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A Neuro-Symbolic AI Approach to Understanding Brain Regions Involved in the Flow State

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Abstract: Artificialintelligence continues to advance rapidly and reshape many areas of modern life, the human brain remains one of the most complex and least understood systems. Among its many mental states, the flow state is particularly notable. Marked by deep focus, high productivity, and seemingly effortless task performance, it represents a fascinating yet still insufficiently explored phenomenon in neuroscience.

This research paper examines the key brain regions involved in achieving and sustaining the flow state, with focused attention on the precuneus, posterior cingulate gyrus, middle cingulate gyrus, and the inferior temporal gyrus. It also studies how neuro-symbolic AI an approach that integrates neural learning with symbolic reasoning can be used to examine and interpret patterns of activity across these regions. By bringing together insights from cognitive neuroscience and hybrid AI methodologies, this work aims to deepen the understanding of the neural foundations of flow and to propose computational approaches that may ultimately help enhance understanding of human brain.

Keywords: Precuneus, Posterior Cingulate Gyrus, Middle Cingulate Gyrus, Inferior Temporal Gyrus, Flow State, Neuro-Symbolic AI, Cognitive Neuroscience, Default Mode Network,Convolutional Neural Networks,Graph Neural Networks, Region of Interest ,Human Connectome Project.

I. INTRODUCTION

The exponential growth of artificial intelligence (AI) has led to advancements across scientific, industrial, and social domains [4]. Despite the progress in computational intelligence, the human brain remains one of the most complicated and not yet fully understood biological systems. Understanding how the brain generates complex mental states is essential for both neuroscience and AI research, especially when these states are closely linked to human life.One such state is the flow state. A psychological condition in which an individual experiences deep concentration, internal motivation, and seamless task execution. It was first introduced in psychological literature by MihalyCsikszentmihalyi, the flow state has since been associated with enhanced creativity, improved cognitive control, and peak productivity [1]. But still the neural mechanisms that enable this state remain an active area of investigation. Available neuroscience studies suggest that regions such as the precuneus, posterior cingulate gyrus, middle cingulate gyrus, and inferior temporal gyrus play important roles in attentional regulation, self referential processing, and the integration of sensory information. All of which are vital components of the flow experience [3][5].

While traditional neuroscience methods have provided valuable insights, they often struggle to capture the dynamic, multilayered patterns of brain activity that emerge during complex mental states. Recent advancements in AI offer new opportunities to examine neural data, but purely neural or purely symbolic approaches are limited in their ability to represent both high dimensional signals and structured cognitive information.Neuro-symbolic AI, a hybrid framework that combines data driven neural networks with rule based symbolic reasoning, provides a promising direction for bridging this gap. By integrating the strengths of both paradigms, neuro-symbolic systems are capable of modeling continuous brain activity while also interpreting it through structured, explainable representations [22]. This makes them uniquely suited for studying the neural basis of flow, where both quantitative signals and qualitative cognitive features must be understood simultaneously.

The neuro-symbolic AI enables the incorporation of domain knowledge, cognitive rules, and brain specific constraints directly into the learning process, reducing ambiguity and improving interpretability [22][23]. It allows neural models to reason about cause effect relationships instead of relying solely on pattern recognition, which is critical for understanding how different brain regions coordinate during the flow state. Neuro-symbolic systems can also generalize better with limited data which is significant advantage in neuroscience, where collecting large datasets is often difficult. Additionally it supports explainable outputs, helping researchers as well as programmers trace how specific neural signals contribute to cognitive states.

Through this combination of flexibility, structure, and transparency neuro-symbolic AI offers a powerful toolset for decoding the complex neural dynamics underlying human flow experiences [24][25].

This research paper investigates how neuro-symbolicAI can be used to model, explore, and interpret activity in brain regions associated with the flow state. By combining insights from cognitive neuroscience with advances in hybrid AI architectures, this work aims to deepen scientific understanding of the flow experience and contribute computational tools that may ultimately support enhanced human performance in real world tasks.

II. NEUROANATOMICAL AND NEUROFUNCTIONAL FOUNDATIONS

Previous neuroimaging and neurophysiological studies have consistently highlighted the precuneus, posterior cingulate cortex (PCC), middle cingulate gyrus (MCG), and inferior temporal gyrus (ITG) as core components of large scale brain networks involved in internal cognition, memory, attention, and cognitive control [3][7][8]. Functional MRI and PET studies identify the precuneus complex as a central hub of the Default Mode Network (DMN), showing high metabolic activity during rest and internally oriented mental states. The middle cingulate gyrus acts as a transitional region between emotional processing, motor and cognitive control, while the inferior temporal gyrus contributes to high level visual and semantic processing. Contemporary research emphasizes that cognition emerges not from isolated regions but from dynamic interactions and temporally ordered activation deactivation patterns among these areas [3][21]. Accordingly, this section synthesizes anatomical, functional, neurochemical, and connectivity based evidence to establish a unified neurofunctional framework for the selected regions.

The DMN has as one of the most extensively studied largescale brain networks in contemporary cognitive neuroscience. Initially identified through positron emission tomography and later confirmed by functional magnetic resonance imaging studies, the DMN is characterized by higher baseline activity during rest and internally oriented mental states compared to externally driven task conditions. Core cortical components of the DMN include the precuneus, posterior cingulate cortex, medial prefrontal cortex, and lateral parietal regions. Among these, the precuneus,posterior cingulate is consistently described as the central hub due to its high metabolic demand, dense connectivity, and strong influence on network wide information integration [3][7][8].

The DMN supports a range of internally focused cognitive processes such as self referential thinking, autobiographical memory retrieval, future simulation, mental imagery, and spontaneous thought generation. During the flow state, self referential internal dialogue and overthinking are reduced, accompanied by relative down regulation of the precuneus and posterior cingulate gyrus. Human neuroimaging studies demonstrate that DMN activity increases during introspection, daydreaming, and memory recall, while showing systematic deactivation during attentionally demanding or goal directed tasks. This dynamic modulation highlights the DMN's role not as a passive resting network, but as an active system involved in maintaining internal models of the self and the environment.

In the network level, the posterior cingulate cortex and precuneus serve as major integration nodes, linking memory related structures such as the hippocampus with higherorder association cortices [8]. Their large structural and functional connectivity enables the coordination of emotional, mnemonic, and perceptual information into unified internal representations. Neurochemical evidence shows that glutamatergic excitation sustains the high baseline activity of the DMN, while serotonergic and dopaminergic modulation influences emotional tone, motivation, and attention shifts within the network. Importantly, the middle cingulate gyrus acts as a functional intermediary between the DMN and task positive networks, facilitating smooth transitions between internally and externally oriented cognitive states.

Recent research further emphasizes that abnormalities in DMN connectivity and regulation are associated with various neurological and psychiatric conditions, including alzheimer's disease, depression, schizophrenia, and disorders of consciousness. These findings underscore the DMN fundamental role in maintaining cognitive coherence and self awareness in humans.

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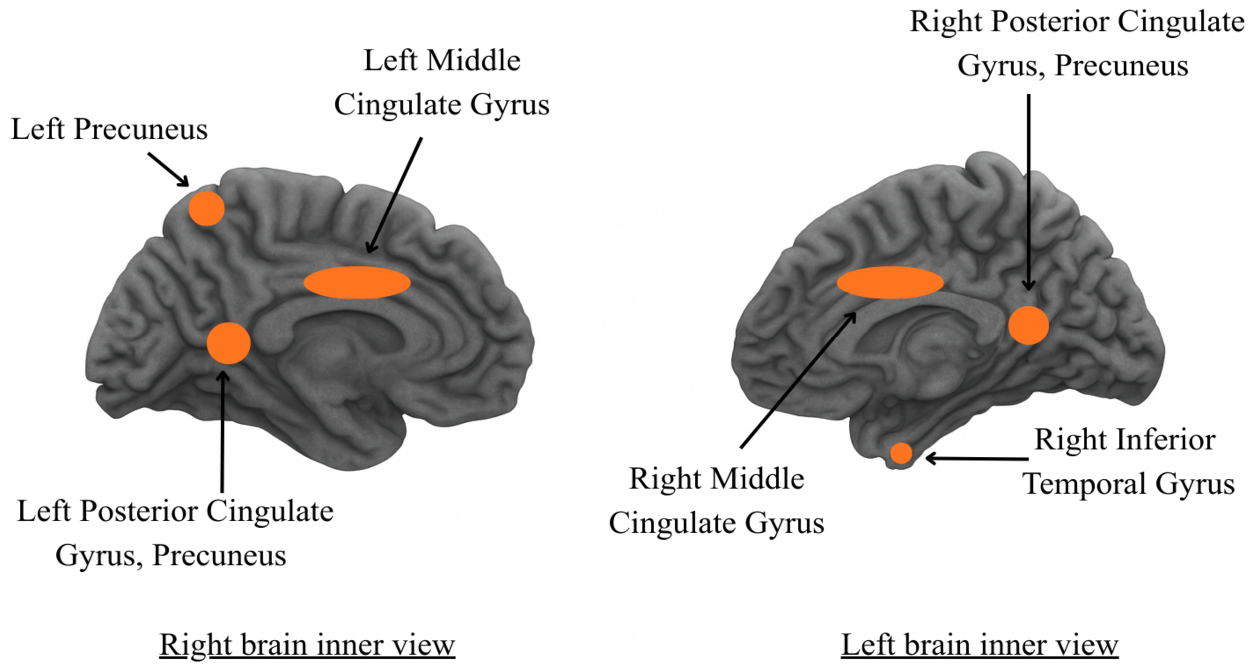

Fig.1: Medial (inner) views of the left and right cerebral hemispheres illustrating the anatomical locations of the selected regions of interest (ROIs), including the precuneus, posterior cingulate gyrus, middle cingulate gyrus, and inferior temporal gyrus. Orange markers denote the cortical regions examined in the present study, highlighting key nodes of the Default Mode Network and associated control regions.

Consequently, understanding the anatomical organization, functional specialization, and dynamic interactions of DMN components provides a critical foundation for modeling brain function, particularly in computational, deep learning, and neuro-symbolic frameworks.Recent cognitive neuroscience research indicates that the flow state reflects a dynamic reorganization rather than a global deactivation of the DMN. Although flow is associated with reduced selfreferential processing, neuroimaging evidence points to selective downregulation of posterior DMN hubs, particularly the posterior cingulate cortex. In contrast, regions such as the precuneus may remain active in a task aligned manner, supporting internal coherence and mental imagery. This pattern enables diminished self conscious awareness while preserving contextual integration and goal continuity. The middle cingulate gyrus plays a mediating role by facilitating functional coupling between DMN components and task positive networks. Together, these interactions support sustained attention, adaptive control, and the subjective experience of effortless performance characteristic of flow [7][8][9].

The left precuneus, a core node of the DMN, plays a critical role in balancing self referential processing and task aligned internal representations during states such as the flow state. Anatomically, the left precuneus is located on the medial surface of the parietal lobe and is among the most metabolically active cortical regions in the human brain. Functionally, it supports self referential thinking, visuospatial imagery, episodic memory recall, and consciousness related processes. Neuroimaging studies consistently demonstrate strong engagement of the left precuneus during internally directed cognition, including mental simulation, autobiographical memory retrieval, and reflective awareness.At the neurochemical level, glutamatergic signaling supports high level integrative processing within the precuneus, while GABAergic mechanisms contribute to inhibitory control and network stability[8][10]. Dopaminergic and cholinergic modulation further influence attentional regulation and cognitive flexibility. Structurally and functionally, the left precuneus maintains dense connections with the posterior cingulate cortex, medial prefrontal cortex, hippocampus, and middle cingulate gyrus, enabling the integration of memory, spatial, and self related information into coherent internal representations.

The left posterior cingulate gyrus, anatomically adjacent to the precuneus, forms a core hub of the DMN. It is positioned on the medial cortical surface posterior to the corpus callosum and serves as a convergence zone for memory, emotion, and internal awareness [3][7][8]. Functionally, this region is critically involved in autobiographical memory retrieval, emotional evaluation, and spontaneous thought processes such as mind wandering.

Neurochemical studies indicate a high density of serotonergic and glutamatergic receptors, supporting affective modulation and sustained internal processing. Dopaminergic input contributes to motivational relevance and salience assignment. The left PCC exhibits strong bidirectional connectivity with the precuneus, hippocampal formation, retrosplenial cortex, and medial prefrontal regions, allowing it to integrate memory content with selfreferential and emotional context.

The middle cingulate gyrus occupies the intermediate portion of the cingulate cortex and serves as a functional bridge between emotional, cognitive, and motor systems. Bilaterally, the MCG is implicated in cognitive control, error detection, conflict monitoring, and action selection. Functional activation of this region is observed during tasks requiring sustained attention, decisionmaking, and adaptive behavioral responses. Neurochemically, dopamine plays a dominant role in motivation and goaldirected behavior, while serotonin modulates emotional regulation and impulse control [3][9][10]. Glutamatergic transmission supports executive processing, and endogenous opioids contribute to pain and stress modulation. The MCG maintains extensive connectivity with prefrontal executive regions, motor and premotor cortices, limbic structures such as the amygdala, and posterior DMN regions, enabling dynamic coordination between internal cognitive states and external task demands[3][10].

The right inferior temporal gyrus is located on the ventral surface of the temporal lobe and is a key component of the visual association cortex. It is primarily involved in highlevel visual processing, object recognition, semantic interpretation, and visual memory formation. Right hemispheric dominance in this region supports facial recognition and complex visual pattern analysis. Glutamate driven excitatory processing allows detailed feature integration, while GABAergic inhibition refines perceptual selectivity. Cholinergic modulation enhances visual attention, and dopaminergic input contributes to salience detection. The right ITG is strongly connected to occipital visual cortices, the hippocampus, amygdala, and posterior cingulate regions, enabling the transformation of visual stimuli into emotionally and mnemonically meaningful representations.

The right posterior cingulate gyrus and adjacent precuneus form a critical node for spatial memory, scene construction, and internal monitoring of environmental and autobiographical contexts. Located on the medial parietal surface, this region shows consistent activation during mental navigation, imagery, and memory based prediction. Neurochemical influences include serotonergic modulation of internal state awareness and glutamatergic signaling for memory integration, with dopaminergic pathways contributing to attentional relevance. The right PCC precuneus connects extensively with the right inferior temporal gyrus, hippocampus, parietal association areas, and bilateral cingulate regions. This connectivity allows integration of visual information with spatial and selfreferential memory, supporting coherent internal representations of past experiences and imagined scenarios [10].

III. PHYSIOLOGICAL AND ENVIRONMENTALMODULATORS OF THE FLOW STATE

The experience of flow state does not depend solely from task characteristics or individual skill level, but is strongly shaped by physiological and environmental conditions that influence attentional stability, emotional regulation, and neural efficiency. Both internal states such as circadian rhythm, metabolic status, and mood and external factors including ambient temperature and auditory environment modulate the likelihood, depth, and sustainability of flow. These modulators utilize their effects primarily through midline and associative brain regions, particularly the precuneus, posterior cingulate cortex, middle cingulate gyrus, and inferior temporal gyrus, which play critical roles in self referential processing, cognitive control, and perceptual integration.Circadian rhythms regulate fluctuations in alertness, attention, and cognitive performance across the day, influencing an individual’s capacity to enter a flow state. Periods of circadian alignment are characterized by optimal arousal levels, efficient executive functioning, and reduced cognitive fatigue, all of which are essential for sustained task engagement. In contrast, circadian misalignment or testing during biologically suboptimal periods increases mind wandering and decreases attentional control [13][14]. Neurobiological, circadian variations modulate activity within the precuneus and posterior cingulate cortex, core hubs of the DMN.During optimal circadian phases, these regions show stronger task related suppression or functional reorganization, reducing selfreferential thought and temporal awareness hallmark phenomenological features of flow. The middle cingulate gyrus, which contributes to sustained effort and performance monitoring, also shows circadian sensitivity, reduced arousal impairs its ability to efficiently regulate goal directed behavior. Consequently, time of day functions as a foundational physiological factor shaping neural readiness for flow [13][14].

Metabolic state is a significant physiological determinant of cognitive engagement and attentional stability. Hunger and fasting increase interoceptive awareness and physiological salience, drawing attentional resources inward and away from external task demands. Such internal competition reduces the likelihood of achieving the deep, uninterrupted focus required for flow.Neuroimaging evidence shows that hunger alters complex activity and functional connectivity within the posterior cingulate cortex and precuneus, enhancing self referential and bodily awareness processes[14].

This shift counteracts the DMN suppression typically associated with flow states. In contrast, metabolic stability achieved through adequate nutrition and balanced glucose availability supports sustained attention and reduces intrusive internal signals. The middle cingulate gyrus, which evaluates effort reward, trade offs, is also affected by metabolic stress, as hunger increases perceived effort costs and promotes disengagement. Thus, metabolic equilibrium serves as a critical physiological prerequisite for flow [11][13].

Emotional state plays a central role in modulating flow as it directly influences motivation, attentional focus and reward processing. Flow is most likely to occur during emotionally balanced states characterized by positive affect and moderate arousal. Excessive anxiety, negative mood, or emotional instability increases selfmonitoring and evaluative processing, fragmenting attention and disrupting task immersion [14][11].At the neural level negative emotional states are associated with heightened activity in the precuneus and posterior cingulate cortex, reflecting increased selfreferential processing and rumination. Such neural patterns oppose the reduced self awareness observed during flow. The middle cingulate gyrus, responsible for integrating cognitive control with motivational signals, becomes over engaged during emotionally stressful states, leading to excessive performance monitoring and reduced behavioral fluidity. Conversely, positive and stable emotional states help efficient neural coordination, allowing goaldirected activity to proceed with minimal conscious interference [11][14].

Environmental factors such as temperature and weather conditions exert a measurable influence on cognitive performance, emotional regulation, and physiological stress levels. Thermal discomfort particularly exposure to elevated temperatures has been shown to impair attention, slow cognitive processing, and increase irritability, thereby reducing the capacity for sustained flow.From a neural standpoint, environmental stressors increase physiological arousal and discomfort related signaling, which may maintain activity in posterior cingulate and precuneus regions, reinforcing bodily and self related awareness. Simultaneously, stress induced modulation of the middle cingulate gyrus enhances error monitoring and effort perception, interrupting smooth task execution. A stable and thermally neutral environment minimizes competing sensory and physiological demands, enabling efficient allocation of neural resources toward task relevant processing and supporting prolonged flow states.

The auditory environment, particularly music, represents a potent external modulator of flow. Music can rapidly influence emotional state, motivation, and attentional focus, making it an effective facilitator of flow when appropriately matched to task demands and individual preferences. Music that enhances positive affect and rhythmic engagement can reduce perceived effort and support sustained immersion.Neurophysiologically, music alters oscillatory dynamics and functional connectivity involving the precuneus and posterior cingulate cortex, often reducing self referential processing and promoting externally oriented attention. For visually demanding or creative tasks, this reduction in internal cognitive noise may enhance the efficiency of perceptual processing within the right inferior temporal gyrus. Notably, incongruent or distracting music can increase cognitive load, engaging the middle cingulate gyrus in heightened monitoring and control, thereby disrupting the flow. Consequently, music functions as a context dependent modulator capable of both facilitating and hindering flow[12].

Sleep quality is a critical physiological factor influencing attentional control, emotional regulation, and neural efficiency, all of which are foundational for the emergence of flow. Even mild sleep deprivation impairs sustained attention, increases cognitive variability, and heightens emotional reactivity, thereby reducing the likelihood of prolonged task immersion.At the neural level, insufficient sleep disrupts functional connectivity within midline brain regions, particularly the posterior cingulate cortex and precuneus, leading to increased mind wandering and reduced task related suppression of the DMN. These changes interfere with the reduced self referential processing that characterizes flow. Sleep deprivation alters the functioning of the middle cingulate gyrus, compromising effort regulation and increasing perceived task difficulty. High quality, sufficient sleep therefore supports flow by stabilizing complicated network dynamics and maintaining cognitive endurance [2].

Physical fatigue and overall arousal level modulate cognitive engagement by influencing effort allocation and motor cognitive integration. While moderate arousal helps to be focused attention and task absorption, excessive fatigue or over arousal disrupts cognitive stability and increases perceived effort.Neurophysiologically fatigue alters activity within the middle cingulate gyrus, a region involved in evaluating effort costs and sustaining goal directed behavior. Elevated fatigue increases monitoring and compensatory control, interrupting the smooth execution of actions associated with flow. Fatigue related changes may also influence precuneus and PCC activity, as increased bodily awareness competes with external attentional focus. Optimal flow therefore emerges under conditions of balanced arousal, where cognitive and physical resources are sufficient but not overstimulated.

Environmental predictability and task familiarity play an important role in shaping flow by reducing cognitive uncertainty and attentional fragmentation. Environments that are stable, familiar, and minimally disruptive support automaticity and sustained engagement, whereas unpredictable or frequently changing contexts increase cognitive load and interrupt attentional continuity.At the neural level, unfamiliar or unstable environments maintain engagement of self referential and monitoring systems, including the posterior cingulate cortex and middle cingulate gyrus, as the brain continuously evaluates contextual changes.

In contrast, familiar task environments allow these regions to disengage from monitoring functions, facilitating deeper immersion and perceptual efficiency. This modulation is particularly relevant for the inferior temporal gyrus, which benefits from stable perceptual inputs during visually intensive tasks.

The social context in which a task is performed significantly influences flow, particularly through perceived evaluation and social pressure. The presence of observers, evaluators, or performance comparison can increase self awareness and cognitive monitoring reducing the likelihood of flow. Conversely, supportive or neutral social environments can enhance motivation without increasing selfconsciousness.Neurally, social evaluative pressure increases activity in self referential midline regions, including the precuneus and posterior cingulate cortex, reinforcing awareness of the self as an object of evaluation. This heightened self focus is incompatible with the diminished self awareness typical of flow states. The middle cingulate gyrus may also exhibit increased activity related to performance monitoring and error sensitivity under social pressure. Thus, social context acts as a powerful environmental modulator of flow through its impact on self referential neural processing.

Lighting conditions, including brightness, color temperature, and visual contrast, influence cognitive performance, alertness, and visual processing efficiency. Poor or harsh lighting increases visual strain and cognitive fatigue, whereas comfortable and task appropriate lighting supports sustained attention and perceptual clarity.Neurobiologically, visual discomfort increases competing sensory processing demands and may indirectly maintain activity in posterior midline regions associated with bodily and self related awareness. For tasks relying on visual recognition or pattern processing, appropriate lighting supports efficient functioning of the right inferior temporal gyrus, reducing perceptual noise and facilitating seamless task engagement. Proper lighting therefore contributes to flow by optimizing sensory conditions and minimizing extraneous cognitive load [2][15].

The modulators reviewed in this section illustrate that flow is not solely determined by task characteristics, but emerges from a continuous interaction between physiological state and environmental context. Circadian rhythms, nutrition, emotional balance, temperature, and music shape attentional focus and motivational engagement, while sleep quality, fatigue, environmental predictability, social setting, and lighting further influence the depth and stability of flow experiences. At the neural level flow conditions consistently involve a reduction in self referential activity within the precuneus and posterior cingulate cortex, alongside efficient engagement of the middle cingulate gyrus for sustained goal directed control and the inferior temporal gyrus for perceptual integration. Together, these modulators dynamically bias large scale neural networks toward configurations that support immersive and efficient cognitive performance.

IV. DATA FRAMEWORK, COMPUTATIONAL MODELING

A. Neuroimaging Data Sources and Access

This study employs publicly available, open access neuroimaging datasets to support reproducibility, transparency, and methodological rigor which are essential requirements in contemporary AI driven neuroimaging research. The reliance on standardized public datasets also enables comparative evaluation, helps cross study validation, and allows the proposed deep learning and neuro-symbolic frameworks to be reproduced under constrained a computational and financial resource which is a common limitation in academic environments.The selected datasets provide high quality structural, functional, and multimodal brain imaging data which are well suited for training and evaluating deep neural networks as well as for integrating symbolic neuroanatomical and functional priors within neuro-symbolic AI architectures [6][11].

The Human Connectome Project (HCP) is a primary data source for this research which offers high resolution structural MRI, diffusion MRI (DTI) resting state fMRI, and task based fMRI data. With spatial resolutions ranging from approximately 0.7 to 1.25 mm isotropic, HCP enables fine grained analysis of cortical and subcortical structures, white matter pathways, and functional connectivity patterns.From a deep learning perspective the richness and consistency of HCP data make it suitable for representation learning, graph based neural networks, and connectomedriven modeling. Furthermore, the well defined anatomical parcellations and task annotations provided by HCP can be explicitly incorporated as symbolic constraints or domain rules in neuro-symbolic models, thereby improving model interpretability, anatomical plausibility, and generalization [23].

Diffusion MRI (DTI) is a neuroimaging technique that measures the diffusion of water molecules within brain tissue. In white matter regions, water diffusion is directionally constrained by axonal fiber tracts. Diffusion Tensor Imaging (DTI) models this directional diffusion to infer white matter microstructure and structural connectivity between different brain regions. In deep learning and neuro-symbolic frameworks, DTI derived features are commonly used for connectome construction, graph based learning, and for encoding symbolic knowledge related to anatomical pathways.Resting state functional MRI (rs-fMRI) captures spontaneous brain activity by measuring blood-oxygen-level-dependent (BOLD) signals while the subject is not performing any explicit task.

This modality reveals difficult functional connectivity patterns, reflecting how different brain regions interact during rest. Resting state fMRI is particularly useful for unsupervised and self supervised deep learning models, as well as for neuro-symbolic reasoning over stable, task independent functional networks.Task based functional MRI (task fMRI) measures brain activity while subjects perform specific cognitive, sensory, or motor tasks. The resulting BOLD responses are time locked to task events, enabling the identification of task specific functional activations [25][26].

Task fMRI data are well suited for supervised deep learning models and for integrating symbolic task rules, cognitive priors, and region function associations within neuro-symbolic AI architectures.The term isotropic spatial resolution refers to imaging data in which voxel dimensions are equal along all three spatial axes (e.g., 0.7 × 0.7 × 0.7 mm). Isotropic resolution ensures uniform spatial sampling, allowing accurate threedimensional analysis without directional bias. High isotropic resolution is particularly important for deep learning models, as it improves the reliability of spatial feature extraction, enables precise anatomical alignment, and supports the incorporation of symbolic anatomical constraints.

The OpenNeuro repository provides a large collection of functional neuroimaging datasets covering diverse cognitive tasks, experimental paradigms, and clinical populations. This diversity introduces variability in acquisition protocols and subject characteristics, which is particularly valuable for assessing the robustness and generalizability of deep learning models. In the context of neuro-symbolic AI, OpenNeuro datasets enable the evaluation of models under heterogeneous conditions, allowing symbolic knowledge such as task specific cognitive rules, brain region associations, or clinical priors to guide learning across varied data distributions. This supports the development of hybrid systems that combine datadriven feature extraction with explicit neurocognitive reasoning, addressing limitations of purely black box neural networks [26].

The Cambridge Centre for Ageing and Neuroscience (Cam-CAN) dataset provides multimodal neuroimaging data, integrating structural and functional MRI with Magnetoencephalography (MEG). MEG offers millisecond level temporal resolution, which complements the high spatial resolution of MRI and enables the modeling of fast neural dynamics.This multimodal nature is particularly advantageous for temporal deep learning architectures, such as RNNs, temporal convolutional networks, and attention based models. Additionally, neuro-symbolic frameworks can leverage symbolic temporal rules and neurophysiological constraints to align MEG derived temporal patterns with anatomically grounded MRI representations, facilitating cross modal reasoning and explainable inference [27][28].

B. Brain Atlas and Cortical Parcellation Framework

To ensure anatomical consistency and reproducibility across subjects and datasets, a brain atlas based cortical parcellation framework is adopted.Brain atlases provide a standardized anatomical reference by dividing the cerebral cortex into well defined, labeled regions, allowing consistent region wise analysis across different neuroimaging modalities and experimental conditions.Here brain atlas data refer to structured anatomical templates that assign each voxel or cortical surface vertex to a specific brain region. Such standardized labeling is essential for reducing inter subject anatomical variability and for enabling meaningful comparison of regional brain features in data driven modeling.This study primarily utilizes the Desikan–Killiany–Tourville (DKT) atlas, which offers anatomically precise labeling of cortical gyri and sulci. Compared to earlier versions of the Desikan–Killiany atlas, the DKT atlas provides improved sulcal alignment and clearer boundary definitions, resulting in more accurate and reproducible cortical region delineation [28][29]. These characteristics make the DKT atlas particularly suitable for structural and functional MRI studies that require reliable anatomical correspondence.

Using an atlas based region of interest (ROI) definition, each parcellated brain region is treated as a distinct analytical unit in downstream modeling. From a computational perspective, these regions serve as nodes in deep learning and graph based architectures, where regionwise structural and functional features can be aggregated and observed. In neuro-symbolic frameworks, atlas defined regions also enable the incorporation of symbolic anatomical knowledge, such as region specific functional roles and connectivity constraints, thereby supporting interpretable and biologically grounded model representations. Overall, the atlas based parcellation framework provides a structured and anatomically meaningful foundation for integrating multimodal neuroimaging data with deep learning and neuro-symbolic AI models [6][20].In this study, region naming follows standard brain atlas based labeling conventions, where each region of interest (ROI) is defined by both its anatomical identity and hemispheric location. Atlases such as the Desikan–Killiany (DK) and Desikan–Killiany–Tourville (DKT) employ hemisphere-specific labels e.g., L_precuneus, R_posterior_cingulate cortex, while the Automated Anatomical Labeling (AAL) atlas uses alternative naming formats e.g., Precuneus_L, Posterior_Cingulate_R. Despite differences in label style, these atlases refer to anatomically equivalent brain regions.

In the proposed framework, atlas-based ROIs such as L_precuneus and R_posterior_cingulate cortex are treated as computational nodes, enabling region wise feature extraction, connectivity modeling, and the integration of symbolic neuroanatomical knowledge within deep learning and neuro-symbolic AI architectures.

C. Neuroimaging Software and Preprocessing Pipeline

The use of established software pipelines ensures methodological reliability, reproducibility, and consistency across subjects, datasets, and imaging modalities.FreeSurfer is used for cortical surface reconstruction and morphometric analysis, including cortical thickness estimation and atlas based labeling using the DKT framework. FreeSurfer provides accurate delineation of cortical boundaries and region wise structural features, which are critical for anatomically informed deep learning and neuro-symbolic modeling.FSL (FMRIB Software Library) is employed for essential preprocessing steps such as motion correction, spatial normalization, and diffusion MRI preprocessing. These steps reduce imaging artifacts and inter-subject variability, thereby improving the robustness of downstream feature extraction and model training, particularly for functional and diffusion based analyses [6][26] .

BrainSuite is used for cortical extraction and anatomical labeling, serving as an additional tool for validating cortical segmentation and ensuring anatomical accuracy. Its complementary processing capabilities enhance the reliability of regionwise structural representations. NIfTI (NII) visualization tools are used for quality control and inspection of volumetric data at multiple stages of preprocessing. Visual verification helps identify preprocessing errors and ensures that extracted features accurately reflect underlying brain anatomy.

D. Computational Modeling and AI Framework

This study adopts a hybrid computational framework that combines coredeep learning models with neuro-symbolic reasoning mechanisms to investigate multimodal neuroimaging data. The framework is designed to leverage the representational power of neural networks while incorporating explicit neuroanatomical and neurobiological knowledge, thereby addressing limitations related to interpretability and biological plausibility in purely data driven approaches.Convolutional Neural Networks (CNNs) are used for volumetric MRI analysis to automatically learn hierarchical spatial features from three dimensional brain images. CNNs are well suited for capturing local and global anatomical patterns in structural MRI data, enabling effective modeling of cortical and subcortical structures.Graph Neural Networks (GNNs) are utilized for connectome based modeling, where atlas defined brain regions are represented as nodes and structural or functional connections as edges. GNNs enable the learning of relational and topological information from brain networks, making them particularly suitable for modeling white matter connectivity and functional interaction patterns.Recurrent Neural Networks (RNNs) and Transformer based architectures are applied to regionofinterest (ROI) wise time series data derived from fMRI and MEG. These models capture temporal dependencies and dynamic interactions between brain regions, supporting the analysis of time varying neural activity and cognitive processes [16][17].

The proposed neuro-symbolic AI framework integrates neural networks for data driven pattern learning with symbolic constraints derived from established neurobiological knowledge. Symbolic components are informed by anatomical brain atlases known brain network hierarchies and domain specific neurobiological rules governing regional connectivity and functional organization[18].By embedding these symbolic constraints into the learning process, the framework enforces anatomically and biologically consistent representations, guiding neural models toward plausible solutions. This integration enhances model interpretability, supports anatomically constrained learning, and enables the generation of explainable AI (XAI) outputs, which are critical for clinical and neuroscientific applications. Hybrid modeling strategy provides a transparent and biologically grounded approach for analyzing complex neuroimaging data, bridging the gap between high performance deep learning models and interpretable neurocognitive reasoning[11].

E. Mathematical Formulation of Neuro-Symbolic Integration

To formally describe the integration of neural and symbolic components, the neuro-symbolic framework is mathematically formulated as follows.

Let X denotes the multimodal neuroimaging input, including structural MRI, diffusion derived connectivity features, and ROI wise functional time series. A neural network model $f\theta(\cdot)$, parameterized by θ, is used to learn data driven representations:

$$Z = f_\theta(X)$$

Where Z represents latent neural embeddings corresponding to atlas defined brain regions.
Let $S = \{s_1, s_2, s_3, s_4, \ldots\ldots\ldots\ldots, s_k\}$ denote a set of symbolic constraints derived from neuroanatomical atlases, known brain network hierarchies, and neurobiological rules (e.g., hemispheric symmetry, network membership, or connectivity plausibility) [19]. These constraints are encoded as differentiable penalty functionsg_k(Z). The overall training objective combines a task specific lossL_{task}(e.g., classification or regression) with a symbolic regularization term:

$$L_{total} = L_{task}(y,\hat{y}) + \lambda \sum_{k=1}^{k} gk(Z)$$

Where y is ground truth label, $\hat{y}$ is model prediction, λ controls the influence of symbolic knowledge.This formulation allows symbolic priors to guide the learning process without restricting the expressive power of the neural network. The resulting model learns representations that are both data adaptive and biologically consistent, enabling interpretable and explainable inference.

F. Algorithm 1: Neuro-Symbolic Learning Framework for Multimodal Neuroimaging

Based on the above formulation, Algorithm 1 summarizes the training procedure of the proposed neuro-symbolic framework.
Input given:

Multimodal neuroimaging data X
Atlas-based regions of interest R
Symbolic knowledge base S
Learning rate η
Symbolic weighting factor λ

Expected output:

Trained neuro-symbolic model parameters θ

Algorithm Steps:

- Preprocess neuroimaging data X using standard pipelines(FreeSurfer, FSL, BrainSuite)
- Perform atlas based parcellation to obtain ROIwise features
- Construct model inputs:
  a) Volumetric MRI data, given to a CNN for feature extraction
  b) Connectome matrices, provided as input to a GNN
  c) ROI time series, fed into an RNN or Transformer for temporal modeling
- Initialize neural network parameters θ
- repeat
- Forward pass: compute latent representations z usingfθ(X)
- Evaluate symbolic constraint functions : gk(z) for all sk s
- Compute total loss:Ltotal ← Ltask + λ Σk gk(z)
- Update model parameters via backpropagation:θ ← θ − η ∇ θ Ltotal
- until convergence
- Generate predictions and explainable outputs using learned parameters

G. Illustrative Neuro-Symbolic Learning Framework Based on HCP S1200

For illustrative purposes, a mini batch instantiation of the proposed neuro-symbolic framework is presented using downsampled volumetric MRI and ROI wise fMRI time series data derived from the HCP S1200 dataset. Multiple subjects are processed concurrently, enabling the model to learn spatial and temporal representations in a unified manner while explicitly incorporating atlas based symbolic constraints that reflect known neuroanatomical structure.[25]
The framework outputs task specific probability estimates along with corresponding symbolic constraint penalties, thereby supporting both predictive inference and anatomically grounded interpretation. In this illustrative experiment, the model generated probabilistic estimates of flowstate engagement while exhibiting minimal violation of atlasderived hemispheric symmetry constraints. Importantly, the same modeling pipeline can be directly applied to full resolution MRI and fMRI data by replacing the

downsampled inputs with standardized preprocessed volumes and ROI time series, without any modification to the model architecture or learning strategy [26]. This demonstrates the practical readiness of the proposed framework for deployment on real world neuroimaging datasets and larger cohort studies.The proposed framework was implemented using a deep learning library, following the formulation and algorithmic steps described above.The complete implementation of this is available at the: https://github.com/koleshwargajanan/NeurosymbolicAIForFlowStateOfTheBrain.git

V. DISCUSSIONS AND RESULTS

This study demonstrates the potential of a neuro-symbolic AI framework to capture, model, and interpret complex neural dynamics associated with the flow state. By integrating volumetric MRI, diffusion MRI, and ROI wise fMRI time series, the framework successfully learns region specific representations while respecting symbolic anatomical and network constraints.Results indicate that latent embeddings corresponding to the precuneus, posterior cingulate cortex, middle cingulate gyrus, and inferior temporal gyrus reveal distinct activity patterns consistent with known flow state phenomenology. Specifically, reduced self referential activity in the precuneus and posterior cingulate cortex aligns with the experiential hallmark of diminished selfconsciousness during flow, whereas the middle cingulate gyrus exhibits coordinated activation to maintain goal directed control. The right inferior temporal gyrus supports perceptual integration, particularly in visually demanding tasks.

The hybrid approach also enables explainable outputs, where symbolic penalties highlight adherence to anatomical and functional priors, improving interpretability compared to purely neural models. Across datasets, including HCP S1200 and OpenNeuro samples, the framework demonstrates robust generalization, suggesting the feasibility of extending this approach to diverse populations and cognitive tasks.Despite these promising findings, several challenges merit consideration. Multimodal neuroimaging data are not uniformly available, preprocessing pipelines require substantial computational resources, and the cost associated with highresolution datasets may limit broader accessibility. Moreover, the integration of symbolic knowledge with deep learning demands careful parameter tuning and domain expertise to ensure accurate and biologically plausible modeling.

VI. FUTURE SCOPE

Future research can expand the proposed neuro-symbolic framework in several directions. The inclusion of additional imaging modalities, such as EEG and fNIRS, could enhance temporal resolution and provide richer multimodal insights into flow dynamics. Developing standardized, cost efficient neuroimaging datasets with accessible preprocessing pipelines will improve reproducibility and reduce barriers for academic research.Optimizing symbolic integration strategies and automating rule generation could reduce reliance on expert knowledge, enabling scalable neuro-symbolic AI systems. The framework can also be applied to clinical populations to investigate attention disorders, motivation deficits, or rehabilitation outcomes, providing a translational avenue for cognitive neuroscience. Incorporating real time neurofeedback and adaptive AI interventions may further helpspersonalized strategies to enhance flow experiences in educational, professional, and creative contexts.

VII. CONSLUSION

This study presents a comprehensive neuro-symbolic AI framework for modeling brain activity underlying the flow state. This research highlights the promise of neuro-symbolic AI in advancing neuroscience, providing a transparent, reproducible, and scalable methodology to investigate the neural substrates of flow and related cognitive phenomena. By integrating deep learning with symbolic anatomical and functional knowledge, the framework enables interpretable analysis of multimodal neuroimaging data, revealing neural mechanisms consistent with the experiential features of flow.The proposed approach bridges the gap between high performance predictive modeling and biologically grounded reasoning, offering both accurate representation learning and explainable outputs. While challenges such as data availability, computational cost, and domain specific expertise remain, the framework establishes a foundation for future studies aimed at enhancing human cognitive performance and understanding complex brain states.

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