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Article

# Research on the effect of biosensing technology on the dissemination of health information in ideological and political education

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**Abstract:** Biosensing technologies, which monitor physiological responses such as Heart Rate Variability (HRL), Skin Conductance Level (SCL), and Electroencephalogram (EEG) activity, offer a novel approach to enhancing the dissemination of health information in ideological and political education (IPE). In this context, health information encompasses topics such as mental health, stress management, and healthy lifestyle practices, all crucial to students' overall well-being. Traditional health education methods cannot often capture real-time physiological and emotional responses, which can improve engagement and learning outcomes. This research explores the effectiveness of biosensing technology in enhancing the dissemination of health information within IPE. It examines how physiological data can be utilized to assess student engagement, emotional responses, and learning outcomes related to health. A mixed-methods approach was adopted, combining quantitative data from wearable biosensors (heart rate monitors, Galvanic Skin Response (GSR) sensors, EEG headsets) with qualitative feedback from students. Physiological data were preprocessed using signal filtering techniques, such as the Savitzky-Golay Filter, and features such as heart rate variability, skin conductance, and EEG alpha waves were extracted using the Kalman Filter (KF). A Modified Runge-Kutta Optimizer Integrated with Deep Belief Networks (MRKO-DBN) classifier was employed to predict student engagement based on these features. The research revealed that physiological responses, particularly heart rate variability and skin conductance, were strongly correlated with student engagement. The MRKO-DBN model achieved accuracy in predicting engagement. Qualitative feedback further confirmed that Biosensing technology significantly improved students' engagement. Integrating Biosensing technology into health education within ideological and political contexts offers significant potential for enhancing student engagement and learning outcomes. By providing real-time, personalized feedback, it fosters a more interactive and responsive learning environment.

**Keywords:** biosensing technologies; ideological and political education; health information; Modified Runge-Kutta Optimizer Integrated with Deep Belief Networks (MRKO-DBN); student engagement

## 1. Introduction

Health information plays a progressively important role in current IPE [1]. As civilizations evolve and face new tasks, the integration of health-related knowledge into educational structures is vital for shaping people who are not only politically aware but also physically and mentally healthy. In this context, the dissemination of health information includes a broad range of topics, from physical well-being to mental health, and includes practical knowledge, societal norms, and policies that guide individuals towards a healthier lifestyle [2]. The importance of integrating dissemination health information into IPE lies in its potential to adopt a complete view of individual and collective well-being, which is fundamental for national development [3]. Traditionally, this education focused on fostering political awareness, moral integrity, and social responsibility. However, with the development in the complexity of society and globalization, this education has expanded to the scope of health problems that influence the effectiveness of individuals in contributing to society. The promotion of health literacies in the IPE system can both help reduce the likelihood of adverse health outcomes and support the strengthening of social stability and national well-being [4].

It develops individual responsibility for the health of the person as well as the responsibility of society towards maintaining health standards [5]. This includes analyzing how socioeconomic status, education, political systems, and health are correlated. Students are supposed to learn how some government policies may have an impact on the health of people and communities [6]. Thus, focusing on social cohesiveness and national unity, the system of education endeavors to produce a population that is not only knowledgeable of the existing political infrastructure but also knows how politics influence the populace's health [7]. Moreover, health information in IPE also plays a key role in determining community approaches toward healthcare schemes. By teaching students about the structure and function of healthcare systems, including the position of universal health coverage and access to medical services, educational programs help to align citizens with the goals of national health systems [8]. This integration assists in the fight against stigma and enables people with issues of mental health to seek treatment and human support. Thus, it promotes the development of a society with increased empathy and support for its members. The integration of health information into IPE is a step in the right direction in changing the culture of society to a healthier and more socially responsibility-oriented [9]. It enables learners to appreciate the role of health problems in social, political, and economic determinants and prepare for the essential role of enhancing the well-being of society. This shows that as public health challenges persist, health information in IPE will play an even more significant role in building health literacy, capable as well as health-oriented societies [10].

This research explores the efficiency of Biosensing technology in enhancing the dissemination of health information within IPE.

## Key contribution

- Combining quantifiable data from wearable biosensors, such as heart rate monitors, GSR sensors, and EEG headsets, with qualitative responses from students.
- Data preprocessing involved using the Savitzky-Golay filter to smooth physiological signals (heart rate, skin conductance, and EEG) and reduce noise. The KF was then employed for feature extraction, refining key metrics like heart rate variability, skin conductance, and EEG alpha waves.
- An MRKO-DBN classifier was employed to predict student engagement levels based on these features.

The remaining research is addressed in the sections that follow: Part 2 provides a summary of previous research. Part 3 presents the suggested method. In Part 4, the results of using the approach were evaluated and explained. Part 5 describes the discussion of the research. The conclusion is shown in Part 6.

## 2. Related work

To minimize the generation of negative feelings and behavioral issues among college students and encourage their mental health development, Tao [11] examined the concept of mastering the fundamental psychological condition of students using the support of online political and ideological learning classrooms and also explored the mechanism of influence between the students' mental health and proposed intervention recommended accordingly.

To detect health misinformation, Zha et al. [12] suggested a model that combined peripheral-level variables like language, sentiment, and user behavioral characteristics with central-level features like dependent features. It further represented the characteristics of user engagement, the following behavioral aspects were stated: Starting a conversation, interacting with others, having an impact, mediating relationships, and being independent of information.

The conventional data control method and data categorization technique were improved in Li et al. [13] and an effective cloud-based online learning administration system was proposed that might be an excellent online education task. It was impossible to separate the control of IPE from the development of students' ideal personalities and high moral standards. Students serve as teachers' tools in the traditional IPE setting and face-to-face communication between teachers and students was essential for the successful development of college students' IPE in the traditional setting.

To enable keep track of vital signs and identify biological and psychological alterations in students, Souri et al. [14] suggested an Internet of Things (IoT)-based approach for student healthcare monitoring. The model analyzes data using Machine Learning(ML) techniques; the support vector machine has the greatest accuracy, at 99.1%. The model performs better than techniques for multilayer perceptron neural networks, random forests, and decision trees.

Using the hierarchical regression test, Zhao and Jinle [15] examined the integrated development and implementation of IPE and Ideological and Ethical Education (IEE) in educational institutions based on the beneficial psychological character of entrepreneurship. The findings showed that there were significant differences in college students' psychological qualities related to entrepreneurship by grade, gender, and family geography. IPE, IEE, and the psychological character of entrepreneurship were all influenced by entrepreneurial self-efficacy. College students' innovation efficiency and the positive psychological aspects of entrepreneurship could be enhanced by the integrated building of IPE and IEE.

Internet technology was proposed by Jiao and Yu [16] to re-invent the teaching method of the Ideological and Political (IAP) classroom. First, the significance of the IAP course was thoroughly examined, as was the precise definition and implementation procedure of MCT over the Internet. As well as a theoretical analysis of the synergy between MCT and IAP classrooms, the instructional situation of cloud learning classes was explored from the perspective of the basic design and operation of Mobile Cloud Training (MCT) platforms.

A platform for deep learning-based innovative IPE had been developed by Yun et al. [17] to increase restrictions on how multinational corporations might operate or limit their access to high-quality funding and trading for instruction. Quality analysis of information supervision was introduced to decrease the perception of social threat through appropriate strategic evaluation and execution. Companies utilized the realization ideological education strategy to solve domestic issues through economic ties.

To enhance the evaluation effect of IPE, Wang [18] investigated artificial intelligence (AI) algorithms. It combined concepts from ML with the condition of political and ideological teaching currently to create a fuzzy statistical hierarchy process model of the quality of political and ideological teaching. Additionally, it built a model network framework using a three-tier structure based on fuzzy assessment features.

The impact of educational providers and educational goals were among the many risk variables that were impacted in IPE. To enhance data awareness and the way that people thought about IPE, Feng and Yulong [19] presented the Deep Learning-Based Innovation Path Optimization Methodology (DL-IPOM) to improve the quality of IPE, DL-IPOM was combined with the political educational collaborative analysis.

The use of biosensors for human health monitoring was examined by Muñoz-Urtubia et al. [20]. With a primary emphasis on 13 journals and more than 881 keywords, it examined 275 identifications published in 161 journals. It identified areas of innovation, cooperation, and technological obstacles that might direct future research and discovered an exponential tendency in biosensor research for health monitoring. The emphasized how crucial it was to find productive writers and deal with technical issues.

The connection between political ideology and assessments of the COVID-19 threat was examined by Calvillo et al. [21]. It expected conservatives to consider COVID-19 as less threatening because of the Republican leadership's initial rejection of it and the politicized media coverage that occurred. The prediction was confirmed by two preregistered online studies. Conservative was linked to increased support for the ideas that the media had overstated the virus's impact and that the virus's propagation was a conspiracy, as well as a perception of less emotional vulnerability to the infection and a lower level of its severity.

To address a gap in the current empirical evaluations of COVID-related behaviors, Young and Bleakley [22] proposed the ideological health spirals model (IHSM), which conceptualized relationship discussion, and media choices actions as results of identity-driven reasons shaped by political and psychological factors. The model described how social sorting, political polarization, and media fragmentation all contribute to communication gaps that lead to gaps in normative, efficacy-related, and attitudinal views, which in turn influence health behaviors.

Communication has emerged at a historic intersection due to the Internet's rapid expansion and the widespread usage of smartphones, and it had an enormous impact on opinions, habits, and lifestyles. College students had emerged as the primary user group of micro-communication since they were the group that was most open to new concepts; the benefits and drawbacks of micro-communication's impact on college students' IPE were examined and focused improvement strategies were suggested to integrate micro-communication with these subjects and find agreement between the two groups Zeng et al. [23].

The political and ideological teaching in higher schooling had grown into a system that was both national and institutionalized, as demonstrated by Liu et al. [24]. It showed how political and ideological education methods institutionalize conformity and patriotism as suitable ideological perspectives for learners. It provided factual support for the formal instruction, party-led structures, and diverse activities that collectively comprise higher education political and ideological education.

To enhance the quality of education, Xu [25] examined the ideological and political programs at universities, with the challenges and strategies of implementing meta-universe technology. It commenced by discussing how meta-universe technology affects the teaching of politics and ideology, emphasizing how it might improve the interaction and viability of instruction. But it also had issues with teacher preparation, technology integration, and unequal student involvement.

## 3. Methodology

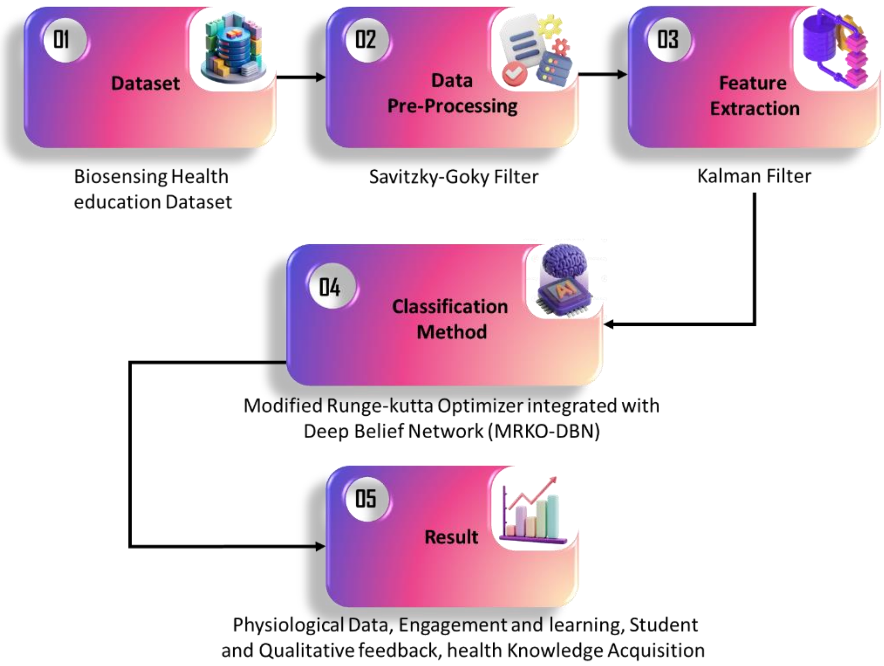


**Figure 1.** Flow of methodology.

A dataset of publicly available biosensing data was collected from wearable sensors, including heart rate monitors, GSR sensors, and EEG headsets, for analysis within the context of IPE. During the preprocessing stage, the physiological signals were filtered using signal processing techniques like the Savitzky-Golay Filter. For feature extraction, the KF was applied to extract key features, such as heart rate variability, skin conductance, and EEG alpha waves, which are indicators of student engagement and emotional responses. Though the focus was on forecasting student engagement, a novel approach was developed by integrating the MRKO-DBN for enhanced classification. Application of this approach demonstrated increased efficiency of classifying and interpreting the data of students' physiological states to generate more precise dissemination of health information about the level of their involvement during the lessons conducted within the framework of health education programs, as presented in **Figure 1**.

### 3.1. Data collection

Data has been collected from Kaggle source-https://www.kaggle.com/datasets /ziya07/bio sensing-health-education-dataset/data. This dataset has been intended to explore the relationship between physiological indicators, session appearances, and student commitment in health education situations. Essential physiological data features include Heart Rate (HR), which describes the reaction of the autonomic nervous system to being under stress or relaxed, and also Skin Conductance (SC), which measures the emotional arousal state and EEG activity which is particularly dominant by alpha waves, a description of the person's state of cognitive engagement.

### 3.2. Data preprocessing using savitzky-golay filter

Physiological data were preprocessed using signal filtering methods, precisely the Savitzky-Golay filter. This method is used to increase signal-to-noise of raw physiological signals, like heart rate or skin temperature while preserving the significant data trends. The Savitzky-Golay filter applies polynomial smoothing to the signal, which improves its accuracy and reliability, ensuring that subsequent analysis or interpretation of the physiological data remains precise and informative for understanding health-related patterns in educational contexts.

#### 3.2.1. Savitzky-golay filter

The noisy simulated EEG signal is subjected to the Savitzky-Golay filtering with different frame sizes and order values. While changing the values iteratively, effort should be taken to ensure that the polynomial's order is not beyond the frame size. There are variations in the frame size and polynomial order, respectively. A spectrum of values is used to obtain and evaluate the filtered signal. To assess the pattern of filtering action for various parameter values, the correlation between the original simulated signals and the filtered signals for various values, frame size, and order is beneficial, as shown in Equation (1).

$$COR = \frac{\sum_{j=1}^{m}(W_j - \overline{W})(W_j - \overline{W})}{\sum_{j=1}^{m}(W_j - \overline{W})(W_j - \overline{W})^2} \tag{1}$$

Dataset $W = \{W_1 \ldots .. W_m\}\overline{W}$ is the sample mean in this instance and the dataset $Z = \{Z_1 \ldots Z_m\}\bar{Z}$, is the sample mean. If the correlation among the simulated signal and the Savitzky-Golay filtered signal is 1, and the associated frame size and order values are ideal, then the filtering is ideal.

### 3.3. Feature extraction using KF

Features such as heart rate variability, skin conductance, and EEG alpha waves were extracted using the KF. The KF is an analytical method that increases the accuracy of such physiological signals by eliminating noise while updating the ongoing real-time calculations. Using these features, it explores how biosensing technology helps in an improvement of understanding the emotional and cognitive conditions and the subsequent, better distribution of dissemination health information in education.

**KF**

The KF is an analytical model that provides an estimate of the state of a dynamically evolving system based on probabilistic measures. The process of popularizing health information in IPE contributes to enhancing data accuracy to facilitate decision-making and response strategies. Equations (2) and (3) examine the system model.

$$w_{l+1} = Ew_l + x_l \tag{2}$$

$$z_l = Gw_l + u_l \tag{3}$$

where the state is denoted by $l$ and the time step by $l$. The measurement is represented by $z_l$, the state transitions and measurement matrices are represented by $E$ and $G$ , and the zero-mean processing noise and measurement noise, with covariance's $R$and $Q$, respectively, are represented by $x_l$ and $u_l$. KFs are provided in Equations (4)–(8).

$$O_l^- = EO_{l-1}^+E^S + R \tag{4}$$

$$L_l = O_l^- G^S (GO_l^- G^S + Q)^{-1} \tag{5}$$

$$\widehat{w}_l^- = E\widehat{w}_{l-1}^+ \tag{6}$$

$$\widehat{w}_l^- = \widehat{w}_l^- + L_l(z_l - G\widehat{w}_l^-) \tag{7}$$

$$O_l^+ = (J - L_l G)O_l^- \tag{8}$$

where $J$ represents the identity matrix for $l = 1,2, \dots,.$ A priori estimates of the condition $w_l$given measurement up to and including time $l - 1$ are denoted by the symbol$\widehat{w}_l^-$. A posteriori estimates of the condition $w_l$ given measurement up to and included time are denoted by$\widehat{w}_l^-.l$, $O_l^-$is the probability of the subsequent estimate error $w_l - \widehat{w}_l^-$,$L_l$ is known as Kalman benefit, and $O_l^-$ represents the probability of the a priori measurement error$w_l - \widehat{w}_l^+$. Initialization of the Kalman filter is done using Equations (9) and (10). Where the expectation operator is $F(.)$.

$$w_0^+ = F(w_0) \tag{9}$$

$$O_0^+ = F[(w_0 - w_0^+)(w_0 - w_0^+)^S] \tag{10}$$

The KF, which is the minimum variance filter, minimizes the trace of the $\{x_l\}$ and $\{u_l\}$ are Gaussian uncorrelated, and white. Although nonlinear filters might work better, the Kalman filtering is the minimum-variance linear filter when $\{x_l\}$ and $\{u_l\}$ are non-Gaussian. The least variance filter may be obtained by modifying Equations (4)–(8) if $\{x_l\}$and $\{u_l\}$have correlations or are colored. The equality criteria have been satisfied by the approach. Equation (11) is implemented, or the limitations of inequality Equation (12) is applied.

$$Cw_l = c \tag{11}$$

$$Cw_l \leq c \tag{12}$$

where $c$ represents a known vector and $C$ represents a known matrix. Finding a condition estimate $\widehat{w}_l$ that corresponds with the limitations may be desirable in this situation by Equations (13) or (14).

$$C\widehat{w}_l = c \tag{13}$$

$$C\widehat{w}_l \leq c \tag{14}$$

### 3.4. MRKO-DBN

The MRKO-DBN provides a more sophisticated solution for improving and interpreting biosensing data concerning IPE. This method is likely to integrate the iterative optimization capability of MRKO techniques, and the classification functionality of DBN. The MRKO algorithm helps in achieving faster convergence in DBN through updates of parameters and can learn non-linear biosensing data, like heart rate variability, skin conductance, and EEG features. Thus, applying MRKO for optimization, the DBN model can leverage real-time physiological data to better predict the level of student engagement and their emotional reactions. This results in better dissemination of health information, individualized teaching and learning, as well as better educational achievements. The integration of MRKO with DBN thus offers a solid foundation for enhancing biosensing technology interface and educative content in IPE. Algorithm 1 shows the pseudo-code of MRKO-DBN.

**Algorithm 1** MRKO-DBN

```
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import StandardScaler
def load_biosensing_data():
   biosensing_data = np.load('biosensing_data.npy')
return biosensing_data
def preprocess_data(data):
   scaler = StandardScaler()
   scaled_data = scaler.fit_transform(data)
return scaled_data
class DBN:
def __init__(self, layers):
self.layers = layers
self.model = self.build_model()
def build_model(self):
model = tf.keras.Sequential()
for layer in self.layers:
```

**Algorithm 1** (*Continued*)

```
        model.add(tf.keras.layers.Dense(layer, activation = 'relu'))
        model.add(tf.keras.layers.Dense(1, activation = 'sigmoid'))
        model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
  return model
def train(self, X_train, y_train, epochs = 10, batch_size = 32):
    self.model.fit(X_train, y_train, epochs = epochs, batch_size = batch_size)
    def predict(self, X_test):
return self.model.predict(X_test)
def mrko_optimizer(model, X_train, y_train, max_iter = 100):
    best_params = model.get_weights()
    best_accuracy = 0
    for iteration in range(max_iter):
params = model.get_weights()
adjusted_params = mrko_adjust_params(params)
        model.set_weights(adjusted_params)
model.train(X_train, y_train)
accuracy = evaluate_model(model, X_train, y_train)
if accuracy > best_accuracy:
best_accuracy = accuracy
best_params = adjusted_params
model.set_weights(best_params)
return model
def mrko_adjust_params(params):
adjusted_params = params + np.random.randn(*params.shape) * 0.01
return adjusted_params
def evaluate_model(model, X, y):
 predictions = model.predict(X)
    accuracy = np.mean((predictions == y))
def main():
biosensing_data = load_biosensing_data()
X = preprocess_data(biosensing_data)
y = np.load('engagement_labels.npy')
X_train, X_test = X[:int(0.8 * len(X))], X[int(0.8 * len(X)):]
y_train, y_test = y[:int(0.8 * len(y))], y[int(0.8 * len(y)):]
dbn_model = DBN(layers = [64, 32, 16])
optimized_model = mrko_optimizer(dbn_model, X_train, y_train)
test_accuracy = evaluate_model(optimized_model, X_test, y_test)
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
if _name_ == "_main_":
main()
```

### 3.4.1. DBN

DBN is a kind of neural network used for unsupervised learning and is architected with several layers of connected nodes. In health information dissemination, DBNs can recognize and enhance patterns in Biosensing data in IPE communication. DBN training using a greedy learning method. To estimate a lower bound for the log probability assigned to the data by the DBN. Consider learning a DBN that has two hidden feature levels. Stacks of Restricted Boltzmann Machines (RBMs) are used in the greedy technique. Then proceed by using parameter $X$ to train the bottom RBM. The combined distribution of the RBM $o(u, g^1|X^1)$ is an important observation. $X^1$ is the identical value of a DBN where $X^2 = X^{1^S}$ is the weight of the second layer. To improve the fitness of the training data, by separating and improving $X^2$. The DBN's for any approximate distribution $R(g^1|u)$. The following Equation (15) is the variation lower bound for log-likelihood.

$$In\ o(u|X^1, X^2) \geq \sum_{g^1} R(g^1|u)[In\ o(g^1|X^2) + In\ o(u|g^1, X^1)] + \mathcal{G}\big(\mathcal{R}(g^1|u)\big) \tag{15}$$

where the entropy function is denoted by $\mathcal{G}(.)$. It establishes $\mathcal{R}(g^1|u) = o(g^1|u,\ X^1)$ and is defined by RBM. First, the bound is tight for $X^2 = X^{1^S}$, where $R$ is the true factorial posterior of the DBN over $g^1$. The true probability of the model will therefore rise in response to any increment in the bound. Using frozen $X^1$ to maximize the bound of Equation (15) is equivalent to maximizing. This is the same as using vectors from $R(g^1|u)$ to train the second layer RBM, as data shown in Equation (16).

$$\sum_{g^1} R(g^1|u) In\ o(g^1|X^2) \tag{16}$$

By using $g^2$ vectors obtained from a second RBM to train a third RBM, this approach can be expanded. The log-likelihood itself may fall, but the lower limit on the log-likelihood is assured to be improved and it initializes $X^3 = X^{2^S}$. Several iterations of this greedy, layer-by-layer training produce a deep, hierarchical model. The total number of hidden elements of the new RBM does not have to match the number of visible components of a lower-level RBM because installing a new layer $k$ usually does not initialize $X^k = X^{k-1^S}$.

Consider an identical DBN model that has two hidden feature layers. Equation (17) is the joint distribution model.

$$o(u, g^1, g^2) = o(u|g^1) o(g^2, g^1) \tag{17}$$

In the above instance $o(g^1, g^2)$ is the joint distribution determined by the following layer RBM, and $o(u|g^1)$ is defined by Equation (17). Keep in consideration that $o(u|g^1)$ has been adjusted. It can quickly calculate an unnormalized likelihood $o^*(u, g^1) = Zp(u, g^1)$ by directly adding up $g^2$. Using the variation lower bound of Equation (15) and the approximate factorial distribution $R$, which obtain Equation (18) as a product of the greedy learning process.

$$In \sum_{g^1} o(u, g^1) \geq \sum_{g^1} R(g^1|u) In\ o^*(u, g^1) - In\ Y + \mathcal{G}\big(R(g^1|u)\big) = A(u) \tag{18}$$

Given that $R$ is factorial, the entropy component $\mathcal{G}(.)$ can be calculated analytically. Annealed Importance Sampling (AIS) is used to estimate the function of partition $Y$ on the highest level RBM. Additionally, a straightforward Equation (19) can be used to estimate the expectation term.

$$\sum_{g^1} R(g^1|u) In\ o^*(u, g^1) \approx \frac{1}{N} \sum_{j=1}^{N} In\ o^*\big(u, g^{1(j)}\big) \tag{19}$$

where $g^{1(j)} \sim R(g^1|u)$ this Equation (19) estimator's variance will be equivalent to $\frac{1}{N}$ as long as in $o^*\big(u, g^{1(j)}\big)$ has a finite variance. In general, to determine the lower bound averages across the test set of $M_S$ samples, Equation (20) is presented.

$$\frac{1}{M_s}\sum_{m=1}^{M_s} A(u^m) \approx \frac{1}{M_s}\sum_{m=1}^{M_s}\left[\frac{1}{N}\sum_{j=1}^{M} In\, o^*\left(u^m, g^{1(j)}\right) + \mathcal{G}\left(R(g^1|u^m)\right)\right] - In\,\hat{Y} = q_A - In\,\hat{Y} = \hat{q}_{Bound} \quad (20)$$

Asynchronously, the variation of the estimate caused by the approximation will scale as $\frac{1}{M_s N}$. The experimental findings section demonstrates that if $M_s$ is big, the number of $N$ might be small. The error in the estimation of $\hat{Y}$ will primarily dominate the error spectrum of the total estimate $\hat{q}_{Bound}$ in Equation (20). To obtain impartial estimations of $\hat{Y}$ and its standard deviation $\hat{\sigma}$ as well as $In(\hat{Y} \pm \hat{\sigma})$ are reported. It is currently simple to estimate this lower bound for DBN using additional layers. Consider a DBN that has $K$ hidden layers. The estimated probability distribution $R$ and joint distribution of the model are provided in Equation (21).

$$\begin{gathered} o(u, g^1, \ldots\ldots, g^K) = o(u|g^1) \ldots o(g^{K-2}|g^{K-1}) o(g^{K-1}, g^K) \\ R(g^1, \ldots., g^K|u) = R(g^1|u) R(g^2|g^1) \ldots R(g^K|g^{K-1}) \end{gathered} \quad (21)$$

It is at the moment possible to derive the bound using Equation (18). The majority of the computational resources will be used to estimate the top-level RBM's partition function $Y$.

#### 3.4.2. MRKO

MRKO enhances iterative computational methods by refining approximation accuracy in dynamic systems, enabling more precise modeling of dissemination of health information in IPE, especially in Biosensing technology applications. Despite being a promising optimization method, the RKO has certain drawbacks, including slow convergence, getting trapped in suboptimal areas, and an unbalanced exploration and exploitation phase. To address the drawbacks of RKO, an effective substitute variation known as ERKO is developed. Specifically, MRKO employs the following three techniques to keep the algorithm from being trapped in local minimum regions:

- To improve the exploration and exploitation stages of classical RKO, non-linear operators (NO) are introduced in recently updated candidate solutions.
- This results in comparison better transition from the exploration to the exploitation stage and turns the appropriate time of the search.
- In early versions, implement chaotic local searching (CLS) to adequately explore the specified search space. The following provides specifics on the MRKO algorithm's mathematical formulation.

*The non-linear operators*

The distribution of recently updated coordinates in the traditional RKO algorithm is based on two motion phases: Exploration and exploitation. Random transfers between them have the potential to isolate every individual in local optima. The NO, which is non-linear and capable of handling more complicated issues than linear operators, is suggested here for successfully transitioning from exploration to exploitation. Additionally, rather than turning the signal stage in the standard RKO algorithm at random, the NO performs so at a reasonable search time. Where $\emptyset \geq 1$ is constant. The given NO is shown in Equation (22).

$$NO = \sin\left(\emptyset - \frac{s}{S}\right) \quad (22)$$

*Various configurations for recently updated candidate solutions*

In both exploitation and exploration search, the RKO algorithm operates in static behavior, updating candidate solutions solely based on the positions of other agents without adjusting parameters to the present stage of the search, such as consuming time. This implies that the agents do not transition gradually from exploitation to exploration, and it may waste approximately half of the search in every stage without dynamic changes. By adding a non-linear operator (NO) to update candidate solutions in the manner described below, this disadvantage can be avoided. The exploration stage is given in Equation (23) and the exploitation stage is given in Equations (24)–(29).

$$w_{m+1} = q \times w_m + NO \times (1-q) \times w_{q1} + SF \times SM + \mu \times w_t \quad (23)$$

$$w_{m+1} = q \times w_{best} + NO \times (1-q) \times w_{kbest} + SF \times SM + \mu \times w_{t'} \quad (24)$$

$$w_t = randm(w_n - w_d) \quad (25)$$

$$w_{t'} = randm(w_{q1} - w_{q2}) \quad (26)$$

$$\mu = 0.5 + 0.1 \times randm \quad (27)$$

$$SF = 2(0.5 - rand) \times e \quad (28)$$

$$e = b \times \exp\left(-a \times \frac{s}{S}\right)) \quad (29)$$

where $b$ and $a$ are constants, $w_{best}$ is the global ideal, and $w_{kbest}$ is the ideal position at each iteration.

*Phase of exploration with CLS*

One method for creating randomized behavior for potential solutions at the start of the search is chaos. This makes it possible to effectively search the specified area. There are several types of chaotic maps, including Sine, Piecewise, Logistic, and Circle. Depending on the logistic map, it present a chaotic map here. With randomly produced solutions$\left(D_q\right)$, the suggested map is associated with the non-linear operation that is adaptable to the goal solution$\left(D_q\right)$. The recommended chaotic map is provided in Equations (30)–(32).

$$D = (1-\omega) \times w_S + \omega \times D_q \quad (30)$$

$$\omega = NO \times rand \quad (31)$$

$$D_q = rand \times (V - K) + K \quad (32)$$

## 4. Result

The experimental design involved data collecting biosensing data, including heart rate, skin conductance, and EEG activity to evaluate students' engagement and cognitive response during health education sessions. Wearable sensors were used to collect data in class, while engagement, learning outcomes, and students' feedback were also recorded. The analysis was conducted using Python 3.12 operated on Windows 11 with an 11th-generation Core i7 processor and 32 gigabyte (GB) of random access memory (RAM). The MRKO-DBN model applied to the analysis of the physiological indicators, including qualitative data such as student feedback and health knowledge acquired, to determine the effectiveness of biosensing technology in enhancing the dissemination of health information in ideological and political education.

### 4.1. Physiological data parameters

The integration of Biosensing technology enhances the dissemination of health information in IPE by offering real-time physiological data parameters. The results indicate that the MRKO-DBN model significantly outperforms the standard DBN in analyzing various physiological parameters, **Table 1** and **Figure 2** show that the MRKO-DBN model outperforms the standard DBN in the analysis of physiological data. It attains accuracy in HRV (55% to 75%), SCL also improves (from 62% to 80%), EEG Alpha Waves Wave Power increases (from 58% to 72%), and EEG Beta Waves rises (from 65% to 82%), thereby showing its improved capability in the personalization of health information dissemination in ideological and political education.

**Table 1.** Physiological data parameters result.

| Physiological Data Parameters | Standard DBN | MRKO-DBN (Proposed) |
| --- | --- | --- |
| HRV | 55% | 75% |
| SCL | 62% | 80% |
| EEG Alpha Wave Power | 58% | 72% |
| EEG Beta Wave Power | 65% | 82% |

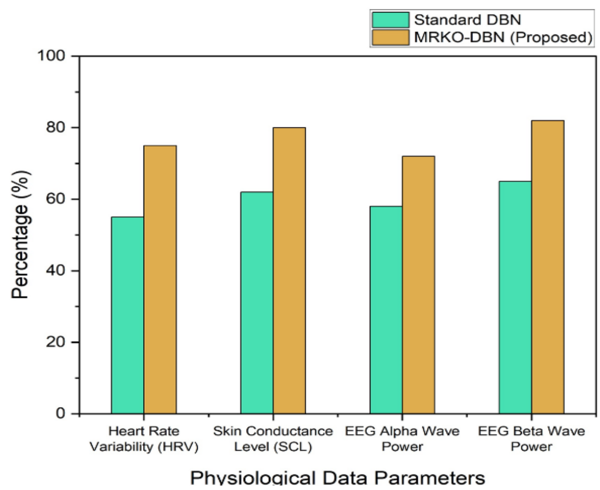


**Figure 2.** Physiological data parameters result.

### 4.2. Engagement and learning outcome

The combination of MRKO-DBN in student engagement and learning outcome prediction demonstrates significant improvements over the standard DBN model. The results indicate that the MRKO-DBN model significantly outperforms the standard DBN in analyzing various physiological parameters, **Table 2** and **Figure 3** highlights superior performance of the MRKO-DBN model in contrast to the standard DBN as far as students' involvement is concerned (68% to 85%), levels of attention (63% to 80%), cognitive load (70% to 85%), learning outcomes (72% to 88%), and emotional response (71% to 87%). This progress underscores the efficacy of MRKO-DBN in improving health education dissemination in ideological and political education.

**Table 2.** Engagement and learning outcome result.

| Engagement and Learning Outcome | Standard DBN | MRKO-DBN (Proposed) |
|---|---|---|
| Student Engagement Prediction | 68% | 85% |
| Attention Level | 63% | 80% |
| Cognitive Load (via HRV and SCL) | 70% | 85% |
| Learning Outcomes Improvement | 72% | 88% |
| Emotional Response (Positive) | 71% | 87% |

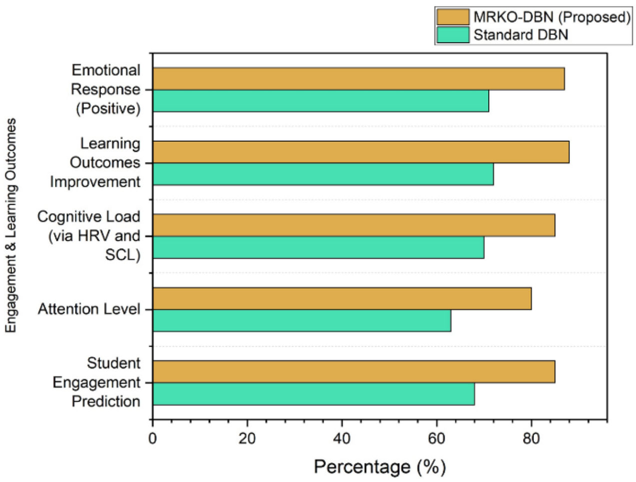


**Figure 3.** Engagement and learning outcome result.

### 4.3. Student and qualitative feedback

The data compares student and qualitative feedback between the standard DBN and the proposed MRKO-DBN. In terms of perceived engagement, the MRKO-DBN showed a significant improvement, **Table 3** and **Figure 4** present the substantial gains in student feedback between the MRKO-DBN model and the standard DBN. There was a perceived engagement from (68% to 85%). The percentage of real-time monitoring feedback increased from (70% to 87%). The percentage of positive emotional experiences also increased from (69% to 84%). Students' experience with the biosensing technology improved from 66% to 81%. Behavioral responses rose from (72% to 88%). These results indicate how MRKO-DBN increases interest, emotional involvement, and overall satisfaction, thereby improving the effectiveness of health education in ideological and political education.

**Table 3.** Student and qualitative feedback result.

| Parameter | Standard DBN | Proposed MRKO-DBN |
|---|---|---|
| Perceived Engagement | 68% | 85% |
| Feedback on Real-Time Monitoring | 70% | 87% |
| Emotional Experience (Positive) | 69% | 84% |
| Experience with Biosensing Technology | 66% | 81% |
| Behavioral Response | 72% | 88% |

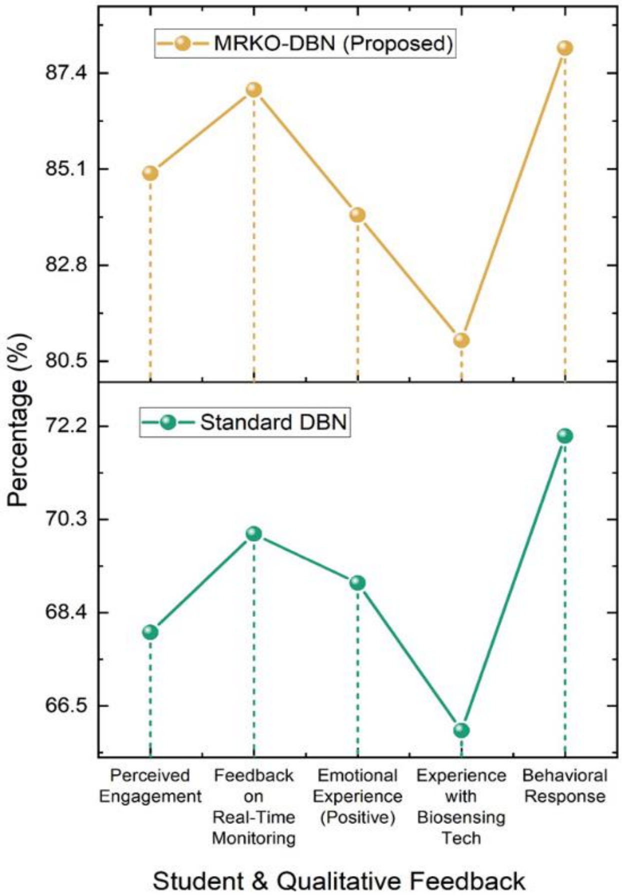


**Figure 4.** Student and qualitative feedback result.

### 4.4. Health knowledge acquisition

The use of biosensing technology enhances the distribution of dissemination health information in IPE by providing real-time health knowledge acquisition. The MRKO-DBN model outperforms the standard DBN model, **Table 4** and **Figure 5** illustrate that the MRKO-DBN model outperforms the standard DBN model in health knowledge acquisition. Students' engagement in health issues increased from (70% to 85%), and the enhancement of health behavior rose from (50% to 70%). Emotional responses increased from (60% to 75%), and data retention improved from (50% to 70%). Classroom engagement with health information also increased from (65% to 80%), which reflects the effectiveness of the MRKO-DBN model in enhancing health education within ideological and political education.

**Table 4.** Health knowledge acquisition.

| Health Knowledge Acquisition | Standard DBN | MRKO-DBN (Proposed) |
|---|---|---|
| Involvement of students with health-related topics | 70% | 85% |
| Effects on health and social behavior | 50% | 70% |
| Emotional response to health-related issues | 60% | 75% |
| Retention of health data over time | 50% | 70% |
| Classroom engagement with health-related information | 65% | 80% |

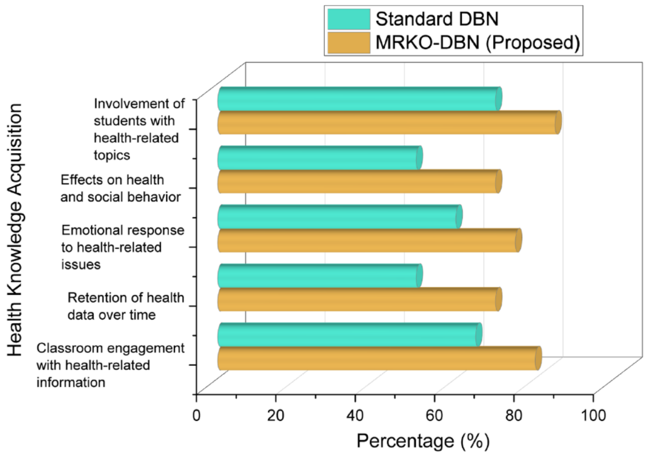


**Figure 5.** Health knowledge acquisition result.

## 5. Discussion

The combination of the MRKO-DBN approach and the application of biosensing technologies in the promotion of dissemination of health information within IPE has produced promising results. Based on the data, it can be noted that the MRKO-DBN model produces a noticeably higher performance than the standard DBN model for several parameters, including physiological data parameters, learning outcomes, engagement levels, students, and qualitative feedback regarding the model, as well as the increased general health information. In physiological data parameters, the MRKO-DBN model outperforms the standard DBN model, achieving 75% accuracy in HRV compared to standard DBN at 55%. SCL increased from 62% to 80%, while EEG alpha wave power improved from 58% to 72%, showcasing the model's enhanced ability to analyze physiological data for a more personalized learning experience. In engagement and learning outcomes, the MRKO-DBN improves student engagement prediction accuracy to 85%, compared to the standard DBN of 68%. Learning outcomes increased from 72% to 88%, significantly boosting learning outcomes and emotional responses, which represents from 71% to 87%. In student and qualitative feedback, the MRKO-DBN model shows an increase in perceived engagement (85% to 68% with standard DBN), an increase in real-time monitoring satisfaction (87% to 70%), and an improvement in behavioral response (88% to 72%). In health knowledge acquisition, the MRKO-DBN model increases students with health-related topics from 70% to 85%, classroom engagement with health information from 65% to 80%, and emotional responses to health issues from 60% to 75%, illustrating its effectiveness in health education dissemination.

The proposed MRKO-DBN model outperforms the traditional models with a significant improvement in the accuracy of analyzing physiological data, including HRV, SCL, and EEG alpha waves, thereby enhancing the personalized learning experience. It further improves student engagement prediction accuracy, learning outcomes, and emotional responses. The MRKO-DBN further boosts real-time monitoring satisfaction, behavioral responses, and health knowledge acquisition. Therefore, it can prove more effective in disseminating health information in the ideological and political education context.

## 6. Conclusion

The integration of biosensing technology into the dissemination of health information within IPE offers a promising new approach to enhancing student engagement and learning outcomes. Data collection involved monitoring physiological responses, such as HRV, SCL, and EEG activity, using wearable biosensors. The collected physiological data were pre-processed through signal filtering techniques, including the Savitzky-Golay Filter, and feature extraction was performed using the KF. The MRKO-DBN classifier was employed to predict student engagement levels based on these features, achieving high predictive accuracy. The results revealed a strong correlation between physiological responses; the model achieved the highest improvements in physiological data, with EEG beta wave power at (82%), student engagement prediction at (85%) in engagement and learning outcome, behavioral response ratings at (88%) in student and qualitative data, and health-related topic engagement at (85%) in health knowledge acquisition. Despite the promising outcomes, a limitation of this research lies in the static nature of the data, which may not fully capture dynamic changes in physiological responses during class. Future research could address this limitation by incorporating real-time physiological data streaming and considering additional factors, such as individual learning preferences, emotional states, and stress levels, to improve the model's personalization and applicability across diverse educational contexts.

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## References

1. Gao, H.W., 2023. Innovation and development of ideological and political education in colleges and universities in the network era. International Journal of Electrical Engineering & Education, 60(2_suppl), pp.489–499.
2. Gkinton, E., Telonis, G., Halkiopoulos, C. and Boutsinas, B., 2022, September. Quality of life and health tourism: A conceptual roadmap of enhancing cognition and well-being. In International Conference of the International Association of Cultural and Digital Tourism (pp. 651–666). Cham: Springer International Publishing.
3. Germain, E., 2024. Well-being and equity: A multi-disciplinary framework for rethinking education policy. In Thinking Ecologically in Educational Policy and Research (pp. 6–17). Routledge.
4. Godziewski, C., 2022. The politics of health promotion. The Politics of Health Promotion in the European Union.
5. Benati, I. and Coccia, M., 2022. Global analysis of timely COVID-19 vaccinations: improving governance to reinforce response policies for pandemic crises. International Journal of Health Governance, 27(3), pp.240–253.
6. Kim, D.K.D. and Kreps, G.L., 2020. An analysis of government communication in the United States during the COVID-19 pandemic: recommendations for effective government health risk communication. World Medical & health policy, 12(4), pp.398–412.
7. Kraft, M.E. and Furlong, S.R., 2020. Public policy: Politics, analysis, and alternatives. Cq Press.
8. Samuel, J., Flores, W. and Frisancho, A., 2020. Social exclusion and universal health coverage: health care rights and citizen-led accountability in Guatemala and Peru. International journal for equity in health, 19, pp.1–9.
9. Twyford, E.J., Musundwa, S., Tanima, F.A. and George, S., 2024. Bridging the gap: sustainable development goals as catalysts for change in accounting education and society. Meditari Accountancy Research, 32(5), pp.1758–1786.
10. Holland, S., 2022. Public health ethics. John Wiley & Sons.
11. Tao, Y., 2022. EVALUATION AND ANALYSIS OF THE EFFECT OF NETWORK IDEOLOGICAL AND POLITICAL EDUCATION ON ALLEVIATING COLLEGE STUDENTS’MENTAL HEALTH. Psychiatria Danubina, 34(suppl 2), pp.207–207.
12. Zhao, Y., Da, J. and Yan, J., 2021. Detecting health misinformation in online health communities: Incorporating behavioral features into machine learning based approaches. Information Processing & Management, 58(1), p.102390.
13. Li, K., Jing, M., Tao, X. and Duan, Y., 2023. Research on online management system of network ideological and political education of college students. International Journal of Electrical Engineering & Education, 60(2_suppl), pp.377–388.
14. Souri, A., Ghafour, M.Y., Ahmed, A.M., Safara, F., Yamini, A. and Hoseyninezhad, M., 2020. A new machine learning-based healthcare monitoring model for student’s condition diagnosis in Internet of Things environment. Soft Computing, 24(22), pp.17111–17121.
15. Zhao, X. and Zhang, J., 2021. The analysis of integration of ideological political education with innovation entrepreneurship education for college students. Frontiers in psychology, 12, p.610409.
16. Jiao, Y. and Liu, Y., 2021. The teaching optimization algorithm mode of integrating mobile cloud teaching into ideological and political courses under the internet thinking mode. Scientific Programming, 2021(1), p.6492009.
17. Yun, G., Ravi, R.V. and Jumani, A.K., 2023. Analysis of the teaching quality on deep learning-based innovative ideological political education platform. Progress in Artificial Intelligence, 12(2), pp.175–186.
18. Wang, Y., 2021. Ideological and political teaching model using fuzzy analytic hierarchy process based on machine learning and artificial intelligence. Journal of Intelligent & Fuzzy Systems, 40(2), pp.3571–3583.
19. Feng, L. and Dong, Y., 2022. Teaching quality analysis of college ideological and political education based on deep learning. Journal of Interconnection Networks, 22(Supp05), p.2147006.
20. Muñoz-Urtubia, N., Vega-Muñoz, A., Estrada-Muñoz, C., Salazar-Sepúlveda, G., Contreras-Barraza, N., Salinas-Martínez, N., Méndez-Celis, P. and Carmelo-Adsuar, J., 2024. Wearable biosensors for human health: A bibliometric analysis from 2007 to 2022. Digital health, 10, p.20552076241256876.
21. Calvillo, D.P., Ross, B.J., Garcia, R.J., Smelter, T.J. and Rutchick, A.M., 2020. Political ideology predicts perceptions of the threat of COVID-19 (and susceptibility to fake news about it). Social Psychological and Personality Science, 11(8), pp.1119–1128.
22. Young, D.G. and Bleakley, A., 2020. Ideological health spirals: An integrated political and health communication approach to COVID interventions. International Journal of Communication, 14, p.17.

23. Zeng, Z., 2020. Research of Micro-Communication on Ideological and Political Education of College Students. International Journal of Social Sciences in Universities, p.93.
24. Liu, X., Xiantong, Z. and Starkey, H., 2023. Ideological and political education in Chinese Universities: structures and practices. Asia Pacific Journal of Education, 43(2), pp.586–598.
25. Xu, X., 2023. Practical Dilemmas and Coping Strategies of Meta-Cosmos in Helping the High Quality Development of Ideological and Political Education in Colleges and Universities. Applied Mathematics and Nonlinear Sciences, 9(1).