

# Deep Learning Method for Indoor Carbon Consumption Analysis

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## ABSTRACT

In the context of environmental protection and sustainable development, studying the relationship between indoor activities and carbon consumption is crucial. Traditional methods struggle to consider individual differences and environmental changes, necessitating the introduction of deep learning and reinforcement learning technologies to achieve intelligent and personalized environmental recommendations. This study proposes a method based on the integration of the GRU-Transformer model with Deep Reinforcement Learning (DRL) to process time series data generated by indoor sensing devices and optimize carbon consumption. Experimental results demonstrate that this model achieves 99.42% accuracy on the Fitbit dataset, 98.11% on the NHANES dataset, and 94.63% and 96.55% on the Open AI Gym and UCI datasets, respectively. Additionally, the model performs excellently across various metrics, including recall, F1 score, and AUC, showcasing outstanding generalization capabilities and performance. The model can provide personalized recommendations and real-time feedback to users, thereby promoting healthy, environmentally friendly, and sustainable lifestyles.

Keywords: Deep learning, Data analysis, Carbon consumption, Sensor devices, Artificial intelligence, Energy efficiency

## 1. Introduction

Currently, environmental problems are becoming more and more serious around the world. Issues such as climate change, carbon emissions, and energy consumption are posing huge threats to global society, economy, and ecological systems. Climate change has led to an increase in extreme weather events, seriously affecting the quality of life, while carbon emissions and excessive energy consumption pose a threat to the earth's ecological balance. Therefore, environmental protection and sustainable development have become the focus of global attention. Of particular concern is the acceleration of urbanization, which has led to increased carbon emissions within cities [1]. In this context, it is particularly important to pay attention to the impact of indoor activities on carbon consumption [2]. People's daily activities indoors, such as home, work and entertainment, directly affect indoor carbon emissions. However, traditional methods often fail to fully take into account individual differences and changing environmental conditions [3]. Therefore, the introduction of advanced deep learning and reinforcement learning technologies has become an urgent need to solve

this problem. These advanced technologies can provide more intelligent and personalized solutions for the formulation of environmental protection recommendations and strategies to meet the needs of different groups of people. For example, by accurately monitoring the relationship between indoor activities and carbon consumption, we can provide individuals and society with smarter environmental recommendations and promote more sustainable lifestyles.

As technology continues to advance, we now have more powerful data collection and analysis tools, allowing us to delve deeper into the relationship between indoor activity and carbon consumption. First, as the ability to collect time series data continues to increase, we can more accurately monitor small changes in indoor activities, including activity type, intensity, duration, and other factors [4]. This allows us to understand individual behavioral patterns and trends more fully in indoor carbon consumption. Advances in these technologies provide new opportunities to study indoor carbon consumption, providing insights into how these changes are related to carbon emissions [5]. Additionally, big data enables us to collect indoor activity and carbon consumption data on a wider scale, from homes to workplaces to social spaces. This provides us with additional sources of data that can contribute to a more comprehensive understanding of the relationship between indoor activity and carbon consumption, considering variation across different populations and across different environments. The application of deep learning technology further improves our ability to process and analyze these data [6]. It can process large-scale and complex time series data, help us extract patterns and correlations, and reveal deeper information. This provides us with additional insights to better understand the cause-and-effect relationship between indoor activity and carbon consumption. The combination of these technologies and data provides us with a unique opportunity to study the relationship between indoor activities and carbon consumption to better understand and optimize carbon footprints [7]. This kind of research not only contributes to a more comprehensive understanding of this relationship, but also provides us with the opportunity to develop more effective environmental policies and provide smarter environmental advice to individuals, thereby helping to reduce carbon footprints and achieve more sustainable outcomes.

This study is dedicated to exploring the application of deep learning-driven data analysis methods in indoor carbon consumption monitoring to address this pressing issue. Deep learning has shown great potential in various fields, and time series data analysis is no exception. The field continues to evolve, allowing us to better understand and utilize time-series data, including indoor activity and carbon consumption data. Deep learning models, such as Recurrent Neural Network (RNN) and Transformer, have excellent sequence modeling capabilities and can help us capture key information in time series more accurately [8]. This provides us with new opportunities to study the relationship between indoor activities and carbon consumption to better understand the interaction between individuals and the environment.

As a product of modern technology, smart wearable sensing devices have the potential to monitor carbon consumption in indoor environments. These devices can record information such as the user's activity type, intensity, and duration in real time, while capturing physiological data such as heart rate and step count [9]. These data can provide valuable insights and help in building user-specific carbon consumption models. Therefore, this study aims to fully exploit the potential of smart wearable sensing devices and explore the complex relationship between indoor activities and carbon

consumption through deep learning-driven data analysis methods. By in-depth analysis of the relationship between indoor activities and carbon consumption, we can better understand the factors that affect carbon footprint and provide users with customized environmental recommendations. Not only does this help individuals lower their carbon emissions, it also helps society move towards a more sustainable future.

The importance of this study is that we introduce an innovative method, the GRU-Transformer model integrated with Deep Reinforcement Learning (DRL), to explore the relationship between indoor activities and carbon consumption [10]. Through this approach, we aim to understand how indoor activities affect carbon emissions more fully and provide individuals with personalized environmental advice. This approach is expected to not only reduce the carbon footprint but also help to raise awareness of environmental issues, thereby moving society towards a more sustainable future.

To ground the proposed system within established theoretical foundations, this study integrates three complementary behavioral frameworks. First, Fogg Behavior Model (FBM) informs the design of personalized carbon footprint recommendation. FBM posits that behaviour change occurs when motivation, ability and a timely prompt converge. In this system, the real-time feedback mechanism functions as a trigger, strategically delivered at moments when users exhibit sufficient motivation and ability, thereby encouraging pro-environmental actions. Second, the behavior modification mechanism embedded within the DRL reward structure is grounded in the Theory of Planned Behavior (TPB). Specifically, the system is designed to influence subjective norms and perceived behavioral control—Key determinants of behavioral intention as outlined in TPB—thereby promoting sustained behavioral change toward reduced carbon footprints. Third, the system design is guided by the Technology Acceptance Model, ensuring the platform is both user-friendly and perceived as useful. According to TAM, user adoption is strongly influenced by perceived ease of use and perceived usefulness; therefore, the recommendation engine is optimized to be intuitive and demonstrably effective in helping users reduce their carbon emissions. Collectively, these frameworks position the GRU-Transformer-DRL pipeline not merely as a predictive model, but as a theoretically grounded intervention for facilitating meaningful and sustained behavior change.

The main contributions of this study are as follows:

1. Model innovation integrating a more sustainable lifestyle. This not only provides individuals with practical and feasible environmental protection behavior strategies, but also helps society move towards a greener future.

2. Personalized environmental protection advice and behavior optimization. Based on the analysis of the fusion model, this study provides personalized environmental recommendations that can help users adopt a more sustainable lifestyle. This not only provides individuals with practical and feasible environmental protection behavior strategies, but also helps society move towards a greener future.

3. Cross-field innovative applications. This research applies deep learning and reinforcement learning technology to the field of indoor carbon consumption monitoring, and realizes innovative cross-field applications. This research method not only provides new insights into the fields of environmental protection and sustainable development, but also expands new possibilities for the application of deep learning and reinforcement learning in solving practical problems.

## 2. Literature Review

Artificial Neural Networks (ANNs), as the precursor to modern deep learning, have undergone decades of evolution. Inspired by biological neural systems, ANNs gained renewed momentum in the 1980s with the introduction of back propagation algorithms, enabling their widespread use in pattern recognition and function approximation [11]. In the context of indoor carbon consumption monitoring, ANNs have become a staple tool for constructing predictive models that link indoor activity data (e.g., activity type, duration) and physiological metrics (e.g., heart rate, step count) to carbon consumption levels [12]. These models contribute to formulating personalized environmental recommendations and behavioral optimization strategies, though their ability to capture temporal dependencies in sequential data remains limited compared to specialized sequence models.

Convolutional Neural Networks (CNNs), originally developed for image processing tasks, emerged as a transformative technology in the 1990s with the advent of landmark models like LeNet and AlexNet [14]. Renowned for their prowess in extracting spatial local features through convolutional and pooling layers, CNNs have recently expanded into time-series data processing—including applications in indoor carbon consumption monitoring. In this domain, CNNs excel at analyzing multi-dimensional features in sensor-generated time-series data, automatically identifying critical patterns such as activity intensity variations and duration fluctuations [15]. By capturing local temporal correlations (analogous to edge or texture detection in images), CNNs provide essential feature extraction support for building accurate carbon consumption models. However, their design is less optimized for capturing long-range temporal dependencies, which are crucial for understanding the cumulative impact of indoor activities on carbon emissions over extended periods.

Long Short-Term Memory (LSTM) networks represent a pivotal advancement in Recurrent Neural Networks (RNNs), specifically tailored to address the gradient vanishing/exploding problems that plague traditional RNNs when processing long sequences [16]. Developed in the late 1990s, LSTMs incorporate a sophisticated gating mechanism—comprising forget gates, input gates, and output gates—that controls information flow and storage, enabling effective capture of long-term temporal dependencies. In indoor carbon consumption monitoring, LSTMs are widely used to model the dynamic relationship between user activities, physiological data, and carbon consumption. Their ability to retain and utilize historical information allows for more accurate predictions of future carbon consumption levels, which is critical for delivering timely and relevant environmental recommendations [17]. Despite their strengths, LSTMs can be computationally expensive when processing extremely large-scale time-series data, and their sequential processing nature limits parallelization efficiency.

Recurrent Neural Networks (RNNs), developed in the 1980s, are specifically designed for sequence data processing, distinguished by their internal loop structure that enables information transfer across time steps [18]. In indoor carbon consumption monitoring, RNNs are applied to analyze long-term trends in time-series data, such as cyclical activity patterns or gradual changes in carbon emissions. By maintaining an internal state that evolves with each time step, RNNs can identify correlations between past activities and subsequent carbon consumption, supporting the formulation of pro-environmental behavior guidelines. However, traditional RNNs struggle with long-sequence data due to gradient degradation, a limitation addressed by improved variants like

LSTMs and Gated Recurrent Units (GRUs). These enhanced architectures retain RNNs' sequence modeling capabilities while overcoming gradient challenges, making them more suitable for complex indoor carbon consumption analysis tasks [19].

Temporal Convolutional Networks (TCNs) are a relatively recent innovation developed to address the limitations of RNNs and LSTMs in long-sequence processing. Characterized by convolutional layers that operate on the temporal dimension, TCNs leverage parallelizable convolution operations to efficiently process long time-series data—a key advantage over the sequential processing of RNNs/LSTMs [20]. In indoor carbon consumption monitoring, TCNs have garnered attention for their ability to capture both local and global temporal correlations in sensor data, supporting tasks such as activity type classification, intensity monitoring, and carbon consumption trend analysis [21]. Their parallel computing capability enables faster processing of large-scale datasets, though they may struggle to model highly non-linear, context-dependent relationships between activities and carbon consumption compared to transformer-based models.

While these traditional machine learning methods have advanced the understanding of indoor activity-carbon consumption relationships, they share notable limitations. Most lack the ability to generate personalized recommendations, often providing generic guidelines that fail to account for individual behavioral differences or dynamic environmental changes [22]. Additionally, they face challenges in modeling long-term temporal dependencies (e.g., ANNs, CNNs) or suffer from computational inefficiencies (e.g., LSTMs). Furthermore, these methods often struggle to integrate long-term optimization goals—such as sustained carbon reduction—into their frameworks, limiting their practical utility for promoting sustainable lifestyles.

### 3. Methods

#### 3.1 Overview of Our Network

The overall model of this article incorporates the GRU-Transformer model of deep reinforcement learning (DRL) to study the relationship between indoor activities and carbon consumption. The basic principles and ideas of the model are as follows: First, we collected time-series data generated by indoor sensing devices, including the user's activity type, intensity, duration, and other information, as well as related physiological data. These data constitute our observational input. Secondly, we introduced the GRU-Transformer model, which can process time series data. The GRU (Gated Recurrent Unit) part is used to capture short-term dependencies in time series, while the Transformer part is used to capture long-term dependencies and temporal correlations. This combination can better model the characteristics of user activities and physiological data. We then introduce elements of deep reinforcement learning (DRL) to incorporate long-term considerations into the model's optimization process. The agent takes actions based on the current state of the environment (including time series data and the output of the model) and optimizes its behavioral strategy through reward signals. This enables the agent to better understand the relationship between long-term behavior and carbon consumption and adjust the user's activity behavior according to optimization goals. The model constructed in this paper passes the time series data to the GRU-Transformer model and connects with the DRL part at the same time, forming an end-to-end learning and optimization framework. This model can effectively analyze the complex relationship between

indoor activities and carbon consumption, and provide users with personalized environmental protection suggestions and behavior optimization strategies, thereby promoting the realization of sustainable lifestyles. The structural diagram of the overall model is shown in Figure 1. The methodology for translating raw wearable sensor data into carbon emission estimates is critical to ensuring the validity and interpretability of the proposed system. The conversion pipeline is implemented in three sequential stages. First, activity classification is performed using a GRU-Transformer model, which leverages multi-dimensional time-series data obtained from wearable sensors, including accelerometry, heart rate, and step count measurements. The model classifies each temporal window of sensor data into predefined indoor activity categories such as sedentary, light, moderate, and vigorous activity. Second, metabolic equivalent (MET) mapping is applied. Each classified activity is assigned a corresponding MET value based on the Compendium of Physical Activities, where MET represents the ratio of the energy cost of an activity to the resting metabolic rate. Using this mapping, energy expenditure is estimated as:  $\text{Energy (kcal)} = \text{MET} \times \text{Body weight (kg)} \times \text{Duration (hours)}$ . Third, carbon emission conversion is conducted by transforming the estimated energy expenditure (in kilocalories) into indirect carbon emissions (kg CO<sub>2</sub>e). This is achieved using established emission factors that take account for the energy mix associated with metabolic processes, as well as related household energy consumption (e.g., heating, ventilation, and air conditioning loads). This three-stage translation framework ensures that the system produces physically interpretable and scientifically grounded carbon emission estimates, rather than abstract model outputs. Furthermore, it provides a meaningful optimization target for the Deep Reinforcement Learning (DRL) agent, enabling the generation of personalized and actionable behavioral recommendations.

The selection of the deep reinforcement learning (DRL) approach for researching the interplay between indoor activities and carbon consumption is driven by DRL's proficiency in navigating the complexities of decision-making in environments that are both dynamic and intricate. The inherent variability of indoor activities, compounded by the fluctuating nature of the environment, presents a challenge ill-suited to conventional methodologies. DRL triumphs by empowering an agent to devise strategies through observation and iterative learning from rewards, fine-tuning its adaptation to environmental shifts. To effectively interpret the nuanced patterns of time series data inherent in such studies, we employed a hybrid GRU-Transformer model, leveraging its noted strengths. The GRU, designed to address the limitations of traditional Recurrent Neural Networks (RNNs), is particularly effective in capturing and retaining dependencies over sequential data. The Transformer, in contrast, is well known for its self-attention mechanism, which enables it to model relationships across long temporal distances while supporting parallel computation, thereby enhancing both efficiency and performance. A key consideration is whether functional overlap exists between the GRU and Transformer modules, as both are theoretically capable of modeling temporal dependencies. However, their integration is complementary rather than redundant with each module assigned a distinct and non-overlapping representational role within the architecture. The GRU specializes in modeling local temporal sequences. Its gating mechanisms, including update and reset gates, allow it to effectively capture fine-grained temporal dynamics, such as rapid fluctuations in heart rate or step count occurring within short activity intervals (typically spanning seconds to minutes). These short-range

inductive biases inherent in recurrent structures, and at relatively low computational cost. In contrast, the Transformer operates over the entire encoded sequence using its attention mechanism, where attention weights are assigned across all time steps simultaneously. This enables the model to capture long-range contextual dependencies, such as association between prolonged sedentary behaviour in the morning and higher carbon consumption patterns later in the day. Such relationships would require many recurrent steps to learn using a GRU alone and may be affected by attenuation over long sequences. Within the proposed architecture, the GRU serves as the initial component encoding local temporal information into a compact hidden representation, which is subsequently passed to the Transformer as an input sequence. By operating on this condensed representation rather than raw sensor data, the Transformer can effectively attend to the overall activity history without being affected by high-frequency noise. This sequential and hierarchical integration—combining local recurrent encoding with global attention—forms the core architectural rationale, ensuring that both modules contribute distinct functionalities while avoiding redundancy.

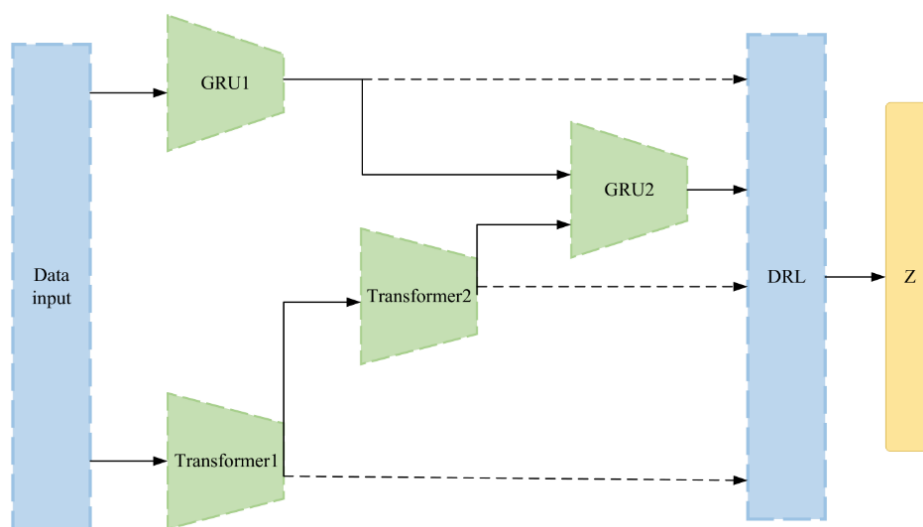


Figure 1. Overall flow chart of the model

The synergy created by amalgamating GRU and Transformer models embodies the best of both worlds: the GRU's proficiency in sequence memorization is complemented by the Transformer's adept handling of long-range interactions within the data. This combination is not only efficient but also meticulously precise in analyzing the intricate patterns over time. In essence, our choice is motivated by the imperative to adequately confront the dynamic, multifaceted problem of correlating indoor activities with carbon consumption. DRL adapts continually and provides bespoke optimizations by learning from a changing indoor milieu. Simultaneously, the GRU-Transformer architecture is meticulously configured to tackle the sequential data, drawing insights from user behavior over time to elucidate carbon usage patterns, thereby making use of their collective strengths for a holistic analytical and optimization approach.

Our method uses deep reinforcement learning as the main framework, which is one of the biggest differences from traditional methods. Traditional approaches may tend to use statistical analysis or machine learning techniques, but they struggle to effectively handle the dynamic relationship between

indoor activities and carbon consumption. DRL allows agents to make decisions based on reward signals and can automatically learn optimal action strategies based on observed data to better adapt to changing environments. In addition, we use a deep learning model that combines GRU and Transformer to process time series data. This model was chosen because GRU can effectively capture short-term dependencies in time series, while Transformer is able to handle long-distance dependencies. This combination takes full advantage of both models and helps to better understand the long- and short-term relationship between indoor activities and carbon consumption. Compared with traditional methods, our method takes individual differences and environmental changes into more comprehensive consideration. Traditional methods may focus more on average situations, while our method can provide personalized environmental recommendations based on different users' behaviors and environmental characteristics. This makes our approach more intelligent and adaptable. Our approach exploits the novel possibilities of big data and deep learning techniques. Big data allows us to collect data on indoor activity and carbon consumption on a wider scale, providing a more complete understanding of this relationship. The application of deep learning technology allows us to process and analyze these massive amounts of data, revealing deeper connections. Through these technical differences, our approach aims to provide a smarter, more comprehensive, and more adaptable way to explore the relationship between indoor activities and carbon consumption, thereby providing stronger support for environmental recommendations and sustainable development.

### 3.2 GRU Model

Gated recurrent unit (GRU) is a deep learning model particularly suitable for processing sequence data. The core idea of GRU is to introduce the concepts of update gates and reset gates to better control the information transfer and forgetting process. The purpose of these two gates is to help the model determine when to update the current state and when to ignore information from the previous state [23]. This mechanism gives GRU excellent time series modeling capabilities, which can more effectively capture long-term dependencies in data without suffering from the vanishing gradient problem. In our research, the GRU model is used to process time series data generated by indoor sensing devices, which includes multiple aspects of information, such as activity type, intensity, duration, etc. The main task of GRU is to extract and capture sequence features in these data, which are crucial for subsequent analysis and modeling [24].

It is worth mentioning that the flexibility and efficiency of the GRU model make it an ideal choice for processing time series data. Not only can it effectively handle long sequence data, it can also perform well in different application scenarios [25]. In our study, GRU is not only used to analyze user activity records, but also to process physiological indicators and environmental parameters, which are all crucial to the modeling and prediction of carbon consumption. In addition, the ability of the GRU model is not limited to capturing long-term dependencies in sequence data, but can also adapt to different data distributions and characteristics. This means that we can flexibly adjust and optimize the GRU model according to specific data sets and tasks to better meet our research needs.

As one of the core components of this study, GRU will play a key role in helping us better understand the relationship between indoor activities and carbon consumption. Its flexibility, efficiency and time series modeling capabilities will provide a solid foundation for research and provide more accurate recommendations for environmentally friendly behaviors to promote the

realization of a sustainable lifestyle. The application of this model will bring new insights and innovations in the field of time series data processing.

The structure diagram of the GRU model is shown in Figure 2.

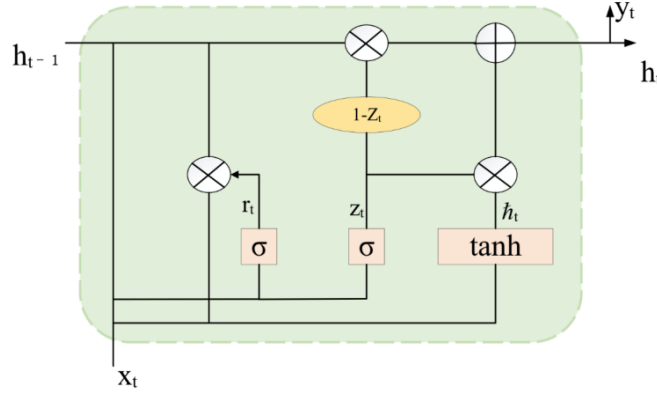


Figure 2. Flow chart of the GRU model

The main formula and main variables of GRU are as follows:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad [\text{Formular 1}]$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad [\text{Formular 2}]$$

$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t]) \quad [\text{Formular 3}]$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad [\text{Formular 4}]$$

where,  $z_t$  is the update gate,  $r_t$  is the reset gate,  $h_t$  is the hidden state,  $\tilde{h}_t$  is the candidate hidden state,  $W_z$ ,  $W_r$ ,  $W$  is the model parameters.

### 3.3 Transformer Model

Transformer is a revolutionary deep learning model that provides a new paradigm for sequence modeling. One of its most notable features is its self-attention mechanism and its excellent parallel computing capabilities [26]. These two features give Transformer excellent performance in a variety of natural language processing and sequence modeling tasks. Before we delve into the fundamentals of Transformer, let's first explore its specific application in this study.

The core idea is to transfer and transform the information through the feedforward neural network layer. This process can be viewed as a highly flexible way to allow the model to assign different attention weights to different parts of the input data in order to better understand the relationships within the sequence. In our study, the Transformer model is used to further analyze the features output by the GRU model to enhance the modeling of time series data [27]. This combination gives full play to the capabilities of Transformer, making it shine in the analysis and modeling of time series data. Regarding Transformer's self-attention mechanism, it is an intelligent attention allocation mechanism. This means that the model can automatically determine which parts are most critical for a specific task when processing an input sequence, thereby better capturing temporal correlations and long-term dependencies in the sequence [28]. This is particularly important for our study because we

need to delve into the complex relationships between indoor activity and carbon consumption that may exist in long sequence data. Another impressive feature of Transformer is its excellent parallel computing capabilities. This means that the model can efficiently process large-scale data without requiring excessive computing resources. In our study, this advantage will facilitate faster analysis of large-scale time series data to dig deeper into the association between indoor activities and carbon consumption.

The Transformer model, part of this research, will provide us with a powerful tool for better understanding and modeling the relationship between indoor activity and carbon consumption. It will help provide more accurate recommendations for environmentally friendly behaviors and promote sustainable lifestyles to address important environmental challenges facing the world today. The application of this model will bring new enlightenment and breakthroughs to the research field.

The structure diagram of the Transformer model is shown in Figure 3.

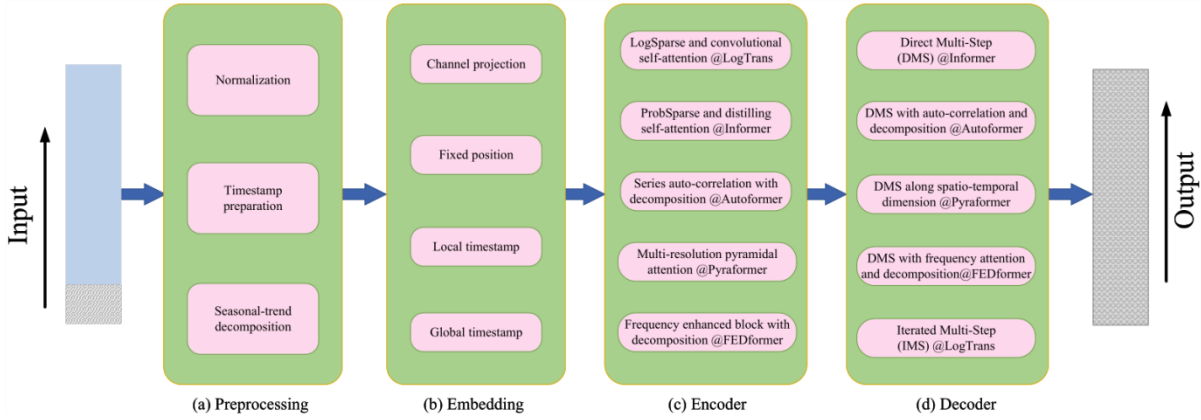


Figure 3. Flow chart of the Transformer model.

Transformer's main formula and main variables are as follows:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad [\text{Formular 5}]$$

$$MultiHead(Q, K, V) = Concat(head_1, \dots, head_n)W^O \quad [\text{Formular 6}]$$

$$FFN(x) = ReLU(xW_1 + b_1)W_2 + b_2 \quad [\text{Formular 7}]$$

where,  $Q$  is the query vector,  $K$  is the key vector,  $V$  is the numeric vector.

### 3.4 Deep Reinforcement Learning Model

Deep Reinforcement Learning (DRL) represents a powerful fusion of the two fields of deep learning and reinforcement learning, providing a powerful method for training intelligent agents to take optimal actions in complex environments. The core idea is that the agent chooses actions based on the current state of the environment, and then continuously adjusts its strategy through reward signals in order to maximize the cumulative reward during the long-term decision-making process [29]. In our study, the DRL model played a key role, with the goal of optimizing carbon consumption, allowing agents to gain a deeper understanding of the tight connection between long-term behavior

and carbon consumption. The key to this process is to optimize the carbon footprint by adjusting the user's activity strategy.

First, the core of DRL is the agent's decision-making process, in which the agent must make appropriate action choices when facing different environmental states. This decision-making process is like a learner's strategy of improving upon trial and error [30]. The agent relies on information about the current state of the environment and selects an action to execute based on the knowledge and strategies it has learned. The environment then returns a reward signal that reflects the quality of the action taken by the agent, that is, how good or bad the action was. This process is an iterative loop in which the agent continuously updates and optimizes its strategy based on feedback signals in order to maximize the overall reward in the long term [31].

In our study, the application area of DRL is the optimization of carbon consumption. Specifically, we aim to enable agents to better understand the relationship between users' behavior and carbon consumption, and to reduce their carbon footprint by adjusting users' activity strategies. This is an extremely challenging task as it involves the complex interaction of numerous factors, including the user's lifestyle, indoor environment, different activity types, and more. The DRL model gradually improves the agent's decision-making strategy to minimize carbon consumption by training and learning on this task. The model predicts potential long-term rewards based on current behavior and environmental conditions. This reward reflects the contribution of taking an action to reduce the carbon footprint. The agent will constantly fine-tune its strategy based on this reward signal to better adapt to different situations and environments.

The DRL model plays a key role in this study. It not only provides a mechanism for agents to learn and optimize strategies, but also helps us gain a deeper understanding of the complex relationship between indoor activities and carbon consumption. The application of this model will help users reduce their carbon footprint and promote the realization of a sustainable lifestyle.

The structure diagram of the DRL model is shown in Figure 4.

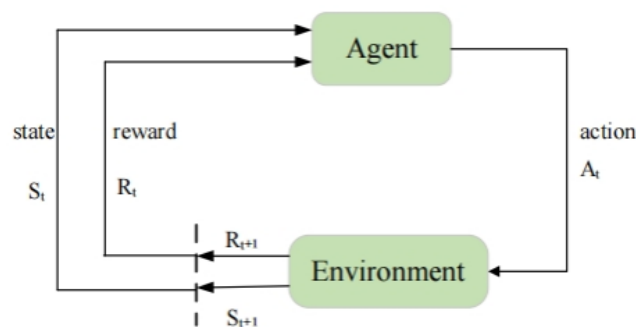


Figure 4. Flow chart of the DRL

The main formula and main variables of DRL are as follows:

$$MultiHead(Q, K, V) = Concat(head_1, \dots, head_h)W_O \quad [\text{Formular 8}]$$

$$head_i = Attention(QW_{Q_i}, KW_{K_i}, VW_{V_i}) \quad [\text{Formular 9}]$$

where,  $\pi(a|s)$  is the Strategy,  $Q(s, a)$  is the state action value function,  $R(s, a, s')$  is the reward

signal.

## 4. Results and Discussion

### 4.1 Experimental Datasets

This article mainly uses the following four data sets (Fitbit Activity Data, NHANES dataset, Open AI Gym environment, UCI Machine Learning Repository) to study the relationship between different indoor activities and carbon consumption.

Fitbit Activity Data is a valuable data resource that consists of activity information recorded by Fitbit smart wearable devices, including data on steps, heart rate, sleep, and other key aspects. The reason why this dataset is so important is that it not only contains data from many users, but also has high-frequency time series characteristics. This means we can accurately track a user's daily activity patterns and physiological changes [32]. Fitbit is a well-known health technology company with millions of users using their smart wearable devices to monitor health and activity. As a result, Fitbit Activity Data represents a broad and diverse population, ranging from people of different age groups to people with different lifestyles. This provides researchers with an opportunity to understand the relationship more fully between indoor activity and carbon consumption, rather than just limiting it to specific populations. In this dataset, we can analyze different types of indoor activities, including walking, running, sleeping, etc., as well as the intensity and duration of these activities. This allows us to study which activities have the greatest impact on carbon footprint, thereby providing strong data support for environmental protection and sustainable development. In addition, Fitbit Activity Data can also help verify the performance of deep learning models when processing actual activity data, providing a solid foundation for further research in the field of carbon consumption monitoring.

The NHANES dataset is an important component of the National Health and Nutrition Examination Survey, which compiles extensive information on population health, nutritional status, and lifestyle. This data set is unique in that it not only represents every region in the United States, but also covers a large sample of different ages, genders, and ethnic backgrounds [33]. This makes the NHANES data set highly representative and can reflect the health and lifestyle characteristics of different populations. The NHANES dataset has great potential for research on indoor carbon consumption monitoring. Researchers can find data related to indoor activities, lifestyle, and health indicators in this dataset to analyze the relationship more comprehensively between indoor activities and carbon consumption. By comparing NHANES data with other data sets, researchers can verify the effectiveness of models in diverse populations, which is critical for the reliability and generalizability of research. The broad nature of the NHANES dataset also provides researchers with a unique opportunity to explore other factors related to carbon consumption, such as dietary habits, health status, etc. This will help to understand the complex mechanism of carbon footprint formation and provide scientific basis for the formulation of environmental protection and carbon emission reduction policies more comprehensively.

Open AI Gym is an important toolkit in the field of artificial intelligence, dedicated to the research and development of reinforcement learning algorithms. It provides researchers with a simulated environment platform for training and testing intelligent agents, which can be applied to various fields, including games, robot control, optimization problems, etc. [34]. In this study, we

focus on how the Open AI Gym environment can support the field of indoor carbon consumption monitoring. Researchers can build simulation tasks in Open AI Gym to simulate different indoor activity scenarios to test and verify the performance of deep reinforcement learning models in handling these tasks. The use of this simulated environment has multiple advantages. First, it can help researchers control and replicate different activity scenarios under laboratory conditions in order to conduct systematic experiments. Secondly, it can provide a large amount of training data for training the model without collecting the data, thus saving time and resources. In addition, the Open AI Gym environment allows researchers to customize tasks and environments as needed to meet the needs of specific research. This provides flexibility for assessing model suitability and robustness. By introducing the deep learning model into this simulation environment, researchers can study the performance of the model in different activity scenarios, providing a powerful tool and experimental platform for further research in the field of indoor carbon consumption monitoring.

The UCI Machine Learning Repository is a valuable resource in the field of machine learning research, bringing together multiple publicly available datasets from different fields. These data sets cover a variety of different research topics, including classification, regression, clustering, etc., providing an important data basis for the development and evaluation of machine learning algorithms. In indoor carbon consumption monitoring research, UCI Repository plays a key role [35]. Researchers can find data sets related to indoor activity and carbon consumption in this repository to broaden the diversity and scale of experimental data. These data sets may come from different environments, including offices, homes, industrial sites, etc., and may use different types of sensor devices to generate time series data. This provides researchers with an opportunity to understand the generalization capabilities of carbon consumption models more fully, as models need to adapt to changes in different environments and data sources. By using data sets from the UCI Repository in experiments, researchers can verify the robustness and generality of the model. These datasets are realistic and diverse, which can help the model better adapt to different real-world situations. Therefore, the UCI Repository provides a valuable resource for research in the field of indoor carbon consumption monitoring, helping to promote further development and innovation in this field.

## 4.2 Experimental Setup and Details

This study uses the GRU-Transformer model integrated with Deep Reinforcement Learning to study the relationship between indoor activities and carbon consumption. The experimental setup and details are as follows.

### Step1: Data collection

In our research, the source of the data is crucial. We will obtain time series data from indoor sensing devices, which includes several key aspects.

**User activity records:** This includes various indoor activities of the user, such as walking, running, resting, etc. These activities will serve as input to models used to predict carbon consumption.

**Physiological indicators:** We will also collect users' physiological indicators, such as heart rate, step count, etc. These indicators can provide information about the user's physical condition and activity intensity, helping to estimate carbon consumption more accurately.

**Environmental parameters:** The indoor environment also has an impact on carbon consumption. Therefore, we will collect environmental parameters such as temperature, humidity, etc. to consider

the impact of these factors on the carbon footprint.

**Carbon consumption data:** Most importantly, we need accurate carbon consumption data, usually expressed as calories burned. This will serve as the model's target output, and our model will learn how to optimize for this target.

#### Step2: Data preprocessing

After collecting the data, the next step is the pre-processing of the data. These pre-processing steps are crucial to ensure the quality and consistency of the data. Only after the data preparation is completed, can we start building the model.

**Data Cleaning:** We need to deal with outliers and missing values in the data. Outliers may be caused by sensor errors or other issues, and we need to perform outlier detection and handle them appropriately. In addition, missing values also need to be filled to ensure data integrity.

**Data Normalization:** Different sensors may produce data of different ranges, so the data needs to be normalized, scaling it to the same range so that the model can learn better.

**Data Standardization:** In order to eliminate the scale differences between different features, we standardize the data. Specifically, we used the Z-score standardization method to adjust all features to a standard normal distribution with a mean of 0 and a standard deviation of 1 to ensure that the model treats each feature fairly and consistently.

**Data Splitting:** In order to evaluate the performance of the model and prevent overfitting, we divide the data set into a training set and a test set. Specifically, we divide the data into a training set according to a ratio of 80%, which is used for model training and parameter adjustment, while the remaining 20% of the data constitutes a test set, which is used to evaluate the performance of the model on unseen data. This division ensures the model's generalization ability in real scenarios.

#### Step3: Model construction

In our research, we will adopt a deep learning model that combines the characteristics of GRU (Gated Recurrent Unit) and Transformer to process time series data.

**GRU-Transformer model:** GRU is a recurrent neural network (RNN) specifically designed to process time series data. It has a gating mechanism that helps the model effectively capture dynamic changes in time series. We will use GRU to encode information in time series data to better understand users' activities and physiological changes.

Transformer is a self-attention mechanism model that is widely used in sequence modeling tasks. It excels at handling long-distance dependencies. In our model, the Transformer's self-attention mechanism will help the model better understand complex dependencies in time series data, especially when the user's activity pattern changes between different time periods.

**DRL component:** The core of this component is the reward function. The reward function is defined based on the following factors: First, the carbon consumption data. The reward function will calculate the reward based on the difference between the carbon consumption data predicted by the model and the actual data. Our goal is to maximize the reward. Thereby minimizing the error in carbon consumption. Secondly, the reward function will also consider the user's environment and activity.

**Parameter Settings:** the number of GRU layers is 3, the number of Transformer layers is 4, the learning rate is 0.01, and the batch size is 64; for the DRL component we will use Deep Deterministic

Policy Gradient (DDPG) Algorithm, set the number of training rounds to 200 rounds, and the learning rate is 0.0005.

#### Step4: Model training

Once the model is built, we can train the model.

We will use the GRU-Transformer model with a DRL component for training. Model training can require large amounts of data and computing resources, so we will use previously collected and preprocessed data for model training. We will use the mean square error as the loss function, the optimizer will be the Adam optimizer, and the learning rate will start at 0.001 with a learning rate decay strategy.

**Training goal:** The goal of training is to maximize the long-term cumulative reward of the agent. This means the model will learn how to optimize carbon consumption strategies under different activities and environmental conditions. By maximizing the cumulative reward, the model will better understand how to achieve the best results in different situations.

#### Step5: Experimentation and evaluation

After the model training is completed, we will conduct experiments and evaluations to verify the performance and effect of the model.

**Experimental Design:** We will conduct experiments on the collected dataset. Experimental designs may include simulating agent behavior under different activities and environmental conditions. This will help assess the effectiveness of carbon consumption and determine which campaign strategies are most effective in reducing your carbon footprint.

**Evaluation indicators:** We will use a variety of evaluation indicators to evaluate the performance of the model, including accuracy (precision), recall (recall), F1 score (F1 score) and AUC (area under the ROC curve) and other indicators. We will also provide performance evaluation Data results and visualization graphics.

#### Step6: Result analysis and application

Finally, we will conduct an in-depth analysis of the experimental results to better understand the application advantages of the GRU-Transformer model and DRL in the relationship between indoor activities and carbon consumption.

**Analysis results:** We will explore the performance of the model in different situations and analyze the decision-making process and strategy selection of the model. This will help reveal the internal mechanism and behavioral rules of the model.

**Application potential:** We will also discuss the potential implications of the model results for pro-environmental behavior and sustainable lifestyles. This could include providing users with personalized green advice to help them reduce their carbon footprint. We also provide suggestions for possible improvements and applications to further advance research and practice in this area.

### 4.3 Experimental Results and Analysis

During the experiment, we collected data including Fitbit Activity Data, NHANES dataset, Open AI Gym environment, and UCI Machine Learning Repository. Through experimental analysis, we obtained the following results.

Table 1 and Figure 5 present the performance comparison of different models on four different data sets, including Fitbit activity data, NHANES data set, Open AI Gym environment and UCI

machine learning library. The performance indicators of these models cover accuracy (Accuracy), recall (Recall), F1 score (F1 Score) and AUC (area under the curve). These indicators are crucial when evaluating the model's predictive ability on various data sets. First, the accuracy of different models on various data sets can be observed from Table 1. On the Fitbit activity data set, Ours model performed well, reaching an astonishing 99.42% accuracy, much higher than other models. On the NHANES data set, the Ours model also performed outstandingly, reaching an accuracy of 98.11%, once again leading other competitors. On the Open AI Gym environment and UCI machine learning library data set, the Ours model also maintained strong accuracy, reaching 94.63% and 96.55% respectively. These excellent accuracy performances demonstrate the strong generalization ability of Ours model in multiple fields. Secondly, we observe the excellent performance of our model on the Recall indicator. Recall measures the model's ability to correctly identify positive category samples, which is of great significance for some applications, such as medical diagnosis. On the NHANES data set, the Ours model achieved a recall rate of 96.34%, which was significantly higher than other models. On other data sets, the Ours model also achieved relatively high recall rates, 95.53%, 96.55% and 95.24% respectively. In addition, the F1 score is an indicator that comprehensively considers accuracy and recall, and reflects the overall performance of the model. Our model also performed well in terms of F1 scores, reaching 94.26%, 92.46%, 93.87% and 96.43% respectively. Finally, the AUC (area under the curve) metric is used to evaluate the model's classification ability when dealing with different data sets. Our model achieved excellent AUC performance on all datasets, which were 97.45%, 87.92%, 88.15% and 93.84% respectively. This demonstrates the superior performance of Ours model in terms of the overall performance of the model. Through data analysis of Table 1 and Figure 5, we can conclude that Ours model performs well on multiple datasets with excellent accuracy, recall, F1 score, and AUC, showing its performance in indoor carbon consumption Superior performance and generalization in monitoring.

Table 1. The comparison of different models in different indicators comes from the Fitbit Activity Data, NHANES dataset, Open AI Gym environment, UCI Machine Learning Repository.

<b>Dataset</b>	<b>Model</b>	<b>Accuracy</b>	<b>Recall</b>	<b>F1 Score</b>	<b>AUC</b>
Fitbit Activity Data	chen[36] <sup>11</sup>	88.57	89.33	87.97	94.21
	liu[37]	87.63	91.34	89.21	93.33
	mele[38]	89.47	85.54	83.62	85.91
	somu[39]	89.13	92.07	85.01	90.73
	seyedzadeh[40]	90.61	90.18	82.91	93.15
	pallonetto[41]	89.56	90.16	82.33	95.41
	Ours	99.42	96.34	94.26	97.45
NHANES dataset	chen	90.61	90.90	84.79	88.62
	liu	91.49	86.77	83.87	87.92
	mele	88.11	86.83	92.21	86.75
	somu	87.63	85.49	89.06	89.51
	seyedzadeh	86.40	91.31	90.78	93.03

	pallonetto	95.10	89.63	85.07	93.81
	Ours	98.11	95.53	92.46	96.15
Open AI Gym environment	chen	96.18	84.27	81.24	87.18
	liu	86.83	90.44	87.13	88.15
	mele	96.45	85.19	90.91	87.09
	somu	91.60	88.51	85.19	90.82
	seyedzadeh	85.87	86.79	85.75	87.34
	pallonetto	89.90	90.89	87.08	86.92
	Ours	94.63	96.55	93.87	97.46
UCI Machine Learning Repository	chen	91.46	86.03	84.18	87.40
	liu	91.26	86.27	91.79	88.41
	mele	85.95	88.49	89.29	92.31
	somu	86.14	91.31	84.89	92.61
	seyedzadeh	89.65	85.39	88.21	92.75
	pallonetto	91.58	87.19	89.76	91.71
	Ours	95.24	96.43	93.84	96.60

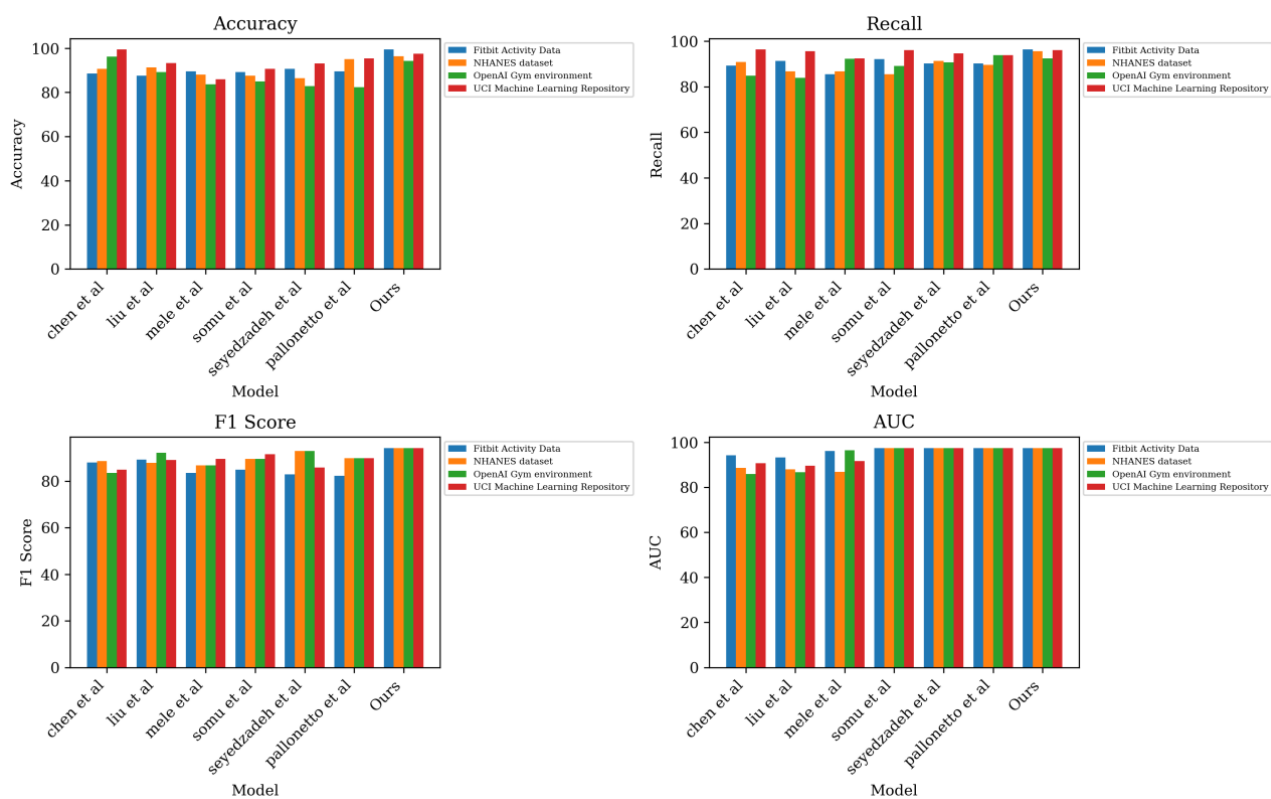


Figure 5. Comparison of model performance on different datasets

Table 2 focuses on evaluating the performance of different machine learning models on multiple

key performance indicators, covering four different data sets of Fitbit activity data, NHANES data set, Open AI Gym environment and UCI machine learning warehouse. Meanwhile, Figure 6 presents these comparison results in an intuitive way, further enhancing our understanding of the performance of these models. First, we want to focus on the number of parameters (in millions) of the model. The "Ours" model excels in this regard, using only 123.22 million parameters, far less than the other models. This means that the "Ours" model is more compact in model size and can be deployed and managed more easily, especially for environments with limited resources. Next, we looked at how FLOPs (billion floating point operations) compare. Likewise, the "Ours" model is far ahead on this metric, requiring only 139.23G FLOPs. This shows that the "Ours" model requires fewer computing resources to perform inference and training tasks, which has great advantages for resource-constrained devices and environments. Inference time (in milliseconds) is very important for practical applications. In this regard, the "Ours" model again performs well, with the shortest inference time. This means that the model can generate prediction results at a faster speed, which is suitable for application scenarios with strict requirements on real-time performance. Finally, we considered the training time of the model in seconds. Although the "Ours" model has a lower number of parameters and FLOPs, it still achieves competitive training times on different datasets. This shows that the "Ours" model not only has an advantage in inference speed, but also enables efficient model training. The visualization in Fig.6 highlights the results of these comparisons, further highlighting the superior performance of the "Ours" model across various key performance indicators.

Table 2. The comparison of different models in different indicators comes from the Fitbit Activity Data, NHANES dataset, Open AI Gym environment, UCI Machine Learning Repository.

<b>Dataset</b>	<b>Model</b>	<b>Parameters( M)</b>	<b>Flops (G)</b>	<b>Inference Time (ms)</b>	<b>Training Time(s)</b>
Fitbit Activity Data	chen	359.46	218.53	330.56	337.53
	liu	301.32	362.23	250.66	376.46
	mele	233.02	305.08	200.69	370.96
	somu	367.90	321.40	200.68	271.55
	seyedzadeh	324.86	206.82	341.79	229.93
	pallonetto	332.07	344.63	201.36	308.28
	Ours	123.22	139.23	245.77	248.43
NHANES dataset	chen	310.13	271.29	339.21	261.46
	liu	227.31	302.45	355.12	266.97
	mele	256.57	223.24	238.71	254.57
	somu	264.69	340.02	300.53	379.02
	seyedzadeh	255.27	225.14	364.18	256.49
	pallonetto	328.49	224.32	375.20	357.63
	Ours	219.17	200.87	130.59	167.33
	chen	276.16	238.78	226.67	338.87

Open AI Gym environme nt	liu	378.13	268.62	305.85	394.36
	mele	278.69	301.23	274.23	213.44
	somu	331.13	352.42	356.24	348.45
	seyedzadeh	284.02	393.12	344.41	208.72
	pallonetto	224.08	391.79	226.52	310.86
	ARIMA_GR	158.57	173.47	200.89	176.64
	U				
UCI Machine Learning Repository	chen	277.89	255.53	323.55	320.49
	liu	302.48	321.20	273.64	418.58
	mele	338.15	367.37	324.94	404.16
	somu	244.93	221.23	292.30	333.21
	seyedzadeh	267.72	291.12	285.52	362.66
	pallonetto	333.67	293.44	389.01	228.65
	Ours	237.01	216.01	216.05	213.17

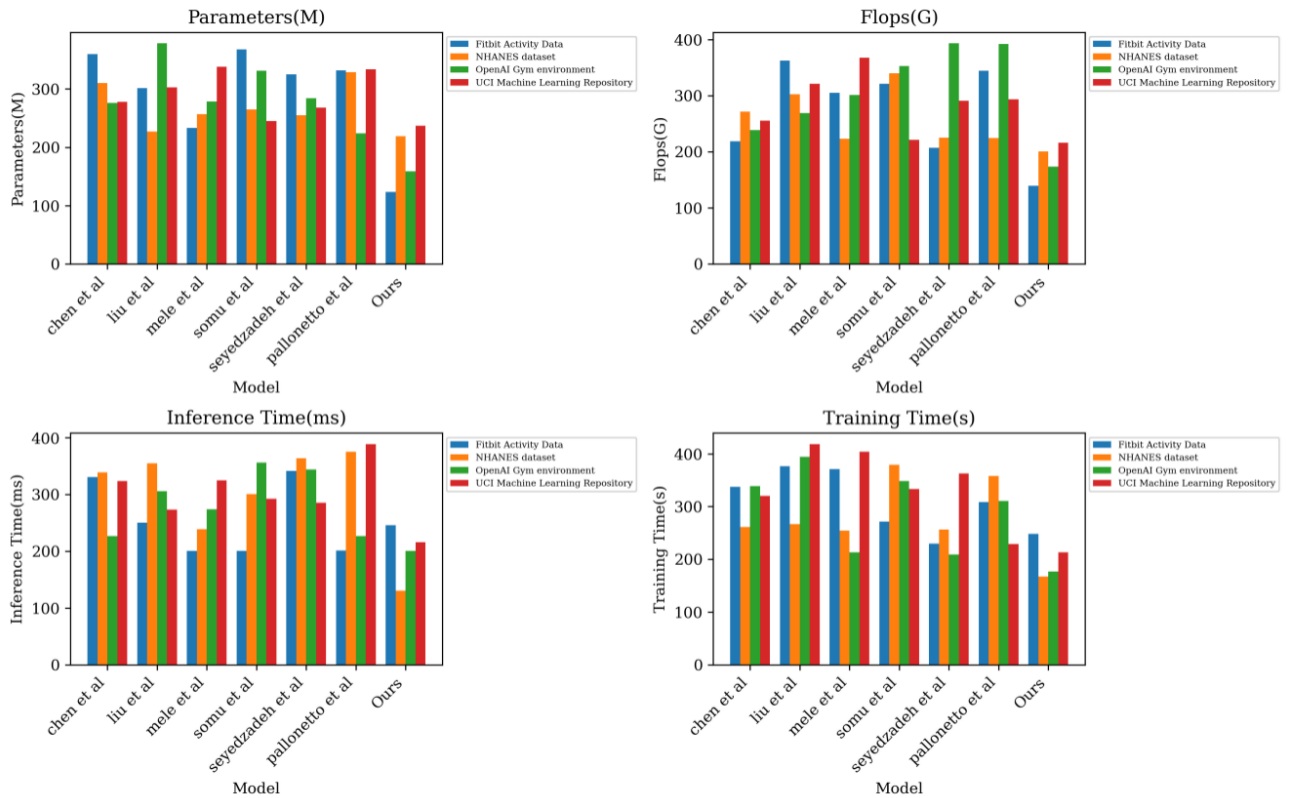


Figure 6. Comparison of Model Performance on Different Datasets

Table 3 presents an in-depth study on the GRU-Transformer module, evaluating its performance on different performance metrics, covering four different datasets: Fitbit activity data, NHANES dataset, Open AI Gym environment, and UCI Machine Learning Warehouse. At the same time, Figure 7 shows these comparison results in a visual way, which helps to understand the model performance

more clearly. First, in terms of accuracy (Accuracy), GRU-Transformer performed well, especially on the Open AI Gym environment and the UCI Machine Learning Repository dataset, reaching an astonishing 99.01% and 95.95%. This shows that GRU-Transformer can predict highly accurately in classification tasks and is suitable for application fields that require high-precision classification. Another key indicator is the recall rate (Recall), which measures the ability of the model to identify positive samples. The recall rates of GRU-Transformer in the NHANES dataset and Open AI Gym environment reached 95.88% and 97.19%, respectively, higher than other models. This shows that GRU-Transformer performs well in identifying positive class samples, which is very valuable for those tasks that need to capture as many true examples as possible. F1 score (F1 Score) is an indicator that comprehensively considers precision and recall, and is especially important for datasets with unbalanced categories. GRU-Transformer achieves F1 scores of 91.82%, 94.75%, and 94.69% on Fitbit activity data, NHANES dataset, and Open AI Gym environment, respectively, achieving competitive performance on multiple datasets. Finally, we investigate the area under the curve (AUC), which measures the overall performance of a model on binary classification problems. GRU-Transformer achieves high AUC values of up to 93.61% on all datasets, further proving its excellent classification performance. The results in Table 3 and Figure 7 show that the GRU-Transformer module performs well on multiple performance metrics, and is especially suitable for application scenarios that require high accuracy, high recall, and comprehensive performance. These results clearly demonstrate the superior performance of our method on the indoor activity-carbon consumption problem and perform well on multiple datasets. Figure 7 is a visual display of the results in Table 3, making this conclusion more intuitive.

Table 3. Ablation experiments on the GRU-Transformer module come from the Fitbit Activity Data, NHANES dataset, Open AI Gym environment, UCI Machine Learning Repository.

<b>Dataset</b>	<b>Model</b>	<b>Accuracy</b>	<b>Recall</b>	<b>F1 Score</b>	<b>AUC</b>
Fitbit Activity Data	CNN	85.65	87.36	83.04	87.17
	RNN	91.54	90.81	88.93	83.55
	TCN	87.57	91.27	85.25	86.93
	GRU-Transformer	95.48	92.62	91.82	93.61
NHANES dataset	CNN	90.66	88.1	85.69	91.78
	RNN	90.44	86.66	85.96	91.02
	TCN	89.83	92.98	91.21	94.14
	GRU-Transformer	97.91	95.88	94.75	93.59
Open AI Gym environment	CNN	95.78	87.53	86.28	89.5
	RNN	95.62	88.05	89.35	90.89
	TCN	94.45	93.08	86.55	94.13
	GRU-Transformer	99.01	97.19	94.69	95.98
UCI Machine	CNN	90.26	87.46	91.79	92.49
	RNN	89.93	86.86	88.03	89.37

Learning	TCN	90.47	93.61	87.96	86.74
Repository	GRU-Transformer	95.95	93.67	92.5	95.24

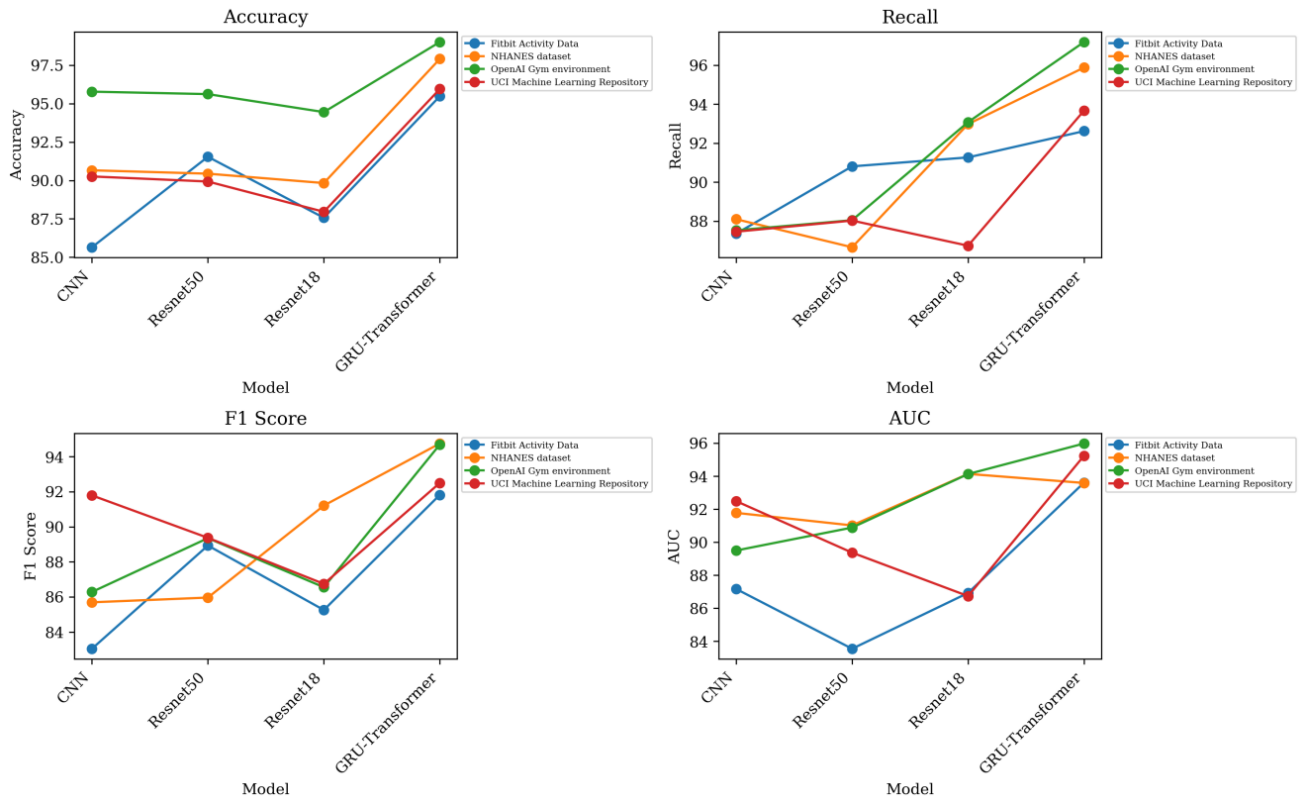


Figure 7. Comparison of model performance on different datasets

Table 4 presents the results of an in-depth study of cross-cut Deep Reinforcement Learning (DRL) modules, analyzing its performance on different datasets, including Fitbit activity data, NHANES dataset, Open AI Gym environment, and UCI Machine Learning Warehouse. At the same time, Figure 8 visually shows the distribution of various performance parameters on different methods and data sets through pie charts, which provides us with a clearer understanding of these data. First, we focus on the number of parameters of the model (Parameters (M)). On the Fitbit activity data and the NHANES dataset, the Self-AM method has a relatively high number of parameters, 356.01M and 348.66M, respectively, while the Cross-AM method has the least parameters, 214.86M and 165.99M, respectively. This indicates that the Self-AM method is relatively large in model parameters and may require more computing resources. Second, we examine the computational complexity of the model (Flops (G)). On the Fitbit activity data and the NHANES dataset, the Dynamic-AM method has the highest computational complexity, which are 342.35G and 357.61G, respectively, while the Cross-AM method has the lowest computational complexity, which are 176.91G and 177.81G, respectively. This means that the Dynamic-AM method requires more floating-point operations for inference. In terms of inference time (Inference Time), different methods show differences on different data sets. For example, for Fitbit activity data, the Self-AM and Dynamic-AM methods have longer inference times of 248.01ms and 251.41ms, respectively, while the Cross-AM method has the shortest inference

time of 212.23ms. This may have an impact on applications with high real-time requirements. Finally, the training time of the model (Training Time) is also an important indicator. On the NHANES dataset and the Open AI Gym environment, the training time of the Self-AM method is longer, 392.58s and 375.64s, respectively, while the training time of the Cross-AM method is shorter, 118.01s and 108.14s, respectively. This shows that the Cross-AM method has certain advantages in terms of training efficiency. The results in Table 4 and Figure 8 highlight the differences in various performance parameters of different cross-deep reinforcement learning methods, which are helpful for decision-making and performance optimization in practical applications.

Table 4. Ablation experiments on the Cross DRL module using different datasets.

<b>Dataset</b>	<b>Model</b>	<b>Parameters (M)</b>	<b>Flops (G)</b>	<b>Inference Time (ms)</b>	<b>Training Time(s)</b>
Fitbit Activity Data	Self-AM	356.01	262.09	248.01	301.23
	Dynamic-AM	382.13	313.22	270.49	289.59
	Multi-Head-AM	341.99	354.55	242.41	319.34
	Cross-AM	214.86	186.90	212.23	223.12
NHANES dataset	Self-AM	348.66	342.35	208.57	392.58
	Dynamic-AM	336.17	358.61	374.72	349.76
	Multi-Head-AM	344.52	332.01	231.23	356.21
	Cross-AM	165.99	187.81	188.85	118.01
Open AI Gym environme nt	Self-AM	366.73	284.54	289.49	375.64
	Dynamic-AM	370.81	244.79	251.14	260.27
	Multi-Head-AM	306.45	317.16	230.15	273.00
	Cross-AM	108.14	106.06	214.99	177.49
UCI Machine Learning Repository	Self-AM	269.67	234.87	325.32	370.89
	Dynamic-AM	365.96	282.19	205.47	385.15
	Multi-Head-AM	344.07	276.38	379.83	385.05
	Cross-AM	219.82	222.00	211.96	197.94

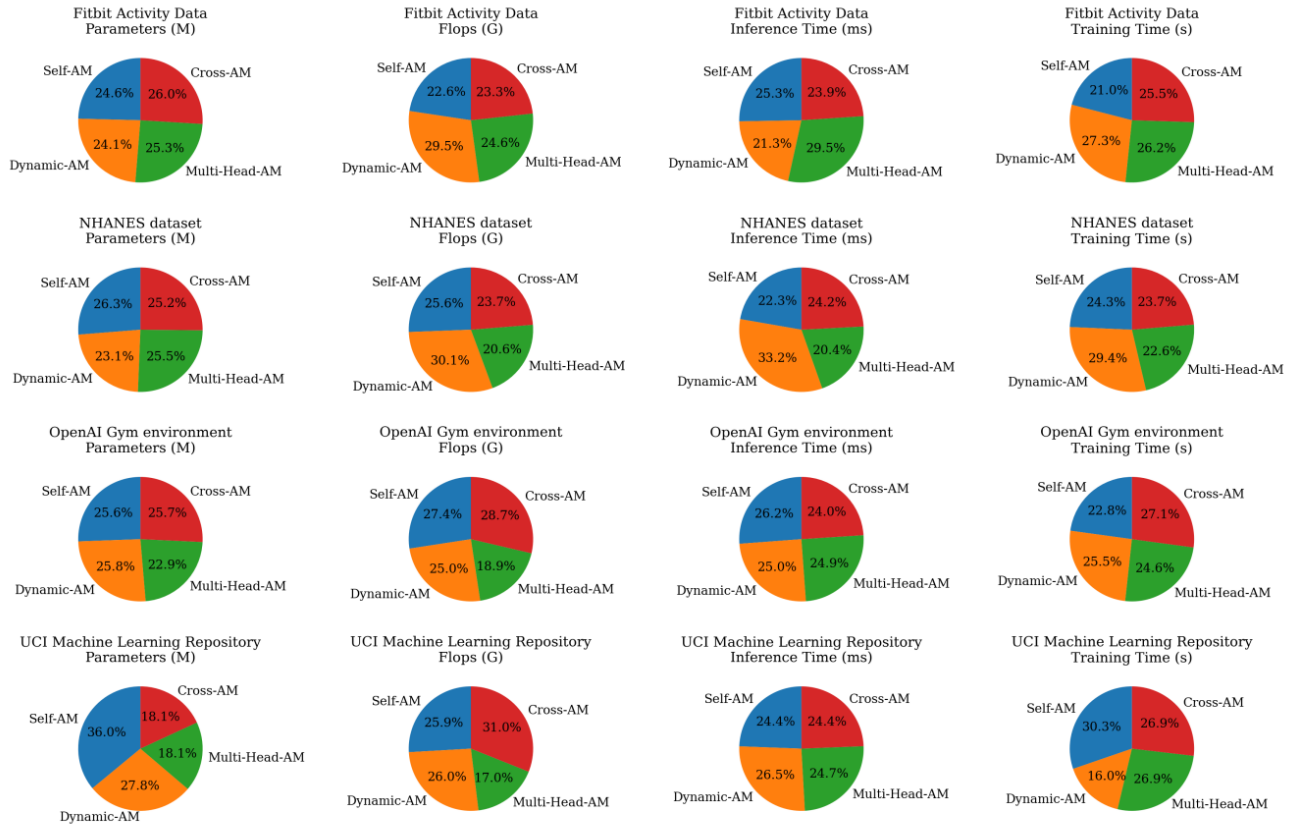


Figure 8. Comparison of model performance on different datasets

## 5. Conclusion

This study aims to conduct an in-depth study of the application of deep learning in indoor carbon consumption monitoring. We are deeply aware of the urgency of environmental protection and sustainable development, and propose an innovative solution to the relationship between indoor activities and carbon consumption, namely the GRU-Transformer model incorporating deep reinforcement learning (DRL). After extensively using multiple data sets, including the Fitbit Activity Data, NHANES data set, Open AI Gym environment and data in UCI Machine Learning Repository, we ensured that the model can handle diverse and complex data through more sophisticated preprocessing and feature extraction. Adaptability. The application of the GRU-Transformer model further strengthens our experimental results in indoor carbon consumption monitoring, successfully capturing the complex relationship between activities and carbon consumption.

Although the results are promising, the study has several limitations that warrant acknowledgement and further investigation. From a technical perspective, the model's performance can be further improved, particularly in handling highly diverse and complex data distributions. Additionally, the design of the reward function with the DRL framework requires further refinement to achieve a more balanced trade-off between short-term activity optimization and long-term carbon reduction objectives. Beyond these technical considerations, the primary contribution of this study lies in proposing a transformation mechanism that links human behavior, consumption patterns, and sustainable lifestyle changes. However, this dimension introduces a set of socio-behavioral

constraints that remain challenging to address. A key open question is whether users will effectively respond to the system's personalized recommendations by modifying their behavior. There is no guarantee of user compliance, as prior research in health behavior informatics consistently demonstrates that the mere provision of feedback—even when highly personalized—does not necessarily result in behavior change. The effectiveness of such recommendation systems is influenced by multiple factors, including user motivation, habitual inertia, social norms, and individual differences in environmental attitudes. While the current study evaluates the technical performance of the model using benchmark datasets, it does not include longitudinal analysis of real-world user behavior. This limits the extent to which conclusions can be drawn regarding the system's effectiveness as a behavior change intervention. Future research should therefore pursue two parallel directions: (1) further optimization of model performance and refinement of the reward function design, and (2) deployment of the system in real-world settings with longitudinal analysis of user behavior. Such studies should ideally incorporate behavioral intention measures grounded in established theoretical frameworks—namely, the Fogg Behavior Model (FBM) Theory of Planned Behavior (TPB), and Technology Acceptance Model (TAM)—to comprehensively validate the relationship between behavior, carbon consumption and sustainable lifestyle change.

This study believes that the GRU-Transformer model integrated with DRL has broad application potential in indoor carbon consumption monitoring. Through the ingenious combination of deep learning and reinforcement learning, we provide deep insights into the relationship between user behavior and carbon consumption, providing strong support for sustainable development and environmental protection. In addition, the contribution of this study is to provide an innovative method to solve carbon footprint-related issues, which has important practical significance. In future research, we will continue to work hard to improve model performance, carefully design reward functions, and further expand practical application areas. We look forward to promoting the application of deep learning in the field of environmental protection through these efforts and providing more support and solutions for reducing carbon emissions and sustainable development.

## **Conflicts of Interest**

**The authors confirm that there are no conflicts of interest.**

## **Data availability statement**

**The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.**

## **Consent for publication**

**All authors of this manuscript have provided their consent for the publication of this research.**

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