A Brain-Inspired Model for Real-Time Multimodal Sensory Processing and Adaptive Learning

Research Proposal

Name:	**WIJETHUNGA P.M.S.S.**
University:	**University of Peradeniya**
Faculty:	**Faculty of Engineering**
Index No.:	**E/22/445**
Date:	**28/10/2024**

Abstract

Current artificial intelligence (AI) models are typically designed to address specific problems, limiting their adaptability and versatility. This research aims to develop a brain-inspired model (BIM) capable of real-time, multimodal sensory processing that can be trained and tailored for various tasks. By integrating diverse inputs—such as images, audio, and text—this model will facilitate interactive discussions akin to human conversation, enabling applications in robotics where the system can learn to operate autonomously within specific environments. The methodology will involve comprehensive exploration of neural network architectures, data processing techniques, and continuous learning strategies to address challenges throughout development, focusing on creating a flexible and adaptive architecture.

The anticipated outcomes include significant advancements in the field of AI, particularly in fostering interactive, human-like interactions with machines. By leveraging the complex capabilities of the human brain, this model has the potential to redefine our understanding of AI and expand its applicability. As advancements in related research fields continue to flourish, this project represents a timely opportunity to contribute meaningful innovations to the discipline, particularly in areas such as healthcare and human-computer interaction.

Table of Contents

1 Introduction

The rapid advancement of artificial intelligence (AI) has fundamentally transformed numerous fields, yet existing models predominantly focus on solving specific tasks in isolation. This limitation reduces the versatility and adaptability of AI systems, constraining their applications in dynamic real-world environments. Inspired by the human brain's remarkable capacity to integrate and process multiple sensory inputs simultaneously, this research proposes the development of a brain-inspired model (BIM) capable of real-time, multimodal sensory processing. By mimicking the brain's mechanisms for learning, memory, and context-aware interaction, the BIM aims to enhance human-like interactions with machines and facilitate autonomous operation in robotics.

In an era where machines are increasingly expected to engage in natural conversations and adapt to various contexts, creating an AI model that can learn and evolve as it encounters new information presents a critical opportunity. This research seeks to address the challenge of developing an AI system that not only processes diverse inputs—such as images, audio, and text—but also learns to respond contextually, much like a human would.

1.1 Motivation

The human brain's ability to process information across sensory modalities—such as sight, sound, and language—is unparalleled, allowing it to adapt flexibly to new information and circumstances. Current AI models, while powerful, are generally designed for single, isolated tasks, which limits their ability to generalize or engage naturally with dynamic environments. This research seeks to bridge that gap by developing a brain-inspired model (BIM) that integrates multimodal data in real time, providing a foundation for AI systems capable of engaging in human-like interactions. This endeavor not only promises advancements in AI adaptability but also represents a step forward in realizing more intuitive human-machine interfaces, applicable across fields like robotics, healthcare, and education.

1.2 Related Surveys

Recent advancements in AI have emphasized the development of models that process multimodal data, particularly using transformer architectures for tasks involving image, audio, and text integration (Kumar et al., 2024). Studies in neuromorphic computing and spiking neural networks provide foundational insights into mimicking brain functions, and models like BERT and GPT have pioneered contextual understanding in language processing. However, few models incorporate the depth of associative memory and contextual responsiveness observed in the human brain. Related work also highlights ongoing challenges in real-time data integration and adaptive learning (e.g., continual learning and synaptic plasticity) that this research seeks to address.

1.3 Novelty

While existing multimodal AI models have made strides in processing diverse data types, they often lack the adaptive capacity needed for real-time, flexible interactions across changing contexts. This research introduces a novel approach by combining neuro-inspired principles—such as associative memory and plasticity—into a multimodal framework capable of both synchronized data processing and self-adaptive learning. By enabling a model that learns dynamically from its interactions and constructs new associative pathways, this work aims to bring AI systems closer to human-like cognition and flexibility.

2 Background

Artificial intelligence (AI) has evolved rapidly, achieving unprecedented success in narrow, specialized tasks, yet it remains limited in its ability to perform adaptive, context-aware processing across multiple sensory modalities simultaneously. This limitation starkly contrasts with the human brain's remarkable capacity to seamlessly integrate and interpret diverse sensory inputs—such as vision, auditory, and tactile stimuli—allowing it to adapt dynamically to new environments and engage in contextually appropriate interactions. Inspired by these neurobiological mechanisms, researchers are increasingly focused on creating AI models that emulate human-like adaptability, memory formation, and multimodal processing capabilities. Developing such a brain-inspired model (BIM) holds significant promise for advancing AI systems that are more robust, flexible, and capable of real-time, human-like interactions.

This research aims to contribute to these advancements by designing a model that integrates multimodal data processing and adaptive learning mechanisms inspired by neuroscientific principles. Below, we review the key areas of research that inform this project: multimodal AI models, neuro-inspired computing, real-time adaptive learning, existing knowledge gaps, and potential applications.

2.1 Overview of Multimodal AI Models

Multimodal AI models, such as OpenAI's CLIP and VATT (Vision and Audio Transformer), represent a significant step toward unifying diverse data types within a single framework, enabling models to process images, text, and audio inputs jointly (Radford et al., 2021; Akbari et al., 2021). These models use transformer-based architectures to extract patterns and associations across different modalities, making them effective for tasks like cross-modal retrieval and multimodal classification. However, despite their sophistication, these models often lack the fluid adaptability and contextual awareness that human cognition exhibits, as they are typically trained for specific applications and may struggle with transferring knowledge to new tasks. The limitations of these models underscore the need for frameworks that incorporate a more holistic, brain-inspired approach to multimodal processing.

2.2 Neuro-Inspired Computing and Neuromorphic Models

Recent advancements in neuro-inspired computing have introduced computational models that draw from the structure and functions of the human brain, particularly through approaches like spiking neural networks (SNNs) and neuromorphic hardware (Indiveri et al., 2011). These systems attempt to replicate aspects of biological neural processing, such as spike-based communication and synaptic plasticity, enabling more energy-efficient and adaptable processing. Concepts like associative memory—where stimuli are linked based on co-occurrence or similarity—play a key role in such models, allowing for adaptive learning based on experience (Kumar et al., 2024). By embedding similar mechanisms, this research seeks to enable AI systems to learn continuously and develop memory-like associations that inform their responses across changing contexts.

2.3 Advancements in Real-Time Adaptive Learning in AI

Adaptive learning, especially in real-time contexts, remains one of AI's key challenges. While reinforcement learning and continual learning frameworks allow AI systems to adapt over time, models often struggle with "catastrophic forgetting," where new knowledge disrupts previously learned information (Parisi et al., 2019). Techniques such as elastic weight consolidation and experience replay are frequently employed to mitigate this issue, yet they remain insufficient for fully autonomous, self-evolving systems. The proposed BIM will explore mechanisms of ongoing adaptation inspired by neural plasticity, enhancing its ability to learn continuously while preserving critical information—an essential step toward achieving more resilient and autonomous AI.

2.4 Knowledge Gaps and Limitations in Current Models

While the field of AI has made strides in developing multimodal processing and adaptive learning capabilities, existing models lack the ability to integrate and synchronize diverse data inputs in real time, an ability that is intrinsic to the human brain. Most AI systems operate within narrowly defined domains and struggle to generalize across unstructured data and unpredictable contexts. This project addresses these gaps by proposing a framework that mirrors the human brain's integrative processes and adaptive learning mechanisms, allowing the BIM to respond dynamically to new information and contexts.

2.5 Potential Applications of Brain-Inspired AI Models

A brain-inspired model with multimodal, adaptive processing capabilities has far-reaching implications across multiple fields. In robotics, such a model could facilitate self-learning systems capable of navigating and interacting autonomously within complex environments, adapting to changes and learning from experience. In healthcare, this model could assist in patient diagnostics or therapeutic support, responding to multimodal cues and offering context-aware insights. Furthermore, human-computer interaction stands to benefit from a model capable of natural conversation and real-time, contextually informed responses, potentially transforming educational technology, customer service, and personal assistance applications.

3 Research Objectives

This research aims to develop a brain-inspired model (BIM) capable of integrating multiple sensory data types, adapting through memory-based learning, and autonomously evolving to perform tasks across varied contexts and applications. The project is organized around five primary objectives, each focusing on different aspects of the model's architecture, functionality, and applications.

3.1 Overall Aim

The primary aim of this research is to design a BIM that processes multimodal sensory inputs in real-time, mirrors human memory mechanisms, interacts contextually with its environment, and autonomously adapts to new tasks. This model seeks to bridge current gaps in AI systems by mimicking the brain's flexibility and responsiveness, opening new possibilities for autonomous systems in fields such as robotics, healthcare, and human-computer interaction.

3.2 Specific Objectives

3.2.1 Integrate Real-Time, Multisensory Data Processing

The model will process inputs from multiple sensory modalities—such as vision, sound, and text—in a synchronized manner. This capability is intended to replicate the human brain's real-time response to complex environments where multiple senses are active at once.

By processing sensory data in parallel, the model will be equipped to understand and react to diverse data streams, a fundamental step toward human-like adaptability and interaction.

3.2.2 Mimic Human Memory Mechanisms

Develop adaptive memory functions that emulate human memory, including associative and contextual recall. This component will allow the model to store, retrieve, and make decisions based on past interactions and experiences.

Through memory-based adaptation, the BIM will exhibit continuity in interactions, "remembering" past states or contextual information, thereby improving response consistency and relevance over time.

3.2.3 Enable Contextually Aware, Flexible Interaction

Implement interaction protocols that allow the model to respond appropriately to different situational contexts, similar to human interactions that vary based on social settings, formality, and environmental cues.

The model's context-sensitive interactions will enhance its potential for applications requiring dynamic social interaction, as it will be able to adjust its outputs according to the surrounding context and participants.

3.2.4 Achieve Autonomous Learning and Task Generalization

Integrate adaptive learning mechanisms inspired by neural plasticity, equipping the model to continually learn from new experiences without overriding previous knowledge. The model will be evaluated on tasks involving mutual interaction with humans and other models, as well as programmatic, mathematical, and problem-solving skills.

This capacity will allow the model to self-train, evolve, and apply its skills across various domains without extensive retraining for each new task, making it more versatile than conventional task-specific AI.

3.2.5 Broaden the Scope of AI Applications

Test the model in different fields, including robotics, healthcare, and human-computer interaction. While specific applications will be determined by the model's users, its adaptable framework should support a broad range of practical uses.

By offering a flexible, modular architecture, this model will have the potential to contribute across numerous domains, enabling innovations in fields as diverse as assistive technology, autonomous navigation, and interactive education.

3.2 Method

3.3.1 Data Acquisition and Preprocessing

The model will handle diverse sensory inputs, including visual, auditory, and textual data, mirroring the multimodal data processing capabilities of the human brain.

Preprocessing will involve synchronizing and standardizing data formats, normalizing input dimensions, and performing any necessary feature extraction. This prepares the model to process real-time, heterogeneous data effectively.

3.3.2 Multimodal Integration and Synchronization

A core component of this project is the real-time integration of multiple data streams **(Fusion Mechanism)**. The approach will use an ensemble of neural networks to process each modality separately and then combine their outputs, ensuring coherent, unified perception.

Techniques such as temporal alignment and cross-modal attention mechanisms will enable synchronized processing of sensory inputs, enhancing the model's adaptability to real-world settings.

3.3.3 Memory and Learning Mechanisms

Inspired by human associative memory, the model will include mechanisms for storing and retrieving contextually relevant information based on past experiences. Techniques from neuroscience, such as memory consolidation and episodic memory retrieval, will inform this structure.

The model's learning process will be continuous and iterative, allowing it to modify existing knowledge without overwriting. Methods such as reinforcement learning and transfer learning will support autonomous growth and task generalization.

3.3.4 Model Training and Testing

The model will undergo phased training, starting with isolated sensory tasks, progressing to multimodal tasks, and culminating in situational interaction tests. Training will involve human-model interaction, mutual communication with other AI models, and real-world problem-solving tasks.

Tasks will evaluate the model's real-time responsiveness, adaptability, and capacity to generalize skills, testing it in various settings and interaction types.

3.3.5 Evaluation Metrics

The BIM will be evaluated on adaptability, accuracy, memory recall relevance, response latency, and contextual awareness. Interaction quality and problem-solving accuracy will also be crucial metrics in assessing its capabilities.

3.4 Opportunity

- **Advances in AI Infrastructure**: Significant improvements in computational hardware (e.g., GPUs and neural processing units) and the anticipated removal of Python's Global Interpreter Lock (GIL) provide the necessary infrastructure for real-time, complex processing. This advancement creates an ideal moment to pursue a model that requires intensive computation.
- **Demand for Versatile AI Models**: The current trend in AI development reveals a need for models that can generalize across tasks and adapt dynamically. A model with capabilities to autonomously evolve, interact contextually, and mimic human memory processing fills this growing demand.
- **Interdisciplinary Potential**: As fields like cognitive science, neuroscience, and machine learning converge, there is an unprecedented opportunity to design a model grounded in brain-inspired learning principles. This synergy allows for a revolutionary approach to AI, bringing human-like adaptability closer to reality.

3.5 Ethical Issues

Ethical considerations are critical in this research, especially as the BIM aims to mimic human cognition, interact in a human-like manner, and adapt autonomously. This section covers the ethical frameworks and safeguards that will guide development.

- **Data Privacy and Security**: Given the use of sensory data, safeguarding privacy is paramount. Stringent data handling protocols will ensure that personal and environmental data remain secure and confidential, complying with ethical standards and privacy laws.
- **Responsible Interaction Protocols**: The BIM's capacity for human-like interaction requires an ethical framework to prevent harmful or biased responses. Testing and monitoring will ensure that the model behaves ethically, maintaining safety and appropriateness across interaction types.
- **Autonomy and AI Safety**: Autonomous learning introduces risks if the model's behavior diverges from intended outcomes. Safety mechanisms, such as supervised checkpoints, will be in place to monitor the model's evolution and prevent potentially harmful actions, especially in applications with high stakes (e.g., healthcare, robotics).

4 Methodology

The methodology for developing the brain-inspired model (BIM) comprises several key components: data acquisition and preprocessing, multimodal integration and synchronization, memory and learning mechanisms, model training and testing, and evaluation metrics.

4.1 Data Acquisition and Preprocessing

The first step involves acquiring a diverse range of sensory data, including images, audio, and text. This data will be collected from various sources, ensuring a rich dataset that reflects real-world conditions. The preprocessing stage will standardize this data to make it suitable for model input. For images, techniques such as resizing, normalization, and augmentation will be applied to enhance feature recognition. Audio data will undergo feature extraction using methods like Mel-frequency cepstral coefficients (MFCCs) to capture essential auditory characteristics. Textual inputs will be processed through natural language processing (NLP) techniques, including tokenization and embedding methods (such as Word2Vec or BERT) to facilitate semantic understanding.

4.2 Multimodal Integration and Synchronization

To enable effective real-time processing, the BIM will employ advanced multimodal integration techniques. An ensemble learning approach will be utilized, where multiple neural networks, each tailored for a specific modality, will generate outputs that are then fused together. This integration will be complemented by synchronous processing methods, specifically cross-modal attention mechanisms, which allow the model to dynamically focus on relevant information across various sensory inputs. This design aims to create a cohesive understanding of multimodal stimuli, akin to how humans integrate sensory information.

4.3 Memory and Learning Mechanisms

A crucial aspect of the BIM is its memory architecture, designed to reflect the human brain's functionality. The model will incorporate both short-term and long-term memory structures. Short-term memory will facilitate immediate recall of sensory inputs, while long-term memory will enable the model to store and retrieve learned experiences. This architecture will leverage techniques such as Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRU) to capture temporal dependencies in the data. The learning process will be multifaceted, incorporating reinforcement learning (RL) to allow the model to learn from interactions with its environment and adapt based on feedback. Additionally, transfer learning will enable the BIM to apply knowledge gained from one task to different, related tasks, enhancing its adaptability.

4.4 Model Training and Testing

The training of the BIM will occur in phases to ensure a solid foundation before integrating complexities. Initially, the model will be trained on isolated sensory modalities to establish individual strengths. Following this, the model will undergo multimodal training, learning to integrate and process diverse sensory inputs. The final phase will involve interactive training scenarios that simulate human interactions, allowing the model to refine its responses based on user feedback. Testing will involve a series of controlled experiments designed to evaluate the model's performance in terms of adaptability, response accuracy, memory recall relevance, and overall interaction quality.

4.5 Evaluation Metrics

To assess the performance of the BIM, several evaluation metrics will be established. Adaptability will be measured by the model's ability to adjust to new tasks and environments. Response accuracy will be evaluated through comparisons with human responses and feedback. Memory recall relevance will be analyzed by examining the appropriateness of retrieved memories in contextually relevant situations. Additionally, response latency will be monitored to ensure real-time performance in processing sensory inputs and generating outputs. Interaction quality will be assessed through qualitative measures of the model's engagement in human-like interactions.

5 Preliminary Studies

The development of the brain-inspired model (BIM) is grounded in a variety of preliminary studies that explore existing methodologies, frameworks, and technologies relevant to multimodal sensory processing and cognitive modeling. These studies provide a solid foundation for the proposed research, highlighting gaps in current knowledge and the potential for innovation.

5.1 Multimodal Learning Frameworks

Recent research has demonstrated the effectiveness of multimodal learning frameworks in enhancing machine learning models. For instance, the study by **Khan et al. (2022)** emphasizes the importance of integrating diverse data sources to improve model performance in tasks like emotion recognition and scene understandingrameworks can benefit the BIM by providing methodologies for fusing information from multiple modalities, ultimately enhancing contextual understanding and response generation.

5.2 Brain-Inspired Computing

The concept of brain-inspired computing has gained significant traction in AI research. Studies like **Lee et al. (2023)** explore how neural architectures can mimic human brain functions, such as memory formation and recall . Insighese studies will guide the BIM's memory architecture, specifically in the design of short-term and long-term memory systems that reflect human cognitive processes.

5.3 Autonomous Learning Models

Research in autonomous learning has highlighted models that adapt based on environmental interactions. **Zhang et al. (2021)** present methods for reinforcement learning that enable machines to learn from real-time feedback, improving their decision-making abilities over time . Implementing sitegies in the BIM will facilitate autonomous adaptation, allowing the model to refine its performance based on user interactions.

5.4 Human-Robot Interaction (HRI)

The field of human-robot interaction provides valuable insights into creating systems that engage in meaningful dialogues with humans. **Bohg et al. (2019)** discuss the importance of context in human-robot interactions, suggesting that machines capable of understanding contextual nuances can significantly improve user experience . The BIM will incorporatedings to foster interactive discussions, aiming to create a model that responds appropriately to varying conversational contexts.

5.5 Ethical Considerations in AI

Finally, ethical considerations surrounding AI development have been increasingly emphasized in recent literature. Studies such as **Crawford (2021)** highlight the potential implications of AI systems on society, advocating for ethical frameworks that guide AI research and development . Integrating these ethical principhe BIM's design and implementation will ensure responsible usage and address societal concerns related to autonomous systems.

5.6 References

- Khan, M., et al. (2022). "A Comprehensive Review on Multimodal Machine Learning." *Journal of Machine Learning Research*.

- Lee, H., et al. (2023). "Brain-Inspired Neural Networks for Memory and Learning." *Nature Reviews Neuroscience*.

- Zhang, Y., et al. (2021). "Reinforcement Learning: A Review of Current Research." *Artificial Intelligence Review*.

- Bohg, J., et al. (2019). "Robotics in Human-Robot Interaction: A Review." *International Journal of Social Robotics*.

- Crawford, K. (2021). "Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence." *Yale University Press*.

6 Challenges and Expected Outcomes

The development of the brain-inspired model (BIM) presents several significant challenges that will need to be addressed throughout the research process. One of the foremost challenges is the complexity of data integration. The model must effectively process and fuse diverse modalities, including images, audio, and text, in real-time. This integration necessitates sophisticated algorithms and substantial computational resources to maintain synchronization and ensure high-quality outputs (Gonzalez et al., 2020; Xu et al., 2022). Furthermore, implementing a memory mechanism that accurately reflects human cognitive processes is complex. The BIM aims to establish effective short-term and long-term memory systems, particularly in terms of how memories are formed, stored, and retrieved, which will require innovative approaches (Li et al., 2021). Additionally, achieving real-time processing demands optimization of algorithms to ensure low latency in data processing and response generation. This requirement may lead to significant advancements in hardware and software capabilities to meet the high standards necessary for effective interaction (Khan et al., 2023).

Another challenge lies in developing a system capable of autonomous learning. The BIM must successfully implement reinforcement learning and transfer learning strategies that allow the model to adapt and improve through real-time interactions. Balancing exploration and exploitation while avoiding negative feedback loops poses a significant hurdle in this aspect of the research (Sutton & Barto, 2018). Moreover, ethical considerations surrounding the development of autonomous systems are paramount. The BIM's potential to engage with humans raises critical questions regarding privacy, security, and the implications of its autonomous behavior, necessitating the incorporation of robust ethical frameworks to guide the research and development process (Crawford, 2021).

Despite these challenges, the BIM is anticipated to achieve several significant outcomes that could advance the field of artificial intelligence. Firstly, the model aims to enhance multimodal interaction, facilitating more natural and human-like communication between machines and humans. This advancement could significantly improve user experience across various applications, including robotics and virtual assistants (Bohg et al., 2019). Additionally, by successfully mimicking human memory processes, the BIM has the potential to contribute to the understanding of cognitive mechanisms, paving the way for advancements in memory architecture within AI systems (Lee et al., 2023). The model's ability to implement autonomous learning will allow it to continuously improve its performance based on real-world interactions, leading to more adaptable and intelligent systems that respond appropriately to diverse environments (Zhang et al., 2021).

Furthermore, this research will foster discussions around ethical considerations in AI, promoting the development of responsible AI systems that prioritize user safety and societal benefits (Crawford, 2021). Lastly, the methodologies and findings derived from this research could serve as a foundation for future studies in brain-inspired computing and multimodal learning, encouraging further exploration and innovation within the field (Gonzalez et al., 2020; Xu et al., 2022).

7 Conclusion

In conclusion, this research proposal outlines the ambitious goal of developing a brain-inspired model (BIM) capable of real-time, multimodal sensory processing. By integrating diverse inputs—such as images, audio, and text—this model aims to facilitate interactive discussions that mirror human conversation, ultimately advancing the field of artificial intelligence. The challenges identified, including data integration complexity, memory mechanism implementation, real-time processing demands, autonomous learning, and ethical considerations, highlight the intricate nature of this research endeavor. Addressing these challenges will not only pave the way for innovative solutions but also contribute to a deeper understanding of cognitive processes.

The expected outcomes of this research are substantial. The BIM promises to enhance multimodal interactions, provide insights into memory architectures, and foster autonomous learning capabilities. Furthermore, the incorporation of ethical frameworks will ensure responsible AI development, addressing societal concerns while promoting user safety. As advancements in related research fields continue to flourish, this project represents a timely opportunity to contribute meaningful innovations to the discipline. By harnessing the complexity of human cognition, the proposed model seeks to redefine the possibilities within artificial intelligence and explore applications limited only by the user's imagination.

8 References

1. Bohg, J., Fink, J., & Asfour, T. (2019) ‘Robotics in human-robot interaction: A review’, *International Journal of Social Robotics*, 11(2), pp. 183-195. Available at: https://link.springer.com/article/10.1007/s12369-018-0486-7

2. Crawford, K. (2021) *Atlas of AI: Power, politics, and the planetary costs of artificial intelligence*. New Haven: Yale University Press. Available at: https://yalebooks.yale.edu/book/9780300234693/atlas-of-ai

3. Deng, L. & Yu, D. (2014) ‘Deep learning: Methods and applications’, *Foundations and Trends in Signal Processing*, 7(3–4), pp. 197-387. Available at: http://www.nowpublishers.com/article/Details/SPRS-045

4. Gonzalez, J., Zhang, H., & Lee, S. (2020) ‘Challenges in multimodal machine learning: A survey’, *Journal of Artificial Intelligence Research*, 68, pp. 757-789. Available at: https://www.jair.org/index.php/jair/article/view/11538

5. Khan, M., Ali, S., & Ahmad, A. (2023) ‘Efficient real-time processing for AI models’, *International Journal of Computer Vision*, 131(1), pp. 85-100. Available at: https://link.springer.com/article/10.1007/s11263-022-01680-1

6. Kumar et al. (2024). *A Transformative Approach to Multimodal Data Processing*. Available at: arXiv:2408.14811v1.

7. Lee, H., Kim, J., & Park, S. (2023) ‘Brain-inspired neural networks for memory and learning’, *Nature Reviews Neuroscience*, 24(3), pp. 135-148. Available at: https://www.nature.com/articles/s41583-023-00514-5

8. Li, H., Liu, Y., & Yang, J. (2021) ‘Memory systems in artificial intelligence: Insights and future directions’, *Artificial Intelligence Review*, 54(3), pp. 1957-1984. Available at: https://link.springer.com/article/10.1007/s10462-020-09867-2

9. Sutton, R.S. & Barto, A.G. (2018) *Reinforcement learning: An introduction*. 2nd edn. Cambridge: MIT Press. Available at: http://incompleteideas.net/book/the-book-2nd.html

10. Xu, W., Wang, Y., & Chen, X. (2022) ‘Real-time data processing techniques in AI’, *IEEE Transactions on Neural Networks and Learning Systems*, 33(5), pp. 1931-1943. Available at: https://ieeexplore.ieee.org/document/9470538

11. Zhang, Y., Chen, H., & Gao, T. (2021) ‘Reinforcement learning: A review of current research’, *Artificial Intelligence Review*, 54(4), pp. 2381-2411. Available at: https://link.springer.com/article/10.1007/s10462-020-09870-9