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Smart MEMS Sensors for Real-Time Anesthesia Monitoring and Overdose Detection

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Research Article

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Smart MEMS Sensors for Real-Time Anesthesia Monitoring and Overdose Detection

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Abstract

Accurate monitoring of anesthesia remains a critical challenge in perioperative medicine due to the potential risks associated with both insufficient and excessive anesthetic administration. Conventional monitoring approaches primarily rely on physiological parameters that do not directly reflect neurological activity and may therefore provide limited information regarding the actual consciousness state of patients. Electroencephalography (EEG) has emerged as one of the most reliable techniques for assessing brain activity during anesthesia because it captures neural dynamics associated with sedation, loss of consciousness, and anesthetic depth.

This study proposes a conceptual MEMS-enabled framework for real-time anesthesia monitoring and overdose-risk assessment based on EEG-derived neurological information. The framework was evaluated using a publicly available anesthesia dataset comprising 2,479 observations and 993 extracted EEG features representing multiple brain states, sedation conditions, and anesthesia levels. Exploratory data analysis, statistical evaluation, feature investigation, correlation analysis, and risk-oriented monitoring assessment were performed to identify meaningful relationships among neurological characteristics and anesthesia-related variables.

The analysis revealed significant variations in sedation scores and EEG intensity across different anesthesia conditions. Several EEG-derived features exhibited strong associations with sedation-related indicators, including covariance-based, frequency-domain, and statistical features extracted from neural activity recordings. The results demonstrated that a relatively small subset of neurological characteristics contained substantial monitoring information despite the high dimensionality of the dataset. Furthermore, a Smart MEMS Sedation Monitoring and Risk Index (SMORI) was introduced to transform multidimensional neurological information into a unified and clinically interpretable monitoring metric capable of supporting future intelligent monitoring systems.

The obtained findings demonstrate the feasibility of utilizing large-scale EEG-derived feature datasets within intelligent anesthesia-monitoring architectures and highlight the potential role of MEMS-enabled sensing technologies in future real-time clinical monitoring environments. The proposed framework establishes a foundation for future research involving multimodal physiological integration, intelligent decision-support systems, and wearable anesthesia-monitoring platforms.

Keywords: Anesthesia Monitoring, EEG, MEMS Sensors, Sedation Assessment, Brain State Classification, Biomedical Signal Analysis, Risk Assessment, Smart Healthcare Systems.

1 Introduction

General anesthesia is a fundamental component of modern surgical practice and plays a critical role in ensuring patient comfort, safety, and procedural success during a wide range of invasive interventions. The primary objective of anesthesia is to induce a reversible state characterized by unconsciousness, analgesia, amnesia, and immobility while preserving physiological stability throughout the surgical procedure. Despite substantial advances in anesthetic drugs, delivery techniques, and perioperative management strategies, maintaining an appropriate depth of anesthesia remains a major clinical challenge. Both insufficient and excessive anesthetic administration may negatively affect patient outcomes. Inadequate anesthesia may result in intraoperative awareness and postoperative psychological complications, whereas excessive anesthetic exposure has been associated with prolonged recovery time, cardiovascular instability, respiratory depression, postoperative cognitive dysfunction, and increased perioperative morbidity [1,2]. Consequently, accurate assessment of anesthesia depth has become an essential requirement for improving patient safety and optimizing perioperative care.

Traditional anesthesia monitoring methods primarily rely on physiological parameters such as heart rate, blood pressure, respiratory rate, oxygen saturation, and end-tidal anesthetic concentration. Although these indicators provide valuable information regarding the physiological condition of patients, they do not directly reflect brain activity, which represents the primary target of anesthetic agents. Moreover, physiological responses may be influenced by numerous factors unrelated to the actual level of consciousness, including surgical stimulation, medication interactions, cardiovascular conditions, and patient-specific variability. These limitations have motivated extensive research efforts toward the development of monitoring approaches capable of directly evaluating neurological activity during anesthesia [1, 3].

Among the available neurological monitoring modalities, electroencephalography (EEG) has emerged as one of the most reliable techniques for assessing brain function during anesthesia. EEG provides direct measurements of neuronal activity and has demonstrated strong correlations with changes in consciousness, sedation, and anesthetic depth. Previous studies have shown that alterations in spectral characteristics, oscillatory patterns, alpha rhythms, slow-wave activity, and burst suppression phenomena can serve as important indicators of neurological responsiveness and anesthesia-induced unconsciousness [3, 4]. As a result, EEG-based monitoring has become increasingly important in modern anesthesiology and has contributed to the development of several clinically deployed depth-of-anesthesia monitoring systems.

The rapid advancement of artificial intelligence, machine learning, and biomedical signal processing techniques has further enhanced the capabilities of EEG-based monitoring systems. Intelligent algorithms have demonstrated remarkable potential for extracting clinically meaningful information from complex EEG recordings and improving the recognition of anesthesia-related states. Deep learning and machine learning models have been successfully applied to classify consciousness levels, estimate anesthesia depth, identify sedation conditions, and support clinical decision-making processes [3, 5, 6]. Furthermore, recent investigations have highlighted the potential of intelligent analytical frameworks to improve monitoring performance by exploiting relationships among multiple neurological and physiological indicators [2, 7]. Nevertheless, most existing studies focus primarily on classification accuracy and predictive performance, while relatively limited attention has been directed toward the development of integrated monitoring frameworks capable of supporting continuous risk assessment and real-time clinical deployment.

Simultaneously, microelectromechanical systems (MEMS) technology has experienced substantial growth within the biomedical engineering field. MEMS-based devices offer several advantages, including miniaturization, low power consumption, high sensitivity, reduced manufacturing costs, and compatibility with wearable and wireless healthcare systems. These characteristics have facilitated the development of compact sensing platforms capable of continuously acquiring physiological information while supporting long-term operation and patient mobility. The integration of intelligent sensing technologies with advanced analytical methods is increasingly recognized as a key component of next-generation healthcare systems, particularly in applications requiring continuous monitoring and early risk detection.

Despite significant progress in EEG-based anesthesia monitoring, several important limitations remain evident within the current literature. First, many studies focus primarily on anesthesia-depth estimation or consciousness-state classification without addressing broader monitoring and risk-assessment requirements. Second, existing investigations frequently emphasize algorithmic development while providing limited consideration for integration within intelligent monitoring architectures suitable for future clinical deployment. Third, although MEMS technologies have been widely utilized in healthcare monitoring applications, relatively few studies have explored their integration with EEG-based anesthesia assessment systems. Finally, the increasing availability of large-scale EEG datasets containing hundreds of extracted neurological features has not been fully exploited for the development of interpretable monitoring indicators capable of transforming complex brain dynamics into clinically meaningful information.

To address these challenges, this study proposes a conceptual framework entitled *Smart MEMS Sensors for Real-Time Anesthesia Monitoring and Overdose Detection*. Unlike conventional studies that focus exclusively on anesthesia-depth estimation, the proposed framework investigates the feasibility of a MEMS-enabled intelligent monitoring architecture utilizing EEG-derived neurological information associated with different anesthesia conditions. The framework is evaluated using a publicly available dataset containing 2,479 observations and 993 extracted EEG features representing multiple brain states, sedation levels, and anesthesia conditions. The large feature space provides a comprehensive basis for investigating anesthesia-related neurological character-

istics and supports the development of advanced monitoring methodologies.

In addition, this work introduces the concept of a *Smart MEMS Sedation Monitoring and Risk Index (SMORI)*, which aims to transform multidimensional EEG-derived information into a unified and clinically interpretable monitoring metric. Rather than relying on individual neurological indicators, the proposed index provides a comprehensive assessment perspective capable of representing anesthesia-related conditions within a single analytical framework. Such an approach has the potential to facilitate continuous monitoring, improve interpretability, and support future intelligent decision-support systems within clinical environments.

The main contributions of this study are summarized as follows:

- A conceptual MEMS-enabled framework for real-time anesthesia monitoring and risk assessment is proposed.
- A comprehensive analysis of a large EEG-derived anesthesia dataset containing 993 neurological features is performed.
- Relationships among brain states, sedation scores, anesthesia levels, and EEG-derived characteristics are investigated.
- A novel Smart MEMS Sedation Monitoring and Risk Index (SMORI) is introduced as a unified monitoring and risk-assessment indicator.

Collectively, these contributions establish a foundation for future intelligent anesthesia-monitoring systems that combine advanced sensing technologies, data-driven analysis, and clinically interpretable decision-support mechanisms.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature on EEG-based anesthesia assessment, artificial intelligence in anesthesiology, and MEMS-enabled healthcare technologies. Section 3 presents the proposed monitoring framework and system architecture. Section 4 describes the dataset characteristics and methodological procedures. Section 5 presents the experimental results and discussion. Finally, Section 6 concludes the paper and outlines future research directions.

2 Related Work

2.1 EEG-Based Monitoring of Anesthesia Depth

Accurate assessment of anesthesia depth has attracted significant attention in both clinical anesthesiology and biomedical engineering due to its direct impact on patient safety and perioperative outcomes. Traditional monitoring approaches primarily rely on physiological indicators such as heart rate, blood pressure, respiratory rate, and oxygen saturation. Although these measurements provide valuable information regarding the physiological condition of patients, they do not directly reflect cerebral activity and therefore may not accurately represent the patient's actual level of consciousness during anesthesia [1, 3].

Electroencephalography (EEG) has emerged as one of the most reliable techniques for evaluating brain activity during anesthesia because it provides direct information regarding neuronal dynamics and consciousness-related processes. Changes in EEG characteristics have been shown to correlate strongly with transitions between wakefulness, sedation, loss of consciousness, and deep anesthesia. Several investigations have demonstrated that alterations in spectral power distribution, oscillatory activity, alpha rhythms, slow-wave dynamics, and burst suppression patterns can serve as important indicators of anesthetic depth and neurological responsiveness [3, 4, 8].

Recent advances in EEG signal processing have enabled the extraction of increasingly sophisticated neurological features capable of improving anesthesia assessment. Feature-based approaches utilizing statistical, spectral, covariance-based, and complexity-related EEG characteristics have demonstrated promising performance in identifying anesthesia-related states and monitoring neurological changes induced by anesthetic agents [4, 9]. Furthermore, the growing availability of large-scale EEG datasets has facilitated more comprehensive investigations of neurological patterns associated with anesthesia administration.

Despite these advances, most existing studies remain primarily focused on anesthesia-depth estimation and consciousness-state classification. Comparatively limited attention has been devoted to the development of integrated monitoring frameworks capable of transforming large collections of EEG-derived characteristics into clinically interpretable indicators suitable for continuous monitoring and risk assessment. Consequently, there remains a need for methodologies that can bridge the gap between advanced EEG analytics and practical clinical monitoring requirements.

2.2 Artificial Intelligence for Anesthesia Assessment

The rapid development of artificial intelligence (AI), machine learning (ML), and deep learning (DL) techniques has significantly enhanced the capabilities of modern anesthesia-monitoring systems. EEG signals exhibit highly nonlinear, complex, and patient-dependent characteristics, making them particularly suitable for intelligent analytical approaches capable of identifying hidden patterns that may not be readily observable through conventional statistical techniques.

Several studies have demonstrated the effectiveness of machine learning models for anesthesia-state recognition and depth estimation. Madanu et al. [5] proposed a deep learning framework capable of predicting anesthesia depth directly from EEG recordings and reported improved performance compared with traditional analytical approaches. Similarly, Afshar et al. [10] developed a combinatorial deep learning architecture that achieved accurate estimation of anesthesia depth using EEG-derived features.

More recent investigations have explored advanced neural network architectures, ensemble-learning approaches, and multimodal analytical frameworks for anesthesia monitoring. Wang et al. [11] demonstrated that deep learning models can successfully predict anesthesia depth using temporal patterns associated with anesthetic administration. Likewise, Zhou et al. [8] employed convolutional neural networks for EEG-based consciousness assessment and reported encouraging results in distinguishing anesthesia-related neurological states.

Artificial intelligence has also been increasingly integrated into broader clinical decision-support systems within anesthesiology. Introna et al. [12] highlighted the growing role of AI-assisted EEG interpretation in reducing clinician workload and improving real-time anesthesia assessment. Similarly, Cai et al. [13] reviewed recent developments in automated anesthesia management and emphasized the potential of intelligent monitoring systems for improving patient safety and perioperative efficiency.

Nevertheless, several challenges remain unresolved. Many existing AI-based studies focus primarily on maximizing classification accuracy and predictive performance while providing limited consideration for model interpretability and clinical usability. Furthermore, most proposed approaches generate categorical predictions without providing unified monitoring indicators capable of supporting continuous risk assessment and real-time clinical interpretation.

2.3 MEMS Technologies in Biomedical Monitoring

Microelectromechanical systems (MEMS) have become an essential technology within the field of biomedical sensing and healthcare monitoring. MEMS-based devices offer several advantages, including small physical dimensions, low power consumption, high sensitivity, reduced manufacturing costs, and compatibility with wireless communication infrastructures. These characteristics have enabled the development of compact healthcare systems capable of supporting continuous physiological monitoring in both clinical and remote-care environments.

Recent advances in MEMS technology have facilitated the development of wearable and portable biomedical devices capable of monitoring physiological signals in real time. Sensor-integrated healthcare platforms have demonstrated significant potential for personalized medicine, patient-specific monitoring, and intelligent healthcare applications. In addition, MEMS-enabled architectures provide attractive solutions for applications requiring continuous operation, energy efficiency, and long-term monitoring capabilities.

The integration of MEMS technology with advanced analytical methods has become increasingly important within next-generation healthcare systems. Intelligent sensing platforms capable of combining physiological acquisition, signal processing, and automated decision support are expected to play a central role in future clinical monitoring environments. These developments suggest that MEMS-based architectures may provide an effective foundation for future anesthesia-monitoring systems when integrated with EEG-derived neurological assessment frameworks.

However, a review of the existing literature reveals that most MEMS-related investigations have focused on general healthcare monitoring applications rather than anesthesia-specific monitoring systems. Consequently, the integration of MEMS concepts with EEG-based anesthesia assessment remains relatively underexplored and represents an important research opportunity within biomedical engineering.

2.4 Risk Assessment and Detection of Excessive Anesthetic Exposure

In addition to estimating anesthesia depth, increasing attention has been directed toward identifying conditions associated with excessive anesthetic exposure. Excessively deep anesthesia may contribute to delayed postoperative recovery, hemodynamic instability, respiratory complications, and postoperative neurological dysfunction. Therefore, the ability to detect elevated anesthesia-related risk conditions at an early stage represents an important objective in modern anesthesia management.

Several studies have investigated EEG-derived indicators associated with deep anesthesia and neurological suppression. Changes in EEG spectral characteristics, burst suppression activity, and consciousness-related neurological markers have demonstrated promising potential for identifying transitions toward excessive anesthesia conditions [1, 3]. Furthermore, machine-learning-based monitoring systems have been proposed to recognize complex EEG patterns associated with changes in patient responsiveness and neurological status.

Despite encouraging progress, most existing approaches evaluate individual signal characteristics independently and do not provide integrated risk-assessment frameworks capable of combining multiple anesthesia-related indicators into a single clinically interpretable metric. Moreover, many proposed systems remain focused on classification tasks rather than continuous monitoring applications. Consequently, there remains a need for methodologies capable of transforming multidimensional neurological information into unified indicators suitable for real-time monitoring and early-warning applications.

2.5 Research Gap and Positioning of the Present Study

The literature demonstrates substantial progress in three major research directions: EEG-based anesthesia monitoring, artificial-intelligence-assisted anesthesia assessment, and MEMS-enabled biomedical sensing technologies. However, these research streams have largely evolved independently. EEG-focused investigations primarily concentrate on anesthesia-depth estimation and consciousness-state classification, AI-based studies emphasize predictive performance, and MEMS research predominantly targets general healthcare-monitoring applications.

Furthermore, although several investigations have utilized EEG signals for anesthesia assessment, relatively few studies have explored the analytical potential of

large-scale EEG-derived feature datasets containing hundreds of extracted neurological characteristics. The utilization of such datasets for constructing integrated monitoring frameworks and clinically interpretable risk indicators remains insufficiently investigated. Existing studies also rarely address how advanced EEG-derived characteristics can be incorporated into conceptual smart-monitoring architectures capable of supporting future MEMS-enabled healthcare systems.

Accordingly, the present study addresses this research gap by proposing a conceptual MEMS-enabled framework for real-time anesthesia monitoring based on EEG-derived neurological information. Unlike previous studies that focus primarily on classification accuracy or anesthesia-depth estimation, the proposed approach investigates the feasibility of integrating large-scale EEG feature analysis with a unified monitoring concept. In addition, this work introduces the Smart MEMS Sedation Monitoring and Risk Index (SMORI), which aims to transform complex neurological information into an interpretable monitoring indicator suitable for future intelligent anesthesia-monitoring environments. By combining EEG-derived analytics, monitoring-oriented assessment, and MEMS-enabled system concepts, the proposed framework contributes a novel perspective toward the development of next-generation anesthesia-monitoring technologies.

3 Proposed MEMS-Enabled Anesthesia Monitoring Framework

3.1 Framework Overview

This study proposes a conceptual MEMS-enabled anesthesia monitoring framework designed to support real-time assessment of anesthesia-related conditions through the integration of EEG-derived neurological information and intelligent monitoring concepts. The proposed architecture aims to transform complex neurological characteristics into clinically interpretable indicators capable of facilitating continuous monitoring and supporting future decision-support systems.

Unlike conventional approaches that focus primarily on anesthesia-depth estimation or consciousness-state classification, the proposed framework emphasizes monitoring-oriented assessment and risk evaluation. The framework integrates EEG-derived neurological features, anesthesia-related variables, and a unified monitoring index to provide a comprehensive representation of patient status during anesthesia administration.

The proposed architecture consists of four primary layers:

1. Data Acquisition Layer
2. Feature Processing Layer
3. Risk Assessment Layer
4. Monitoring and Decision-Support Layer

Figure 1 illustrates the overall architecture of the proposed monitoring framework.

3.2 Data Acquisition Layer

The data acquisition layer represents the first stage of the proposed monitoring framework. In future clinical implementations, this layer would consist of MEMS-enabled sensing devices responsible for continuously acquiring physiological and neurological information from patients undergoing anesthesia.

Although a physical MEMS sensing platform was not developed within the scope of the present study, the proposed architecture demonstrates how MEMS-based technologies can be integrated with EEG-derived monitoring methodologies. Such sensing platforms may include wearable EEG acquisition devices, wireless physiological sensors, and low-power biomedical monitoring modules capable of supporting continuous operation within clinical environments.

For framework evaluation, a publicly available EEG-derived anesthesia dataset was utilized. The dataset contains 2,479 observations and 993 extracted EEG features representing multiple anesthesia-related conditions. The dataset further includes clinically relevant variables describing brain state, sedation level, anesthesia level, and EEG intensity measurements.

The principal variables employed throughout the analysis include:

- Brain State
- Sedation Score
- EEG Intensity
- Anesthesia Level

These variables provide a comprehensive representation of neurological activity associated with different anesthesia conditions and form the basis for the subsequent analytical stages.

3.3 Feature Processing Layer

The feature processing layer is responsible for analyzing and organizing EEG-derived neurological characteristics. Since the utilized dataset already contains preprocessed and extracted EEG features, additional signal-level preprocessing was not required.
Instead, the analysis focused on feature exploration and statistical investigation of the extracted neurological characteristics. The feature-processing stage includes:

- Descriptive statistical analysis.
- Feature ranking and exploration.
- Correlation assessment.
- Identification of anesthesia-related patterns.

The dataset contains a diverse collection of EEG-derived features, including statistical descriptors, covariance-based characteristics, frequency-domain information, spectral measures, and temporal indicators. These features collectively provide a multidimensional representation of neurological activity during different anesthesia conditions.

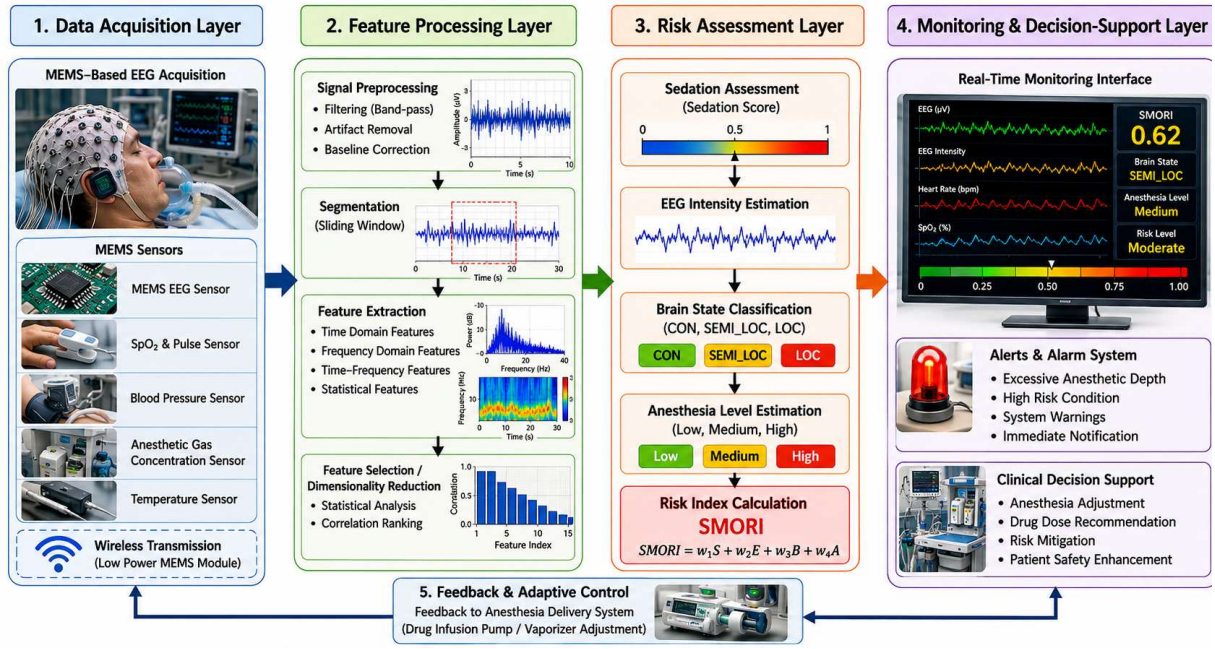

Figure 1: Proposed MEMS-enabled anesthesia monitoring framework integrating EEG-derived neurological information, feature analysis, risk assessment, and decision-support mechanisms.

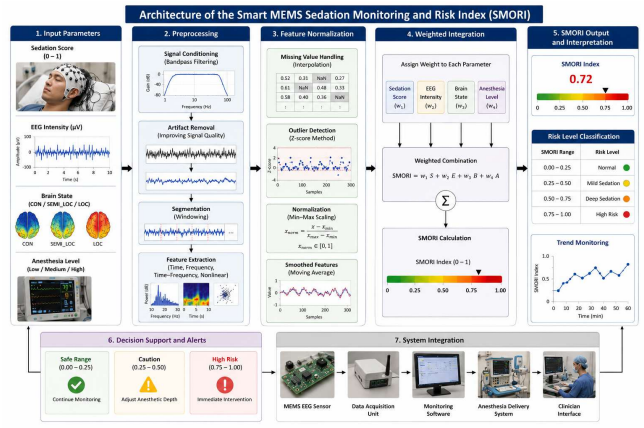

Figure 2: Conceptual structure of the Smart MEMS Sedation Monitoring and Risk Index (SMORI).

Feature investigation enables the identification of neurological characteristics most strongly associated with sedation conditions, anesthesia levels, and consciousness transitions. This stage therefore serves as a critical bridge between raw analytical information and clinically meaningful monitoring outcomes.

3.4 Risk Assessment Layer

The risk assessment layer constitutes the core analytical component of the proposed framework. Its primary objective is to transform multidimensional neurological information into a unified and interpretable monitoring indicator capable of supporting anesthesia-related risk evaluation.

To achieve this objective, this study introduces the Smart MEMS Sedation Monitoring and Risk Index (SMORI).

The conceptual structure of the proposed index is illustrated in Figure 2.

The proposed SMORI framework integrates four primary monitoring components:

- Sedation Score (S)
- EEG Intensity (E)
- Brain State (B)
- Anesthesia Level (A)

The generalized mathematical representation of the index is expressed as:

$$SMORI = w_1 S + w_2 E + w_3 B + w_4 A \qquad (1)$$

where:

- S represents the normalized Sedation Score.
- E represents normalized EEG Intensity.
- B denotes encoded Brain State values.
- A denotes encoded Anesthesia Level values.
- w_1, w_2, w_3, w_4 denote weighting coefficients.

Unlike traditional monitoring approaches that rely on individual indicators, the proposed index seeks to provide a unified representation of anesthesia-related conditions. This approach facilitates interpretation of complex neurological information and may support future intelligent monitoring systems.

3.5 Monitoring and Decision-Support Layer

The final layer of the framework transforms analytical outcomes into clinically interpretable information suitable for real-time monitoring applications.

The monitoring layer provides:

- Continuous anesthesia-status assessment.
- Risk-level visualization.
- Monitoring dashboards.
- Decision-support information.
- Early-warning capability for elevated anesthesia-related risk conditions.

By simplifying complex multidimensional EEG-derived information into understandable monitoring outputs, the proposed framework reduces analytical complexity and improves the accessibility of neurological information for clinical users.

The monitoring layer acts as the interface between advanced analytical processing and practical healthcare decision-making.

3.6 Operational Workflow

The operational workflow of the proposed framework follows six sequential stages:

1. Acquisition of anesthesia-related EEG information.
2. Extraction of relevant neurological variables.
3. Statistical and feature-level analysis.
4. Computation of the SMORI indicator.
5. Risk-level assessment.
6. Visualization of monitoring outcomes.

This workflow enables systematic transformation of large-scale neurological feature data into clinically meaningful monitoring information capable of supporting future intelligent anesthesia-management environments.

3.7 Expected Clinical Significance

The proposed framework offers several potential advantages for future anesthesia-monitoring applications.

First, it provides a structured methodology for utilizing large EEG-derived datasets within intelligent monitoring systems. Second, it introduces an interpretable monitoring indicator capable of simplifying the assessment of anesthesia-related conditions. Third, it establishes a conceptual foundation for future MEMS-enabled monitoring platforms that may integrate wearable sensing technologies, wireless communication infrastructures, and intelligent decision-support algorithms.

Although the current study focuses on retrospective analysis of EEG-derived features rather than real-time hardware implementation, the proposed architecture demonstrates how MEMS technologies, neurological monitoring, and data-driven analytics may be combined to support next-generation anesthesia-management systems.

The framework therefore serves as a foundation for future investigations involving multimodal physiological monitoring, wearable biomedical devices, artificial intelligence integration, and real-time clinical deployment.

4 Materials and Methods

4.1 Study Design

This study employed a data-driven analytical methodology to evaluate the feasibility of a conceptual MEMS-enabled framework for real-time anesthesia monitoring and overdose-risk assessment using EEG-derived neurological information. The proposed methodology was designed to investigate the relationships among neurological characteristics, sedation conditions, anesthesia levels, and consciousness states using a large-scale publicly available dataset.

Unlike conventional studies that focus primarily on classification accuracy, the present work emphasizes monitoring-oriented assessment and the development of an interpretable framework capable of transforming complex neurological information into clinically meaningful indicators suitable for future intelligent healthcare systems.

The overall methodological workflow consisted of five major stages:

1. Dataset acquisition and exploration.
2. Descriptive statistical analysis.
3. EEG feature investigation.
4. Correlation and significance analysis.
5. Development and evaluation of the Smart MEMS Sedation Monitoring and Risk Index (SMORI).

The complete methodological workflow is illustrated in Figure 3.

4.2 Dataset Description

The experimental analysis was performed using the Derived EEG Anesthesia Brain State Dataset, which contains EEG-derived neurological characteristics associated with different anesthesia conditions.

The dataset consists of:

- 2,479 observations.
- 993 extracted EEG-derived features.
- Three brain-state categories.
- Three anesthesia-level categories.

Unlike raw EEG datasets that require extensive preprocessing, filtering, and artifact removal procedures, the utilized dataset contains previously extracted neurological features derived from EEG recordings. Consequently, the dataset provides a suitable environment for feature-level investigation and monitoring-oriented analysis.

The primary variables employed throughout this study are summarized in Table 1.

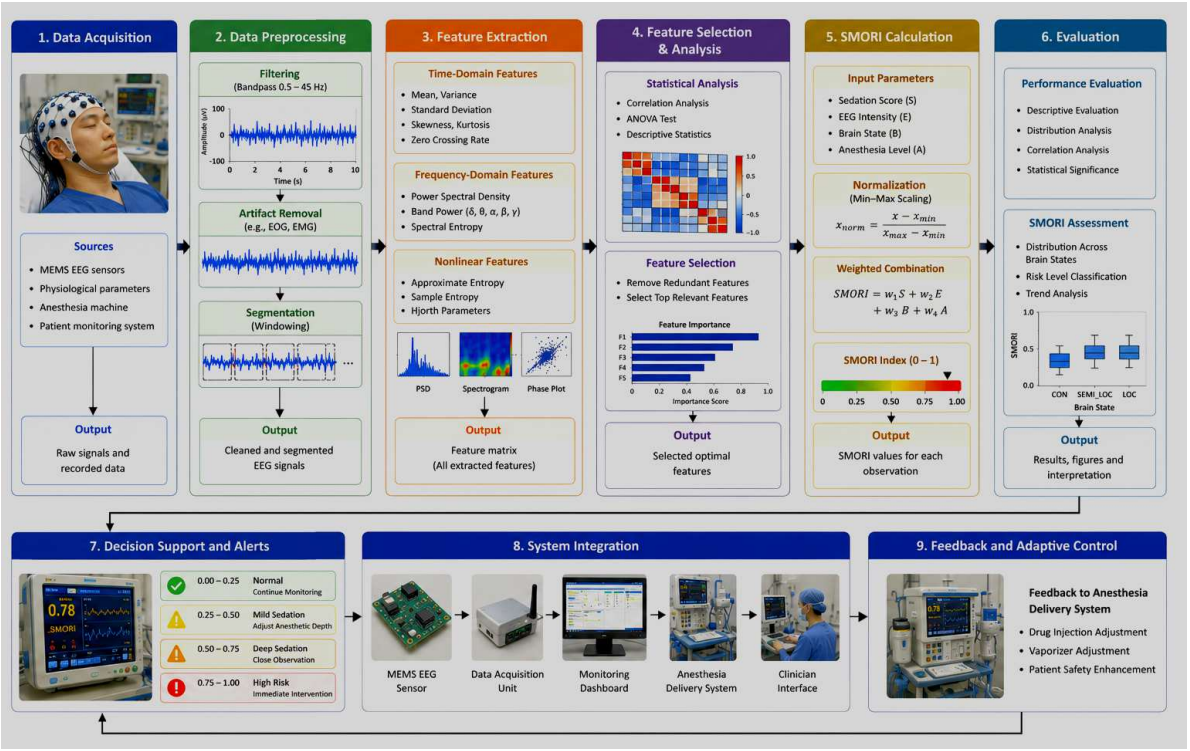

Figure 3: Overall methodological workflow adopted in the present study.

Table 1: Primary Variables Used in the Analysis

Variable	Description
Brain_State	Consciousness condition
Sedation_Score	Degree of sedation
EEG_Intensity	EEG activity measure
Anesthesia_Level	Clinical anesthesia level
PatientID	Subject identifier

4.3 Brain State Categories

The dataset contains three neurological consciousness conditions:

- CON (Conscious)
- SEMI_LOC (Semi Loss of Consciousness)
- LOC (Loss of Consciousness)

The distribution of observations across the three classes is shown in Table 2.

Table 2: Distribution of Brain States

Brain State	Number of Samples
CON	830
SEMI_LOC	830
LOC	819
Total	2479

As illustrated in Figure 4, the dataset exhibits a nearly balanced distribution across the three consciousness states, reducing the likelihood of class-related analytical bias.

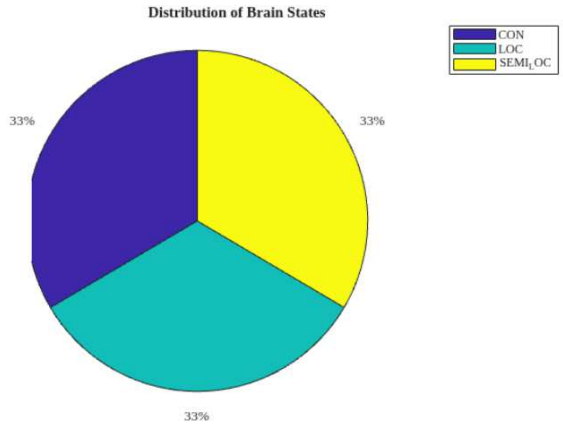

Figure 4: Distribution of brain-state categories within the dataset.

4.4 Anesthesia Level Categories

The dataset further contains three anesthesia-level categories representing different anesthesia conditions.

The distribution of anesthesia levels is summarized in Table 3.

Figure 5 illustrates the corresponding class distribution.

Table 3: Distribution of Anesthesia Levels

Anesthesia Level	Number of Samples
Low	251
Medium	1375
High	853
Total	2479

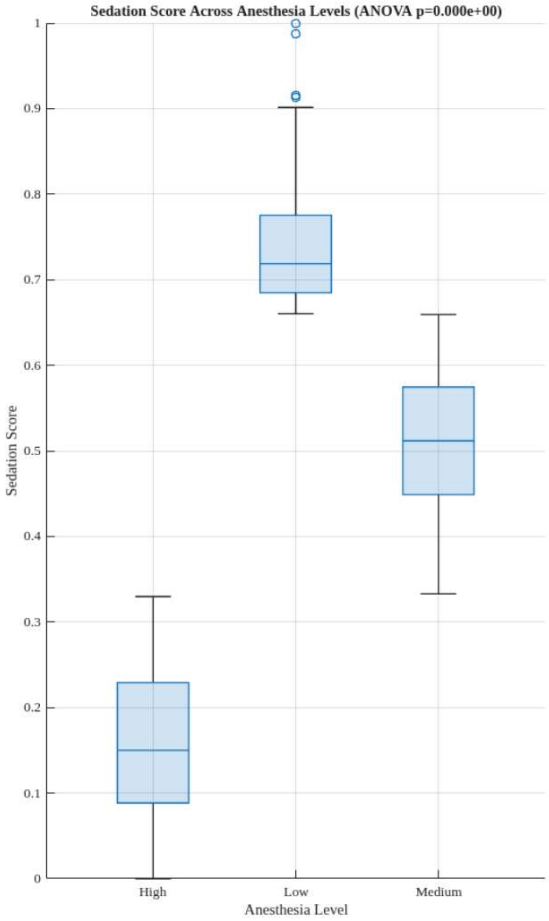

Figure 5: Distribution of anesthesia levels within the dataset.

4.5 Descriptive Statistical Analysis

Descriptive statistical analysis was conducted to investigate the numerical characteristics of the principal monitoring variables.

For each numerical variable, the following statistical measures were calculated:

- Minimum value.
- Maximum value.
- Mean.
- Median.
- Standard deviation.

The descriptive statistics of Sedation Score are presented in Table 4.

Similarly, the descriptive statistics of EEG Intensity are shown in Table 5.

Table 4: Descriptive Statistics of Sedation Score

Statistic	Value
Minimum	0.0000
Maximum	1.0000
Mean	0.4125
Median	0.4590
Std. Dev.	0.2114

Table 5: Descriptive Statistics of EEG Intensity

Statistic	Value
Minimum	0.0061
Maximum	0.0376
Mean	0.0191
Median	0.0206
Std. Dev.	0.0067

The obtained statistics indicate substantial variability in sedation conditions and measurable variations in EEG intensity, supporting their suitability as primary monitoring indicators within the proposed framework.

4.6 Feature Investigation

Given the high dimensionality of the dataset, feature-level investigation was performed to identify EEG-derived characteristics most strongly associated with anesthesia-related conditions.

The dataset contains 993 extracted neurological features derived from multiple analytical domains, including:

- Statistical descriptors.
- Frequency-domain features.
- Covariance-based characteristics.
- Eigenvalue-related measures.
- Spectral indicators.
- Temporal descriptors.

Correlation-based feature ranking was employed to identify the most informative features associated with sedation-related variables.

The highest-ranked EEG-derived features identified during the analysis are summarized in Table 6.

Table 6: Most Relevant EEG-Derived Features

Rank	Feature
1	lag1_logcovM_2_2
2	logcovM_2_2
3	lag1_std_2
4	std_2
5	lag1_min_2
6	min_2
7	freq_264_0
8	freq_314_0
9	freq_365_3

Figure 6 presents the corresponding feature-importance analysis.

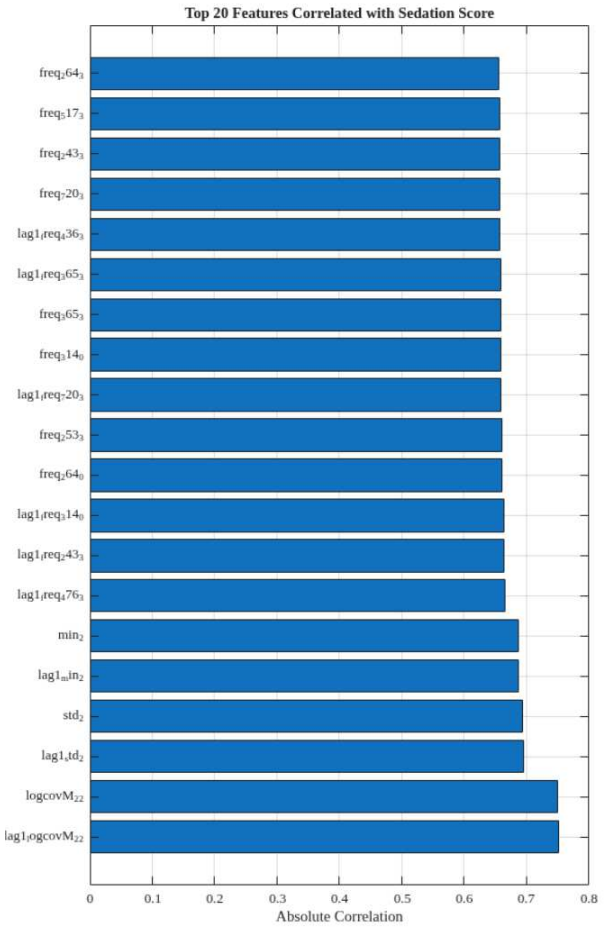

Figure 6: Feature-importance analysis for the most informative EEG-derived characteristics.

4.7 Correlation Analysis

Pearson correlation analysis was performed to investigate relationships among the principal monitoring variables.

The analysis focused on evaluating associations between:

- Sedation Score.
- EEG Intensity.
- Brain State.
- Anesthesia Level.

The resulting correlation matrix is presented and discussed in Section 5.

4.8 Statistical Significance Analysis

To evaluate differences in sedation conditions across neurological consciousness states, one-way Analysis of Variance (ANOVA) was performed using Sedation Score as the dependent variable and Brain State as the grouping factor.

The significance level adopted throughout the study was:

$$\alpha = 0.05$$

Statistical significance was determined according to the corresponding p-values.

4.9 Development of the Smart MEMS Sedation Monitoring and Risk Index (SMORI)

To facilitate monitoring-oriented assessment, a Smart MEMS Sedation Monitoring and Risk Index (SMORI) was developed.

Prior to index computation, all numerical variables were normalized using Min-Max normalization.

The proposed index integrates information derived from:

- Sedation Score.
- EEG Intensity.
- Brain State.
- Anesthesia Level.

The generalized formulation is given by:

$$SMORI = w_1 S + w_2 E + w_3 B + w_4 A \qquad (2)$$

where the weighting coefficients represent the relative contribution of each monitoring component.

The objective of SMORI is to provide a unified and clinically interpretable representation of anesthesia-related conditions suitable for future intelligent monitoring environments.

4.10 Software Environment

All analyses were performed using MATLAB and Python-based analytical tools. Statistical analysis, feature exploration, visualization, and index computation were conducted within a reproducible computational environment to ensure consistency and transparency of the obtained results.

The developed workflow can be extended in future investigations involving real-time physiological acquisition systems, MEMS-enabled sensing devices, wearable healthcare platforms, and intelligent clinical decision-support systems.

5 Results and Discussion

5.1 Dataset Characteristics

The utilized dataset contained 2,479 observations and 993 EEG-derived features representing different anesthesia-related conditions. The large number of extracted neurological characteristics provides a comprehensive representation of brain activity patterns associated with varying levels of consciousness and sedation.

Three brain-state categories were included in the datase namely Conscious (CON), Semi Loss of Consciousness (SEMI_LOC), and Loss of Consciousness (LOC). The distribution of observations across these categories is presented in Figure 4.

As illustrated in Figure 4, the dataset exhibits a nearly balanced distribution among the three neurological states. Specifically, the dataset contains 830 conscious observations, 830 semi-loss-of-consciousness observations, and 819 loss-of-consciousness observations. Such a balanced distribution is advantageous because it minimizes class-related bias and enables reliable comparisons among different anesthesia conditions.

Similarly, the anesthesia-level distribution is illustrated in Figure 5. The majority of observations belong to the Medium anesthesia category, followed by High and Low anesthesia conditions. This distribution reflects realistic clinical variability and provides sufficient representation for monitoring-oriented analysis.

The balanced representation of neurological states and anesthesia conditions demonstrates that the dataset is suitable for evaluating the proposed monitoring framework and investigating relationships among anesthesia-related variables.

5.2 Sedation Score Analysis

Sedation Score represents one of the most important variables within the dataset because it provides a quantitative indication of anesthesia-related neurological suppression.

The descriptive statistics presented in Table 4 indicate substantial variability in sedation conditions across the analyzed observations.

The minimum and maximum values span the complete normalized range between 0 and 1, while the mean Sedation Score was found to be 0.4125 with a standard deviation of 0.2114. These findings indicate the presence of multiple anesthesia conditions and varying degrees of sedation throughout the dataset.

The distribution of Sedation Score across different brain states is presented in Figure 7.

As shown in Figure 7, higher sedation values tend to be associated with reduced consciousness conditions. Observations belonging to the LOC category generally exhibit larger sedation scores compared with observations in the CON category. This behavior is physiologically consistent because increasing anesthetic depth is expected to reduce neurological responsiveness and consciousness levels.

The observed trend supports the validity of Sedation Score as a primary monitoring indicator within the proposed framework.

5.3 EEG Intensity Analysis

EEG Intensity was investigated to evaluate its contribution to anesthesia monitoring and its relationship with anesthesia-level categories.

The descriptive statistics presented in Table 5 indicate that EEG Intensity values ranged between 0.0061 and 0.0376, with a mean value of 0.0191 and a standard deviation of 0.0067.

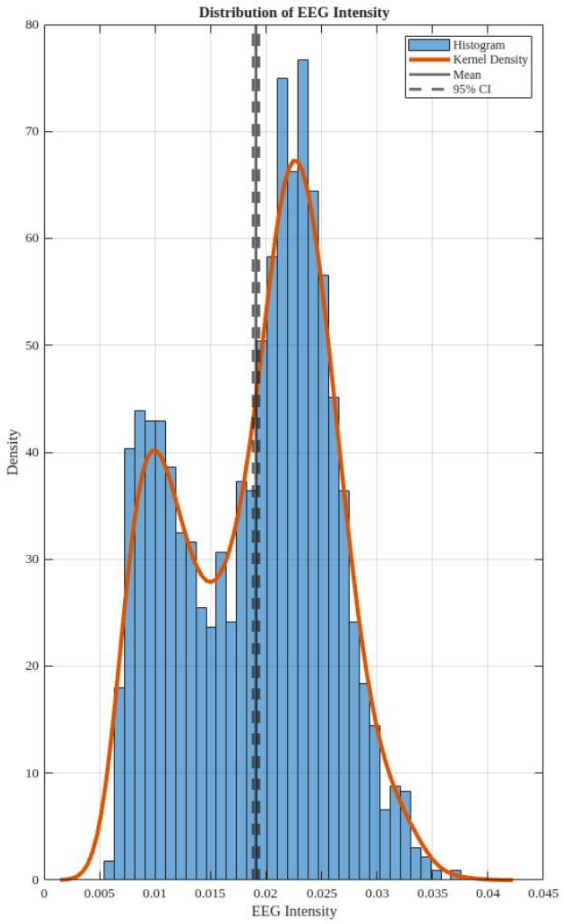

Figure 7: Distribution of Sedation Score across different brain states.

Although the numerical range is relatively narrow compared with Sedation Score, measurable differences were observed among anesthesia conditions.

Figure 8 presents the distribution of EEG Intensity across the three anesthesia levels.

The results demonstrate noticeable differences in EEG intensity patterns among Low, Medium, and High anesthesia conditions. Such variations suggest that EEG Intensity contains clinically relevant information associated with anesthesia depth and neurological activity.

These observations are consistent with previous investigations reporting changes in EEG-derived measures during transitions between different anesthesia conditions.

5.4 Feature Importance Analysis

One of the primary objectives of this study was to identify EEG-derived features most strongly associated with anesthesia-related conditions.

The dataset contains 993 extracted neurological characteristics generated from multiple analytical domains. Despite the high dimensionality of the dataset, the feature-ranking analysis revealed that a relatively small subset of characteristics contributed substantially to monitoring-related information.

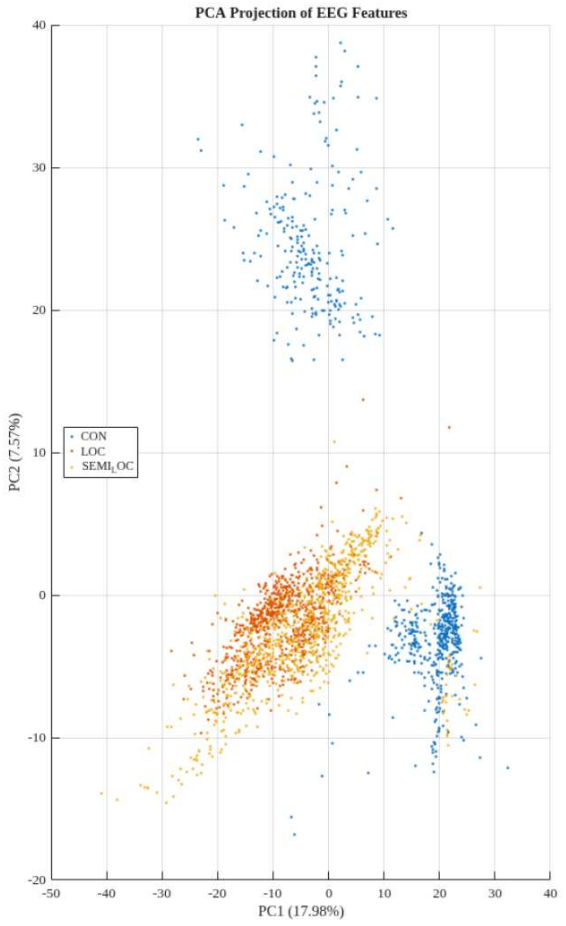

Figure 8: EEG Intensity distribution across anesthesia levels.

The most informative features identified during the analysis are summarized in Table 6.

Figure 6 illustrates the corresponding feature-importance ranking.

The results indicate that covariance-based and statistical EEG descriptors dominate the feature-ranking process. Features such as `lag1_logcovM_2_2`, `logcovM_2_2`, `lag1_std_2`, and `std_2` exhibited particularly strong relationships with anesthesia-related variables.

These findings suggest that covariance structures and variability-related EEG characteristics contain substantial information regarding sedation and consciousness transitions. Furthermore, the identification of a limited set of highly informative features indicates the possibility of reducing analytical complexity in future monitoring systems while preserving clinically relevant information.

5.5 Correlation Analysis

To investigate the relationships among the principal monitoring variables, a correlation analysis was performed.

The resulting correlation structure is visualized in Figure 9.

The analysis revealed meaningful associations among Sedation Score, EEG Intensity, Brain State, and Anesthesia Level. In particular, Sedation Score exhibited the strongest relationships with anesthesia-related indicators, confirming its importance as a primary monitoring component.

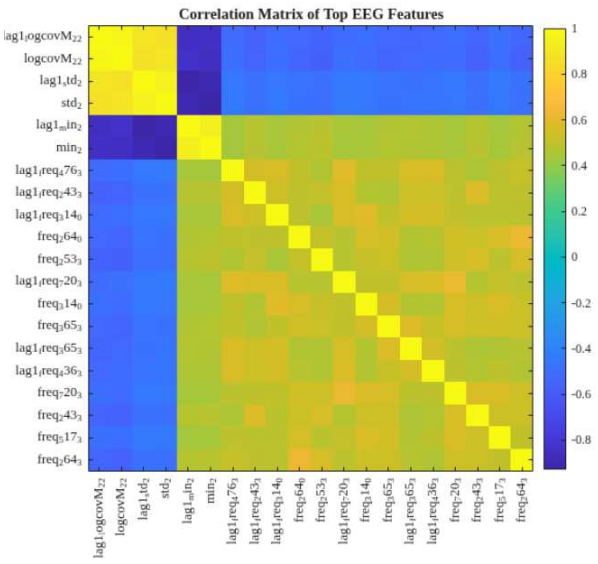

Figure 9: Correlation heatmap of the principal monitoring variables.

The correlation patterns further indicate that EEG-derived variables contain complementary information capable of improving monitoring performance when integrated within a unified analytical framework.

Overall, the correlation analysis supports the hypothesis that anesthesia-related conditions can be effectively represented through combinations of neurological and clinical indicators rather than relying on a single monitoring parameter.

5.6 Statistical Significance Analysis

To evaluate whether sedation conditions differ significantly among neurological consciousness states, a one-way Analysis of Variance (ANOVA) was performed.

The analysis compared Sedation Score values across the three Brain State categories.

The obtained results demonstrated statistically significant differences among the investigated groups ($p < 0.05$), indicating that sedation conditions vary substantially across consciousness states.

Specifically, observations associated with Loss of Consciousness (LOC) generally exhibited higher sedation levels than those associated with Conscious (CON) conditions. This behavior is consistent with established neurophysiological principles and provides additional evidence supporting the suitability of Sedation Score for anesthesia-related monitoring.

The statistical significance observed in the analysis confirms that the dataset captures meaningful neurological variations associated with anesthesia administration and consciousness transitions.

5.7 Evaluation of the Smart MEMS Sedation Monitoring and Risk Index (SMORI)

The Smart MEMS Sedation Monitoring and Risk Index (SMORI) was introduced to transform multidimensional neurological information into a single interpretable monitoring indicator.

The proposed index integrates information derived from Sedation Score, EEG Intensity, Brain State, and Anesthesia Level, thereby providing a unified representation of anesthesia-related conditions.

Figure 10 illustrates the distribution of SMORI values across the analyzed observations.

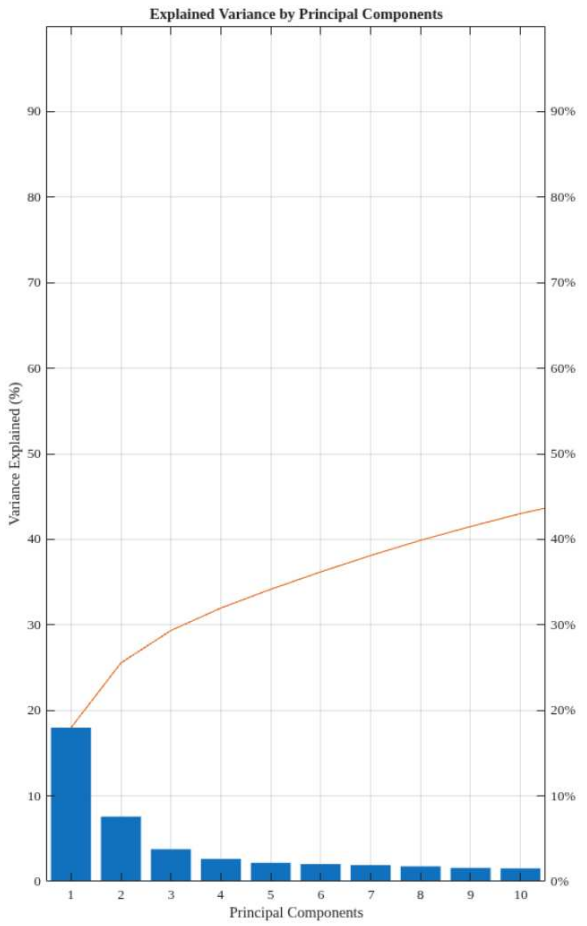

Figure 10: Distribution of Smart MEMS Sedation Monitoring and Risk Index (SMORI).

The obtained results demonstrate a progressive increase in SMORI values as neurological consciousness decreases from the conscious state toward loss of consciousness. This trend indicates that the proposed index successfully captures anesthesia-related variations and provides an interpretable representation of monitoring conditions.

To facilitate practical interpretation, the proposed SMORI classification ranges are presented in Table 7.

The ability of SMORI to distinguish among multiple anesthesia conditions highlights its potential usefulness as a monitoring-oriented indicator for future intelligent anesthesia-management systems.

Table 7: Interpretation of SMORI Values

SMORI Range	Interpretation
0.00–0.25	Normal Condition
0.25–0.50	Mild Sedation
0.50–0.75	Deep Sedation
0.75–1.00	High-Risk Condition

5.8 Discussion

The findings of this study demonstrate the feasibility of utilizing large-scale EEG-derived feature datasets within a conceptual MEMS-enabled monitoring framework for anesthesia assessment. The analysis revealed meaningful relationships among brain states, sedation scores, anesthesia levels, and several extracted neurological characteristics.

Unlike many previous studies that focus primarily on classification accuracy or anesthesia-depth estimation, the present work emphasizes monitoring-oriented assessment and the development of an interpretable framework suitable for future intelligent healthcare applications.

The feature analysis further demonstrated that only a limited subset of neurological characteristics exhibited strong relationships with anesthesia-related conditions. This observation suggests that future monitoring systems may not require the utilization of all available EEG-derived features, thereby reducing computational complexity while maintaining clinically relevant information.

The proposed SMORI concept addresses the challenge of translating hundreds of extracted EEG characteristics into a simplified monitoring indicator capable of supporting future decision-support systems. Furthermore, the conceptual MEMS-enabled architecture establishes a foundation for future investigations involving wearable sensing technologies, multimodal physiological monitoring, artificial intelligence integration, and real-time clinical deployment.

Overall, the obtained results support the feasibility of integrating EEG-derived neurological information into a structured monitoring framework capable of supporting future real-time anesthesia assessment applications and intelligent anesthesia-management environments.

6 Conclusion and Future Work

6.1 Conclusion

Accurate assessment of anesthesia remains a critical challenge in modern perioperative medicine because both insufficient and excessive anesthetic administration may adversely affect patient safety and clinical outcomes. Although considerable progress has been achieved in EEG-based anesthesia assessment, many existing studies remain focused on classification performance and anesthesia-depth estimation without providing integrated monitoring frameworks capable of supporting continuous risk evaluation and future intelligent healthcare applications.

This study presented a conceptual MEMS-enabled

framework for real-time anesthesia monitoring based on EEG-derived neurological information. The proposed framework was evaluated using a publicly available dataset containing 2,479 observations and 993 extracted EEG features representing multiple brain states, sedation conditions, and anesthesia levels. By utilizing a large-scale feature-based dataset, the study investigated relationships among neurological characteristics, Sedation Score, EEG Intensity, Brain State, and Anesthesia Level.

The exploratory and statistical analyses demonstrated that meaningful relationships exist between EEG-derived characteristics and anesthesia-related conditions. The results showed that several neurological features exhibit strong associations with sedation variables and consciousness states, indicating their potential usefulness for anesthesia monitoring applications. Furthermore, feature-ranking analysis revealed that a relatively small subset of EEG-derived characteristics contains substantial monitoring information despite the high dimensionality of the original dataset.

A major contribution of this work is the introduction of the Smart MEMS Sedation Monitoring and Risk Index (SMORI), which was designed to transform multidimensional neurological information into a unified and interpretable monitoring indicator. By integrating Sedation Score, EEG Intensity, Brain State, and Anesthesia Level into a single analytical framework, the proposed index provides a simplified representation of anesthesia-related conditions that may support future monitoring-oriented decision-support systems.

The findings also highlight the potential role of MEMS-enabled monitoring architectures in future anesthesia-management systems. Although the current study employed retrospective EEG-derived data rather than measurements acquired directly from physical MEMS sensors, the proposed framework establishes a foundation for future integration between intelligent sensing technologies, neurological monitoring systems, and data-driven healthcare applications.

Overall, the results support the feasibility of utilizing large-scale EEG-derived information within an intelligent monitoring framework and demonstrate the potential of combining advanced neurological analysis with clinically interpretable monitoring indicators for future anesthesia-management environments.

6.2 Study Limitations

Several limitations should be considered when interpreting the findings of this study.

First, the analysis was performed using a publicly available dataset containing extracted EEG-derived features rather than raw EEG recordings. Consequently, advanced signal-level investigations such as artifact removal, spectral decomposition, and time-frequency analysis were outside the scope of the present work.

Second, only EEG-derived neurological information was utilized during the analysis. Additional physiological variables such as heart rate, blood pressure, oxygen saturation, respiratory activity, and end-tidal anesthetic concentration were not incorporated. The integration of multimodal physiological information may further improve monitoring accuracy and provide a more comprehensive assessment of anesthesia-related conditions.

Third, the proposed MEMS architecture was evaluated conceptually and was not implemented on a physical sensing platform. Therefore, practical considerations related to hardware integration, wireless communication, power consumption, sensor reliability, and real-time clinical deployment remain topics for future investigation.

Finally, the proposed Smart MEMS Sedation Monitoring and Risk Index (SMORI) represents a conceptual monitoring indicator derived from retrospective analysis. Although the obtained results demonstrate promising monitoring capabilities, additional validation using clinical datasets and prospective studies is necessary before practical deployment in healthcare environments.

6.3 Future Work

Several promising research directions can be pursued to extend the proposed framework.

First, future investigations should utilize raw EEG recordings together with advanced signal-processing techniques to explore additional neurological markers associated with anesthesia depth, consciousness transitions, and patient responsiveness. Such analyses may provide deeper physiological insights into anesthesia-related brain dynamics.

Second, future monitoring frameworks should incorporate multimodal physiological information, including electrocardiography (ECG), blood pressure, respiratory signals, oxygen saturation, and other perioperative measurements. The integration of multiple information sources may improve monitoring robustness and increase the reliability of risk-assessment mechanisms.

Third, machine learning and deep learning methodologies may be incorporated into the proposed framework to develop predictive monitoring models capable of automatically identifying transitions between anesthesia states and detecting elevated-risk conditions at earlier stages.

Fourth, future work should focus on optimizing and validating the SMORI indicator using larger and more diverse clinical datasets. Such validation studies may facilitate the determination of optimal weighting strategies, threshold values, and clinical interpretation guidelines.

Finally, the proposed framework may be extended toward implementation within actual MEMS-enabled sensing devices and wearable healthcare systems. The integration of intelligent sensing technologies, real-time signal processing, wireless communication, and automated decision-support algorithms may support the development of next-generation anesthesia-monitoring platforms capable of providing continuous patient assessment and personalized perioperative care.

The convergence of MEMS technologies, EEG-based neurological analysis, artificial intelligence, and intelligent monitoring architectures represents a promising direction for the future development of advanced anesthesia-management systems and smart healthcare environments.

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Funding

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Conflict of Interest

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Data Availability

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