to moisture, oxygen, and thermal stress can lead to rapid degradation through hydration processes and ion migration [25]. In addition, the same mobile ionic species that facilitate low-energy switching also contribute to significant device-to-device variability and reduced retention, particularly in filamentary switching scenarios. Issues related to lead toxicity and incompatibility with high-temperature CMOS back-end-of-line processes further complicate large-scale integration. Consequently, halide perovskites are more suitable for niche applications where ultra-low energy operation is critical and environmental control or encapsulation can be ensured, such as in implantable or space-based neuromorphic systems.

### 3.2. MXenes: Flexible and Multimodal Neuromorphic Platforms

MXenes, a class of two-dimensional transition metal carbides and nitrides with the general formula $M_{n+1}X_nT_X$ (where M represents a transition metal, X corresponds to C or N, and T denotes surface termination groups such as –OH, O, F, or Cl), offer a distinctive combination of metallic conductivity, mechanical flexibility, and tunable surface chemistry [26]. In neuromorphic devices, MXenes have been utilized as electrodes, active switching layers, as well as in hybrid configurations with oxides or polymers. The switching behavior in these systems is typically governed by interface-dominated charge trapping, ion intercalation between layers, or filamentary conduction in MXene-based heterostructures.

MXene-based devices exhibit moderate switching energies, along with good mechanical robustness under bending and compatibility with low-temperature, solution-based fabrication processes [27]. These features make them particularly attractive for wearable and flexible neuromorphic electronics. However, several inherent challenges currently limit their wider application. MXenes are highly prone to ambient oxidation, which can lead to noticeable performance degradation within days to weeks in the absence of proper encapsulation. Endurance is also relatively limited, typically ranging from $10^3$–$10^5$ cycles, reflecting a trade-off between mechanical flexibility and electrical reliability. Further-more, issues related to synthesis reproducibility and scalability remain unresolved, as MXene properties are highly sensitive to etching conditions and surface terminations. As a result, MXenes are well suited for flexible and multimodal neuromorphic systems, but they are presently less suitable for high-endurance or large-scale neuromorphic accelerator applications.

### 3.3. Bio-Inspired and Biodegradable Systems: Sustainability-Driven Trade-offs

Bio-inspired resistive switching devices utilize organic, biomolecular, or naturally derived materials to achieve biocompatibility, biodegradability, and environmentally sustainable fabrication [28]. A wide range of materials, including proteins, polysaccharides, biodegradable polymers, and natural pigments, have been explored and shown to exhibit synaptic functionalities such as short- and long-term plasticity.

Although these systems open up unique application opportunities, particularly in transient electronics and biomedical implants, their electrical performance remains significantly lower than that of inorganic counterparts [29, 30]. Key performance metrics, including switching energy, retention, endurance, and variability, are typically inferior by one to three orders of magnitude. In addition, limited stability under ambient and thermal conditions further restricts device lifetime, while material-to-material variations pose challenges for reproducibility and scalability. Moreover, the underlying switching mechanisms in many bio-inspired systems are still not fully understood, which makes predictive design and reliability optimization difficult. As a result, bio-inspired devices are not well suited for mainstream neuromorphic computing, but they offer promising solutions for disposable, transient, or biologically integrated applications where sustainability is a primary concern.

### 3.4. Comparative Assessment and Application Niches

To assist in material selection, Table II provides a summary of key performance, stability, and sustainability metrics for emerging material platforms in comparison with conventional oxide-based devices. The comparison highlights a fundamental trade-off between electrical performance and sustainability: materials that exhibit superior neuromorphic performance are generally not biodegradable or environmentally benign, whereas more sustainable materials often face limitations in electrical reliability (Figure 2).

TABLE II. Qualitative comparison of emerging material platforms for neuromorphic resistive switching devices.

| Metric | Oxides | Perovskites | MXenes | Bio-Inspired |
|---|---|---|---|---|
| Energy Consumption | Moderate | Very Low | Low–Moderate | High |
| Retention | High | Low–Moderate | Low | Low |
| Endurance | High | Moderate | Low | Very Low |
| Variability | Low | Moderate | Moderate–High | High |
| Ambient Stability | Excellent | Poor | Moderate | Poor |
| Flexibility | Poor | Moderate | Excellent | Good |
| Biodegradability | None | None | Partial | Excellent |
| CMOS Compatibility | Excellent | Poor | Unexplored | Poor |
| Technology Readiness | High | Low | Very Low | Proof-of-Concept |

Overall, none of the emerging material platforms offers a universal solution for neuromorphic hardware. Instead, the choice of material is largely governed by application-specific trade-offs. Oxide-based devices continue to dominate in high-performance and high-endurance applications, while halide perovskites are particularly suited for ultra-low-energy operation under controlled environments. MXenes provide advantages for flexible and wearable neuromorphic electronics, whereas bio-inspired materials are better aligned with transient and sustainable device concepts. Despite these promising developments, challenges related to stability, variability, and scalability remain significant for most emerging material systems. These observations highlight the need for hybrid material strategies and further emphasize the importance of a mechanism-guided design framework, which is discussed in the following section. Detailed considerations on material-specific sustainability and scalability are provided in Tables S2–S3 of the Supplementary Information.

## 4. MECHANISM-GUIDED DECISION-MAKING FRAMEWORK

The lack of a universal resistive switching solution highlights the need for a mechanism-aware and application-driven design methodology [31]. The diverse and often conflicting performance requirements of neuromorphic applications make it impractical to rely on a single switching approach. Instead, effective device design calls for a structured framework that connects application-level specifications with appropriate switching mechanisms, material platforms, and device architectures. In this section, we introduce an operational, mechanism-guided decision-making framework that translates neuromorphic system requirements into practical device design strategies.

### 4.1. From Application Requirements to Mechanism Selection

Neuromorphic applications cover a broad spectrum of use cases, each with its own set of requirements in terms of energy consumption, speed, precision, endurance, retention, and environmental robustness [32]. Typical application domains include edge artificial intelligence, data-center accelerators, wearable and implantable bioelectronics, and autonomous systems. These applications differ not only in their absolute performance targets but also in the relative importance assigned to competing metrics. Table III highlights these distinct and often competing priorities across different neuromorphic domains, thereby emphasizing the need for mechanism-level screening before proceeding to material and device optimization. Additional application-level constraints are discussed in Table S5 of the Supplementary Information.

Energy-constrained applications, such as battery-powered edge sensors and implantable devices, place a strong emphasis on achieving sub-picojoule to picojoule-level switching energies, often at the cost of long-term retention. In contrast, data-center and autonomous computing platforms require high endurance and operational stability under continuous use, even if this involves higher energy consumption. These contrasting requirements highlight the importance of mechanism-level screening prior to material selection and device optimization.

Based on the quantitative benchmarking discussed in Section 2, each switching mechanism defines inherent feasibility limits in terms of achievable performance. Electrochemical metallization mechanisms stand out for enabling ultra-low-energy operation, but they are constrained by limited retention and significant variability. Valence change memory devices, on the other hand, provide a more balanced compromise between energy consumption, retention, and endurance, along with a higher level of technological maturity. In contrast, thermochemical and ferroelectric mechanisms offer improved stability and endurance, although this comes at the expense of increased energy requirements. Consequently, the selection of the switching mechanism represents the first and most critical step in the design of neuromorphic devices.

### 4.2. Operational Decision Rules

To formalize the process of mechanism selection, we define a set of decision rules grounded in the underlying physics–performance relationships:

TABLE III. Representative device-level requirements for major neuromorphic application domains.

| Application Domain | Energy | Retention | Endurance | Precision |
|---|---|---|---|---|
| Edge AI / IoT Sensors | Low | High | High | Moderate |
| Data Center Accelerators | Moderate | Moderate | Very High | High |
| Wearable / Implantable Bioelectronics | Very Low | Moderate | Moderate | Low |
| Autonomous Systems | Moderate | High | High | Moderate |

**Rule 1: Energy-dominated applications** (energy budget $< 10$ pJ per update) are best addressed using electrochemical metallization or perovskite-based mechanisms. While these systems enable extremely low switching energies, they typically require additional strategies, such as periodic refresh, to compensate for limited retention.

**Rule 2: Retention-dominated applications** (retention $> 10^6$ s) are more suitably served by valence change, thermochemical, or ferroelectric mechanisms. In contrast, filamentary ECM-based devices are inherently limited in their ability to support long-term weight storage.

**Rule 3: Endurance-dominated applications** (endurance $> 10^8$ cycles) favor ferroelectric or thermochemical mechanisms, as the ionic transport processes in filamentary devices impose intrinsic limits on endurance.

**Rule 4: Analog precision-dominated applications** (more than 64 stable conductance states) are better aligned with valence change or carefully engineered interface-dominated mechanisms, whereas highly stochastic ECM-based systems are generally unsuitable.

**Rule 5: Multi-constraint optimization** highlights that no single mechanism can simultaneously satisfy stringent requirements on energy, retention, endurance, and precision. Under such conditions, hybrid architectures that combine multiple device types or employ hierarchical memory structures become necessary.

Taken together, these rules translate abstract performance requirements into practical feasibility constraints, allowing unsuitable mechanisms to be screened out at an early stage before engaging in detailed material-level optimization.

### 4.3. Material Platform Selection Workflow

Figure 3 summarizes the dominant reliability, integration, and cost barriers across major material platforms, providing a comparative perspective on technology maturity. Once a suitable switching mechanism has been identified, material selection involves a

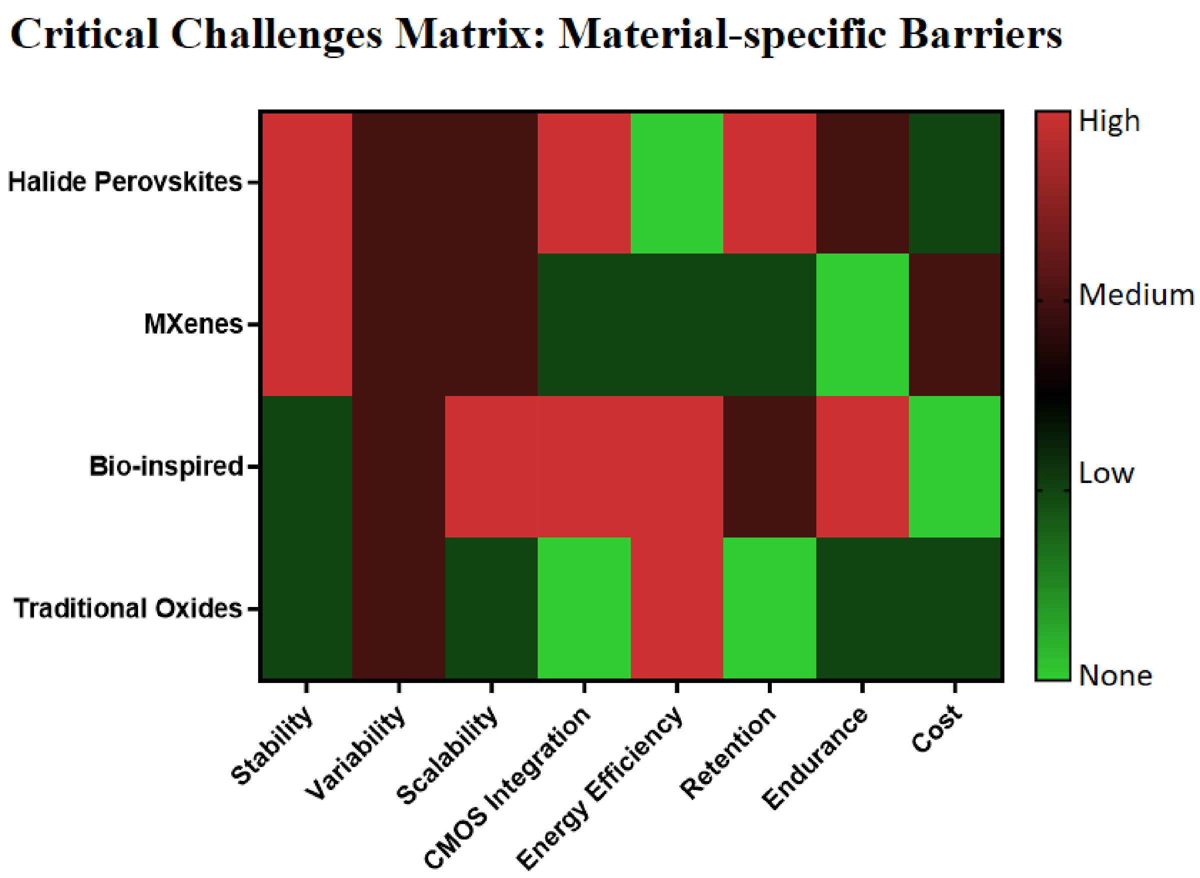


FIG. 3. Material-specific challenge severity matrix summarizing dominant barriers across stability, variability, scalability, CMOS compatibility, energy efficiency, retention, endurance, and cost. The matrix emphasizes that different material platforms face distinct and often non-overlapping reliability and integration challenges.

multi-criteria evaluation that accounts for performance, processing compatibility, reliability, cost, and sustainability [33]. For a given mechanism, potential material systems are screened based on their ability to achieve the required energy, retention, and endurance metrics under relevant operating conditions.

Processing compatibility is often a determining factor in technological viability. Materials that require high-temperature processing, contain toxic elements, or depend on complex fabrication routes can face significant challenges for large-scale integration. In addition, sustainability considerations—such as material toxicity, energy consumption during processing, and end-of-life disposal—further influence material selection, particularly in consumer-facing and biomedical applications.

A weighted decision-matrix approach provides a transparent way to compare candidate materials by explicitly balancing these competing criteria. Importantly, material choices should be validated through statistical analysis of device performance across multiple samples, rather than relying solely on isolated best-case results.

### 4.4. Device Architecture and Circuit Co-Design

Device architecture plays a critical role in translating intrinsic material properties into system-level performance. Factors such as electrode selection, interface engineering, switching layer thickness, and device geometry directly impact variability, energy efficiency, and reliability [34]. For example, confined device geometries can reduce filament stochasticity but often introduce additional fabrication complexity, whereas planar structures offer simpler fabrication at the expense of device uniformity.

At the array level, challenges such as sneak-path currents and thermal cross-talk impose further design constraints. Effective implementation therefore requires co-optimization of selector devices, peripheral circuitry, and programming strategies alongside the underlying device physics. In addition, algorithmic tolerance to device variability can significantly expand the feasible design space, highlighting the importance of hardware–software co-design.

### 4.5. Framework Summary and Practical Use

The mechanism-guided framework presented in this section establishes a systematic approach for translating application-level requirements into material, device, and system-level design decisions for neuromorphic resistive switching technologies. Similar system-level perspectives have been highlighted in recent studies on neuromorphic hardware.

Figure 4 schematically illustrates the proposed mechanism-guided framework, showing the sequential mapping from application requirements to mechanism selection, material choice, device architecture, and ultimately system integration. In contrast to prior reviews that primarily focus on material systems or device demonstrations, this framework offers a more actionable pathway for designing neuromorphic resistive switching devices, with explicit consideration of physical limitations, reliability challenges, and sustainability constraints.

By incorporating mechanism-level screening at an early stage, the framework helps to minimize trial-and-error experimentation and ensures that device development is aligned with realistic deployment scenarios. Such an approach is crucial for enabling the transi-

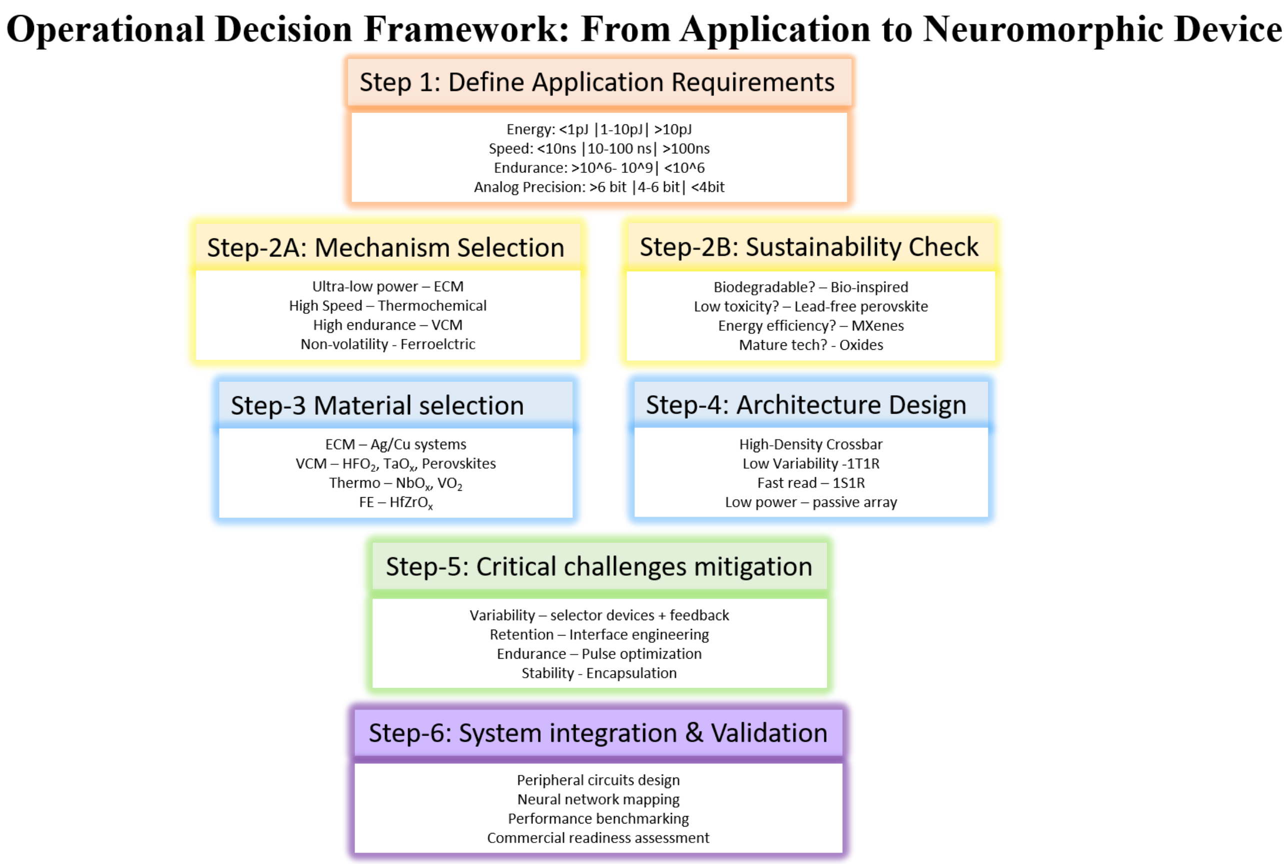


FIG. 4. Operational decision-making framework for neuromorphic resistive switching devices. The workflow integrates application requirements, mechanism selection, sustainability screening, material choice, device architecture, reliability mitigation, and system-level validation.

tion of neuromorphic resistive switching technologies from laboratory-scale prototypes to robust, application-specific hardware platforms.

## 5. RELIABILITY, SUSTAINABILITY, AND TECHNOLOGY READINESS

While performance metrics such as energy efficiency and analog precision often dominate laboratory-scale demonstrations, factors such as long-term reliability, environmental sustainability, and overall technology readiness ultimately determine the practical viability of neuromorphic resistive switching devices. In this section, we bring together the key failure mechanisms, sustainability considerations, and commercialization aspects within a unified assessment framework. A projected technology readiness roadmap for major material platforms is provided in Supplementary Figure S2.

The trilemma shown in Figure 5 highlights the inherent difficulty in simultaneously optimizing performance, reliability, and sustainability.

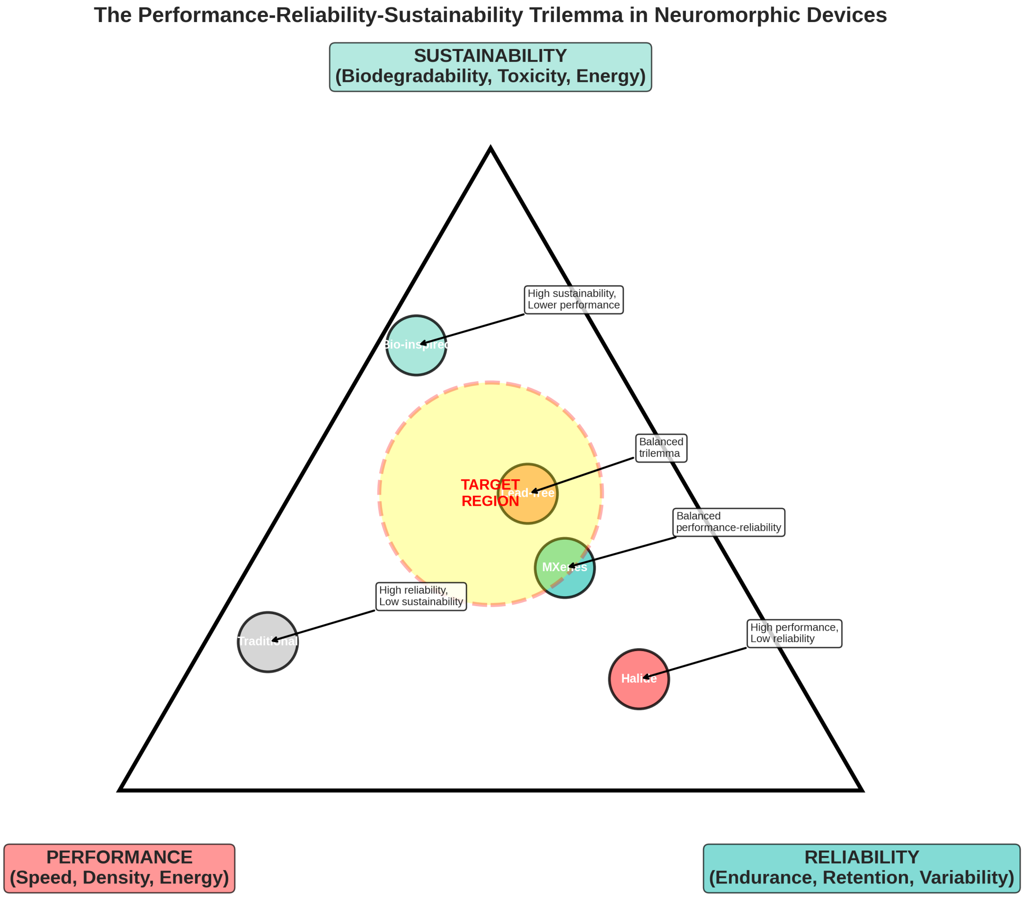


FIG. 5. Conceptual illustration of the performance–reliability–sustainability trilemma in neuromorphic resistive switching devices. Different material platforms occupy distinct regions of the design space, highlighting the absence of a universally optimal solution and motivating application-specific optimization.

### 5.1. Reliability Challenges and Failure Mechanisms

Reliability continues to be a major barrier to the large-scale deployment of neuromorphic resistive switching devices. Across different switching mechanisms and material platforms, the dominant failure modes are typically associated with stochastic ionic transport, structural degradation, and thermal effects [35].

Device-to-device and cycle-to-cycle variability are particularly pronounced in filamentary switching mechanisms, where the formation of conductive paths is highly sensitive to local defect distributions and interfacial conditions. Such variability can significantly impact neural network inference accuracy and often requires compensation strategies, including write–verify schemes or algorithm-level noise tolerance. Retention degradation presents an additional challenge, especially in electrochemical metallization and perovskite-based systems, where spontaneous filament dissolution and ion back-diffusion lead to gradual conductance drift over time.

Endurance limitations generally arise from irreversible material changes, such as ion accumulation, phase segregation, and interfacial reactions. In contrast, ferroelectric and interface-dominated mechanisms tend to exhibit improved endurance, primarily due to the absence of mass transport. However, these systems are not free from reliability concerns, as effects such as fatigue and wake-up behavior can still impact long-term performance. Thermal effects further aggravate these issues by accelerating diffusion processes, inducing cross-talk in densely packed arrays, and, in some cases, triggering runaway degradation under repeated cycling. A comprehensive overview of failure mechanisms across different switching platforms is provided in Table S2 of the Supplementary Information.

### 5.2. Mitigation Strategies and Design Implications

Addressing reliability limitations requires a mechanism-aware design approach rather than relying solely on material substitution. Confining the switching volume through scaled device geometries and engineered interfaces can help reduce stochastic behavior [36], although this often comes at the cost of increased fabrication complexity. In valence change systems, incorporating material stacks with oxygen or ion reservoirs has been shown to improve retention, while the use of encapsulation layers can slow down environmental degradation in moisture-sensitive materials.

At the circuit level, techniques such as adaptive programming, current compliance control, and periodic refresh operations can extend device lifetime, albeit with trade-offs in energy consumption and latency. In addition, algorithm-level tolerance to device non-idealities offers a complementary strategy, allowing acceptable system performance even in the presence of imperfect hardware. These considerations highlight the importance of a co-design approach that integrates materials, devices, circuits, and algorithms.

### 5.3. Sustainability and Environmental Constraints

As neuromorphic hardware progresses toward commercialization, sustainability considerations are becoming increasingly important in guiding material and process selection. Many high-performance resistive switching materials rely on scarce or toxic elements, which raises concerns related to regulatory compliance and environmental impact [37]. In addition, energy-intensive fabrication processes contribute significantly to the overall carbon footprint of neuromorphic systems.

Emerging sustainable material platforms, including bio-inspired and biodegradable systems, offer advantages such as reduced toxicity and improved end-of-life disposal. However, these materials currently lag behind in terms of electrical performance and reliability. As a result, sustainability introduces an additional dimension to the design space, requiring careful balance with performance and stability rather than being treated as a secondary consideration. Hybrid strategies, for instance combining high-performance inorganic switching layers with environmentally benign encapsulation or substrate materials, may provide a practical compromise.

### 5.4. Technology Readiness and Commercialization Outlook

TTechnology readiness varies significantly across different resistive switching platforms. Oxide-based valence change memory and ferroelectric devices currently exhibit the highest level of maturity, supported by well-established fabrication processes and compatibility with existing semiconductor manufacturing infrastructure [38, 39]. In contrast, emerging platforms such as halide perovskites, MXenes, and bio-inspired systems are still at relatively early stages of development, with ongoing challenges related to stability, scalability, and reproducibility.

Successful commercial deployment also depends on factors such as seamless integration with peripheral circuitry, high yield at scale, and cost competitiveness with conventional CMOS-based technologies. Neuromorphic applications that can tolerate moderate endurance requirements or operate under controlled conditions may adopt emerging material systems earlier, whereas applications demanding high reliability are more likely to rely on mature oxide and ferroelectric technologies. Bridging the gap between laboratory-scale demonstrations and practical hardware deployment therefore requires a realistic assessment of technology readiness, alongside continued progress in materials development and device engineering.

## 6. OPEN CHALLENGES AND FUTURE DIRECTIONS

Despite substantial progress in materials, device engineering, and neuromorphic demonstrations, several fundamental challenges still limit the scalability, reliability, and practical adoption of resistive switching technologies. Addressing these issues requires moving beyond incremental improvements toward more comprehensive, mechanism-aware and system-level approaches.

### 6.1. Fundamental Physics Challenges

**Control of stochastic ionic dynamics.** In filamentary switching mechanisms, stochastic ion migration and the evolution of conductive filaments fundamentally limit device uniformity and analog precision [40–42]. Developing approaches to achieve more deterministic control over ion transport—through defect engineering, interface optimization, or spatial confinement—remains a key challenge.

**Energy–retention–endurance trade-off.** Ultra-low-energy switching typically relies on nanoscale conductive paths that are inherently unstable, which in turn leads to limited retention and endurance. Identifying mechanisms or material systems that can alleviate this trade-off without compromising energy efficiency remains an open problem.

**Scaling limits and nanoscale variability.** As device dimensions are aggressively reduced, sensitivity to atomic-scale defects, surface effects, and quantum transport phenomena becomes increasingly pronounced. Understanding how variability evolves at dimensions below the 10 nm regime is therefore critical for the development of high-density neuromorphic systems.

**Thermal effects in dense arrays.** In large crossbar arrays, self-heating and thermal cross-talk can significantly influence device behavior. Developing predictive thermal models that couple electrical, thermal, and material responses is essential for guiding array-level design.

**Interfacial stability and degradation.** A significant fraction of device failure mechanisms originates at metal–insulator interfaces, including interfacial reactions, ion accumulation, and barrier modification. Achieving long-term interfacial stability under repeated electrical stress remains an important and not yet fully understood challenge.

**Mechanism identification and characterization.** For many emerging material systems, switching mechanisms are often inferred indirectly rather than directly observed.

Advanced *in situ* and *operando* characterization techniques are therefore needed to clearly identify the dominant physical processes and support more rational device optimization.

### 6.2. Materials and Device Engineering Directions

Future materials research should place greater emphasis on stability, reproducibility, and process compatibility in addition to conventional performance metrics. Instead of focusing solely on achieving isolated record values, attention needs to shift toward material systems that demonstrate consistent and statistically uniform behavior across large populations of devices. Hybrid material stacks, which can help decouple energy efficiency from retention and endurance, represent a promising direction, although they often introduce additional fabrication complexity [43].

From a device engineering perspective, greater focus is required on architecture-level solutions, including three-dimensional integration, selector optimization, and effective thermal management. The co-optimization of switching layers, electrodes, and surrounding circuitry will be critical for translating material-level advances into scalable and reliable neuromorphic hardware.

### 6.3. System-Level and Application-Oriented Perspectives

At the system level, hardware–algorithm co-design offers a significant opportunity to mitigate the impact of device non-idealities [44]. Neural network models that explicitly incorporate factors such as device variability, noise, and limited precision can relax stringent hardware requirements and broaden the feasible design space.

Application-specific neuromorphic systems may also benefit from heterogeneous memory architectures, where different switching mechanisms are employed for short-term plasticity, long-term storage, and inference tasks. Such hybrid strategies reflect the absence of a universal device solution and enable better alignment between hardware capabilities and application-specific requirements.

### 6.4. Toward Deployable Neuromorphic Hardware

Ultimately, progress in neuromorphic resistive switching technologies should be assessed in the context of realistic deployment scenarios rather than relying solely on laboratory benchmarks. This requires careful consideration of factors such as operating conditions, device lifetime requirements, manufacturability, and sustainability. By aligning future research efforts with these practical constraints, the field can move beyond proof-of-concept demonstrations toward the development of robust, application-ready neuromorphic hardware platforms.

## 7. CONCLUSION

Resistive switching devices provide a promising hardware platform for neuromorphic computing, offering advantages such as scalability, low power consumption, and the ability to emulate key synaptic functions. However, the wide range of switching mechanisms and material systems introduces fundamental trade-offs that cannot be addressed through material optimization alone. In the absence of a clear linkage between switching physics and system-level requirements, progress risks remaining fragmented and largely confined to laboratory-scale demonstrations. Establishing a strong connection between device-level physics and system-level demands is therefore essential for the practical realization of neuromorphic hardware.

In this review, we have proposed a mechanism-guided decision-making framework that directly connects resistive switching physics with performance trade-offs, reliability considerations, sustainability factors, and technology readiness. Through a quantitative analysis of 293 studies, we demonstrate that no single switching mechanism can simultaneously optimize energy efficiency, retention, endurance, and analog precision. Instead, the development of viable neuromorphic hardware requires an application-driven approach to mechanism selection and device engineering.

By examining emerging material platforms including halide perovskites, MXenes, and bio-inspired systems, we identify both their opportunities and inherent limitations, highlighting the need to prioritize stability, reproducibility, and manufacturability alongside peak performance metrics. Importantly, sustainability and environmental considerations are treated here as integral design constraints rather than secondary factors.

The design rules and operational workflows introduced in this work provide practical guidance for navigating the complex design space of neuromorphic resistive switching devices. By emphasizing mechanism-level screening at an early stage and promoting co-design across materials, devices, circuits, and algorithms, the proposed framework supports the transition from proof-of-concept demonstrations to robust and deployable neuromorphic hardware. We expect that this mechanism-centric perspective will help guide future research and contribute to the development of scalable, reliable, and sustainable neuromorphic computing systems.

## SUPPORTING INFORMATION

Supporting Information is available and includes additional comparative analyses and technology readiness projections.

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## AUTHOR CONTRIBUTIONS

**Karuna Kumari**: Conceptualization, literature survey, review and analysis of the published literature, manuscript writing, editing, and overall supervision of the study.

**Shobha Kumari**: Data analysis, figure preparation and visualization, manuscript review, and contribution to the interpretation of results.

All authors reviewed and approved the final manuscript.

## CONFLICT OF INTEREST

The author(s) declare no conflict of interest.

## DATA AVAILABILITY

No new data were created or analyzed in this study. Data sharing is not applicable to this article as no datasets were generated or analyzed during the current study.

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